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Letter to the Editor

Breaking the spline: Why distributed lag non-linear models miss thresholds in environmental psychiatry

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ABSTRACT

This critique evaluates Monti et al.'s investigation into associations between air pollution, apparent temperature, and schizophrenia severity. While their findings indicate significant short- and medium-term effects of PM_{10} and thermal stress on PANSS scores, several methodological limitations warrant caution. Their study relies on residential exposure assignments, which may not capture individual mobility or indoor environments, potentially introducing substantial exposure misclassification. Despite appropriately modeling delayed and non-linear effects, the DLNM's reliance on predefined spline structures may oversimplify the complex, synergistic interactions among atmospheric variables. Seasonal discrepancies—such as the absence of PM_{10} effects in autumn–winter—may reflect unmodeled dependencies or limited pollutant data, particularly for $PM_{2.5}$ and black carbon. To address these constraints, future research should incorporate flexible, data-driven approaches, particularly those capable of uncovering latent structures within environmental mixtures. Unsupervised feature-clustering methods can identify correlated pollutant groupings and reduce dimensional noise, while rank-based correlation metrics provide robust assessment of non-linear dependencies that are often obscured by parametric spline specifications. These non-parametric techniques can complement DLNM by capturing multivariate synergies and interaction patterns that rigid basis structures may overlook. Overall, integrating such approaches is essential for advancing analytical capacity and improving risk assessment for vulnerable psychiatric populations.

Letter to the editor

Monti et al. demonstrated that cumulative weekly increases in PM_{10} during the spring–summer period were associated with a 1.52-point rise in PANSS scores (95% CI: 0.50–2.55) (Monti et al., 2025). Acute effects were also evident on the day of hospital admission, with PM_{10} increments linked to a 0.55-point increase. Their further report that higher apparent temperature (AT) exacerbated symptoms during the autumn–winter period, particularly on day 0 ($\beta = 0.50$, 95% CI: 0.09–0.91) and day -1 ($\beta = 0.30$, 95% CI: 0.10–0.50).

However, their analysis relies on stationary residential exposure data, which may not adequately capture individual mobility or indoor environments. These limitations warrant further consideration.

They employ a distributed lag non-linear model (DLNM) to capture delayed and non-linear associations between pollutants, temperature, and outcomes. Although DLNM is an appropriate framework for modeling lagged and non-linear relationships, it is contingent upon predefined spline specifications (e.g., natural splines with fixed degrees of freedom). As such, it may inadequately capture the complex, synergistic interactions among atmospheric variables that they themselves acknowledge. For example, although AT and individual pollutants are adjusted for separately within seasonal strata, the model may not fully reflect biological interactions in which particular temperature thresholds modify or intensify the pro-inflammatory effects of particulate matter. In an urban environment such as Milan, these parametric constraints may oversimplify the relationship between air quality and thermal stress, potentially obscuring relevant associations.

Their study also recognizes important limitations in exposure assessment. Assigning exposure based solely on the nearest residential monitoring station does not incorporate individual mobility patterns or the considerable proportion of time patients spend in indoor environments, where pollutant concentrations often diverge substantially from ambient measurements. Additionally, the reported seasonal differences—such as the absence of PM_{10} effects in autumn–winter—may reflect unmodeled dependencies or limited data availability, particularly for $PM_{2.5}$ and black carbon (BC), for which the sample sizes were restricted to 623 and 229 admissions, respectively. While DLNM accommodates non-linear lag structures, it does not inherently address residual confounding from unmeasured seasonal variables without incorporating more integrated, multivariate non-linear frameworks.

To address these methodological constraints, future research on environmental risk factors for psychiatric illness could benefit from incorporating non-parametric, data-driven approaches. Techniques such as unsupervised feature selection (e.g., Feature Agglomeration, Highly Variable Gene Selection) (Xie et al., 2025; Zhang et al., 2020) and rank-based correlation metrics (e.g., Spearman's rho, Kendall's tau) (Okoye and Hosseini, 2024; Yu and Hutson, 2024) could identify latent structures within environmental systems. Unlike parametric models, these rank-based methods are inherently robust to outliers and non-normality, which are common characteristics of environmental data. Furthermore, Feature Agglomeration can cluster highly correlated pollutants prior to modeling, thereby reducing noise and mitigating multicollinearity issues that often compromise regression-based frameworks. Such methods may complement DLNM by enabling a more

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flexible characterization of the uncertainty in personal exposure relative to ambient levels. Additionally, incorporating model-agnostic interpretability tools, such as partial dependence plots or accumulated local effects (ALE), could help uncover synergistic interactions between environmental constituents while preserving transparency. Finally, shifting toward longitudinal study designs would facilitate stronger causal inference beyond the associative findings derived from the present cross-sectional analysis.

Based on the foregoing considerations, we briefly summarize the principal strengths and limitations of the commented study. Monti et al.'s analysis exhibits several strengths. First, the use of DLNM offers an appropriate framework for quantifying delayed and non-linear relationships between ambient exposures and schizophrenia severity. Second, the focus on clinically relevant PANSS outcomes in a densely populated urban setting increases translational value. Third, seasonal stratification and reporting of effect estimates with 95% CI across multiple pollutants and AT improve interpretability and robustness. Nonetheless, limitations warrant caution. Residential monitor–based exposure assignment may misclassify personal dose due to mobility and time spent indoors. The reliance on predefined spline specifications within DLNM could obscure temperature thresholds that amplify particulate pro-inflammatory effects, potentially oversimplifying complex synergies. Additionally, smaller subsamples for $PM_{2.5}$ and BC constrain statistical power and may contribute to observed seasonal differences. Finally, residual confounding from unmeasured seasonal factors is difficult to rule out without more integrated multivariate non-linear approaches.

In conclusion, while Monti et al. establish a significant link between environmental exposures and schizophrenia severity, advancing modeling strategies beyond rigid parametric frameworks is essential for capturing complex environmental synergies. The potential for current specifications to obscure the nuanced interplay between thermal stress and pollutants highlights the necessity for methodological evolution. Future research should prioritize the construction of a hybrid analysis strategy that integrates flexible, data-driven approaches with established epidemiological models. Furthermore, utilizing tools to visualize interactions will be critical for disentangling non-linear dependencies that traditional models may overlook. Operationalizing these refinements is vital to ensure robust health risk assessment and effectively safeguard vulnerable psychiatric populations in an era of dynamic environmental change.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Souichi Oka[a,*], Takuma Yamazaki[a], Yoshiyasu Takefuji[b]

[a] *Science Park Corporation, 3-24-9 Iriya-Nishi, Zama-shi, Kanagawa 252-0029, Japan*

[b] *Faculty of Data Science, Musashino University, 3-3-3 Ariake Koto-ku, Tokyo 135-8181, Japan*

[*] Corresponding author.

E-mail addresses: souichi.oka@sciencepark.co.jp (S. Oka), tyamazaki@sciencepark.co.jp (T. Yamazaki), takefuji@keio.jp (Y. Takefuji).