HEI STATEMENT

Synopsis of Research Report 228

Optimizing Air Pollution Exposure Assessment with Application to Cognitive Function

BACKGROUND

There remain important limitations and challenges when assessing long-term exposure to ambient air pollution for use in epidemiological studies. In 2019, the Health Effects Institute issued Request for Applications 19-1 to develop and apply novel, scalable approaches to improve assessments of long-term exposures to outdoor air pollutants that vary widely in space and time.

Dr. Sheppard was one of the five investigators funded under this Request for Applications. Dr. Sheppard and colleagues proposed to advance the understanding of exposure assessment study design features; for example, to investigate the influence of sampling fewer visits per site, fewer days of the week, restricted hours of the day, and fewer seasons. They also included a comparison of health estimates derived from those features. They leveraged detailed air pollution and cognitive function data available at baseline (1994 or later) from the Adult Changes in Thought study in Seattle, which is a cohort study of about 5,400 individuals 65 years of age or older.

What This Study Adds

- The study compared the performance of different exposure assessment study design features on long-term exposure and health estimates in Seattle, Washington.
- It leveraged detailed air pollution data, including a mobile monitoring campaign, and cognitive function data from the Adult Changes in Thought study — a cohort study of older adults.
- The investigators used either the full air pollution dataset or subsets of measurements to develop annual average universal kriging models, machine learning models, and other advanced statistical models.
- The study found that a mobile monitoring study with roadside sampling of ultrafine particles with at least 12 visits per location optimized exposure model performance while limiting costs.
- The study provides practical guidance on future mobile monitoring campaigns, which addresses a clear research gap.

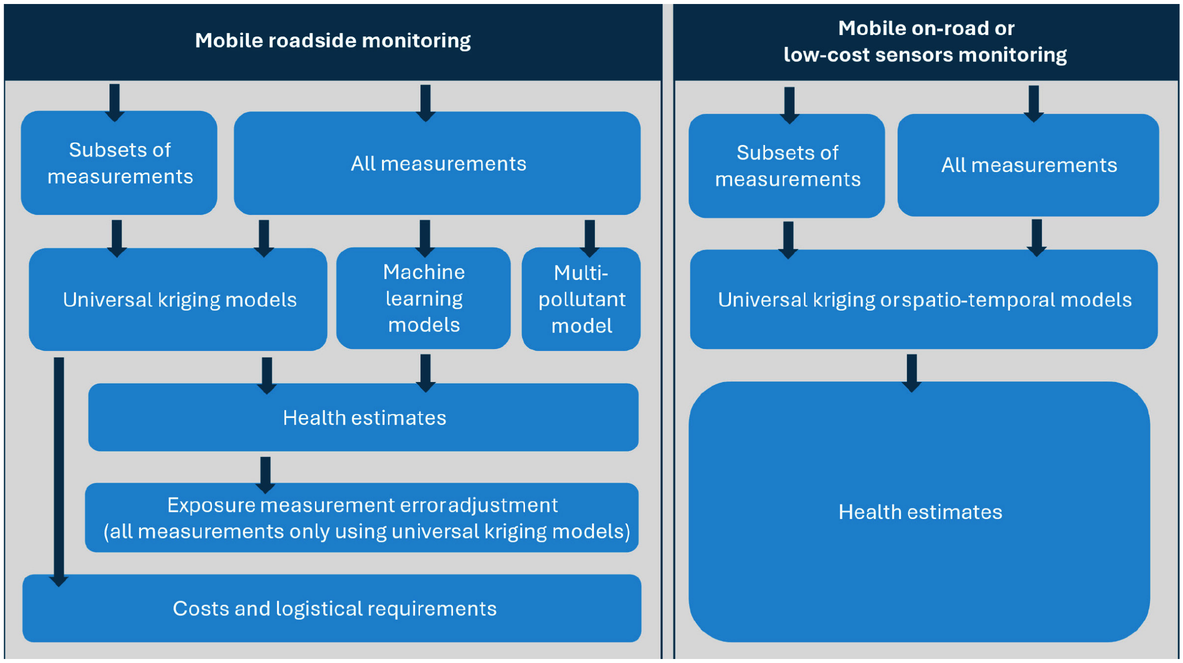
APPROACH

Most analyses focused on ultrafine particle data from a previously conducted mobile roadside monitoring data campaign in 2019–2020 that was designed to capture exposures for the Adult Changes in Thought cohort. In that campaign, short-term measurements were made from a parked vehicle at 309 roadside locations, with about 30 visits made to each site. For the present study, the investigators also conducted analyses using on-road measurements of ultrafine particles between roadside sites along predefined routes, for a total of 5,878 road segments. Each 100-meter segment was visited an average of 28 times. Ultrafine particles were measured with different instruments and size ranges captured, including a P-Trak and a NanoScan. Possible extreme values were replaced with a fixed percentile value for each visit (or segment), averaged across visits and log-transformed for subsequent exposure modeling.

Further analyses were conducted on fine particulate matter and nitrogen dioxide concentrations collected using low-cost sensors at about 115 fixed monitoring sites in 2017–2020, combined with regulatory monitoring data from a much longer time period.

The investigators subsampled measurement data to evaluate various exposure assessment study design features, such as fewer visits per site, fewer days of the week, restricted hours of the day, and fewer seasons. The investigators used either the full dataset or subsets of measurements to develop annual average exposure estimates using a suite of models, including universal kriging, spatiotemporal models, machine

This Statement, prepared by the Health Effects Institute, summarizes a research project funded by HEI and conducted by Dr. Lianne Sheppard at the University of Washington and colleagues. *Research Report 228* contains the detailed Investigators' Report and a Commentary on the study prepared by the HEI Improved Exposure Assessment Studies Review Panel.



