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Mental health impacts of particulate matter exposure and non-optimal temperature among rural and urban children in eastern China

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Yangyang Wu[1,2], Jing Wei[3], Biran Cheng[1], Hong Sun[4], Yidong Zhou[5], Chen Li[1,6], Peng Wang[1,7], Hao Zhang[8], Yiyi Wang[9], Lei Huang[1,10] ✉ & Kai Chen[11,12]

Over 100 million children worldwide suffer from mental distress, with incidence rates steadily increasing. However, the combined impacts of air pollution and non-optimal temperature on schoolchildren's mental health, as well as the disparities across urban and rural schools and between genders, remain insufficiently explored. Utilizing 95,658 mental distress records from school children in eastern China, we developed nine composite exposure scenarios to evaluate the mental health impacts of short-term (0–14 days) exposure to particulate matter (PM) air pollution (i.e., PM_1, $PM_{2.5}$, PM_{10}), average temperature, and temperature variability (including both intra-day and inter-day temperature fluctuations). We found that children's mental distress was significantly associated with PM pollution, particularly in urban schools, with rising risk trends and intensified hazards for finer particles ($PM_{10} < PM_{2.5} < PM_1$). For each 10 μg/m³ increase, the relative risks of mental distress absenteeism for PM_1, $PM_{2.5}$, and PM_{10} were 1.017, 1.011, and 1.008, respectively. Polluted days coupled with warming temperature >10 °C and large intra-day (>10 °C) and inter-day fluctuations (<−2.5 or >0 °C) consistently exhibited higher and increasing risks, with relative risks ranging from 1.031 to 1.534 ($p < 0.05$). Girls, constituting 61.4% of the cases examined, exhibited greater vulnerability than boys, with higher threats and rising trends across all scenarios. Among the affected children, 77.9% didn't receive medical assistance. Given the global warming trend, it's crucial to address the combined impacts of extreme weather and PM pollution on schoolchildren's mental health, particularly for girls and in rapidly urbanizing areas.

Mental illness is increasingly recognized as a significant global public health challenge among children. The Global Burden of Disease Assessment reports an 11.58% increase in disability-adjusted life years attributed to mental disorder in children aged 5–14 over the past 30 years[1], with 14% of this population experiencing severe mental disorders and a consequent reduction in life expectancy of 10 to 20 years[2]. Despite these alarming statistics, children's psychological issues are often neglected and stigmatized, resulting in

[1]State Key Laboratory of Water Pollution Control and Green Resource Recycling, School of the Environment, Nanjing University, Nanjing, China. [2]Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong, China. [3]Department of Atmospheric and Oceanic Science, Earth System Science Interdisciplinary Center, University of Maryland, College Park, MD, USA. [4]Jiangsu Provincial Center for Disease Control and Prevention, Nanjing, China. [5]Department of Statistics, University of California, Davis, CA, USA. [6]Center for Public Health Research, Medical School, Nanjing University, Nanjing, Jiangsu, China. [7]Faculty of Civil Engineering and Mechanics, Jiangsu University, Zhenjiang, Jiangsu, China. [8]Sustainable Energy and Environment Thrust, Function Hub, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China. [9]School of Energy and Environment, Anhui University of Technology, Maanshan, China. [10]Basic Science Center for Energy and Climate Change, Beijing100081China. [11]Department of Environmental Health Sciences, Yale School of Public Health, New Haven, CT, USA. [12]Yale Center on Climate Change and Health, Yale School of Public Health, New Haven, CT, USA.
✉e-mail: huanglei@nju.edu.cn

insufficient societal and parental focus on addressing their mental health needs[3,4].

Emerging evidence underscores the critical role of PM pollution and non-optimal temperatures in exacerbating mental health issues[5–7]. PM can penetrate the brain via the olfactory bulb and blood-brain barrier, affecting stress and emotional regulation[7]. A nationwide survey in China, for instance, detected a 28% increase in the risk of poor mental health among adults for each 10 μg/m³ increase in $PM_{2.5}$ concentration[8]. Additionally, rising temperature may intensify mental crisis, with suicide rates increasing by 1.7% for each 1 °C rise in average temperature[9,10].

While the individual impacts of air pollution and non-optimal temperatures on mental health are well-documented[11,12], the synergistic effects of combined exposure to these environmental stressors remain poorly understood. Such composite exposures may potentiate mental distress through interconnected biological pathways, including neuroinflammation, immune dysregulation, oxidative stress, and neurotransmitter imbalances. Thus, it's imperative to incorporate considerations of children's climate resilience into psychological public health initiatives, tailored to their unique susceptibility to compounded environmental risks. Moreover, existing evidence, primarily derived from adult populations[13], couldn't accurately capture the determinants of children's mental health due to differences in physiological function, behavioral patterns, and social environments. Additionally, reliance on suicide statistics or hospital admissions may overlook individuals without hospital records or with milder conditions[11,14], potentially underestimating the broader health, social, and educational impacts.

Concurrently, there is growing awareness of the urban-rural divide in mental health outcomes[12,15,16]. Urban areas, with higher industrial and vehicular emissions, heat island effects, and dense populations, may pose greater mental health risks, whereas rural areas face challenges such as limited healthcare resources, inadequate air purification and temperature control, and lower awareness of protective measures. Previous evidence also highlights differential psychiatric responses between males and females arising from the intricate interplay of biological, psychological, and social factors[17–19]. Given that current research predominantly focuses on adults[5,8,20], there is a critical need for non-clinical community- or school-centered studies that explore these gender and geographic disparities among schoolchildren.

Mental health disorders are among the leading contributors to the health burden of Chinese children from non-communicable diseases[21]. Considering that children spend roughly one-third of their day in school, school environment substantially influences their mental well-being[22]. This study utilizes a composite exposure framework to assess risk interactions between particulate matter, non-optimal temperature, and schoolchildren's mental distress. The research aims to furnish insights for early intervention strategies within healthcare and education systems to mitigate mental health burdens and foster healthy school environments[22].

Methods

Mental health monitoring among schoolchildren

The study encompasses 89 counties in Jiangsu Province, China (Fig. 1, Fig. S1). Daily records detailing children's absences due to mental distress were sourced from the national school health monitoring system, collaboratively managed by educational institutions and regional disease control centers[23]. The reporting procedure involves the child's guardian or class teacher initially filling out a questionnaire to report symptoms to the school doctor or community hospital. These health professionals then confirm the mental health diagnosis and document the absence's specifics, including duration (start and end dates), type of mental health condition, symptoms presented, individual characteristics, and contextual information from the school and region. This comprehensive documentation process also includes collecting oral symptom descriptions from parents and details of any related outpatient or hospitalization. For absences following hospital visits, medical documentation must be provided to the school, ensuring informed consent for the child's return to class. Quality control of data collection is conducted daily by staff at the regional disease control center (Text S1).

