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Editorial

From Air Quality Monitoring to Health-Oriented Early Warning

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Respiratory diseases are particularly susceptible to changes in the atmospheric environment, including ambient air pollution and meteorological variability[1,2]. In large cities, high population density, complex air pollution mixtures, and rapidly changing weather conditions can contribute to fluctuations in respiratory morbidity and healthcare utilization[3,4]. Although substantial evidence links environmental exposures to respiratory health, fewer studies have translated this knowledge into operational tools that can anticipate near-term healthcare demand. The challenge, therefore, is no longer simply to establish whether atmospheric exposures affect respiratory health, but to determine how such evidence can be converted into timely, locally calibrated, and actionable warnings for health systems.

In this issue of *Biomedical and Environmental Sciences*, Zhao and colleagues[5] address this challenge by developing and validating a city-specific WHAair-LSTM framework for forecasting daily respiratory outpatient visits. The authors first constructed a five-level Warning for Health Risk of Atmospheric Environment index, or WHAair, using city-specific exposure-response relationships between multiple air pollutants and hospital admission data. They then incorporated WHAair, meteorological factors, and recent outpatient visit history into a long short-term memory (LSTM) model. Based on more than 223.7 million hospital visits from Beijing, Tianjin, and Chongqing, the framework showed strong predictive performance and was externally validated in cities with different air pollution profiles. Notably, removing WHAair reduced model accuracy, suggesting that a morbidity-driven composite pollution index can provide meaningful information for short-term respiratory healthcare demand prediction.

More broadly, this work highlights a timely transition in environmental health research: from estimating exposure-related health risks to anticipating their consequences for health systems. The contribution lies not only in model performance, but also in the conceptual shift it represents. This shift is consistent with a broader movement in environmental health research, in which climate-pollution interactions and machine-learning models are increasingly being used to predict healthcare demand[6]. Zhao and colleagues take a further step by converting such epidemiological knowledge into a health-service-oriented prediction framework. For public health practice, the key question is not only whether environmental exposures are harmful, but whether their short-term consequences can be anticipated early enough to guide preparedness and interventions.

The development of WHAair is particularly noteworthy. Conventional air quality indices are primarily designed to describe environmental conditions, whereas WHAair was derived from city-specific exposure-response relationships with health outcomes. This design makes the index more directly relevant to healthcare demand. The inclusion of multiple pollutants also reflects the reality of urban air pollution, where residents are exposed to complex mixtures rather than isolated pollutants. In addition, the consideration of vulnerable groups, including children and older adults, strengthens the public health relevance of the index. A locally calibrated, health-oriented index may therefore provide more actionable information than a general pollution metric when the goal is to warn of impending pressure on respiratory healthcare services.

Another strength is the attempt to evaluate generalizability. Predictive models are often limited by their dependence on the setting in which they

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were developed. The external validation in Tianjin and Chongqing is therefore important, because these cities differ in pollution patterns and urban characteristics. Such validation supports the potential scalability of the framework while also reinforcing the need for local calibration. The future of environmental health warning systems is unlikely to be a single model applied uniformly across all cities; rather, it may be a standardized framework that allows each city to estimate its own exposure-response relationships, define its own risk thresholds, and update predictions as local data accumulate.

The practical value of such a framework will depend on whether prediction can be connected to action. A city-level warning model should not be viewed as an isolated technical product, but as part of a broader preparedness pathway. When elevated WHAair levels and predicted outpatient demand suggest increasing respiratory risk, public health agencies could issue targeted health advisories, especially for children, older adults, and patients with chronic respiratory conditions. Hospitals, clinics, and community health centers could use these warning signals to adjust staffing, prepare respiratory clinics, ensure medication supply, and activate surge plans before patient volume peaks. A five-level health risk index is most useful when each level corresponds to clear actions, such as public communication, outpatient staffing adjustment, protection of vulnerable groups, and emergency resource allocation.

Future work should therefore focus on building operational early warning systems rather than simply improving model performance. City-specific calibration should become a routine component of model deployment, because pollution composition, climate conditions, population vulnerability, and healthcare utilization differ across urban settings. The framework could also be extended through multi-source data integration, combining environmental monitoring, meteorological data, outpatient visits, emergency calls, pharmacy sales, school absenteeism, and respiratory pathogen surveillance[7,8]. As prediction models increasingly use machine learning, transparent reporting, external validation, calibration assessment, and prospective evaluation should become standard expectations before routine implementation[9]. Ultimately, prediction-based warning should be evaluated by whether it improves preparedness, protects vulnerable populations, and optimizes medical resource allocation. The broader implication of Zhao and colleagues' study is clear: the next step for environmental health modelling is not only to predict risk more accurately, but to embed prediction into routine workflows for preparedness, communication, interventions and response.

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