THESIS

EVALUATING PERSONAL $PM_{2.5}$ AND BLACK CARBON EXPOSURE VARIABILITY IN BEIJING'S RURAL COMMUNITIES

Submitted by

Kennedy Hirst

Department of Civil and Environmental Engineering

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Master's Committee:

Advisor: Ellison Carter

Christian L'Orange
Christopher Bareither

ABSTRACT

EVALUATING PERSONAL $PM_{2.5}$ AND BLACK CARBON EXPOSURE VARIABILITY IN BEIJING'S RURAL COMMUNITIES

Exposure to air pollution is a major public health concern, with $PM_{2.5}$ and black carbon (BC) linked to adverse health outcomes. To reduce emissions of $PM_{2.5}$ and BC, the Chinese government implemented the Coal-to-Clean Energy Policy (CCEP) in 2016, reducing indoor $PM_{2.5}$ concentrations. However, its effect on personal exposure remains unclear. This study evaluated the role of time-activity patterns in personal exposure to $PM_{2.5}$ and BC in the context of the policy. Data from the Beijing Household Energy Transition study (winters of 2018-2022) included 252 participants with concurrent indoor and personal $PM_{2.5}$ measurements and GPS-based time-activity data. Geofencing classified participant locations, and generalized linear models assessed exposure determinants. Model performance was evaluated using indoor $PM_{2.5}$ data with and without time-activity adjustments. Personal $PM_{2.5}$ exposure averaged 52.9 $\mu g/m^3$, while BC averaged 1.6 $\mu g/m^3$. The best $PM_{2.5}$ model used indoor $PM_{2.5}$ over the full sampling period (AIC: 489.06, adjusted R^2: 0.59). The top BC model used indoor $PM_{2.5}$ averaged only while participants were home (AIC: 407.59, adjusted R^2: 0.25). On average, participants spent 20.0 hours at home per day (95% CI: 19.4, 20.7). Despite these time-activity trends, the lack of reductions in personal exposure were not explained by time-activity patterns, indicating that other influential factors may be impacting exposure, or the available data was insufficient to fully capture exposure variability. Enhanced time-activity monitoring is necessary to improve exposure assessments and better inform air quality interventions.

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INTRODUCTION

Air pollution is a leading environmental and public health risk, with exposure to fine particulate matter ($PM_{2.5}$) and black carbon (BC) contributing substantially to global and national burdens of disease, including a range of acute and chronic adverse cardiovascular, respiratory, and cognitive health outcomes, among others. Exposure to $PM_{2.5}$ and black carbon, including ambient and household air pollution, was found to have accounted for 6.67 million deaths in 2019, while $PM_{2.5}$ accounted for 652 thousand deaths alone within the nine regions of China in 2015.[1,2] Household energy use, specifically the combustion of solid fuels in the home for cooking and heating, is a significant driver of exposure to household air pollution. In regions of the world where solid fuel use is prevalent, such as the study setting of this thesis – rural China – use of solid fuels for daily cooking and heating is a leading source of exposure to $PM_{2.5}$ and BC. In addition to elevated exposures in the home to household air pollution, air pollutant emissions contribute to degradation of outdoor air quality across large regions in northern China. In response, the Chinese government implemented the Coal-to-Clean Energy Policy (CCEP) in 2016 to reduce household emissions by phasing out coal use for heating.

This master's thesis is situated within the broader Beijing Household Energy Transition (BHET) study, a longitudinal evaluation of air pollution and health impacts resulting from China's Coal-to-Clean Energy Policy (CCEP), implemented in 2016. BHET research has already documented measurable reductions in indoor $PM_{2.5}$ concentrations after policy implementation and identified modest health improvements, including small but consistent reductions in blood pressure—a sensitive indicator of cardiovascular health. Despite these observed improvements,

significant variability in personal exposure measurements remains unexplained, highlighting potential shortcomings in current approaches to assessing individual exposure.[3]

Few existing studies fully account for the role of personal behavior and time-activity patterns in explaining variations in personal exposure to pollutants. Specifically, the amount of time individuals spend at home versus away may significantly influence their exposure, yet this variable remains insufficiently characterized. Geofencing—classifying participants' locations based on GPS data—provides a promising method to more precisely assess exposure patterns and has yet to be extensively applied in studies of this nature.