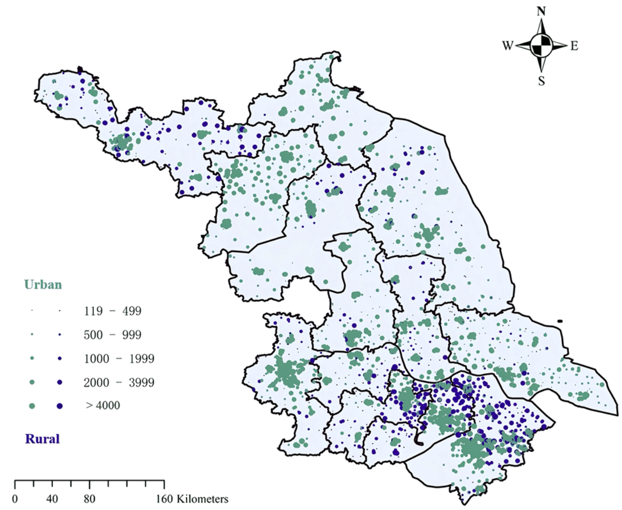

Fig. 1 | Spatial distribution of urban and rural schools across 89 counties in Jiangsu Province, China.

During the data cleaning process, mental health diseases and symptoms were extracted according to the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10), including disorders such as depression, neurasthenia, and anxiety. To mitigate confounding effects, several measures were implemented: (1) potential mental discomfort related to academic stress, other diseases, or physical injuries was controlled based on the text recognition of corpus; (2) COVID-19-related records, including children with COVID-19 or had intersecting activity paths with COVID-19 cases, were excluded; (3) Given the limited and inconsistent evidence linking air pollution to severe mental disorders, especially in children, and the influence of multiple other risk factors such as genetics and family environment[14,24–26], this study focused on short-term exposure effects and excluded absences lasting 1 week or longer to better capture environmentally induced acute responses; (4) for individuals with multiple consecutive absences, only the initial date of the absence period was retained to minimize confounding from repeated events. The geographic coordinates (longitude and latitude) of each school were matched by the geographic information system using a unique identification code for the region and the school. Data extraction, collection, and quality control were facilitated by the Jiangsu Provincial Center for Disease Control and Prevention. The final dataset comprises 95,658 records of personal absences due to mental health issues from 2016 to 2021 across primary and secondary schools. From these records, we derived a multi-school-centered time series dataset summarizing daily counts and rates of mental distress-related absences. Detailed data cleaning procedures and the keywords for identifying mental distress are documented in Text S1, S2.

Overall, the study was based on de-identified data obtained from the Jiangsu Center for Disease Control and Prevention, with no direct participant contact, identifiable information, or collection of biological specimens involved. Data use was authorized for research purposes in accordance with the Declaration of Helsinki.

Particulate matter and non-optimal temperature exposure estimation

High-resolution daily estimates of particulate matter concentrations, including PM_1, $PM_{2.5}$, and PM_{10}, were obtained from the China High Air Pollutants (CHAP) dataset for the period 2016 to 2021, with a spatial resolution of 1 km[27–29]. These exposure data were derived from Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-Angle implementation of Atmospheric Correction (MAIAC) aerosol products using developed spatiotemporal machine learning models. The cross-validation coefficients of determination (CV-R^2) for PM_1, $PM_{2.5}$, and PM_{10} were reported as 0.83, 0.92, and 0.90, respectively[27,28,30]. Using the k-nearest neighbors (k-NN) algorithm implemented in the FNN package in R version 3.6.1, we quantified the daily pollution exposure for each school over the previous 0–14 days. This non-parametric algorithm is favored for its straightforward implementation and effectiveness in handling complex relationships between features and outcomes that are not readily modeled by parametric approaches[31]. It operates by identifying the nearest particulate matter grid center points to each school location based on geographic proximity, thereby accurately estimating localized environmental exposure. The average ambient concentrations of ambient particulate matter in school environment were 23 μg/m³ for PM_1, 38 μg/m³ for $PM_{2.5}$, and 70 μg/m³ for PM_{10}.

Hourly temperature simulation (2-meter temperature index) at a resolution of 9-km was derived from the ERA5-Land meteorological reanalysis dataset, provided by the European Centre for Medium-Range Weather Forecasts[32]. We also derived daily average temperature (DAT) in the past 0–14 days based on 24-h temperature for each school through k-NN algorithm. Moreover, we calculated the accordingly intra-day change (IDC) of temperature derived from max and min hour temperature on the day, as well as IDFs based on the DAT between the lag day and the lag previous day[9].

Co-exposure assessment

Compound environmental exposure scenarios were constructed by first identifying threshold values, then combining averaged 14-day PM concentrations with non-optimal temperatures based on established benchmarks, and finally applying gender-specific stratification.

First, for particulate matter, $PM_{2.5}$ and PM_{10} were categorized according to China national Grade I Ambient Air Quality Standards (GB 3095-2012)[33,34], which define 24-h average concentration limits of 35 μg/m³ and 50 μg/m³, respectively. In contrast, no official standard exists for PM_1. Therefore, a concentration of 22 μg/m³, the median value observed across the study period, was adopted as a threshold to define low and high exposure categories. This choice was based on previous studies that used the median as a PM cutoff in the absence of a regulatory benchmark or in the desire to focus on relative high-low pollution[35–37], which also ensured balanced group sizes and accounted for local pollution patterns. Although the World Health Organization's 24-h guideline value for $PM_{2.5}$ (15 μg/m³) is considered a more generalizable threshold, it was ultimately excluded from stratified analyses because nearly all measurements across the study locations exceeded this value. This limitation is addressed in the discussion. Consequently, PM_1, $PM_{2.5}$, and PM_{10} were classified into low- and high-exposure categories at thresholds of 22 μg/m³, 35 μg/m³, and 50 μg/m³, respectively.

Regarding ambient temperature, no universal standard defines thermally optimal conditions across different climates or health outcomes[38,39]. We therefore adopted an epidemiological approach based on the concept of non-optimal temperature exposure[40]. Non-optimal temperature refers to any ambient temperature that is either higher or lower than the theoretical minimum risk exposure level, which is defined as the temperature associated with the lowest overall health risk for a given location. Specifically, risk thresholds were determined by identifying the minimum-risk temperature using exposure–response curves derived from single-exposure models of temperature related absenteeism. Considering the risk thresholds derived from our single temperature exposure models, we developed specific criteria for categorizing temperature exposure. A threshold of 10 °C was used to differentiate between suitable and unsuitable temperature conditions for DAT and IDC. IDF was further segmented into cooling, suitable, and warming categories, using −2.5 °C and 0 °C as cut-offs. These classifications enable the analysis of the compound impacts of air pollution and temperature variability on health outcomes.

Then, we devised nine composite exposure scenarios by integrating PM_1, $PM_{2.5}$ and PM_{10} with DAT, IDC and IDF including DAT-PM (DAT-PM_1, DAT-$PM_{2.5}$, DAT-PM_{10}), IDC-PM (IDC-PM_1, IDC-$PM_{2.5}$, IDC-PM_{10}), and IDF-PM (IDF-PM_1, IDF-$PM_{2.5}$, IDF-PM_{10}). These scenarios are structured into differentiated levels based on the combinations of particulate matter and temperature conditions. Specifically, DAT-$PM_{1\text{-}10}$ had 4 levels, including (1) Suitable DAT and low-level PM (level 1); (2) Suitable DAT and high-level PM (level 2); (3) Unsuitable DAT and low-level PM (level 3); and (4) Unsuitable DAT and high-level PM (level 4); IDC-$PM_{1\text{-}10}$ had 4 levels, including (1) Suitable IDC and low-level PM (level 1); (2) Suitable IDC and high-level PM (level 2); (3) Unsuitable IDC and low-level PM (level 3); and (4) Unsuitable IDC and high-level PM (level 4); IDF-$PM_{1\text{-}10}$ had 6 levels, including (1) Suitable IDF and low-level PM (level 1); (2) Suitable IDF and high-level PM (level 2); (3) Cooling IDF and low-level PM (level 3); and (4) Cooling IDF and high-level PM (level 4); (5) Warming IDF and low-level PM (level 3); and (4) Warming IDF and high-level PM (level 6). For all scenarios, Level 1 is designated as the reference group against which all other levels are compared.

