Climate Change and Substance Abuse in Bangladesh:

An Analysis of Heat Exposure and Substance Use Patterns

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1. Background

Bangladesh is facing a growing dual public health challenge characterized by the intersection of vulnerability to climate change and substance use, with serious implications for human capital development, labor productivity, and health equity. In this study, substance abuse is defined according to the World Health Organization as the harmful or hazardous use of psychoactive substances, including illicit drugs, that leads to adverse health, social, or economic consequences (World Health Organization, 2014). Substance use in Bangladesh is estimated to affect approximately 2.5 million individuals, with prevalence disproportionately high among youth and young adults aged 15-30, particularly in urban and border regions where poverty, unemployment, and weak community support systems are prevalent (World Bank Group, 2023). These patterns pose a direct threat to long-term economic development and social stability.

At the same time, Bangladesh is among the countries most exposed to the adverse impacts of climate change, including rising average temperatures, recurring heatwaves, and increasing seasonal variability. Heat exposure in this study refers to sustained or extreme ambient temperature conditions experienced by individuals, including seasonal increases in average temperature and periods of unusually high heat, which can impose physiological and psychological stress (Burke et al., 2018). Extreme heat is increasingly recognized as a critical environmental stressor that negatively affects mental health, sleep quality, emotional regulation, and psychosocial well-being (Berry et al., 2010; Clayton et al., 2017). These pathways are particularly prevalent in low- and middle-income countries, where limited access to cooling infrastructure, healthcare, and social protection amplifies vulnerability.

Evidence on the effects of heat on mental health motivates extending the analysis to substance use, which remains underexplored in climate-health research, especially in the Bangladeshi context. There is growing scientific evidence that heat exposure is associated with negative mental health consequences, including anxiety, depression, and elevated risk of suicide(Burke et al., 2018). The results of the ACCLIMATE study further show that the association between heat exposure and suicide risk is mediated by sleep problems, highlighting the importance of behavioral and psychological pathways through which climate stress operates. Substance use is especially critical for preventive policy because, in contrast to suicide, it is a potentially reversible behavioural response to climatic stress.

This study is guided by the Social Determinants of Health (SDH) framework, which reinforces that health behaviours and outcomes are shaped by social, economic, and environmental conditions rather than individual choice alone (Centers for Disease Control and Prevention, 2022; World Health Organization, 2014). Within this framework, upstream structural factors such as unemployment, low household wealth, limited educational attainment, and place of residence shape baseline vulnerability to substance use, and environmental stressors like intense heat can exacerbate these existing disadvantages.

This study leverages seasonal temperature variation to examine heat exposure as a time-varying stressor. The dataset contains validated measures of mental health, emotional regulation, and sleep quality, enabling a thorough examination of how social disadvantage and climate stress interact to affect substance use patterns. The findings aim to inform integrated, climate-resilient public health strategies that address both environmental and social determinants of substance use in Bangladesh.

The study addresses the following research questions:

1. What is the relationship between exposure to heat and substance use in Bangladesh?

2. Does this relationship vary by socio-economic factors, such as employment status, location (rural or urban), wealth, or education?

3. Is the effect of heat on substance use mediated by sleep disruption and emotional dysregulation?

2. Client Expectations

The World Bank Group's Health, Nutrition, and Population Global Practice commissioned this study with the following expectations:

1. Using a SDH framework, identify risk factors for substance use in Bangladesh and empirically assess whether exposure to high temperatures modifies these associations.
2. Write a report that:
   a. contextualizes the substance use landscape in Bangladesh;
   b. situates the study within the existing literature, highlighting the usefulness of a SDH framing;
   c. presents results, including tables, figures, and written descriptions from the analyses;
   d. discusses findings in relation to national and international evidence; and
   e. provides policy recommendations for the Government of Bangladesh.

3. Data

The analysis draws on a two-round household panel dataset from Bangladesh, collected in January 2024 (winter) and May–June 2024 (summer). The survey was conducted using the 2022 Population and Housing Census sampling frame, covering 180 Primary Sampling Units (PSUs) across both rural and urban areas, including city corporations and divisional capitals. This design captures varying temperature conditions across seasons and ensures national representativeness.

Round 1 included 3,746 households (7,492 individuals) and Round 2 included 3,744 households (7,490 individuals). Household attrition between rounds was approximately 5.6%, leaving a balanced panel of 3,521 households. The 225 households that dropped out were replaced within the same PSUs with households of similar characteristics to preserve the sampling design. 320 individuals were no longer in their households due to death, marriage, or migration. Sampling weights are used in all analyses to account for the survey design.

The dataset includes self-reported indicators of substance use as well as sociodemographic and economic data at the individual and household levels. Each PSU was linked to temperature data from 47 meteorological stations operated by the Bangladesh Meteorological Department, enabling localised assessments of heat exposure.

4. Variables of Interest

Outcome Variable

Recent substance use, as determined by self-reported recreational drug use during the previous three months, is the main outcome variable. This is the preferred outcome because it is temporally proximate to the temperature exposure window, making it more credible for examining whether recent heat exposure is associated with recent substance use behavior.

The survey includes two substance use measures: whether the respondent ever used recreational drugs, and whether they used in the past three months. Overall, 4.05% of the sample (607 individuals) reported ever using, and among these users, 47.1% (286 individuals) reported use in the past three months. We use *ever used* as our outcome because it is measured for the full sample (N = 14,982), whereas past-three-months use is only available for those who reported ever using (N = 607). Given the already-low prevalence, restricting to recent users would further reduce statistical power.

Temperature Exposure Variables

Temperature data were collected from 47 weather stations operated by the Bangladesh Meteorological Department and localised to each Primary Sampling Unit (PSU). For each respondent, we recorded daily maximum temperatures for the 15 days preceding their interview.

The dataset includes cumulative counts of days exceeding specific temperature thresholds:

- $>$35°C
- $>$32°C
- $>$30°C
- $>$28°C
- $>$25°C

From these threshold variables, we constructed three mutually exclusive temperature bins as our primary exposure specification:

- Days 28–32°C = (Days >28°C) − (Days >32°C)
- Days 32–35°C = (Days >32°C) − (Days >35°C)
- Days >35°C = original variable

Reference category: Days with maximum temperature below 30°C.

These bins capture cumulative exposure to moderate heat (30–32°C), high heat (32–35°C), and extreme heat (>35°C), with all comparisons made relative to cooler days below 30°C.

Other Variables

The dataset includes standard control variables measured in the survey to account for potential confounding factors. Age is measured categorically using four age groups: 16–35 years, 36–49 years, 50–65 years, and over 65 years, with individuals under 16 years serving as the reference group. Gender is a binary variable indicating whether respondents are female or male. Education level is captured through five categories: no education or below primary (reference group), primary completed, secondary completed, high school completed, and above high school. Employment status includes three categories: employed (encompassing low-skilled wage workers, high-skilled wage workers, white-collar workers, and self-employed), unemployed, and those not in the labour force (such as those too young to work, homemakers, or individuals with disabilities). Employed individuals (across all employment types) serve as the reference group. Household wealth is measured using tertile indicators, which include lowest, middle, and highest wealth tertiles. Location is captured as a binary variable indicating urban or rural residence. Additional controls include individual disability status, administrative division fixed effects, and household sampling weights to ensure population-representative estimates. Detailed descriptions of all control variables are included in Appendix A.

5. Descriptive Statistics

The analytic sample consists of 14,982 individuals across two survey rounds (Table 1). The sample is 44.4% urban, 50% male, and has high employment rates in both rounds (91.6% in winter and 92.0% in summer). Table 2 shows substance use prevalence rising modestly from 3.78% in winter (283 users) to 4.33% in summer (324 users). The low overall prevalence likely reflects underreporting due to stigma and legal sanctions around drug use in Bangladesh, meaning the true prevalence is almost certainly higher and our estimates should be interpreted as lower bounds.

Table 1
Sample Characteristics by Survey Round

Characteristic	Round 1 (Winter)	Round 2 (Summer)	Total
Male (%)	50.0	50.0	50.0
Urban (%)	44.4	44.4	44.4
Employed (%)	91.6	92.0	91.8
N	7492	7490	14982

Table 2
Substance Use Prevalence by Season

Season	N	Ever Used Drugs	Percent
Cool (Winter)	7492	283	3.78
Hot (Summer)	7490	324	4.33