Therefore, this thesis aimed to explore the hypothesis that variability in personal $PM_{2.5}$ and black carbon exposures may be influenced significantly by participant time-activity patterns, particularly their time spent at home versus away. To address this hypothesis, the study's objectives include: (1) characterizing the time participants spend at home versus away and assessing how this influences their $PM_{2.5}$ and black carbon exposure; (2) evaluating how these behavior-driven exposure patterns vary throughout the day; and (3) determining whether restricting indoor $PM_{2.5}$ analysis to periods when participants are home, compared to a full 24-hour period, better explains observed variability in personal exposure.

OBJECTIVES AND RATIONALE

This thesis leveraged the unique and comprehensive dataset from the Beijing Household Energy Transition (BHET) study, offering detailed measurements of outdoor, indoor, and personal air pollution to understand the variability observed in personal exposure levels. The implementation of the Coal-to-Clean Energy Policy (CCEP) provided a unique context to evaluate these dynamics, as prior findings within BHET documented clear reductions in indoor air pollution and modest health improvements, such as decreased blood pressure—a subclinical indicator of cardiovascular health. Yet, despite these positive epidemiologic outcomes, observed variability in personal pollutant exposure remained largely unexplained.

To explore this knowledge gap, this thesis investigated the hypothesis that participant time-activity patterns—particularly the amount of time spent at home versus away—significantly contributed to variability in personal exposure measurements. Given that indoor environments remained significant sources of $PM_{2.5}$, it was hypothesized that variability in personal exposure was largely driven by indoor pollution levels during time spent at home. Additionally, it was hypothesized that individuals who spent more time outdoors, especially during peak pollution periods, had higher personal exposure to ambient pollutants. Thus, systematically investigating the role of time-activity patterns may better explain the observed variability in personal exposure data.

This study specifically evaluated the impact of microenvironments by examining the influence of time spent indoors versus outdoors, emphasizing the importance of participant location for accurately assessing the impacts of household energy interventions. It hypothesized that personal $PM_{2.5}$ exposure was lower among individuals spending more time at home,

reflecting indoor $PM_{2.5}$ reductions due to the coal ban and heat pump subsidies. Nevertheless, a significant portion of the variability was expected to be explained by indoor pollution sources.

A detailed time-of-day analysis was conducted to identify how different daily activities affected personal exposure. The study hypothesized that increased outdoor activity during high-pollution periods led to higher personal $PM_{2.5}$ exposures. Furthermore, the relationship between indoor $PM_{2.5}$ levels and personal $PM_{2.5}$ and black carbon exposure was investigated, with an expectation of strong correlations, particularly for individuals who spent more time at home.

Accordingly, the specific objectives of this thesis are designed to explicitly test these hypotheses by:

1. Characterizing participant behavior regarding time spent at home versus away and examining the extent to which these patterns explained variability in personal $PM_{2.5}$ and black carbon exposure.
2. Performing time-of-day analyses to assess whether certain periods of the day disproportionately influenced pollutant exposure due to participant behavior.
3. Comparing two methodological approaches—using indoor $PM_{2.5}$ data exclusively during periods spent at home versus using data across the entire 24-hour period—to determine which provided a clearer representation of personal exposure dynamics.

To achieve these objectives, geofencing classified participant locations as at home or away using GPS data from personal sampling devices and home coordinates. Minute-averaged indoor $PM_{2.5}$ measurements and 24-hour averaged personal $PM_{2.5}$ and black carbon levels were aligned with GPS data to examine the influence of indoor pollution peaks on personal exposure variability. Generalized linear models explored factors such as duration spent at home, indoor

$PM_{2.5}$ concentrations, and other variables influencing personal exposure. Finally, model comparisons identified which approach (home-specific versus 24-hour indoor $PM_{2.5}$ data) most effectively explained variability and improved explanatory power regarding personal exposure.

The outcomes of this study refined the understanding of personal exposure variability and provided actionable insights for designing targeted air quality interventions, thereby improving individual health outcomes in similar contexts.