Finally, to explore potential gender differences in co-exposure scenarios, we refined the composite exposure indicators into binary variables, where '0' denotes non-composite exposure days, including scenarios of low pollution with suitable temperatures, low pollution with unsuitable temperatures, and high pollution with suitable temperatures; "1" indicates days of identified co-exposure characterized by high pollution with unsuitable temperature conditions. Building on this framework, we integrated gender-specific co-exposure indicators to conduct interaction term tests and subgroup analyses, aiming to assess the differential resilience to environmental stressors between males and females (0–0: males in no co-exposure days, 0–1: females in no co-exposure days, 1–0: males in co-exposure days, and 1–1: females in co-exposure days). Please refer to Fig. S2 for the flowchart of composite indicator construction.

Covariates

We calculated the daily relative humidity (RH) over the past 14 days using air pressure, dew point temperature, and surface temperature data obtained from the ERA5-Land meteorological reanalysis dataset[32]. Other variables covered included year, season, day of the week (DOW), region (urban and rural), gender, grade, medical symptoms, diagnostic causes, medical choice (outpatient, hospitalization, at home), start and end dates of absenteeism, and school enrollment were considered by subgroup analysis or as controls to mitigate potential spatial and temporal confounding factors.

Statistical analysis

We employed a space-time stratified design that integrates quasi-binomial regression models with distributed lag linear and non-linear functions to examine the associations between air pollution, non-optimal temperatures, and the incidence of mental distress among school-aged children[41]. This design adjusts for overdispersion in absenteeism rate[42], and controls for spatial and temporal variations at the school level, accounting for regional and school-specific environmental factors that are constant within the time window. Based on the characteristics of school time-series statistics, the stratum is defined as a categorical variable of the school-specific year and DOW (e.g., school code-year-DOW). This stratification helps address potential confounding factors such as long-term trends, short-term holiday effects, and inter-school variations. The model is specified as follows:

$$\mathrm{logit}(p) = \alpha + \beta_0 * \mathrm{exposure} + \beta_1 * \mathrm{stratum} + \beta^{\mathrm{T}} * \mathrm{covariates} \qquad (1)$$

Where p represents the daily absenteeism rate due to mental distress, α is the intercept, exposure includes particulate matter or non-optimal temperature treated with cross-basis functions with coefficient β_0, stratum adjusts for location-specific temporal window, and covariates are additional confounders with coefficients β^{T}.

For particulate matter, we applied a linear trend using a one-basis matrix in accordance with the previous findings demonstrating a positive linear relationship[43,44], while for non-optimal temperatures, we used a natural cubic spline to capture non-linear effects[45]. When taking the single exposure model, additional external exposure factors were considered as confounders. To account for the influence of RH, a natural cubic spline with three degrees of freedom was utilized. Furthermore, we modeled both lagged and cumulative effects for exposures ranging from 0 to 14 days. The relative risk associated with a 10 μg/m³ increase in particulate matter exposure, along with the corresponding 95% confidence interval (95% CI), was calculated to quantify the potential impact on mental health.

We conducted Pearson correlation analysis and k-means cluster analysis to explore the relationships between PM exposure and temperature environments. Structural equation modeling (SEM) was employed to investigate the path dependencies of PM and temperatures on school absenteeism using daily county-level records. The analysis was performed using the lavaan package in R version 3.6.1. The latent variable PM was defined by three observed indicators (PM_1, $PM_{2.5}$, and PM_{10}). Structural models were estimated with school absenteeism regressed on PM, DAT, IDC, and IDF using the sem function. Model fit was assessed through comprehensive summary statistics and fit indices obtained using the summary and fitMeasures functions. Additionally, path diagrams were generated using the lavaanPlot function, displaying standardized estimates and significance levels.

To evaluate the compound effects on children's mental distress–related absenteeism, we first dichotomized the absenteeism rate based on its median, defining a binary outcome variable. We then employed a conditional logistic regression model with a binomial distribution to assess the interactive effects of various exposure conditions during the past 0–14 days. The reference group was defined as exposure to low PM pollution under suitable temperature conditions. The effects were evaluated using three indicators: the Relative Excess Over Expected Interaction (REOI), the Attributable Proportion due to Interaction (AP), and the Synergy Index (S)[46]. These metrics represent the interaction effect component, the proportion of the total effect attributable to interaction, and the ratio between the total effect and the individual effects, respectively. The formulas are as follows:

$$\begin{aligned}\mathrm{REOI} &= (\mathrm{O}_{11}-1)-(\mathrm{OR}_{10}-1)-(\mathrm{OR}_{01}-1)\\ &= \mathrm{OR}_{11}-\mathrm{OR}_{10}-\mathrm{OR}_{01}+1\end{aligned} \tag{2}$$

$$\mathrm{AP} = \mathrm{REOI}/\mathrm{OR}_{11} \tag{3}$$

$$\mathrm{S} = (\mathrm{OR}_{11}-1)/[(\mathrm{OR}_{10}-1)+(\mathrm{OR}_{01}-1)] \tag{4}$$

Where OR represents the odds of mental health related absenteeism under different exposure scenarios relative to the reference group (low pollution-suitable temperature), OR_{11} represents the odds ratio for the joint exposure to both high PM and non-optimal temperature condition, OR_{10} for PM exposure alone, and OR_{01} for non-optimal temperature alone.

Additionally, the interaction term was induced to explore risk differences and trends associated with gender across exposure scenarios. Specifically, we compared the relative risks among males in composite exposure, females in non-composite exposure, and females in composite exposure, with males in a non-composite exposure environment serving as the reference group.

Sensitivity analysis

We tested the risk trends over 0–14 days and weighted the absence period as an alternative metric to the absence rate evaluation index. We conducted stratified analyses to investigate effect modifications across various dimensions, including gender, region, season, specific mental disorders such as neurasthenia and depression, types of educational institutions, and medical choice. Furthermore, the COVID-19 outbreak was incorporated as a time-stratified adjustment within the basic model to evaluate its comprehensive impacts (Fig. S3). We also performed generalized linear regression models based on overall records to ensure the robustness of the exposure-response relationship (Figs. S4, S5, Table S1). In addition, we further examined the robustness of risk associations after adjusting for O_3 exposure, as well as the potential risks attributable to O_3 under both independent and joint exposure scenarios, to extend the scope of discussion. All analysis was performed by R version 3.6.1 with two-tailed test significance $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 1 | Characteristics of mental distress cases

Characteristic	Observations	Percentage
All cases	95,658	
Age (mean + SD)	14.38 ± 2.34	
Absence days	1.39 ± 1.14	
Gender		
Male	36,941	38.62%
Female	58,717	61.38%
Region		
Urban	78,367	81.92%
Rural	17,291	18.08%
Mental Distress		
Depression	20,551	21.48%
Neurasthenia	20,963	21.91%
Others	54,144	56.60%
Hospital visits		
Yes	19,320	20.20%
No	74,517	77.90%
Unknown	1821	1.90%
Education		
Primary school	10,808	11.30%
Middle school	50,050	52.32%
High school	31,586	33.02%
Others	3214	3.36%
Season		
Spring	38,348	40.09%
Summer	13,094	13.69%
Autumn	24,030	25.12%
Winter	20,186	21.10%

Results

Mental distress characteristics

Mental depression and neurasthenia constituted 43.39% of overall cases (Table 1). The mean age of participants was 14.38 ± 2.34 years, and the average period of absence due to mental distress was 1.39 ± 1.14 days. Seasonal statistics show that cases of absenteeism due to mental discomfort are highest in spring, accounting for 40.09%, followed by autumn at 25.12%. It was noted that only 20.20% of cases sought medical help, while 77.90% chose home care only.