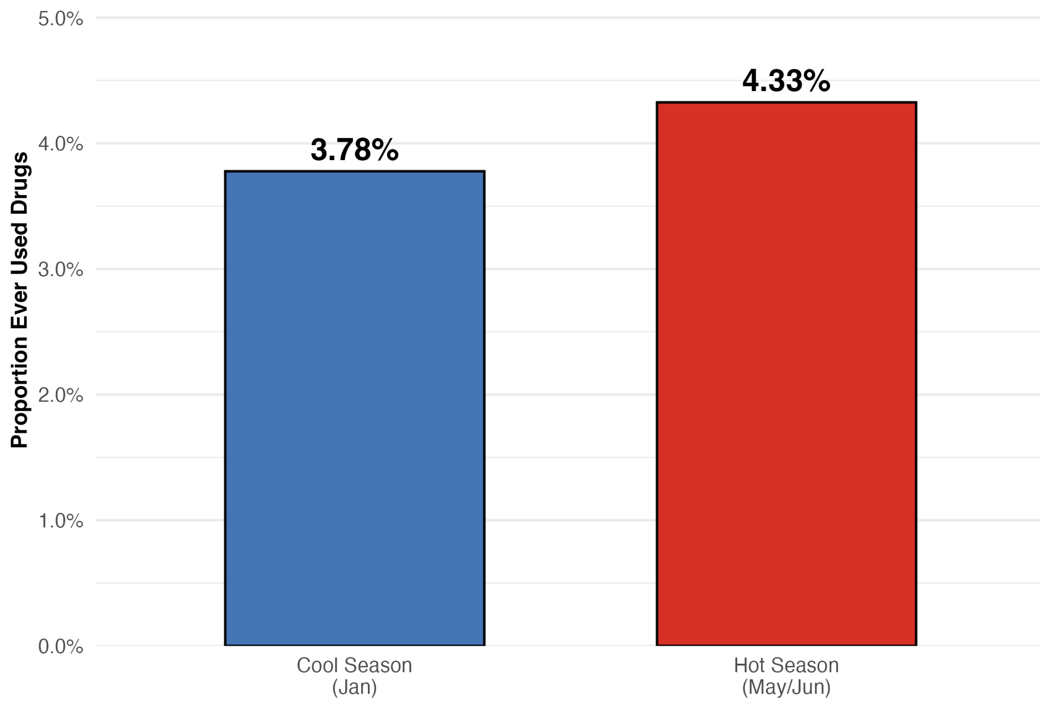

Figure 1

Substance Use Prevalence by Season

Temperature exposure varies vastly across rounds (Figure 2). In Round 1 (winter), no respondent experienced any days above 30°C in the two weeks preceding the survey. In Round 2 (summer), every day was above 30°C for all respondents. As Figure 2 illustrates, exposure was heavily concentrated at higher temperature bins, with respondents experiencing an average of 1.74 days between 30–32°C, 6.17 days between 32–35°C, and 7.09 days above 35°C, meaning the majority of summer days fell in the two hottest bins.

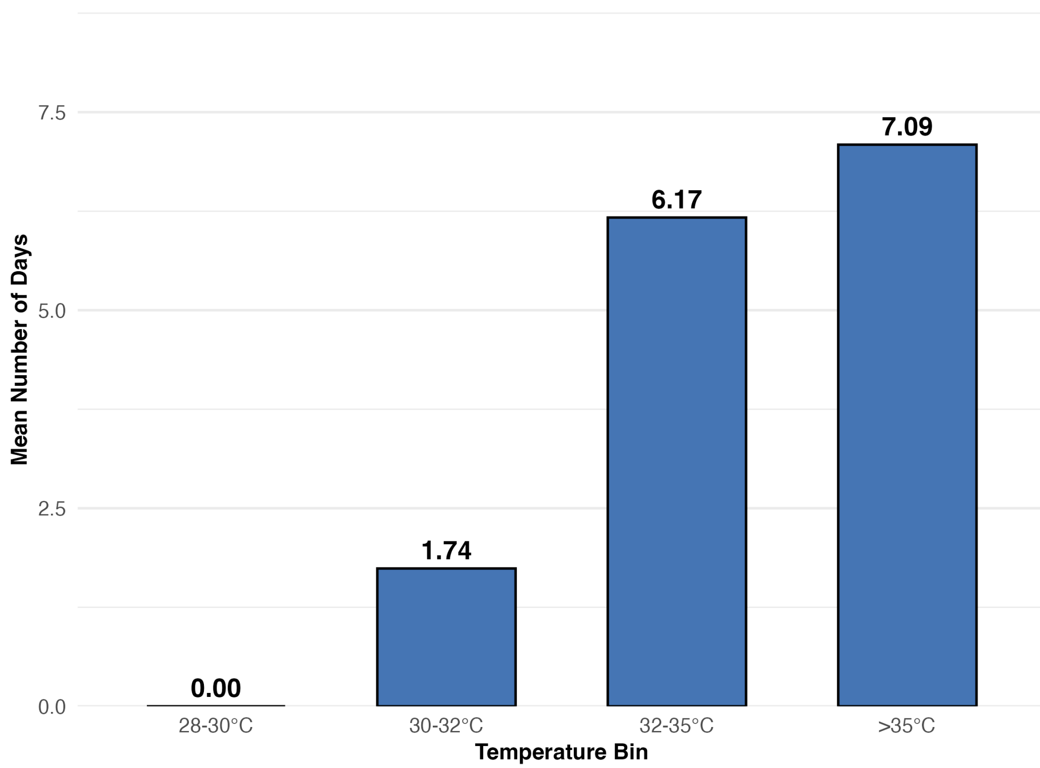

Figure 2

Mean Number of Days per Temperature Bin in the 2 Weeks Preceding Survey (Summer Round)

Table 3 presents substance use prevalence across key sociodemographic characteristics. Beyond the stark gender gap, with men reporting use at 7.32% compared to just 0.8% among women, urban residents show higher prevalence than rural residents (5.46% vs. 2.93%). Among employment groups, employed and unemployed individuals show similar prevalence (6.63% and 6.20% respectively), while those not in the labor force show substantially lower prevalence (1.02%). Education and wealth show no clear monotonic gradient across categories. These patterns are visualised in Figure 3. The figure groups gender and employment status together (panels a–b) as the two characteristics that show the strongest heterogeneous heat effects in the regression analysis, and presents location and age group (panels c–d) as contextual demographic characteristics. The gender gap is the most striking feature, with men reporting use at nearly nine times the rate of women. Among employment groups, those not in the labor force stand out with markedly lower baseline prevalence despite showing the strongest heat effects in the regression analysis, a pattern we return to in Section 7.

Table 3
Substance Use Prevalence by Sociodemographic Characteristics

Group	Category	N	Ever Used Drugs	Percent
Gender				
	Men	7490	548	7.32
	Women	7492	59	0.79
Location				
	Rural	8335	244	2.93
	Urban	6647	363	5.46
Employment Status				
	Employed	7423	492	6.63
	Unemployed	661	41	6.20
	Not in Labor Force	6104	62	1.02
Education				
	No/Below Primary	6264	277	4.42
	Primary	5783	237	4.10
	Secondary	1349	39	2.89
	High School	952	32	3.36
	Above High School	555	18	3.24
Wealth				
	Lowest Tertile	5130	190	3.70
	Middle Tertile	5023	223	4.44
	Highest Tertile	4829	194	4.02

Note: N sums exceed 14,982 due to pooling across both survey rounds.

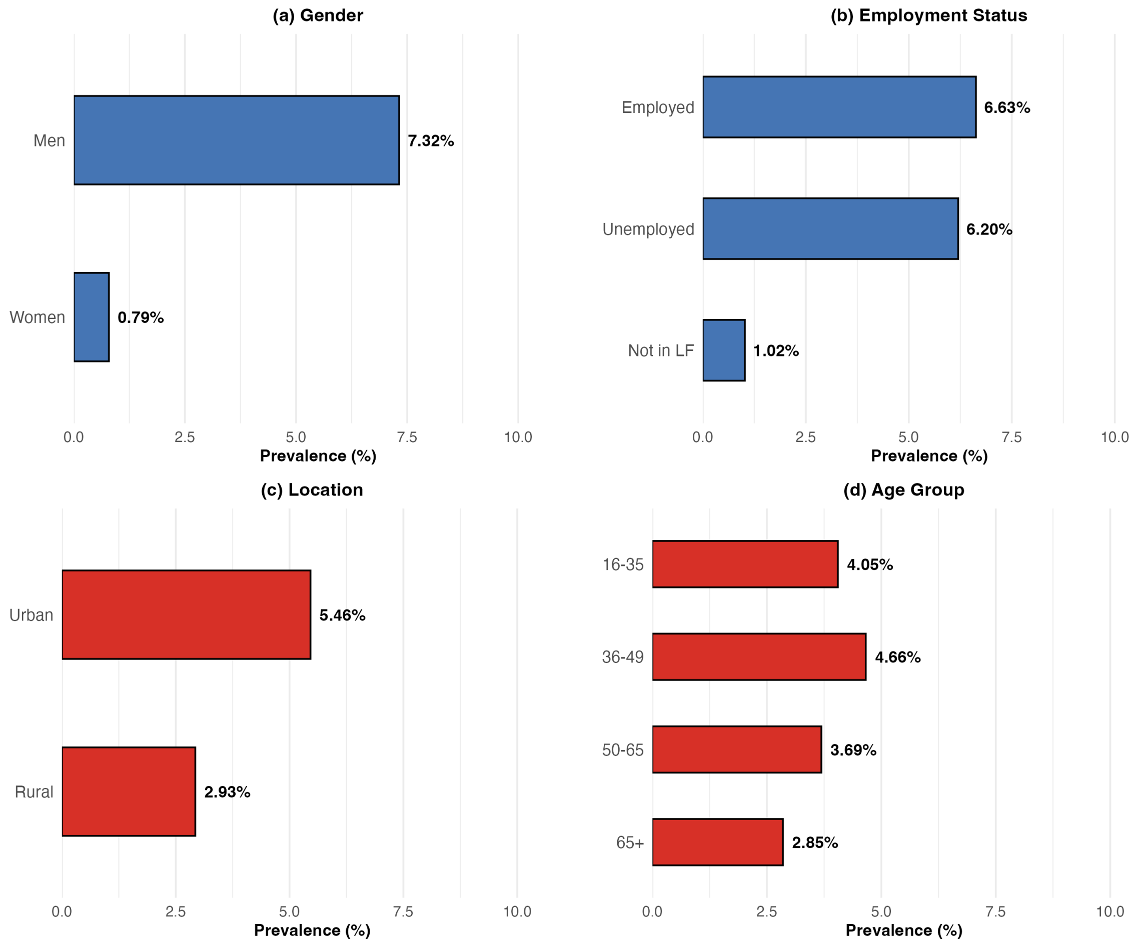

Figure 3

Substance Use Prevalence by Demographic Characteristics. Blue panels = gender and employment status; red panels = location and age group. All figures display the proportion of respondents who ever reported recreational drug use.