LITERATURE REVIEW

Introduction and Health Impacts of $PM_{2.5}$ and Black Carbon 3.1

Particulate matter can range from coarse to fine, composed of many different elements or materials, and can be detrimental to health in many ways. It is composed of a mixture of many different elements, ions and compounds that all can contribute to adverse impacts on health.[4,5] $PM_{2.5}$ refers to fine particulate matter with a diameter of 2.5 micrometers (μm) or smaller, while PM_{10} refers to particulate matter with a diameter between 2.5 and 10 micrometers, often referred to as coarse matter. $PM_{2.5}$ can enter the body through inhalation; Particles of varied sizes are deposited in various regions of the respiratory tract, influencing health outcomes. Particles between 5 and 10 μm can be deposited in the tracheobronchial tree, while smaller particles (1–5 μm) reach the respiratory bronchioles and alveoli.[4] $PM_{2.5}$ and its components can cross many protective barriers within our body, including the blood-air barrier, blood-testis barrier, and placental barriers. This ability to penetrate barriers allows $PM_{2.5}$ to reach sensitive tissues and organs, contributing to systemic health effects.[6,7]

This study focuses on $PM_{2.5}$ as well as black carbon (BC), a primary component of $PM_{2.5}$. Black carbon is a light-absorbing component of particulate matter, generated during the incomplete combustion of fossil fuels and biomass, among other sources.[8] $PM_{2.5}$ and BC, incorporated within air pollution including ambient and household air pollution, was found to have accounted for 6.67 million deaths in 2019, while $PM_{2.5}$ accounted for 652 thousand deaths alone within nine regions of China in 2015.[1,2] Not only can it lead to death, hospitalizations and emergency room visits are highly impacted when $PM_{2.5}$ increases as well. This is true for asthma,

circulatory diseases, hypertension, coronary heart disease, cerebrovascular disease, heart failure, arrhythmia, and atrial fibrillation, especially for vulnerable populations like the elderly.[9–11]

Cardiovascular and Metabolic Effects 3.1.1

$PM_{2.5}$ and black carbon exposure contribute significantly to cardiovascular diseases (CVDs). Black carbon exposure, like $PM_{2.5}$, is linked to increased risks of all-cause and cardiovascular mortality, especially at higher concentrations. This highlights the long-term health impacts of air pollution even in areas with relatively low overall air pollution.[12] It is strongly linked to blood pressure impacts, with higher levels associated with increased blood pressure and related cardiovascular strain, particularly during seasons with elevated concentrations, such as winter.[13] Long-term black carbon exposure is associated with a 6.8% increase in CVD risk among all groups, while short-term exposure increases CVD in the elderly by 1.6% per 1 $\mu g/m^3$.[14] Similarly, $PM_{2.5}$ exposure promotes cellular oxidative potential, generating reactive oxygen species that can cause lung inflammation. These effects are particularly pronounced in winter, where cell death and pro-inflammatory cytokines are higher.[15,16] Similarly, $PM_{2.5}$ is associated with a decrease in overall survival of non-small cell lung carcinoma and could potentially affect in-hospital mortality, although further research is warranted.[17]

Long-term exposure to $PM_{2.5}$ also increases the risk of type two diabetes by promoting inflammation, reducing insulin sensitivity, and impairing glucose uptake.[18] Similarly, during pregnancy, exposure to $PM_{2.5}$ and Sulphur Dioxide in the first and second trimesters modestly, but significantly, increases the risk of gestational diabetes mellitus.[19]

Reproductive and Neurological Impacts 3.1.2

$PM_{2.5}$ exposure affects reproductive health in both men and women, including oxidative stress, hormonal disruption, and physical damage to reproductive organs. In men, it disrupts

spermatogenesis and reduces testosterone, while in women, it impairs ovarian function and increases pregnancy complications.[7] This is because, as previously stated, $PM_{2.5}$ can penetrate protective barriers such as the placental barrier as well as the blood-brain barrier. It also has been implicated in neurodegenerative diseases like Alzheimer's, Parkinson's, and vascular dementia as it can travel through the olfactory bulb to the brain, promoting neuro-inflammation.[6]

Mental Health and Cognitive Performance 3.1.3

Not only can it impact physical health, but it can also impact mental health; $PM_{2.5}$ and black carbon exposure adversely affect mental health and cognitive performance. Long-term $PM_{2.5}$ exposure correlates with higher rates of depression and anxiety, even at low concentrations.[19,20] Cognitive performance can also be impacted; For instance, a study on Major League Baseball umpires revealed that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ (12-hour average) led to a 0.4% higher likelihood of incorrect calls.[21] In addition, $PM_{2.5}$ has social implications, such as an increase in violent crime rates. For every 10% increase in $PM_{2.5}$, there is a 0.14% rise in violent crimes per county per day in the U.S., potentially due to impacted decision making mechanisms.[22]