Children's absence from school due to mental illness is concentrated in the southern region. Significantly higher incidences of mental health issues were reported among females and in urban areas compared to males and rural areas, respectively ($p < 0.001$, Fig. S1). Specifically, females accounted for 61.38% of absences, and urban schools represented 81.92% of these cases, with middle schools contributing more than half (52.32%, G7–G9, Fig. 2).

Particulate matter assessment

We found that exposure to particulate matter has been strongly linked to the onset of mental distress in children, with increased risk corresponding to finer particle sizes (Fig. 3). Specifically, for each 10 μg/m^3 increase in 14-days PM_1, $PM_{2.5}$, and PM_{10} exposure, the relative risks were 1.017 (95CI%: 1.008, 1.025), 1.011 (95CI%: 1.007, 1.016) and 1.008 (95CI%: 1.005, 1.010), respectively. The risk associated with these exposures demonstrated a progressive increase over the 14-day period. Both males and females exhibited substantial risks associated with particulate matter exposure, with no significant gender differences observed. Notably, urban children experienced significantly higher and increasing psychological burden, particularly with PM_1 posing the highest risk of 1.034 (95%CI: 1.024, 1.045),

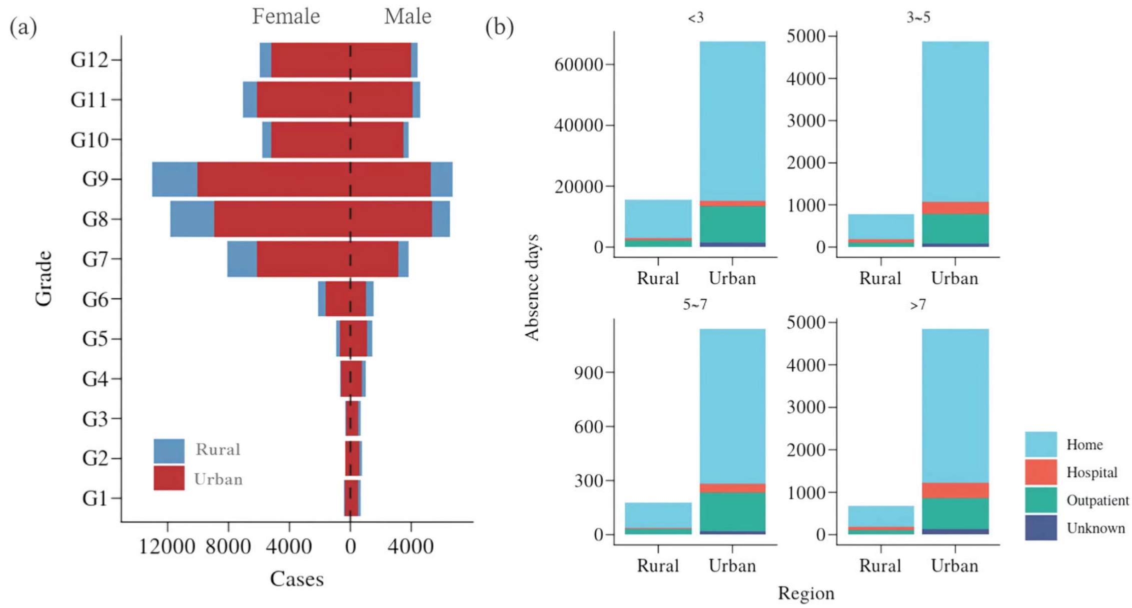

Fig. 2 | Descriptive statistics of children absent from school due to mental distress. a Grade distribution of absent children in urban and rural areas, where G1–G12 represents the first grade of elementary school to the third grade of high school, **b** medical choices for different absence durations (<3, 3–5, 5–7, >7) in urban and rural areas.

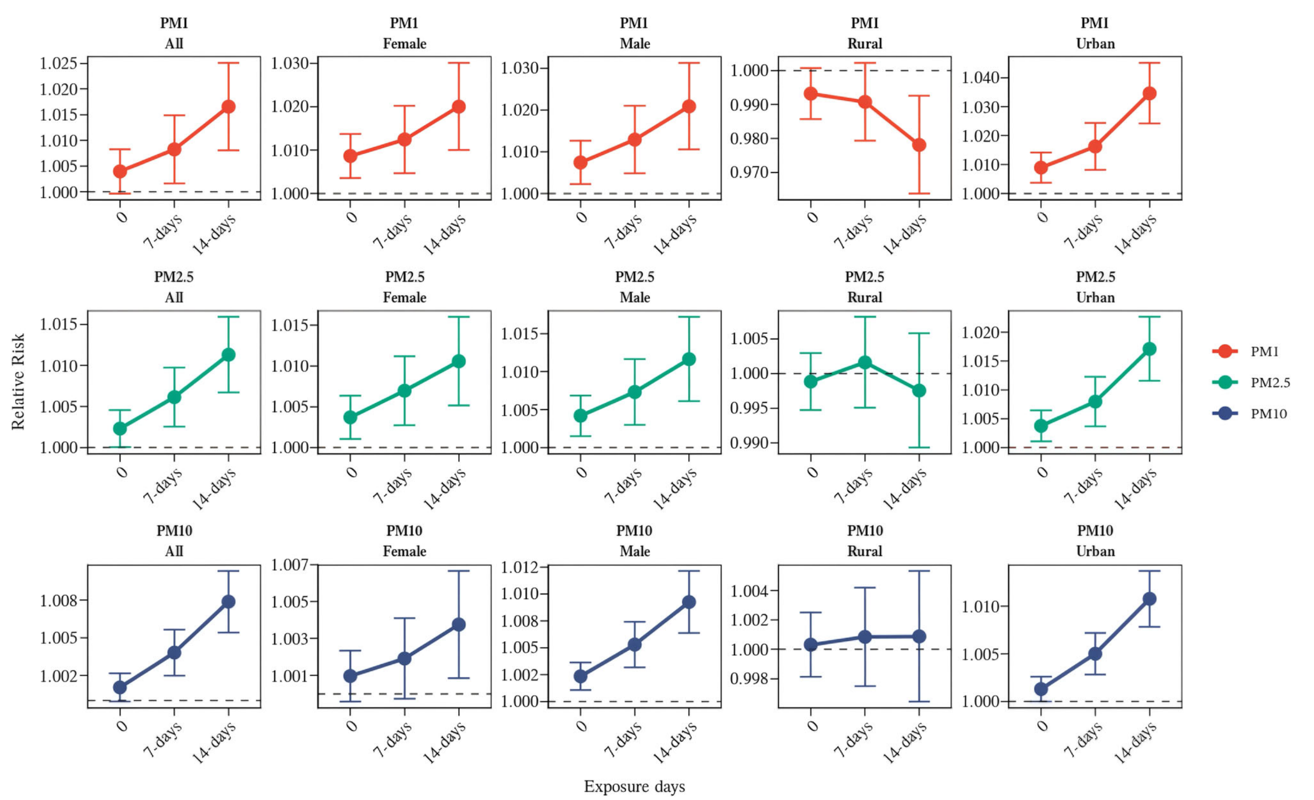

Fig. 3 | Children's mental distress risk trends associated with 0–14 days of exposure to PM_1, $PM_{2.5}$, and PM_{10} across gender and region, where 7-days and 14-days represent the average concentration of particulate matter in the past 7 and 14 days.

while the association wasn't significant in rural schools ($p < 0.05$). We also observed that the risk associated with outpatient care was higher compared to home care, and no significant risk was observed among children who were hospitalized (Fig. S6). Subgroup analyses underscored that, despite heterogeneity in specific strata, the models consistently indicated a robust overall risk associated with 0–14 days exposure (Figs. S6–S13).