6. Empirical Strategy

We employ three distinct estimating equations to examine the relationship between heat exposure and substance use in Bangladesh, and to test whether this relationship varies across socioeconomic groups.

Control Variables

All regression models include the following control variables. Gender is binary (male/female). Education is coded as binary indicators for each level (primary completed, secondary completed, high school completed, above high school), with 'none/less than primary' as the reference category. Employment status includes binary indicators for unemployed and not in labor force, with employed as the reference category. Wealth is measured in tertiles (lowest, middle, highest). Location is binary (urban/rural). Division fixed effects control for variation across Bangladesh's 8 administrative divisions.

Age is excluded from our primary logistic specification due to quasi-complete separation arising from the rare 4.05% prevalence of substance use. Some age groups have very few or zero reported substance use cases, which causes estimation problems as the logistic coefficient is pushed to infinity. Age can be included in linear probability model specifications as a robustness check, since LPM does not have the same separation issues.

Research Question 1: Main Effects

We estimate the following equation using a pooled sample across both survey rounds.

General functional form:

$$y_{i,t} = \beta_0 + \beta_1(\text{Days 30–32})_{i,t} + \beta_2(\text{Days 32–35})_{i,t} + \beta_3(\text{Days} > 35)_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t} \tag{6.1}$$

Logistic-specific transformation:

$$\begin{aligned}\operatorname{logit}(P(y_{i,t}=1)) &= \log\left(\frac{P(y_{i,t}=1)}{1-P(y_{i,t}=1)}\right)\\ &= \beta_0+\beta_1(\text{Days 30–32})_{i,t}+\beta_2(\text{Days 32–35})_{i,t}+\beta_3(\text{Days}>35)_{i,t}+X'_{i,t}\gamma+\varepsilon_{i,t}\end{aligned} \tag{6.2}$$

The dependent variable $y_{i,t}=1$ if respondent i in survey round t ever reported using recreational drugs, 0 otherwise. The temperature exposure variables capture the number of days in the 15 days preceding the survey where the maximum temperature fell within specific ranges: $(\text{Days 30–32})_{i,t}$ measures days between 30–32°C, $(\text{Days 32–35})_{i,t}$ measures days between 32–35°C, and $(\text{Days} > 35)_{i,t}$ measures days above 35°C. The vector $X'_{i,t}$ includes demographic and socioeconomic characteristics: gender, education level, employment status, wealth tertiles, location, and division fixed effects. The term $\varepsilon_{i,t}$ is the error term. Estimation uses weighted logistic regression with robust standard errors clustered at the PSU level.

Days with maximum temperature below 30°C serve as the reference category. Because all winter days fell below 30°C and all summer days exceeded 30°C, our temperature comparison is inherently a seasonal comparison. We cannot fully separate the effect of heat from other seasonal factors (discussed in limitations). As robustness checks, we re-estimate the main specification using an independent linear probability model (ILPM) and a probit model to assess whether results are sensitive to the choice of functional form.

We use population-weighted logistic regression with population-average effects, following the methodology of Mahmud et al. (2024), employing survey sampling weights. For standard errors, we use Huber-White robust standard errors clustered at the PSU level. Because we estimate a logistic regression, the coefficients β_1 to β_3 represent changes in the log odds of reporting substance use.

For easier interpretation, we report results as adjusted odds ratios (AORs), obtained by exponentiating the coefficients ($\text{AOR} = \exp(\beta)$) with 95% confidence intervals. The coefficient $\exp(\beta_i)$ can be interpreted as the change in odds of substance use associated with one additional day in the relevant temperature bin, relative to days below 30°C, holding all other variables constant. For example, if $\text{AOR} = 1.15$, this indicates that each additional day above 35°C is associated with a 15% increase in the odds of reporting recreational drug use compared to days below 30°C.

Simplified Specification

Since we have limited statistical power due to restricted temperature variation within seasons, we also estimate a simpler model with one temperature cutoff:

$$y_{i,t} = \beta_0 + \beta_1(\text{Days above } 30)_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t} \tag{6.3}$$

This specification effectively captures the impact of being in the warm season (May/June) versus winter (January), since every respondent in Round 2 (summer) experienced temperatures above 30°C in the two weeks preceding the survey, while every respondent in Round 1 (winter) experienced 0 days above 30°C. This specification is equivalent to a simple season indicator and does not examine within-season variation. It serves as a robustness check and provides an overall seasonal effect estimate.

Research Question 2: Heterogeneous Treatment Effects

To examine whether the heat–substance use relationship varies by socioeconomic characteristics, we employ two complementary approaches: pooled interaction models and split-sample estimation.

Pooled Interaction Models

For formal tests of heterogeneity, we estimate the following specification for each moderator of interest:

$$y_{i,t} = \beta_0 + \beta_1 Z_i + \beta_2(\text{Days above } 30)_{i,t} + \beta_3\left[Z_i \times (\text{Days above } 30)_{i,t}\right] + X'_{-Z,i,t}\gamma + \varepsilon_{i,t} \tag{6.4}$$

where Z_i is a binary indicator for the socioeconomic characteristic of interest (e.g., Unemployed $= 1$; Employed $= 0$ is the reference group). The coefficient β_1 captures the association of the socioeconomic characteristic Z on substance use, holding heat exposure constant. The coefficient β_2 represents the effect of heat exposure for the reference group (e.g., employed individuals), while β_3 represents the difference in the heat effect for group Z relative to the reference group (e.g., unemployed vs. employed). The vector $X'_{-Z,i,t}$ includes all control variables excluding Z_i to avoid collinearity. Estimation uses weighted logistic regression with clustered standard errors.

Results are reported as adjusted odds ratios (AORs). If $\beta_3 > 0$ (AOR > 1), this indicates that the specified group shows a stronger positive association between heat exposure and substance use compared to the reference group. For example, if the reference group (employed) has AOR $= 1.01$ for heat exposure and the interaction for "not in labor force" has AOR $= 1.11$, then individuals not in the labor force experience an 11% stronger heat effect ($1.01 \times 1.11 = 1.12$ total effect vs. 1.01 for those employed).

Split-Sample Models

To ensure clearer interpretation of effect sizes across groups, we also estimate separate models for each subgroup. This approach estimates the heat–substance use relationship independently within each socioeconomic group, enabling direct comparison of effect magnitudes. While interaction models provide formal statistical tests of heterogeneity, split-sample models avoid the challenges of interpreting interaction effects in nonlinear models and provide more intuitive effect size comparisons.

For subgroups with small sample sizes or limited outcome variation, we simplify the control variable specification to ensure model convergence. Specifically: the unemployed model excludes gender and division fixed effects due to the small sample size ($n = 661$); the "not in labor force" model uses only high school and above-high-school education indicators rather than full education categories to avoid perfect prediction; and the urban-only model excludes division fixed effects to avoid estimation issues with clustered standard errors.

Heterogeneous effects are estimated for employment status (employed, unemployed, not in labor force), location (rural, urban), and gender (male, female). For gender, we test whether women experience differential heat effects. As shown in Table 3, baseline substance use prevalence is substantially lower among women (0.79%) compared to men (7.32%), and this gap in baseline prevalence is important context for interpreting any differential heat effects by gender.

Research Question 3: Mediation Analysis

The heterogeneous effects establish that heat exposure does not operate uniformly across socioeconomic groups, with the strongest associations concentrated among those outside formal employment, rural residents, and women. This pattern raises a follow-up question: by what mechanism does heat actually increase the likelihood of substance use? The mediation analysis addresses whether heat acts directly on behaviour or whether it first disrupts sleep quality or emotional regulation, and that disruption is what pushes individuals toward substance use.

The two pathways we test are sleep disruption and emotional dysregulation. The motivation comes from two sources. First, the broader literature on climate and mental health has established that sustained heat exposure places physiological stress on the body that fragments sleep quality and impairs cognitive and emotional functioning (Berry et al., 2010). Second, Mahmud et al. (2024) analysed this same dataset to examine how heat affects physical and mental health outcomes among Bangladeshi households. Their study found that heat significantly worsens emotional regulation and increases the prevalence of depression and anxiety among the same households we study, establishing that this dataset captures meaningful variation in mental health responses to temperature.