Policy and Intervention Health Impacts 3.1.4

Intervention policies targeting $PM_{2.5}$ have demonstrated significant health benefits. Reduced $PM_{2.5}$ levels have led to improved birth weights, fewer cases of pneumonia, and reductions in ischemic heart disease.[23] For example, China's "Action Plan for Air Pollution Prevention and Control" implemented strict measures to curb $PM_{2.5}$ emissions, resulting in significant reductions in pollution levels and associated health risks.[24] Similarly, the Blue-Sky Policy implemented for the 2008 Beijing Olympics provides a notable example of targeted intervention. This policy included stringent measures such as restricting vehicle use, halting

industrial activities, and reducing construction dust. These efforts led to significant reductions in $PM_{2.5}$ concentrations during the Olympic period, demonstrating the effectiveness of such temporary, but focused, policies in mitigating air pollution and improving public health outcomes.[25] One intervention study showed that acute myocardial infarction decreased by 6.6%, with women benefiting more due to spending more time indoors.[26] Because of these findings, research is warranted for identifying $PM_{2.5}$ and black carbon impacts leading to potential positive epidemiological impacts listed above.

Sources of $PM_{2.5}$ and Black Carbon in Study Area 3.2

$PM_{2.5}$ and black carbon pollution in rural northern China primarily originate from a range of sources, including combustion activities, dust sources, and secondary aerosol formation.[27–31] The relative contributions of these sources vary by season and are influenced by local socio-economic conditions, policies, and meteorological factors.[32] While urban air pollution in China can be dominated by industrial activities and vehicular emissions, rural areas may exhibit a distinct pollution profile characterized partly by household fuel combustion, however, the air transport of pollutants may contribute to both areas.[29,33,34]

One of the dominant sources of $PM_{2.5}$ and black carbon in rural Northern China is household fuel combustion, particularly the burning of coal and biomass for heating and cooking.[5,35] This is especially prominent in winter months when temperatures drop significantly, leading to a surge in coal and wood consumption in low-efficiency stoves. However, policies such as the "2+26" regulation and coal-to-gas transition programs have led to a gradual decline in residential coal use in some areas.[36] Despite these measures, economic constraints and infrastructure limitations may hinder widespread adoption of cleaner alternatives, resulting in persistent pollution from household fuel use.[37]

Seasonal agricultural burning is another contributor to $PM_{2.5}$ and black carbon in rural northern China. Post-harvest open field burning of crop residues in autumn months, particularly wheat straw and corn stalks, releases large quantities of primary particulate matter and precursor gases that facilitate secondary aerosol formation.[38] Despite regulations prohibiting open field burning, the practice persists and continues to contribute to pollution concentrations.[24,39] Compared to urban areas where agricultural burning is largely absent, rural Northern China experiences periodic spikes in $PM_{2.5}$ and black carbon during harvest seasons, contributing significantly to regional air pollution levels.[40,41]

While industrial emissions are typically lower in rural regions than in industrial centers, other localized industrial activities still contribute to $PM_{2.5}$ and black carbon pollution.[5] Although large-scale industrial regulations have led to reductions in urban industrial emissions, industries remain a significant source of pollutants due to weaker oversight.[24] However, there are relatively few industrial pollutants in this study area, limiting their overall impact compared to other pollution sources.[42]

Vehicular emissions are a relatively smaller fraction of rural $PM_{2.5}$ and black carbon pollution but are becoming more prominent with increasing car usage.[24,34,39] Urban exposures are largely driven by traffic-related pollutants, with black carbon and $PM_{2.5}$ levels spiking during commuting periods.[43] Rural exposures, in contrast, are dominated by indoor sources such as cooking and heating with solid fuels like coal and biomass.[3,44,45] Additionally, episodic sources such as fireworks during Spring Festival celebrations lead to short-term but severe increases in $PM_{2.5}$ and black carbon concentrations.[31]