Non-optimal temperature assessment

The impact of ambient temperature on children's mental distress exhibits a more pronounced and discernible risk trend compared to particulate matter exposure between females and males (Fig. 4). As average daily temperatures increased, the incidence of mental discomfort escalated sharply in a super-linear pattern. The adverse health effects of average temperatures exceeding

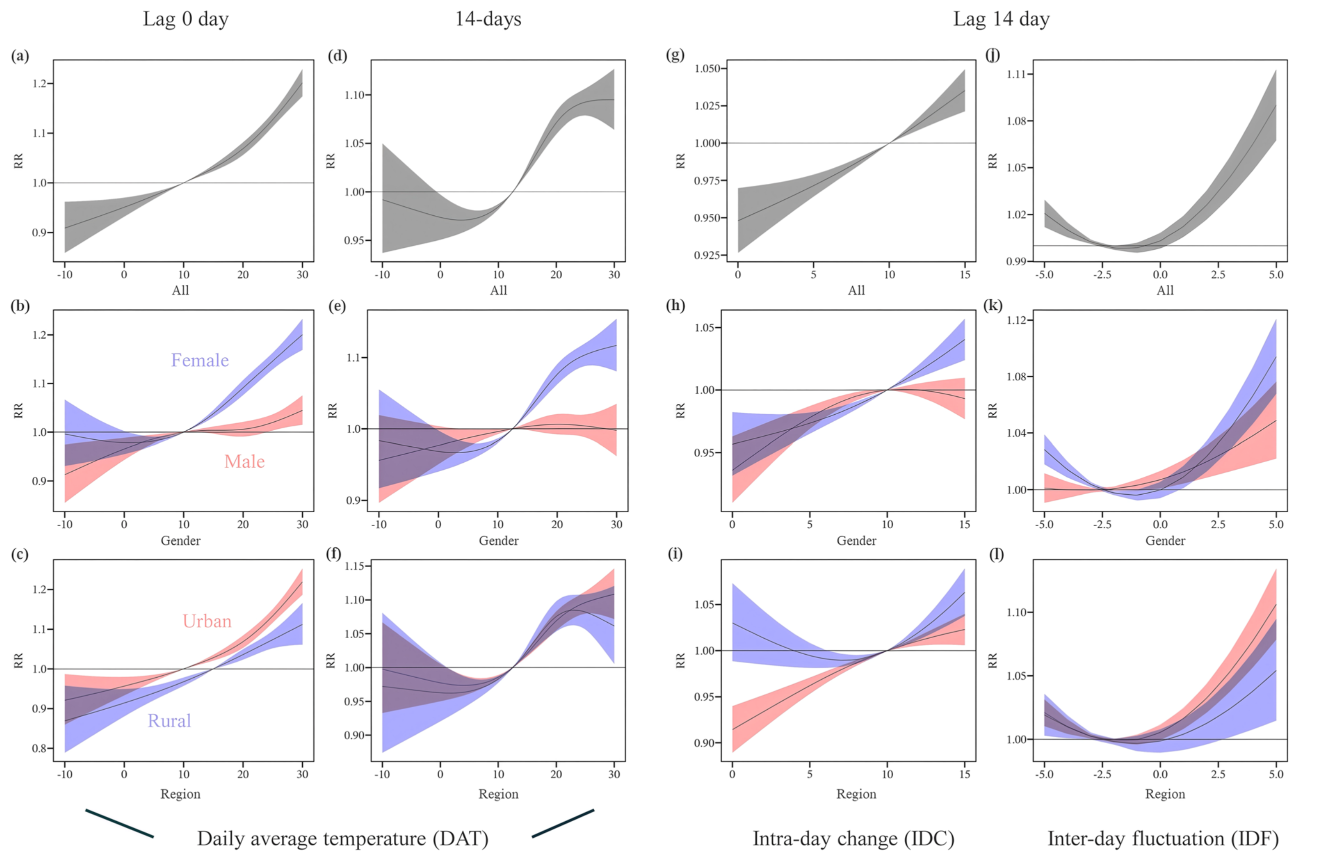

Fig. 4 | Mental health impacts associated with non-optimal temperature environment. **a**–**c** Health risks of exposure to DAT (°C) at lag-0 day, **d**–**f** cumulative risks of exposure to DAT over past 14 days, and **g**–**l** health risks of exposure to IDC (°C) and IDF (°C) at lag-14 day.

10 °C remained significant throughout the 14-day exposure window, albeit with a slight attenuation over time. Females exhibited a heightened vulnerability to elevated temperatures compared to males. Similarly, IDC of temperature exceeding 10 °C consistently correlated with significant mental distress in children, with females demonstrating heightened vulnerability, even with a 14-day lag. This association persisted robustly across both urban and rural environments. Inter-day temperature fluctuations exhibited a J-shaped relationship with mental health outcomes, with considerable health risks observed at both cooling (<−2.5 °C) and warming (>0 °C) segments. Notably, the risk associated with warming temperatures was significantly higher than that for cooling temperatures, especially among females, though the cumulative effect eventually diminished (Fig. 4, Fig. S14). Subgroup analyses confirmed that the risk associated with hot weather and extreme temperature fluctuations remained consistent across different subgroups (Fig. S6, Figs. S10–S16). However, we identified risk heterogeneity related to medical choices; specifically, the increased risk associated with lower temperatures among hospitalized children warrants further attention (Fig. S6).

Composite exposure characteristics

As shown in Fig. 5, the autocorrelation coefficients for average temperature and PM pollution over a period of 0 to 14 days ranged from 0.14 to 0.97 and 0.82 to 0.95 ($p < 0.05$). We found that days with high $PM_{2.5}$ pollution were significantly correlated with lower average temperature and higher intra-day temperature change ($p < 0.05$), with correlation coefficients ranging from 0.32 to 0.48 and 0.06 to 0.21, respectively (Table S2).

Children were broadly exposed to composite exposure environments. Specifically, scenarios involving DAT > 10 °C in conjunction with PM_{10} > 50 μg/m³ account for 45.2% of cases; the combination of IDC > 10 °C with elevated PM_{10} > 50 μg/m³ constitutes 26.4%; unsuitable warming or cooling caused by IDF with PM_{10} > 50 μg/m³ account for 46.1% of occurrences (Fig. 5, Fig. S17).