Theoretical Pathway

We hypothesize that heat does not directly cause substance use but first damages sleep quality and emotional self-regulation, and that these disruptions increase the likelihood of turning to drugs as a coping mechanism. The theoretical chain we test is:

$$\text{Heat Exposure} \rightarrow \text{Sleep Disruption } (M_1) + \text{Emotional Dysregulation } (M_2) \rightarrow \text{Substance Use}$$

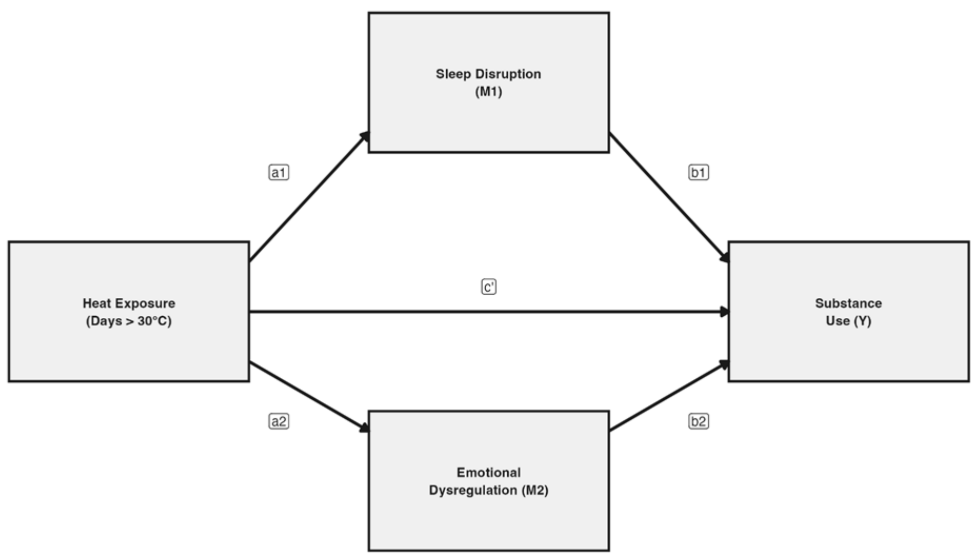

Figure 4

Proposed Mediation Pathways: Heat Exposure and Substance Use. Path labels follow standard mediation notation. Results for each path are reported in Tables 6 and 7.

Note. a1 (α_1 in Eq. 2a) = effect of heat on sleep disruption; a2 (δ_1 in Eq. 2b) = effect of heat on emotional dysregulation; b1 (β_2 in Eq. 3) = effect of sleep disruption on substance use; b2 (β_3 in Eq. 3) = effect of emotional dysregulation on substance use; c′ (β_1 in Eq. 3) = direct effect of heat net of mediators; c (γ_1 in Eq. 1) = total effect of heat on substance use. M1 = MOS Sleep Scale; M2 = Emotional Regulation Score.

The two mediators are treated as operating in parallel: each independently carries part of the heat effect forward to the outcome, and both are controlled simultaneously in the outcome model to ensure the effect of each is estimated holding the other constant. Sleep disruption is measured using the MOS Sleep Scale (*mh_sleep*; continuous; higher scores indicate more sleep problems). Emotional dysregulation is measured using the Emotional Regulation Score (*mh_emotion*; continuous). Both variables are included in both rounds of the survey, enabling us to link within-person changes in heat exposure to shifts in these mental health indicators.

The model has five paths in total. Path a_1 is the effect of heat on sleep disruption: does exposure to more hot days worsen sleep quality? Path a_2 is the effect of heat on emotional dysregulation: does heat impair the capacity for emotional self-regulation? These two paths are estimated separately, each in its own equation, with the full set of covariates held constant. Path b_1 is the effect of sleep disruption on substance use and path b_2 is the effect of emotional dysregulation on substance use. Both are estimated simultaneously in a single outcome equation, which means each mediator's effect on substance use is estimated holding the other constant. This matters because sleep quality and emotional regulation are correlated. People who sleep poorly also tend to struggle with regulating their emotions, and estimating both pathways jointly prevents us from double counting their contributions to the total effect. Path c is the total effect of heat on substance use, capturing everything together before we separate out the mediating channels. Path c' is what remains of that total effect after accounting for both mediators. If heat only worked through sleep and emotional dysregulation, c' would be close to zero because the mediators would explain everything. The indirect effect through each mediator is the product of the relevant a and b paths: $a_1 \times b_1$ for sleep and $a_2 \times b_2$ for emotional dysregulation. The proportion of the total effect that each pathway accounts for is that product divided by c.

Statistical Approach

To test whether each pathway explains a meaningful part of the total effect, we use the Sobel test (Sobel, 1982). The logic is simple. From the a paths, we already know that heat affects both mediators, and from the b paths, we know those mediators are associated with substance use. But seeing those links separately is not enough. What we really need to know is whether they connect into one statistically meaningful chain. The Sobel test does that by multiplying the a and b coefficients to estimate the indirect effect and then tests whether that product is statistically different from zero. The indirect effect through each mediator is computed as:

$$\text{Indirect effect via sleep} = \alpha_1 \times \beta_2$$
$$\text{Indirect effect via emotion} = \delta_1 \times \beta_3$$

The standard error of each indirect effect is:

$$\text{SE}(a \times b) = \sqrt{b^2 \cdot \widehat{\text{se}}_a^2 + a^2 \cdot \widehat{\text{se}}_b^2}$$

A z-statistic is then formed as $z = (a \times b)/\text{SE}(a \times b)$ and tested against the standard normal distribution. If both parts of the pathway are strong, the indirect effect will be large and significant. If one link is weak, the combined effect will be small even if the other link is strong.

One limitation of the Sobel test is that it assumes the indirect effect is normally distributed, which may not be realistic when effects are small or the sample distribution is uneven (Preacher & Hayes, 2004). To address this, we also use bias-corrected bootstrapped confidence intervals based on 1,000 replications, resampling at the PSU level to preserve the clustered structure of the survey data (Preacher & Hayes, 2004). In practice, this means we repeatedly draw new samples from the data, reestimate the indirect effect each time, and then use the distribution of those estimates to build a confidence interval. If that interval does not include zero, we interpret the pathway as a meaningful mediating channel (Preacher & Hayes, 2004). We also report the share of the total effect explained by each pathway, calculated as the indirect effect divided by the total effect c.

Estimating Equations We estimate three linear probability models (LPM via OLS). A common linear specification is used throughout, which keeps all coefficients on the same probability scale and makes the indirect effect directly interpretable in percentage-point units, avoiding the scale incompatibility that arises when mixing logistic and OLS coefficients across equations (Preacher & Hayes, 2004).

Equation 1: Total effect of heat on substance use (path c)

$$Y_i = \gamma_0 + \gamma_1 \,\text{Heat}_i + \gamma_2 X_i + \varepsilon_i \tag{1}$$

where $Y_i = 1$ if individual i has ever used recreational drugs; Heat_i is the number of days with maximum temperature above 30°C in the two weeks preceding the survey; X_i is the full vector of controls (gender, age group, disability status, time spent indoors, education, employment status, household wealth, urban residence, acute illness, non-communicable disease, and division fixed effects); and ε_i is the error term. The coefficient γ_1 is the total effect of heat on substance use (path c).

Equation 2a: Heat → Sleep disruption (path a_1)

$$M_{1i} = \alpha_0 + \alpha_1 \, \mathrm{Heat}_i + \alpha_2 X_i + \mu_i \tag{2a}$$

where M_{1i} is the MOS Sleep Scale score. The coefficient α_1 is path a_1: the effect of heat on sleep disruption.

Equation 2b: Heat → Emotional dysregulation (path a_2)

$$M_{2i} = \delta_0 + \delta_1 \, \mathrm{Heat}_i + \delta_2 X_i + \nu_i \tag{2b}$$

where M_{2i} is the Emotional Regulation Score. The coefficient δ_1 is path a_2: the effect of heat on emotional dysregulation.

Equation 3: Direct effect and b paths (paths b_1, b_2, and c')

$$Y_i = \beta_0 + \beta_1 \, \mathrm{Heat}_i + \beta_2 M_{1i} + \beta_3 M_{2i} + \beta_4 X_i + \eta_i \tag{3}$$

where β_1 is the direct effect of heat net of both mediators (path c'); β_2 is path b_1 (the effect of sleep disruption on substance use, controlling for heat and emotional dysregulation); and β_3 is path b_2 (the effect of emotional dysregulation on substance use, controlling for heat and sleep disruption).

Mediation is confirmed when the bias-corrected bootstrapped confidence interval excludes zero. As a complementary robustness check, we also estimate results using the Stata 19 `mediate` command (StataCorp, 2025), which implements the potential-outcomes framework and decomposes the total effect into natural direct and indirect effects. These results are reported in Appendix 10. Standard errors in all equations are clustered at the PSU level (180 clusters) and population weights are applied throughout.

7. Results

A. Main Effects Results (Research Question #1)

We examined the relationship between heat exposure and substance use using two approaches: a detailed temperature bins model and a simplified model.

Temperature Bins Model

Our first model divided heat exposure into three temperature ranges to examine whether moderate and extreme heat have differential effects on substance use (Table 4, Column 1).

Days between 30–32°C showed a positive association with substance use, with each additional day associated with a 28% increase in odds (AOR = 1.279, 95% CI: 0.998–1.640, $p = 0.052$). Days between 32–35°C showed a similar pattern, with a 29% increase in odds per additional day (AOR = 1.294, 95% CI: 0.978–1.712, $p = 0.071$). Both estimates were marginally significant ($p < 0.10$).