Meteorological conditions play a significant role in determining $PM_{2.5}$ and black carbon concentrations in China. Seasonal variations in temperature, wind patterns, and atmospheric

stability affect the dispersion and accumulation of air pollutants.[46,47] In winter, low temperatures drive increased household fuel combustion, while stable atmospheric conditions and lower boundary layer heights trap pollutants near the surface, exacerbating air quality issues.[27,47] Conversely, summer months experience enhanced photochemical activity, leading to increased secondary aerosol formation; Secondary aerosol formation plays an important role in $PM_{2.5}$ pollution in China.[40,48] Wind patterns also influence pollutant transport, with strong northerly winds often bringing dust from arid regions.[24,48,49] Precipitation events, particularly during monsoon periods, can help reduce pollutant concentrations by washing out airborne particles, however.[30] Knowing this, the interaction between anthropogenic emissions and meteorological conditions greatly influences the spatial and temporal distribution of pollutants across China.

Dust sources, including road dust, soil dust, and construction dust, also contribute to $PM_{2.5}$ pollution in rural China. In contrast to urban areas, where dust pollution is primarily linked to construction activities and vehicular resuspension, rural dust emissions stem largely from natural soil erosion and agricultural land use practices.[28,40,50]

The sources of $PM_{2.5}$ and black carbon in rural northern China reflect a unique combination of traditional fuel use, agricultural practices, and regional dust contributions. While policy measures have led to reductions in certain emissions, challenges remain in fully transitioning rural households away from solid fuels. Previous research in this larger study have identified through source apportionment techniques that the highest sources of this are two dust sources, secondary aerosols, and mixed combustion which includes coal use.[42] Understanding these pollution sources and their variations is important for developing targeted air quality management strategies that address both household and regional-scale contributors.

Modeling and Variability of Personal Exposure to Air Pollution 3.3

Many aspects of daily life could influence the variability of personal exposure. Seasonal differences significantly influence personal exposure to air pollution, with winter months often associated with elevated exposure.[3] In rural households, reliance on solid fuels for cooking and heating leads to significantly higher personal $PM_{2.5}$ exposure, particularly in colder months, when heating activities play a major role in exposure levels.[44] In contrast, during summer, outdoor air quality may have a smaller impact on personal exposure variability compared to winter.[51] Urban settings show increased ambient $PM_{2.5}$ contributions to personal exposure in the winter, except for outdoor workers and stay-at-home workers, which is a large portion of the participants in this study.[45,52,53] Urban and rural settings present distinct exposure profiles due to differences in pollution sources and time-activity patterns, as described previously. Studies reveal that rural households relying on biomass experience household $PM_{2.5}$ levels 15 times higher than WHO guidelines, with kitchens as the primary exposure hotspot.[44]

Personal exposure varies widely depending on individual time-activity patterns and the microenvironments visited throughout the day, keeping in mind geography and season.[54] Activities like cooking and cleaning contribute to indoor pollutant spikes, particularly in households using solid fuels and outdoor factors such as traffic emissions and atmospheric conditions may also influence it. However, time in transit was shown to not make a considerable impact on rural $PM_{2.5}$ variability.[44,52] Time-activity logs and diaries have been commonly used in personal exposure studies, but automated methods like geofencing and wearable sensors are used, if time logs aren't available, by linking location and behavior with pollutant levels in real-time.[55] For example, a study identifying microenvironment classification stated that some air pollutants were dominated by specific workplace locations, showcasing how personal exposure variability could be further explained with factors such as time, location, source, and activity,

even without relying on detailed activity diaries[54]. Therefore, time-of-day variations in air pollution exposure are potentially significant and can guide strategies to explain personal variability.

Personal exposure variability needs to be further identified. Factors such as microenvironment visitation durations, household fuel use, and commuting habits contribute to substantial differences that cannot be captured by ambient or indoor monitors alone. Technologies and applications, including wearable sensors and GPS-based tracking, offer promising solutions for capturing this complexity. These advancements not only improve the accuracy of exposure assessments but also provide valuable data for developing targeted risk-reduction strategies.[43,53]

Modeling Variability 3.3.1

Prior research provides essential guidance on the factors influencing personal $PM_{2.5}$ and black carbon exposures. These variables may significantly contribute to the variability of personal exposures to air pollution, making their careful selection and evaluation important. Several studies have emphasized the importance of outdoor $PM_{2.5}$ concentrations as a dominant predictor of personal exposure variance, although this relationship may differ by season or location.[3] For instance, multiple studies found outdoor $PM_{2.5}$ to be a strong predictor[3,56] while others indicated weaker correlations in certain contexts.[45] Outdoor $PM_{2.5}$ levels have been found to explain 16% of within-individual $PM_{2.5}$ exposure variability, however.[51]