Increased mental health risks associated with composite exposure

Fig. 6 demonstrates that co-exposure to particulate matter alongside non-optimal temperatures significantly amplifies mental health risks in children, with these risks escalating over a 0–14-day exposure period. Compared to baseline conditions of low pollution and suitable temperatures, scenarios featuring high pollution with high average temperatures as well as substantial intra-day and inter-day temperature fluctuations consistently presented elevated risks across all nine composite exposure scenarios, with relative risk estimates ranging from 1.099 to 1.534 (95%CI: 1.379, 1.706, high PM_{10}-warming IDF-14 days) ($p < 0.05$). Notably, in the DAT–PM combined exposure scenarios, the relative risk exhibited a linear increasing trend from the day of exposure to a cumulative lag of 14 days, for DAT–PM_1 (RR = 1.110–1.421), DAT–$PM_{2.5}$ (RR = 1.121–1.425), and DAT–PM_{10} (RR = 1.167–1.451, $p < 0.05$).

Excess risk analysis indicated that, although most exposure combinations demonstrated a significantly heightened mental health threat in environments of high pollution and non-optimal temperatures compared to the baseline, not all combinations exhibited persistent additive risk effects. However, specific interactions involving 14-days cumulative exposure consistently exhibited positive additive effects, including combinations IDF-PM_{10}-14-days, IDF-$PM_{2.5}$-14-days, IDF-PM_1-14-days, IDC-PM_{10}-14-days, DAT-PM_{10}-14-days, and DAT-$PM_{2.5}$-7-days, DAT-PM_1-7-days, with attributable proportions ranging from 1.11% (REOI = 0.02, S = 1.04) to 10.80% (REOI = 0.15, S = 1.67). Path analysis further revealed that particulate matter not only directly contributed to mental discomfort ($p < 0.001$) but also exacerbated health risks through interactions with IDC ($p < 0.05$), DAT ($p < 0.001$), and IDF ($p < 0.001$) (Fig. 6, Fig. S18).

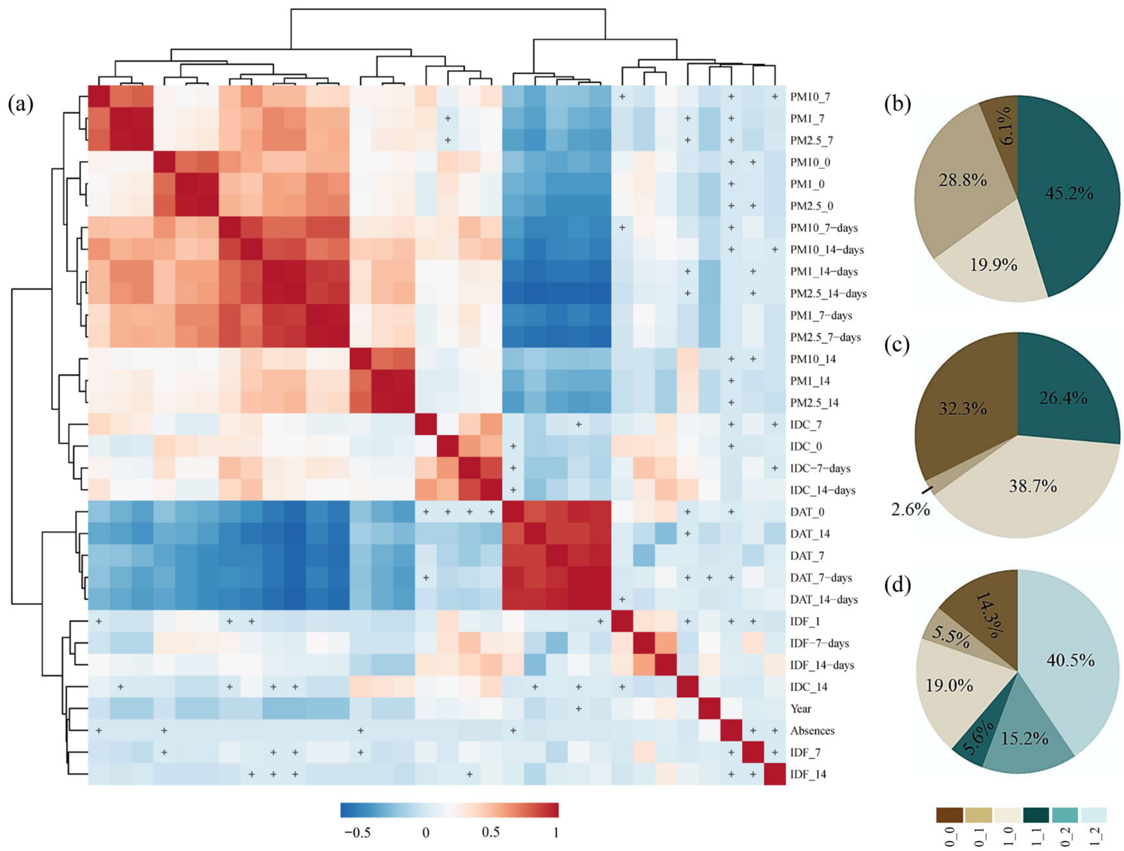

Fig. 5 | Co-exposure characteristics. a Pearson correlation and K-means clustering between particulate matter, DAT, IDC and IDF, where + represents no significant correlation at $p > 0.05$, and **b**–**d** percentage of co-exposure days of DAT-PM_{10}, IDC-PM_{10}, and IDF-PM_{10}, where 0_0 means low PM-suitable temperature; 0_1 means low PM-increasing DAT and IDC, or low PM-cooling IDF; 1_0 means high PM-suitable temperature; 1_1 means high PM-increasing DAT and IDC, or high PM-cooling IDF; 0_2 means low PM-warming IDF; and 1_2 means high PM-warming IDF.

The interaction analysis exploring the relationship between composite exposure and gender demonstrated that females consistently faced significant higher risks than males across both composite and non-composite exposure environments (relative risks for females:1.675–2.323, for males: 0.959–1.386, $p < 0.05$, Fig. 7). Throughout the 0–14 days exposure period, the risk for males remained relatively stable across the combined exposure indices. In contrast, females experienced a progressive increase in risk, with the most pronounced escalation observed in the IDF-PM combination.

Discussion

Children are vulnerable to air pollution and temperature extremes due to their immature immune defense mechanisms, limited protective awareness, and guardians' insufficient coping abilities[47,48]. This study identifies strong links between schoolchildren's mental distress and exposure to particulate matter, average temperature, and temperature variability over 14-days' exposure, based on long-term multi-city, school-based health monitoring system. We noted disparities in health burdens and risk trends both across urban and rural children and between genders, with heightened mental distress consistently reported under composite exposure scenarios. The findings highlight the imperative to address the combined impacts of extreme temperature and air pollution on schoolchildren's attendance amid escalating global climate change.

Single exposure models reveal the differential impacts of exposure to particulate matter and temperature extremes on children's mental health. Aligned with findings from adult studies[20,45,49], our analysis confirms that particulate matter, particularly finer particles, pose significant and escalating threats to children's mental health over a 14-day period. These finer particles, due to larger surface area, can absorb more toxins, exacerbating inflammatory responses, enhancing penetration into the respiratory tract, and potentially crossing the blood-brain barrier, causing more severe mental impairment[7,50]. Additionally, non-optimal temperatures, such as extreme heat, cold snaps, or heat waves, closely correlate with mental health challenges in adults, with our findings extending these associations to children[5,9,45]. For instance, average temperatures exceeding 10 °C were found to precipitate a super-linear increase in mental distress. Meanwhile, it's imperative to continue monitoring significant intra-day (exceeding 10 °C) and inter-day (falling below −2.5 °C or rising above 0 °C) temperature fluctuations due to their profound implications for mental health.