Statement Figure. Schematic overview of the study design.

learning, and other advanced statistical models (**Statement Figure**). They assessed the performance of each model using cross-validation (mobile monitoring data) or a combination of cross-validation and external validation (low-cost sensor data). The investigators reported several measures to test the performance of the exposure models, including the root mean squared error and the mean squared error-based explained variance. The investigators also explored the tradeoffs between universal kriging exposure model performance and logistical features (both cost and time) to identify optimal monitoring designs.

Each model was used to predict the 5-year average ultrafine particles or other pollutant exposures prior to the cognitive function measurement that was obtained at baseline (1994 or later). The investigators applied standard linear regression to assess the association between exposure to ultrafine particles from each exposure model and baseline cognitive function, adjusted for participant age, sex, education, and calendar year (confounder model 1). Some results were also adjusted for participant race and socioeconomic status (confounder model 2).

In all comparisons, the models using all data from the mobile roadside campaign or all the low-cost sensor data were taken as reference models. Because even the reference models contain exposure measurement errors, the investigators quantified the exposure measurement error using bootstrap methods and corrected the health effect estimates accordingly in the reference model for ultrafine particles.

KEY RESULTS

The universal kriging reference model using all ultrafine particle data from the mobile roadside campaign had a cross-validated mean squared error-based explained variance of 0.65 (NanoScan) and 0.77 (P-Trak). The universal kriging model typically performed slightly better than the various machine learning models.

The universal kriging models with restricted mobile roadside sampling of ultrafine particles almost always produced lower-performing exposure models compared to the reference model. The investigators found that a mobile monitoring study with roadside sampling of ultrafine particles with at least 12 visits per location optimized exposure model performance while limiting costs. Furthermore, the investigators noted that it is important that the exposure sampling in mobile monitoring campaigns covers all days of the week, most hours of the day (including early morning and late evening hours), and at least two seasons.

Exposure of ultrafine particles estimated using the reference model was negatively (adversely) associated with cognitive function at baseline when adjusted for participant age, sex, education, and calendar year (confounder model 1). Cognitive function's association with ultrafine particles was –0.020 (95% confidence interval: –0.036 to –0.004) per increase of 1,900 particles/cm^3. The reduced sampling designs led to similar findings in terms of negative (adverse) associations between ultrafine particle exposure and cognitive function at baseline. However, the strength (magnitude) of the observed negative associations sometimes differed substantially, especially for the business and rush hours designs, which decreased associations by up to 60%. The investigators reported that the observed negative associations using confounder model 1 were affected more by features of the mobile monitoring design than by accounting for exposure measurement error in the reference exposure model for ultrafine particles.

Notably, the observed negative association in the reference model disappeared in health models that also adjusted results for race and socioeconomic status (confounder model 2). The null findings from the reference model using confounder model 2 hampered the assessment of the influence of sampling design on health estimates using different exposure estimates for ultrafine particles.

Using mobile on-road data for ultrafine particles, the investigators found that most comparisons identified the same design features or elements as important, although with a few notable differences.

The addition of low-cost sensor data to data from regulatory monitors and other research-grade monitors improved exposure modeling for fine particulate matter. Increasing the number of low-cost sensor locations and repeated measurements resulted in better exposure model performance. In contrast, in most comparisons for nitrogen dioxide, the addition of low-cost sensor data improved exposure estimates only slightly. Largely null findings were reported between fine particulate matter, nitrogen dioxide, and cognitive function for the various exposure models with and without low-cost sensor data. The null results hampered the assessment of the influence of adding low-cost sensor data for health estimates.

INTERPRETATION AND CONCLUSIONS

In its independent review, the HEI Review Panel thought the study was well-motivated and appreciated that it leveraged detailed air pollution and cognitive function data from the Adult Changes in Thought study in Seattle. The study provides practical guidance on future mobile monitoring campaigns, which addresses a clear research gap. The extensive year-long mobile monitoring campaign and the evaluation of various exposure assessment study design features were strengths of the study. Another strength was the extensive air pollution exposure modeling and rigorous evaluation of their performance. The Panel was also impressed by the large number of publications resulting from the work.

Although the Panel broadly agreed with the investigators' conclusions, some limitations should be considered when interpreting the results. Many of the analyses focused on ultrafine particles, and there were few comparisons across pollutants, although more information is presented in the Additional Materials and other publications. For the evaluation of exposure design features using mobile roadside and mobile on-road monitoring data of ultrafine particles, findings were presented in different stand-alone chapters, and different monitoring instruments were selected for various analyses. This makes a direct comparison between the two monitoring approaches difficult. An analysis investigating how the removal of possible extreme values affected the subsequent exposure models was missing from the report, but was included in a paper resulting from this work.

The Panel recommended caution in interpreting the findings from the health analyses and thought some carefully designed simulations would have complemented the real-world health study. The health analyses were considered limited, particularly because most of the exposure models used were based on measurements conducted up to 25 years later than the health outcome. In addition, some analyses lacked adjustment for important confounding variables — most notably socioeconomic status. Further research in other cities and pollutants would be helpful to assess the generalizability of the specific findings related to exposure assessment design.

The comprehensive report includes many findings that will be of broad interest and value to a wide audience.