Days above 35°C showed a negative association, with each additional day associated with 22% lower odds (AOR = 0.784, 95% CI: 0.593–1.036, $p = 0.087$). This non-monotonic pattern suggests behavioural or physiological adaptation at the highest heat levels rather than a simple linear dose-response relationship. As a robustness check, we estimated an alternative specification using wider temperature bins anchored at 28°C (Appendix B).

Simplified Model

The simplified model used all days above 30°C as a single measure (Table 4, Column 2). Each additional day above 30°C increased the odds of substance use by 2% (AOR = 1.020, 95% CI: 1.004–1.036, $p = 0.012$). Because all respondents experienced either 0 days (winter) or 15 days (summer) above 30°C, this specification functions as a season indicator. The cumulative effect over 15 days is approximately 35% higher odds ($1.020^{15} = 1.35$). Figure 5 visualises this seasonal contrast as an adjusted odds ratio.

Control Variables

Several control variables showed strong and consistent patterns across both specifications. Females had substantially lower odds of substance use than males (AOR = 0.138, 95% CI: 0.094–0.204, $p < 0.001$), consistent with the descriptive patterns shown in Table 3. Urban residents showed 68%

higher odds than rural residents (AOR = 1.682, 95% CI: 1.247–2.268, p = 0.001). Education, employment status, and wealth showed modest associations, though most were not statistically significant.

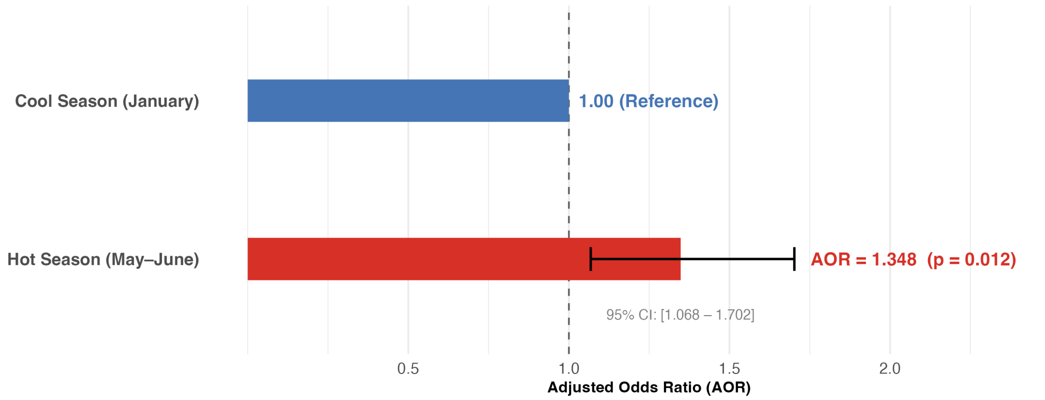

Figure 5

Seasonal Adjusted Odds Ratio for Substance Use. Hot season associated with 35% higher odds of substance use relative to cool season (AOR = 1.348, 95% CI: 1.068–1.702, p = 0.012).

Table 4

Main Effects of Heat Exposure on Substance Use

	(1) Temperature Bins	**(2) Season Proxy (Days >30°C)**
Days 30–32°C	1.279* (0.998, 1.640)	—
Days 32–35°C	1.294* (0.978, 1.712)	—
Days >35°C	0.784* (0.593, 1.036)	—
Days >30°C	—	1.020** (1.004, 1.036)
Urban (=1)	1.682*** (1.247, 2.268)	1.701*** (1.265, 2.285)
Female (=1)	0.139*** (0.094, 0.204)	0.138*** (0.094, 0.203)
N	14,982	14,982

Note: Results reported as Adjusted Odds Ratios (AOR) with 95% confidence intervals.
***p<0.001, **p<0.01, *p<0.05

Interpretation

These results provide clear evidence of a seasonal pattern of substance use in Bangladesh, with higher prevalence during the hot season compared to winter. The temperature bins show marginally significant associations ($p < 0.10$), with moderate heat (30–35°C) associated with higher odds of substance use but extreme heat (>35°C) showing a negative coefficient. This non-monotonic pattern, where the relationship peaks at moderate temperatures and reverses at extremes, suggests behavioural or physiological adaptation at the highest heat levels, rather than a simple linear dose-response relationship. The unexpected finding that extreme heat (>35°C) is associated with lower odds of substance use should not be interpreted as a protective effect. Rather, it likely reflects behavioural adaptation during extreme heat as people stay indoors more and reduce social activities, limiting substance use opportunities, or non-linear physiological responses where extreme heat causes debilitating fatigue unlike the stress response to moderate heat.

B. Heterogeneous Effects Analysis (Research Question #2)

We examined whether the relationship between heat exposure and substance use differs across socioeconomic groups using both pooled interaction models and split-sample estimation. We tested heterogeneity by employment status, location (urban vs. rural), and gender. Our findings reveal important differences in how heat affects vulnerable populations.

Employment Status Results

The interaction models show significant heterogeneity by employment status. While the heat × unemployed interaction was not statistically significant (AOR = 1.023, p = 0.298), the heat × not in labor force interaction indicates an 11% stronger association between heat and substance use compared to employed individuals (AOR = 1.111, $p < 0.001$).

Split-sample estimates (Appendix C) reveal the magnitude of these differences. Among employed individuals (N = 7,423, 6.6% substance use prevalence), heat exposure shows no significant relationship with substance use (AOR = 1.005, 95% CI: 0.988–1.022, p = 0.566). Similarly, unemployed individuals (N = 661, 6.2% prevalence) show no significant heat effect (AOR = 1.032, 95% CI: 0.992–1.074, p = 0.119).

In contrast, individuals not in the labor force (N = 6,104, 1.0% prevalence), including homemakers, students, disabled individuals, and retirees, show a strong and significant heat–substance use association. For this group, each additional day above 30°C increases the odds of substance use by 12% (AOR = 1.119, 95% CI: 1.066–1.176, $p < 0.001$).

Location Results

Our location findings challenge common assumptions about urban heat exposure. While urban areas typically experience higher temperatures due to heat island effects, rural residents show a stronger heat–substance use relationship. The interaction model directly tests whether heat effects differ by location. The heat × urban interaction term is statistically significant and negative (AOR = 0.961, 95% CI: 0.935–0.988, p = 0.005), indicating that urban residents experience a 3.9% weaker heat effect than rural residents. This likely reflects rural disadvantages in adaptive capacity, including limited access to cooling infrastructure, fewer healthcare facilities, and greater outdoor occupational exposure in agriculture, which outweigh the physical temperature differences between urban and rural areas. Split-sample estimates confirming the magnitude of this difference are reported in Appendix C.

Gender Results

Gender is an important moderator of heat–substance use relationships, though the interpretation must consider baseline prevalence differences. Women in Bangladesh report substantially lower substance use overall compared to men, consistent with strong cultural norms against female substance use. The interaction model shows that the heat × female interaction term is statistically significant (AOR = 1.160, 95% CI: 1.104–1.218, $p < 0.001$), indicating that women experience a 16% stronger heat association compared to men.

Split-sample estimates (Appendix C) reveal the magnitude of these gender differences. Among men (N = 7,490, 7.3% substance use prevalence), heat exposure shows no significant association with substance use (AOR = 1.008, 95% CI: 0.993–1.023, p = 0.297). In contrast, among women (N = 7,492, 0.8% prevalence), each additional day above 30°C is associated with a 16% increase in the odds of substance use (AOR = 1.160, 95% CI: 1.094–1.230, $p < 0.001$).

Summary of Heterogeneous Effects

Three main patterns emerge from our heterogeneous effects analysis:

- **Individuals not in the labor force show stronger heat effects:** The heat × not in labor force interaction term is statistically significant (AOR = 1.111, 95% CI: 1.079–1.144, $p < 0.001$), indicating an 11% stronger heat–substance association compared to employed individuals.
- **Rural residents bear a disproportionate burden:** The heat × urban interaction term is statistically significant and negative (AOR = 0.961, 95% CI: 0.935–0.988, p = 0.005). Split-sample estimates reveal rural residents show a 3.6% increase in odds per day above 30°C (AOR = 1.036, p = 0.001), while urban residents show no significant effect (AOR = 0.995, p = 0.599).
- **Women show heightened proportional vulnerability:** The heat × female interaction term is statistically significant (AOR = 1.160, 95% CI: 1.104–1.218, $p < 0.001$). Split-sample

estimates show women experience a 16% increase in odds per day (AOR = 1.160, $p < 0.001$), while men show no significant effect (AOR = 1.008, p = 0.297).

Table 5
Heterogeneous Effects of Heat Exposure: Split-Sample and Interaction Models

Moderator	**Subgroup**	**Heat Effect (AOR)**	**95% CI**
Employment Status			
	Employed (ref)	1.005	0.988–1.022
	Unemployed	1.032	0.992–1.074
	Not in labor force	1.119***	1.066–1.176
	Interaction: Not in labor force	*1.111****	*1.059–1.167*
Location			
	Rural (ref)	1.036***	1.014–1.058
	Urban	0.995	0.978–1.013
	Interaction: Urban	*0.961**	*0.935–0.988*
Gender			
	Men (ref)	1.008	0.993–1.023
	Women	1.160***	1.094–1.230

Note: AOR = Adjusted Odds Ratio. Effects represent the change in odds of substance use per additional day above 30°C. Interaction rows (italicised) are from pooled interaction models.
***p<0.001, **p<0.01, *p<0.05

Interpretation

These patterns reveal that heat–substance use associations are concentrated among specific vulnerable subgroups rather than operating uniformly across the population. The compounded vulnerability of individuals not in the labor force likely reflects their operation outside formal employment structures, with less access to workplace-based adaptive resources or social support networks.