Composite exposures may synergistically exacerbate biological vulnerability[51–53], including alterations in neuroinflammation and immune responses, oxidative stress, cortisol levels, and neurotransmitter imbalances, or could directly influence human emotion and sleep[7,10,54]. Compared to days with single exposures or lower pollution coupled with an optimal temperature environment, concurrent exposure to higher pollution days combined with warming temperature and large inter-day and intra-day temperature fluctuation significantly intensifies mental health risks among children. Despite existing particulate matter standards, children globally, including those in China, face considerable mental health risks due to these combined environmental factors[48]. Although sustained reductions in air pollution have produced widespread health gains, more frequent extreme temperature events may offset these benefits. As climate change intensifies extreme weather events[55], sustained attention to composite exposure is crucial to safeguarding childhood mental well-being.

Notably, while the association between particulate matter and children's mental distress remained robust even after controlling O_3 exposure (Fig. S19), we also observed distinct risk patterns associated with O_3 itself (Fig. S20). Specifically, O_3 exposure on the same day (lag-0) showed the highest acute risk (RR = 1.007, 95% CI: 1.005–1.008), whereas the risk

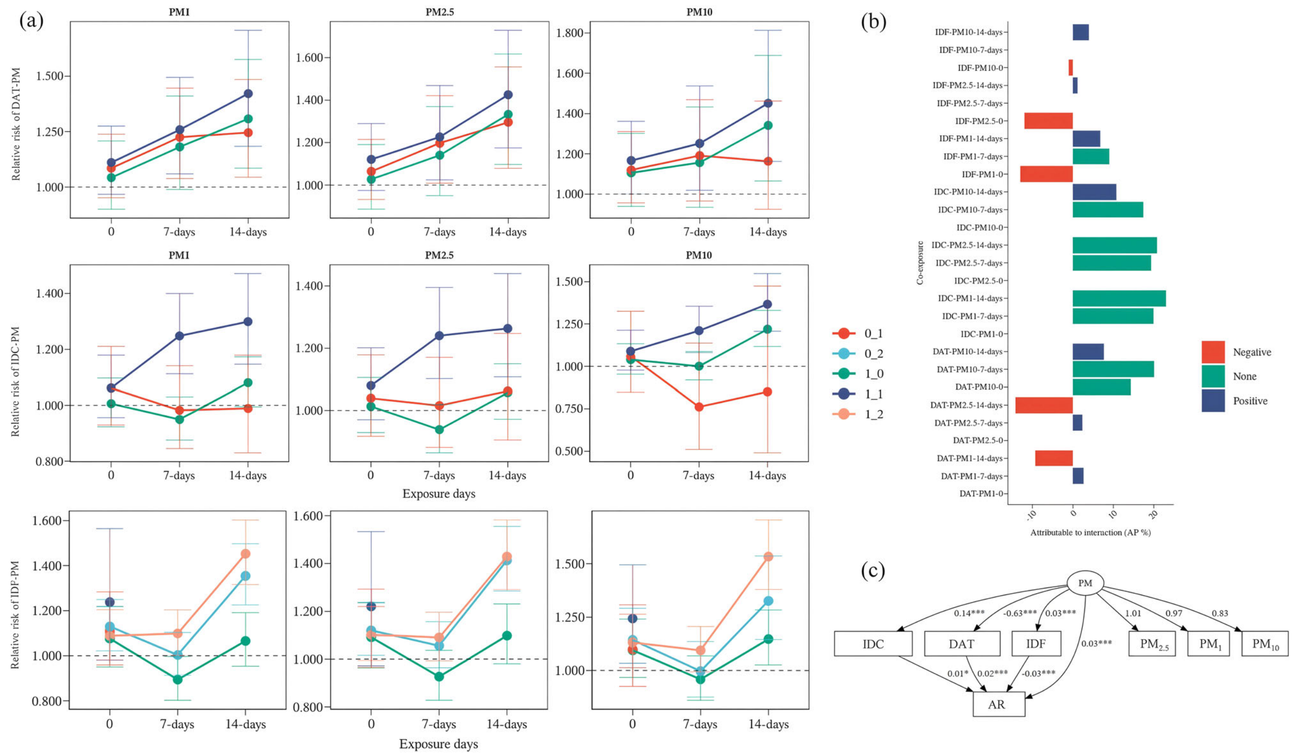

Fig. 6 | Mental health risks associated with composite environmental exposures in the past 14 days. a Evaluation of health risk trends associated with nine different composite exposure scenarios compared with the baseline group (0_0 means low PM-suitable temperature; 0_1 means low PM-increasing DAT and IDC, or low PM-cooling IDF; 1_0 means high PM-suitable temperature; 1_1 means high PM-increasing DAT and IDC, or high PM- cooling IDF; 0_2 means low PM-warming IDF; and 1_2 means high PM-warming IDF, **b** quantifying the contribution of interactive effects to overall risk by AP, where positive means REOI > 0, AP > 0, and S > 1, negative means REOI < 0, AP < 0, and S < 1, none means no compound effect, NA means no significant difference between groups, **c** examination of the path relationships between 14-day cumulative PM, DAT, IDC, and IDF, where AR means daily mental distress-related absence rate, SRMR = 0.079, CFI = 0.924, TLI = 0.855, NFI = 0.924.

diminished after lag-9. However, cumulative exposure over 7 and 14 days remained significantly associated with elevated risk (RR = 1.006–1.007, $p < 0.001$). These temporal patterns may be consistent with the unique biological pathways through which ozone may affect the brain, including systemic inflammation, dopaminergic neuron reduction, and neurotransmitter disruption[56,57]. Furthermore, we found that combined exposure to O_3 and temperature extremes, especially large diurnal temperature ranges, significantly amplified the risk of mental distress, showing a linear increase over 0–14 days (Fig. S21). These findings highlight that the mental health risks of other air pollutants such as O_3 also deserve further attention, particularly regarding their distinct biological pathways and epidemiological patterns under current O_3 pollution and climate change conditions.

Particulate matter-induced mental health crises were significantly more pronounced in urban areas compared to the overall setting, while this association was absent in rural regions. These urban-rural disparities could be attributed to variations in the sources and composition. A study conducted in northern China highlighted such differing biological toxicities, where metals and metalloids such as Pb, Cd, As, Cu, and Zn, as well as inorganic elements from industrial emissions like Ni, Zn, As, Pb, and Cd, induced elevated levels of anxiety and depression[58]. Given China's rapid urbanization and the substantial influx of children into urban environments, there is a pressing need to address the mental health crisis associated with environmental exposure among school-age children relocating to these areas.

The findings revealed no significant gender differences in the risks associated with particulate matter exposure. However, females were identified as more susceptible to the adverse effects of non-optimal temperatures. Under composite exposure scenarios, this susceptibility was markedly pronounced, with females consistently demonstrating increased vulnerability and their risk escalation significantly exceeding that of males. This increased susceptibility may be attributed to variations in hormone levels, thermoregulatory capacity, metabolic rates during development, psychological sensitivity, components differences, and behavioral activity patterns[5,11,45,58]. The intertwined influences complicate control and intervention efforts for compound impacts. In the face of intensifying extreme climate events, there is an urgent need to address the substantial health threats that non-optimal temperatures and their interactions with pollution pose to females. Enhanced understanding of these gender-specific vulnerabilities can inform targeted public health interventions and policies to better protect this at-risk population in a changing climate.