Studies exploring personal exposure variability have reported a broad range of explained variance, contingent on the factors assessed. Household behaviors, including stove type, kerosene use, and adherence to intervention stoves, accounted for up to 48% of black carbon exposure variability.[57] Similarly, household characteristics, behavioral factors, and

environmental conditions contributed to model performance, with explained variance ranging from 45% to 76%.[58]

Indoor sources such as fuel type, cooking duration, and kitchen enclosure type explained 33–54% of personal black carbon variability and 46–60% of household black carbon variability, while indoor $PM_{2.5}$ sources have accounted for 7–28% of between-individual variance in exposure.[51,59] Kitchen characteristics, such as stove type and seasonality, were found to explain 37% of personal $PM_{2.5}$ variability and 49% of kitchen $PM_{2.5}$ variability, while explaining 37% and 47% of personal and kitchen black carbon concentrations, respectively.[60] The relationship between black carbon and $PM_{2.5}$ also showed strong correlations, with personal black carbon and $PM_{2.5}$ measurements correlating at $r = 0.76$ and household black carbon and $PM_{2.5}$ correlating at $r = 0.82$.[59] These findings highlight the complexity of exposure dynamics, with explained variability ranging from as low as 7% to as high as 48%, depending on the pollution sources, household behaviors, and environmental factors considered.[57–60]

Household fuel type, stove type, and stove use duration have been repeatedly identified as significant determinants of exposure in rural settings.[59,60] Fuel type has been a commonly studied model variable in previous work.[3] Some studies have also indicated the importance of ventilation characteristics in influencing exposure levels, though availability of such data varies.[59,60]

Demographic and socioeconomic variables, such as gender, education, and income, have been evaluated for their relevance in exposure studies. Prior research has found that women were typically responsible for cooking, while men were more likely to engage in heating practices involving outdoor solid fuel stoves.[51,61] This led to proportionally lower exposure in women compared to men due to their continued exposure during refueling. However, studies have

presented mixed findings regarding gender, with some showing higher exposures for women,[3] while others indicate minimal differences.[26,59] Prior work also suggests education level and wealth factors can influence exposure through behaviors like fuel choice and time spent in polluted environments.[57,59] Occupation has also been considered an important variable, with research finding notable variability in exposure and time at home based on occupational roles.[57] Some studies have concluded that age had little impact on exposure models, while others have identified that elderly individuals are disproportionately affected by exposure effects.[51]

Smoking status has been widely recognized as a factor influencing indoor $PM_{2.5}$ levels.[3,45,62] The impact of smoking on exposure is often reflected in measured $PM_{2.5}$ concentrations, and studies have considered various methods to account for this factor in modeling approaches. Treatment status under policy interventions, such as coal-to-clean energy programs, has shown mixed effects in past studies,[3] with some research highlighting short-term exposure reductions after treatment while others found that observed changes were likely due to broader environmental shifts.

Geofencing techniques have been widely applied in other studies alongside time activity diaries or logs, allowing for the inclusion of various microenvironments such as in-transit activities.[54,63] However, studies have indicated that accuracy can be improved with complementary datasets such as accelerometer or light intensity data.[44] The ability to capture transit-related exposure remains an area of mixed findings in the literature, particularly in rural versus urban settings.[64]

Geofencing 3.4

Geofencing, the process of defining spatial boundaries to classify locations and activities, has become a tool for assessing personal air pollution exposure as time activity patterns become

more evident through this approach. Recent studies have leveraged advances in GPS technology, sensor networks, and machine learning to refine geofencing methodologies, allowing for greater accuracy in exposure estimation.[65,66] Approaches to geofencing vary widely, incorporating time-activity diaries, rule-based algorithms, machine learning models, and hybrid methods integrating multiple data streams.