Rural residents bear a disproportionate burden despite urban heat island effects making cities physically hotter. This likely reflects rural disadvantages in cooling infrastructure (air conditioning, electric fans), healthcare access, and adaptive capacity. These structural disadvantages appear to outweigh the physical temperature differences, resulting in greater vulnerability among rural populations.

Women's extreme proportional vulnerability is particularly striking given their very low baseline substance use prevalence (0.8%). Heat may disproportionately affect the small population of women who use substances, possibly reflecting compounded marginalisation where gender-based vulnerabilities intersect with substance use stigma.

C. Mediation Analysis Results (Research Question #3)

Table 6 reports the regression coefficients from all four estimating equations and serves as the reference point for the results discussed below.

Total Effect of Heat on Substance Use

Before testing whether sleep or emotional regulation explains any of the relationship between heat and substance use, we first confirm that the relationship exists. Equation 1 estimates the total effect of heat on substance use without any mediators in the model. The results show that each additional day with a maximum temperature above 30°C is associated with a 0.0006 percentage point increase in the probability of ever using recreational drugs ($\gamma_1 = 0.0006$, SE $= 0.0003$, $p = .049$). Across the full seasonal contrast of zero hot days in winter versus fifteen hot days in summer, this cumulates to approximately a 0.875 percentage point increase in substance use probability. This is a small absolute effect, which is expected given that only 4% of the sample reports ever using drugs. But it is statistically significant and consistent with the 35% increase in odds reported in the main effects analysis using logistic regression. Both estimates point in the same direction. There is a real seasonal pattern worth explaining.

This estimate is consistent with the AOR of 1.020 per additional hot day reported in the main logistic model. When baseline prevalence is very small, the absolute probability effect implied by a logistic model is approximately equal to the baseline prevalence multiplied by $(\text{AOR} - 1)$. Using the winter prevalence of 3.78% as the baseline, this gives $0.0378 \times (1.020 - 1) = 0.000756$, which is close to the OLS estimate of 0.000583. The small remaining difference is expected because the two models use different functional forms, not because they are contradicting each other. At baseline prevalence this low, both logistic regression and OLS produce nearly identical absolute probability estimates (Angrist & Pischke, 2009). Both models agree that heat is positively and significantly associated with substance use.

Effect of Heat on the Mediators (Paths a_1 and a_2)

The next question is whether heat actually disrupts sleep and emotional regulation. If it does not, there is nothing to mediate. Equations 2a and 2b test this separately for each mediator, and both confirm that heat significantly affects both.

Each additional hot day increases the MOS Sleep Scale score by 0.216 points ($\alpha_1 = 0.216$, SE = 0.018, $p < .001$). Higher scores on this scale mean more sleep problems, so heat measurably and significantly worsens sleep quality. Each additional hot day also reduces the Emotional Regulation Score by 0.165 points ($\delta_1 = -0.165$, SE = 0.016, $p < .001$). Lower scores mean worse emotional regulation, so heat impairs the capacity for self-regulation as well. Heat clearly disrupts both mental health pathways, which means the preconditions for mediation are satisfied.

Effect of Mediators on Substance Use (Paths b_1, b_2, and c')

Equation 3 introduces both mediators simultaneously alongside heat. This lets us estimate the effect of each mediator on substance use while holding the other constant, and it also gives us the direct effect of heat that remains after accounting for both pathways.

Sleep disruption is significantly and positively associated with substance use. Each additional point on the MOS Sleep Scale increases the probability of substance use by 0.0008 percentage points ($\beta_2 = 0.0008$, SE = 0.0002, $p < .001$), controlling for heat and emotional dysregulation. The chain holds on this side: heat worsens sleep, and worse sleep increases the probability of using drugs.

Emotional dysregulation, however, shows no significant association with substance use once sleep is controlled for ($\beta_3 = -0.0001$, SE = 0.0002, $p = .789$). The reason is that sleep quality and emotional regulation are correlated: people who sleep poorly also tend to struggle emotionally. When both mediators are in the same model, sleep absorbs the explanatory credit and emotional dysregulation adds nothing on top. It is not that emotional regulation does not matter; it is that once you account for sleep, emotional regulation no longer carries independent information about substance use.

The direct effect of heat after controlling for both mediators is 0.0004 (SE = 0.0003, $p = .201$), which is not statistically significant. This means that once sleep and emotional regulation are accounted for, the remaining effect of heat on substance use cannot be statistically distinguished from zero.

Table 6
Regression Coefficients from Each Estimating Equation

	(1) Total Effect	(2) Heat → Sleep	(3) Heat → Emotion	(4) Direct Effect
Panel A: Effect of heat on mediators and substance use				
Heat (days > 30°C)	0.0006^{*}	0.216^{***}	-0.165^{***}	0.0004
	(0.0003)	(0.018)	(0.016)	(0.0003)
Panel B: Effect of mediators on substance use (Equation 3 only)				
Sleep disruption (M_1)				0.0008^{***}
				(0.0002)
Emotional dysregulation (M_2)				-0.0001
				(0.0002)
Observations	14,970	14,970	14,970	14,970
Division FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes

$^{*}p < .05$ $^{***}p < .001$
OLS (linear probability model) throughout. Standard errors in parentheses, clustered at PSU level (180 clusters). Population weights applied. $N = 14{,}970$.

Indirect Effects and Mediation Tests

Knowing that heat affects sleep and sleep affects substance use is not enough on its own. We need to formally test whether the chain from heat through sleep to substance use is statistically meaningful as a whole. We do this using the Sobel test, which multiplies the a and b path coefficients together to estimate the indirect effect and then tests whether that product is significantly different from zero. Table 7 reports the Sobel test results. We also report bias-corrected bootstrapped confidence intervals based on 1,000 replications to provide more reliable inference (Preacher & Hayes, 2004).

The indirect effect through sleep disruption is $a_1 \times b_1 = 0.216 \times 0.000843 = 0.000182$. The Sobel test confirms this is statistically significant ($z = 3.88$, $p < .001$). The bias-corrected bootstrapped 95% CI $[0.000095,\ 0.000269]$ excludes zero, providing strong confirmation that sleep disruption is a genuine mediating channel. Heat worsens sleep, and worse sleep increases the probability of substance use.

The indirect effect through emotional dysregulation is $a_2 \times b_2 = (-0.165) \times (-0.0000534) = 0.0000088$, which is negligible. The Sobel test is not significant ($z = 0.27$, $p = .789$) and the bootstrapped CI $[-0.000052, 0.000071]$ includes zero. Emotional dysregulation does not function as a meaningful mediating channel once sleep is accounted for.

As a complementary robustness check, we also estimated causal mediation effects using the potential-outcomes framework implemented in the Stata 19 `mediate` command (StataCorp, 2025), which includes a heat-mediator interaction term in the outcome equation and produces a slightly more conservative proportion mediated estimate of 24.9% for the sleep pathway compared to 31.1% from the Sobel test. Despite this difference in point estimates, both approaches confirm that sleep disruption is a significant mediating channel and emotional dysregulation is not. Full results are reported in Appendix C.

Table 7

Sobel Test and Bootstrapped Indirect Effects of Heat on Substance Use

Pathway	a	b	$a \times b$	**Sobel** z	**BC 95% CI**	p
Heat → Sleep → Substance Use	0.216	0.000843	0.000182	3.88	[0.000095, 0.000269]	$< .001^{***}$
Heat → Emotion → Substance Use	−0.165	−0.0000534	0.0000088	0.27	[−0.000052, 0.000071]	.789

Note. $^{***}p < .001$. a = OLS coefficient from heat on mediator (Eqs. 2a/2b). b = OLS coefficient from mediator on substance use, controlling for both mediators (Eq. 3). Sobel $z = (a \times b)/\sqrt{b^2 \cdot \widehat{\mathrm{se}}_a^2 + a^2 \cdot \widehat{\mathrm{se}}_b^2}$ (Sobel, 1982). BC 95% CI = bias-corrected percentile bootstrap, 1,000 replications, resampled at PSU level (Preacher & Hayes, 2004). $N = 14{,}970$.

Decomposition of the Total Effect

Figure 6 shows the full decomposition of the total heat effect into its three components. Of the total effect of heat on substance use, 31.1% travels through sleep disruption, 1.5% travels through emotional dysregulation (not significantly different from zero), and the remaining 67.4% is the direct effect that bypasses both mediators. Together the two mediators account for approximately 32.6% of the total effect, with sleep carrying almost all of that mediated share.

This pattern is consistent with partial mediation. Sleep disruption is a confirmed channel through which heat increases substance use risk, but it does not provide a complete picture. The remaining 67.4% direct effect suggests that other mechanisms not measured in this survey also play a role. These could include economic disruption from heat, changes in social activity patterns during hot seasons, or other physiological stress responses. Future research with richer data could test these additional pathways.