Limitations should also be noted in this design. First, due to the lack of large-scale individual exposure monitoring data, we can only use the ambient concentration of PM at the school level from machine learning simulations using satellite inversion. Moreover, the study was conducted in a region with generally high levels of air pollution, which warrants caution when interpreting associations between PM exposure and children's mental health in areas with lower pollution. Second, the impacts of environmental exposure need to be carefully assessed in the post-epidemic era. Although we have eliminated the records of schoolchildren infected or crossing with infected cases from the system records and conducted the robustness test stratified by the outbreak, we couldn't rule out the unpredictable impact of lockdown during non-school periods and fear of COVID-19. Third, this study identifies risk differences related to particulate matter and temperature exposure across various regions and genders from an epidemiological perspective. However, the primary toxic components and their biological mechanisms in relation to composite exposure environments are still unclear. More evidence from multidisciplinary studies, including cellular, organ,

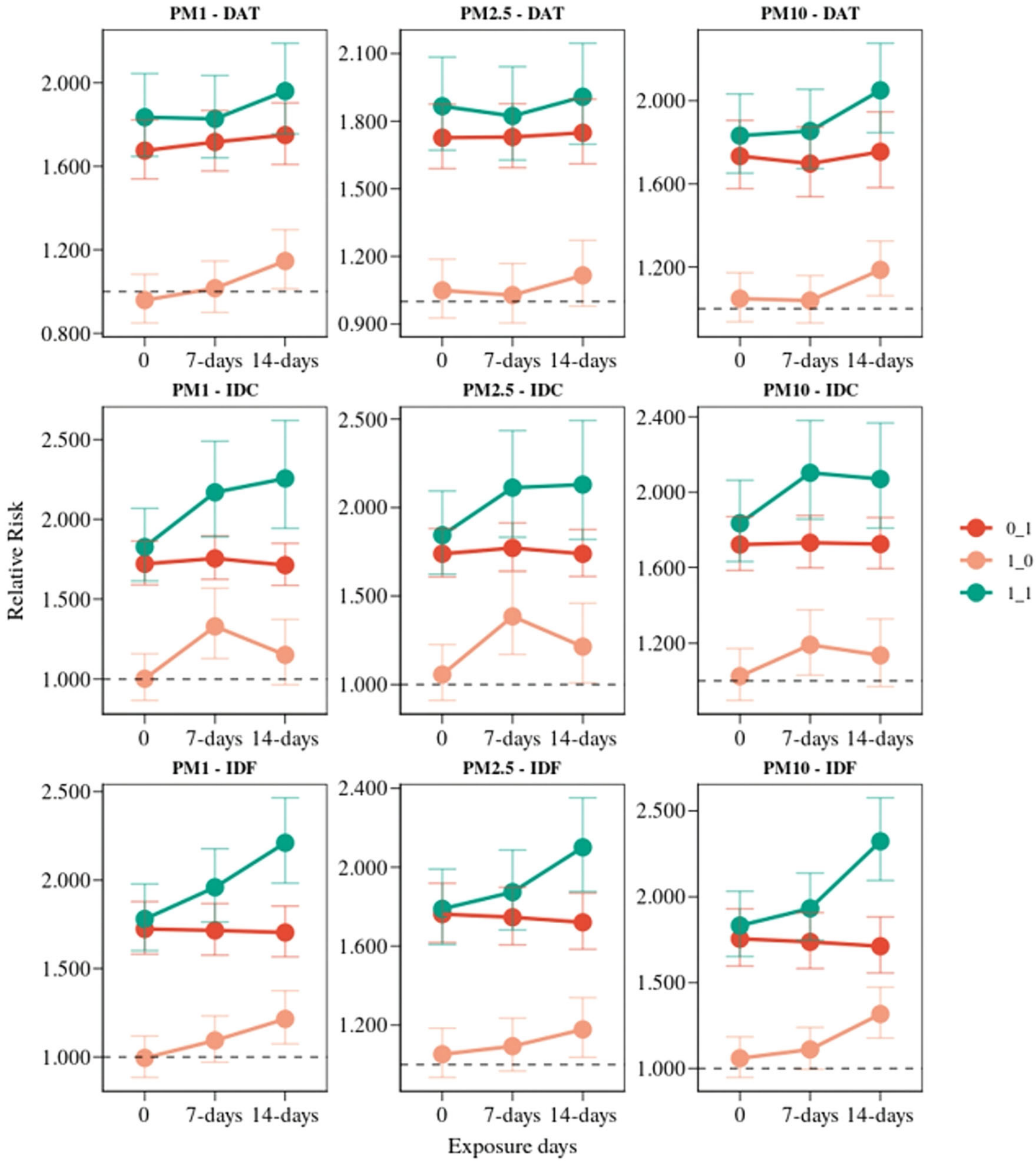

Fig. 7 | Mental health risk differences between males and females across varied exposure conditions. The baseline group is males in a non-composite exposure environment. Comparison groups are defined as follows: 0_1 (red) for females in a non-composite exposure environment; 1_0 (orange) for males in a composite exposure environment; 1_1 (green) for females in a composite exposure environment.

and animal experiments, is needed to deepen understanding on psychological response. Improving the child health monitoring system takes time. This study only covers 89 counties in China due to the substantial costs associated with long-term observation. Future research should urgently include evidence from various countries and regions with different levels of development. Although the use of school absence data underscores the importance of the school environment in shaping children's mental health, some children may continue attending school despite experiencing mental discomfort. This may lead to an underestimation of the mental health risks associated with environmental exposures. Detailed research on the impact of schoolchildren's family background and indoor exposure characteristics on their mental health is also necessary.

This study explores risk trends and disparities among children from both composite and non-composite short-term exposures to air pollution and non-optimal temperatures. The findings provide insights for formulating targeted intervention strategies, informed by detailed characterizations of exposure-response curves differentiated by school type, medical choice, region, and gender, as well as heightened compounded risks amid escalating climate change. We highlight the pressing need to address the growing mental health crisis among females, which is exacerbated by particulate matter, increasing temperatures, and pronounced intra- and interday temperature fluctuations. To effectively mitigate these risks, we advocate for the implementation of a comprehensive school-centered health protection framework. Proposed strategies include the development of an early warning system for composite exposures and equipping under-resourced schools with essential temperature control and air purification systems. As global environmental challenges intensify, prioritizing improvements in air quality, school environments, and individual health monitoring are crucial in the future for safeguarding the mental health of children.

Data availability

The data are not open source. Access should be supported by the corresponding author of the study, including obtaining necessary approvals and signing a data access agreement.

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Author contributions

K.C., L.H., and Y. WU conceived the study. K.C. and L.H. organized and supervised the study. Y. WU led the data cleaning and analysis, and played a central role in preparing tables, figures, and drafting the paper. J.W., B.C., H.S., Y.Z., C.L., and H.Z. supported data cleaning and analysis. K.C., L.H., Y. WU, Y.Z., Y.W., and P.W. reviewed and edited the paper. All authors contributed to the manuscript and approved the final version.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Lei Huang.