Early geofencing techniques relied on simple rule-based classification schemes, in which time-activity diaries or static thresholds for movement were used to define microenvironments.[67] While these methods are computationally efficient and interpretable, technological advancements have enabled the integration of multiple sensors to better determine more complex microenvironments. However, when time and resources are limited, simpler methods remain viable alternatives for exposure assessment. More recent rule-based models have incorporated additional contextual variables such as accelerometer data and time-stamped movement patterns, improving classification accuracy for distinguishing between home, work, transit, and other locations.[66,68]

Machine learning approaches have also enhanced geofencing capabilities by integrating data from multiple sensors, including GPS, accelerometers, and environmental monitors with applied random forest classification to distinguish between major microenvironments, achieving high classification accuracy for home and work locations.[55] Similarly, compared rule-based methods to random forest decision trees, finding that while both performed well for indoor and in-vehicle travel classification, random forest models were more adaptable to complex movement behaviors.[65] However, models require substantial training data and may be sensitive to sensor noise, posing challenges for large-scale implementation.[68]

Hybrid geofencing approaches seek to integrate the strengths of rule-based and machine learning methods. A trajectory-based exposure model has been developed using GPS tracking with geospatial analysis and density-based clustering to enhance spatial resolution in exposure assessments[69] as well as a time-integrated geofencing method that incorporated home-range estimation technique to better characterize individual exposure spaces, utilizing nearest neighbor clustering to refine spatial movement classifications.[70]

Despite these advancements, challenges remain in geofencing implementation, particularly in defining accurate home locations and accounting for temporary exposure shifts and movement variability. The difficulty of capturing exposure variability in peri urban settings, where individuals frequently transition between different microenvironments was highlighted in literature.[56] Additionally, it was demonstrated that high-resolution GPS tracking alone is insufficient for exposure estimation as it fails to account for indoor pollutant concentrations and behavioral factors such as time spent near sources of pollution.[43]

Some studies have incorporated accelerometer data to identify overall movement patterns of participants, as well as speed, distance difference, and distance ratio to further enhance geofencing accuracy.[65,66] Some studies incorporated smartphone-based accelerometers to classify activity states,[43,66] while others used dedicated motion sensors for higher precision.[65]

Additionally, alongside these, rapid changes in relative humidity or ozone levels as an identifying mechanism,[55] provided aid in geofencing to detect transitions between indoor and outdoor environments.[56] Ozone sensors were employed to provide supplementary data for identifying exposure levels, particularly in studies analyzing urban air pollution.[55,56] The number of satellites in use was also analyzed to enhance location accuracy, ensuring more reliable exposure classification.[69] Furthermore, noise sensors have been included to refine

microenvironment detection, particularly in differentiating transit modes,[55] while wearable cameras have been utilized to validate exposure classifications visually. However, their presence may influence participant behavior due to the Hawthorne effect.[56] Previous studies have also explored the use of temperature and speed to improve indoor-outdoor classification in geofencing. Temperature shifts of ±1–2 degrees Celsius over 1–2 minutes have been shown to mark environmental transitions and enhance accuracy.[64,71] Similarly, speed thresholds of 15 to 25 km/h are often used to distinguish active travel from in-vehicle movement, and smoothing speed over one to fifteen minutes helps reduce GPS-related misclassification.[72–74]

Overall, geofencing techniques have evolved from static, rule-based methods to more dynamic approaches that integrate multiple sensor inputs. While machine learning and hybrid models offer improved classification accuracy, they also introduce computational complexity and data availability challenges. Satellite information, in order to enhance accuracy, as well as home location data, can significantly improve geofencing capabilities in the absence of multiple sensors for measurement analysis. Additionally, when time-activity logs or diaries are unavailable, these alternative data sources can provide spatial and contextual information for exposure classification.

Gaps in Existing Literature 3.5

While extensive research has examined $PM_{2.5}$ and black carbon exposures, significant gaps remain in understanding the variability of personal exposures. Despite reductions in ambient and indoor $PM_{2.5}$ following interventions such as the Coal-to-Clean Energy Policy (CCEP), personal exposure variability persists, raising questions about the factors driving individual-level differences in exposure.[3] Current literature suggests that while reductions in

household air pollution are measurable, attributing changes in personal $PM_{2.5}$ and black carbon levels solely to policy interventions remains challenging. [3,42]