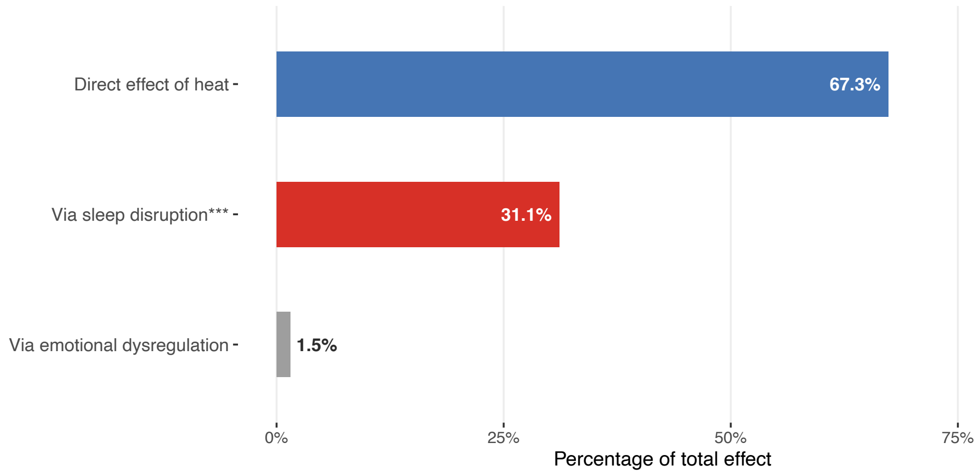

Figure 6

Decomposition of the Total Heat Effect on Substance Use.

Note. Sleep pathway: indirect effect $= 0.000182$; Sobel $z = 3.88$, $p < .001$; BC 95% CI $[0.000091,\ 0.000269]$ excludes zero. Emotion pathway: indirect effect $= 0.0000088$; Sobel $z = 0.27$, $p = .789$; BC 95% CI $[-0.000050,\ 0.000073]$ includes zero.

Summary

Three findings emerge clearly from the mediation analysis. First, heat has a significant total effect on substance use and each additional hot day is associated with a higher probability of drug use, consistent across both logistic and OLS specifications. Second, sleep disruption is a confirmed and statistically significant mediating pathway. Heat worsens sleep quality, and worse sleep significantly increases the probability of substance use. The indirect effect through sleep accounts for 31.1% of the total heat effect, confirmed by both the Sobel test ($z = 3.88$, $p < .001$) and bias-corrected bootstrapped confidence intervals that exclude zero. Third, emotional dysregulation does not function as an independent mediating channel. Although heat significantly impairs emotional regulation, once sleep is controlled for, emotional dysregulation adds no additional predictive power for substance use. The overall pattern is consistent with partial mediation. Sleep disruption is a real and meaningful channel but does not fully account for the relationship between heat and substance use, leaving room for other mechanisms to be explored in future research.

Limitations

Three limitations of the mediation analysis are worth noting. First, we measure sleep and emotional regulation at two points in time but we cannot track how they change day by day as temperatures rise. This means we cannot completely rule out the possibility that some other unobserved factor is driving both sleep problems and substance use at the same time, rather than heat causing one and then the other. Second, the mediation approach assumes that once we control for all the covariates in our model, there is no remaining hidden variable that affects both the mediator and substance use. If something we did not measure affects both sleep quality and drug use independently of heat, our indirect effect estimate would be picking up that relationship rather than the heat pathway. Third, sleep and emotional regulation are correlated with each other in the data. We handle this by estimating both in the same equation, but this means each pathway's contribution is estimated holding the other fixed. In reality both tend to move together when heat rises, so our estimates may understate how much each pathway individually contributes to the total effect.

8. Identification Strategy and Assumptions

Our identification strategy relies on comparing individuals exposed to different temperature levels across the two survey rounds, conditional on observed characteristics. These are associational results and can only be interpreted as causal if we assume heat exposure is as-good-as-random after controlling for demographic characteristics.

We cannot identify:

- Purely causal effects without additional assumptions (potential for omitted variable bias)
- Dose-response at moderate temperatures (limited variation in some temperature ranges)
- Mechanisms (physiological stress vs. economic stress vs. social patterns)
- Long-term effects or adaptation (two survey rounds)

9. Limitations

1. **Low outcome rate and self-reported measure:** Substance use affects about 4% of the sample and is self-reported, which means it is likely underreported due to stigma. With relatively few reported users and limited temperature variation, the analysis is better at detecting larger effects than smaller ones. If underreporting is random, it may weaken our estimates; if it varies with temperature, the direction of bias is unclear.

2. **Seasonal confounding:** Our design compares winter and summer, and we find higher substance use in summer. However, temperature differences are mixed with other seasonal factors such as farming cycles, work patterns, festivals, and changes in substance availability. While we control for factors like employment, we cannot fully separate the effect of heat from these broader seasonal influences. Our results therefore reflect overall summer conditions, not heat alone.

3. **Limited temperature variation:** There is very little variation in temperature within each season. Winter days are all below 30°C, while summer days are all above 30°C and clustered in a narrow range. This makes it difficult to study dose-response relationships and reduces our ability to detect more subtle effects.

4. **Short panel:** The data include only two survey rounds. This limits our ability to study long-term effects, adaptation over time, or differences between short-term and sustained exposure. It also prevents us from using individual fixed effects to control for unobserved differences.

5. **Measurement at the PSU level:** Temperature is measured at the PSU level rather than for each individual. Actual exposure may differ depending on factors like occupation, housing, and time spent outdoors, which introduces measurement error.

6. **Selection into locations:** People may sort into different areas based on characteristics related to both temperature exposure and substance use. We control for observable factors like wealth, education, and urban/rural status, but some unobserved differences may remain.

7. **External validity:** These findings are specific to Bangladesh and may not generalise to other settings with different climates, social norms, or health systems.

Interpretation

Overall, the results should be interpreted as associations after controlling for observed characteristics. They are suggestive of a causal relationship because the findings are consistent across different model specifications, align with theory, and match prior evidence such as Mahmud et al. (2024) on the effects of heat on health. However, stronger causal claims would require additional research designs.

10. Discussion

This study examined the relationship between heat exposure and substance use in Bangladesh using a two-round panel dataset covering winter and summer seasons. Three main findings emerge.

First, we find evidence of a seasonal pattern, with higher substance use prevalence during the hot season. The relationship is non-linear: moderate heat (30–35°C) shows positive associations with substance use, while extreme heat (>35°C) shows a negative association, likely reflecting behavioural adaptation during the hottest conditions.

Second, heat-substance use associations are concentrated among specific vulnerable subgroups rather than operating uniformly across the population. Individuals not in the labor force show an 11% stronger heat association compared to employed individuals. Rural residents experience significant heat effects (3.6% increase per day above 30°C), while urban residents show no significant relationship, despite urban heat island effects making cities physically hotter. Women show a 16% increase in odds per hot day, while men show no significant effect, though this finding must be interpreted cautiously given women's very low baseline prevalence of 0.8%.

Third, the mediation analysis reveals that sleep disruption is a significant pathway through which heat exposure increases substance use risk. Each additional hot day worsens sleep quality, and worse sleep in turn increases the probability of substance use. The indirect effect through sleep accounts for approximately 31% of the total heat effect, confirmed by both the Sobel test ($z = 3.88$, $p < .001$) and bias-corrected bootstrapped confidence intervals that exclude zero. Emotional dysregulation, while also significantly impaired by heat, does not function as an independent mediating channel once sleep is controlled for. This pattern is consistent with partial mediation and suggests that the heat–substance use relationship operates partly through a psychophysiological stress pathway: heat damages sleep, and sleep-deprived individuals are more likely to turn to substances as a coping mechanism. The finding that a substantial direct effect remains after accounting for both mediators points to additional mechanisms not captured by this analysis, including potential economic disruption, changes in social behaviour during hot seasons, and other physiological stress responses that future research should explore.

Interpretation of Heterogeneous Effects

The concentration of heat effects among vulnerable subgroups reveals underlying structural inequalities.

Employment Status

Individuals not in the labor force face differential vulnerabilities during hot weather. This category is heterogeneous, including homemakers (predominantly women), students, retirees, and disabled individuals, and does not necessarily correspond to lower income. The stronger heat association may reflect structural factors such as more time spent at home (possibly without sufficient cooling), lesser mobility or access to air-conditioned public spaces, social isolation, or differential exposure patterns compared to those in formal employment. However, the mechanisms underlying this relationship require further investigation, particularly given the overlap between labor force status and other demographic characteristics such as gender and age.

Location

Rural residents bear a disproportionate burden despite lower absolute temperatures. This pattern reflects rural disadvantages in adaptive capacity, including less access to cooling infrastructure (air conditioning, electric fans), fewer healthcare facilities, limited public health messaging about heat risks, and more outdoor occupational exposure in agriculture. These structural disadvantages outweigh the physical temperature differences, resulting in added vulnerability among rural populations.

Gender

Women's heightened proportional vulnerability must be interpreted cautiously given their very low baseline prevalence. The strong proportional association among women does not mean women have higher absolute rates of substance use during hot weather, as men still show much higher overall prevalence. Rather, it suggests that among the small population of women who do use substances, heat appears to be a particularly strong correlate. This may reflect compounded vulnerabilities: women who use substances may already face greater marginalisation given strong social sanctions, and heat stress may exacerbate these existing vulnerabilities.

Policy Implications

These findings have important implications for climate adaptation and public health policy in Bangladesh and similar contexts, and substantiate that climate-related health interventions must be carefully targeted. Universal heat warnings or cooling centres may miss the populations most at risk including those not in the labor force, rural residents, and women who use substances. Contextualised policy interventions will necessitate addressing the structural inequalities, including limited rural infrastructure, economic marginalisation, and gender-based vulnerabilities, through which heat exposure creates particularly adverse impacts for disadvantaged groups.

Integrating Substance Use Risk into National Heat Action Planning: Substance use risk should be incorporated into Bangladesh's national heat action plan, with targeted protocols for rural upazilas where the heat effect is strongest. Universal heat warnings alone are insufficient, and location-based and population-specific protocols are needed to reach the communities bearing the greatest burden.

Sleep Screening as an Intervention Point: Heat raises substance use risk partly by disrupting sleep quality. Government treatment centres and NGO health programmes should add sleep screening to their protocols during April–September. Sleep quality is modifiable through household-level cooling support and community education on sleep hygiene during peak heat months, and integrating sleep health into substance use prevention upstream could mitigate behavioural escalation before it occurs.

Seasonal Disaggregation of Drug Use Data: The Department of Narcotics Control currently tracks seizures rather than health trends. Requiring seasonal disaggregation of its annual drug use data would enable pre-summer prevention planning at no additional cost, and would provide the monitoring infrastructure needed to evaluate future interventions.

Community Health Worker Protocols: A substance use screen should be added to community health worker visit protocols during summer months to directly reach the three highest-risk groups identified in this study: individuals not in the labor force, rural residents, and women. Female community health workers and non-stigmatising, private access points are necessary design elements for any intervention targeting heat-vulnerable women, given significant barriers to treatment access and social stigma around female substance use.

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Appendix A: Detailed Variable Descriptions

Table 8
Control Variables

Variable	**Description**	**Categories/Values**	**Reference Group**
Age	Age group of the respondent	16–35 years; 36–49 years; 50–65 years; Over 65 years	Under 16 years
Gender	Sex of respondent	Female; Male	Male
Education	Highest level of education completed	No education/below primary; Primary completed; Secondary completed; High school completed; Above high school	No education/below primary
Employment	Employment status	Low-skilled wage worker; High-skilled wage worker; White-collar worker; Self-employed; Unemployed; Not in the labour force	Employed (any type)
Wealth	Household wealth tertile	Lowest tertile; Middle tertile; Highest tertile	Lowest tertile
Location	Place of residence	Urban; Rural	Rural
Disability	Disability status	Has disability; No disability	No disability
Division	Administrative division	Fixed effects for each division	N/A
Weight	Household sampling weight	Continuous	N/A

Appendix B: Sensitivity Analysis

Alternative Temperature Bin Specification

We re-estimated the main impacts model using a different temperature bin specification anchored at a broader 28°C lower threshold as a robustness check. This alternative divides exposure into two bins: Days 28–32°C and Days >32°C, with days below 28°C serving as the reference group, as opposed to three bins (Days 30–32°C, Days 32–35°C, and Days >35°C).

As shown in Table 9, this specification produces substantially attenuated and statistically insignificant estimates across both bins. In contrast to AOR = 1.279 (p = 0.052) and AOR = 1.294 (p = 0.071) in the preferred specification, the Days 28–32°C bin provides AOR = 1.048 (p = 0.644) and the Days >32°C bin yields AOR = 1.016 (p = 0.330). This attenuation results from Days 28–30°C being included in the lower bin, which dilutes the signal focused in the 30–35°C range and has no discernible correlation with substance use. Standard errors are lower under the broader bin specification, but the coefficients themselves are attenuated, indicating that this is an effect size issue rather than a power issue.

We therefore retain the 30°C threshold as our preferred specification. The results appear to be localised in the mild 30–35°C range.

Table 9
Main Effects: Alternative Temperature Bins (28°C threshold)

Variable	**AOR**	**95% CI**	**p-value**
Days 28–32°C	1.048	0.859–1.279	0.644
Days >32°C	1.016	0.984–1.050	0.330
Female	0.138	0.094–0.204	<0.001
Urban	1.701	1.264–2.288	<0.001
Unemployed	0.912	0.604–1.379	0.663
Not in labor force	0.778	0.533–1.137	0.195

Note: All models include education fixed effects, wealth tertiles, division fixed effects, and sampling weights. N = 14,982. Standard errors clustered at PSU level (180 clusters).

Table 10

Comparison of Preferred vs. Alternative Specification

Temperature Bin	**Preferred Spec (30°C threshold)**	**Alternative Spec (28°C threshold)**
Lower bin	Days 30–32°C: AOR = 1.279, p = 0.052	Days 28–32°C: AOR = 1.048, p = 0.644
Middle bin	Days 32–35°C: AOR = 1.294, p = 0.071	(collapsed into upper bin)
Upper bin	Days >35°C: AOR = 0.784, p = 0.087	Days >32°C: AOR = 1.016, p = 0.330

Note: Preferred specification uses days below 30°C as reference category.

Alternative specification uses days below 28°C as reference category.

Appendix C: Causal Mediation Analysis: Robustness Check

As a complementary check on the Sobel test results reported in the main text, we estimated causal mediation effects using the Stata 19 `mediate` command (StataCorp, 2025), which implements the potential-outcomes framework developed by Imai et al. (2010). Rather than comparing a one-unit change in heat exposure, this approach compares the full seasonal contrast: zero days above 30°C in winter versus 15 days above 30°C in summer. It decomposes the total seasonal effect into four components, each defined below and reported in Table 11.

The Total Effect (TE) is the overall effect of moving from winter to summer heat conditions on substance use, combining everything that operates through the mediator and everything that bypasses it (Imai et al., 2010). It is equivalent to the reduced-form seasonal effect estimated in Equation 1. The Natural Indirect Effect (NIE) is the portion of the total effect that operates through the mediator (Imai et al., 2010): the share of the seasonal heat effect that works by first changing sleep quality or emotional regulation and then affecting substance use through that change. The Natural Direct Effect (NDE) is the portion of the total effect that bypasses the mediator entirely, representing the effect of heat on substance use through all other channels not captured by the mediator (Imai et al., 2010). The Pure Natural Indirect Effect (PNIE) is a more conservative version of the NIE that holds the mediator fixed at the level it would take in the absence of heat exposure (Imai et al., 2010). When the outcome model includes a heat–mediator interaction term, as it does here by default, the PNIE is smaller than the NIE and provides a lower bound on the mediated effect. By construction, $\text{TE} = \text{NIE} + \text{NDE}$.

The results are consistent with the Sobel analysis. For the sleep mediator, the Total Effect ($\text{TE} = 0.00873$, $p = .047$) matches the main effects finding. The Natural Indirect Effect ($\text{NIE} = 0.00217$, $p = .028$) is statistically significant, with the confidence interval excluding zero, confirming that sleep disruption mediates a meaningful share of the total seasonal heat effect. This represents approximately 24.9% of the total effect, which is slightly more conservative than the Sobel estimate of 31.1% because the potential-outcomes model includes a heat–sleep interaction term by default, which absorbs some variance attributed to the indirect pathway. The Natural Direct Effect ($\text{NDE} = 0.00657$, $p = .151$) is not statistically significant, consistent with the Sobel finding that the direct effect loses significance once sleep is controlled. For the emotional dysregulation mediator, the NIE (-0.00068, $p = .391$) is not statistically significant, confirming the conclusion from the main analysis. Both approaches agree: sleep disruption is a genuine mediating channel and emotional dysregulation is not.

Table 11

Causal Mediation Analysis: Natural Direct and Indirect Effects of Heat on Substance Use

	Coefficient	**Robust SE**	*p*	**95% CI**
Panel A: Mediator = Sleep Disruption (mh_sleep)				
Total Effect (TE)	0.00873*	(0.00440)	.047	[0.00012, 0.01735]
Natural Indirect Effect (NIE)	0.00217*	(0.00098)	.028	[0.00024, 0.00409]
Natural Direct Effect (NDE)	0.00657	(0.00457)	.151	[−0.00239, 0.01552]
Pure Natural Indirect Effect (PNIE)	0.00336***	(0.00093)	< .001	[0.00155, 0.00517]
Panel B: Mediator = Emotional Dysregulation (mh_emotion)				
Total Effect (TE)	0.00876*	(0.00440)	.046	[0.00014, 0.01739]
Natural Indirect Effect (NIE)	−0.00068	(0.00079)	.391	[−0.00223, 0.00087]
Natural Direct Effect (NDE)	0.00944*	(0.00461)	.041	[0.00040, 0.01848]
Pure Natural Indirect Effect (PNIE)	0.00124	(0.00076)	.100	[−0.00024, 0.00272]
Observations	14,970			
Division FE and controls	Yes			
Clustered SE (PSU)	Yes			

$^{*}p < .05$ $^{***}p < .001$

Estimated using Stata 19 `mediate` command (StataCorp, 2025) with linear models for both outcome and mediator. Treatment contrast: heat = 0 (winter) vs. heat = 15 (summer). Outcome model includes treatment–mediator interaction. TE = NIE + NDE. NIE = natural indirect effect. NDE = natural direct effect. PNIE = pure natural indirect effect (conservative NIE bound). SEs clustered at PSU level (180 clusters). Population weights applied. $N = 14{,}970$.