This literature review synthesizes findings from a wide range of studies that all point to a key limitation in existing personal exposure variability models, that is, the incomplete accounting of individual behaviors and microenvironments. Furthermore, this literature review covers many studies that have advanced personal exposure modeling by improving the characterization of time-invariant inputs (e.g., sociodemographic, smoking status, indoor air pollution sources). However, prior research has also identified a range of time-varying factors. Indoor pollution sources, such as stove use, cooking duration, time spent in transit or different modes of transportation, and time in various locations like work, school, restaurants, or even different rooms within a household, along with household activities like cleaning, have all been used to distinguish microenvironments. However, these variables are often excluded from research due to challenges in data collection. Geofencing methodologies, while increasingly employed in personal exposure research, exhibit gaps. The accuracy of geofencing classifications depends on the availability of supplementary data such as accelerometer readings, light intensity measurements, and time-activity logs, which are often missing or incomplete.[64,67] Geofencing often relies on costly techniques that limits its broader application.[65] It is important to explore low-cost alternatives that can effectively classify indoor and outdoor exposure periods, particularly in rural settings where movement between microenvironments is less structured than in urban areas. Additionally, verifying geofencing classifications without expensive wearable sensors or time logs remains an unresolved challenge, introducing potential classification biases in personal exposure estimates.[64]

Furthermore, prior work suggests that the indirect effects of policy—such as behavioral adaptations to new heating technologies—may introduce additional variability in exposure outcomes, yet this remains underexplored in current literature. Policy interventions targeting $PM_{2.5}$ and black carbon have demonstrated measurable improvements in ambient air quality, yet their impact on personal exposure reduction is less well understood. Studies have found that while $PM_{2.5}$ levels declined following interventions, these reductions were not uniform across populations, with some groups experiencing minimal change in personal exposure levels.[3]

Despite the challenges associated with measurement imprecision, large standard deviations, and potential limitations in explanatory power, identifying variability in personal exposure remains important for advancing the field. The existing literature has highlighted substantial gaps in accounting for time-activity patterns and their role in shaping individual exposure levels, yet these factors remain largely understudied due to the inherent difficulty in capturing them with precision without time activity diaries. Even if the variability observed in this study is limited, refining methods to characterize time-varying behaviors contributes to a more nuanced understanding of exposure dynamics. The ability to distinguish between real variability and measurement noise is essential—not only for improving exposure assessments but also for informing future research on how microenvironments influence personal $PM_{2.5}$ and black carbon exposure. Even if the direct explanatory power of time-activity patterns might appear limited, the act of quantifying them enhances methodological rigor and lays the groundwork for future studies to build upon. This study acknowledges that while some sources of variability may remain unaccounted for, incorporating time-varying variables—however imperfectly measured—advances the precision of personal exposure assessments, providing insights that move the field beyond static, one-size-fits-all exposure models. While there is a total amount of

variability in personal exposure, incorporating time-activity patterns adds valuable insight by identifying gaps in understanding and refining exposure assessments. Even if these patterns do not substantially enhance exposure explanations, they serve as an important step in pinpointing future research directions and methodological improvements.

By addressing these gaps, this study contributes to a more refined understanding of how personal exposure to $PM_{2.5}$ and black carbon is influenced by individual behaviors, environmental conditions, and policy interventions. The findings have provided insights for designing more effective personal exposure assessments and informing future air pollution mitigation strategies.

METHODS

Study Design and Recruitment 4.1

Study Timeline and Waves 4.1.1

Data collection occurred for four winter campaigns. The first wave, conducted in the winter of 2018/2019, collected baseline data before any villages had transitioned to clean energy. At this stage, all households relied on solid fuels, and coal specifically, for space heating. In the second wave, during the winter of 2019/2020, ten villages adopted clean heating technologies as part of the Coal-to-Clean Energy Policy (CCEP), allowing for the evaluation of early program impacts. The third wave occurred in the winter of 2020/2021, which experienced limited data collection due to the COVID-19 pandemic and was not included in this analysis. By the fourth wave, conducted in the winter of 2021/2022, additional villages transitioned to clean energy, resulting in a total of 20 of 50 villages apart of the Beijing Household Energy Transition Study participating in the Coal-to-Clean Energy Policy (CCEP) by the study's conclusion.

Participant Recruitment 4.1.2

Villages were selected based on eligibility for the CCEP to ensure geographic and demographic representation. Within each village, households were randomly recruited, resulting in the enrollment of 300 participants in both wave 2 and 4. The sample size was determined to ensure sufficient statistical power. The inclusion criteria required participants to be adults aged 40 and above and for households to provide informed consent. Study protocols were approved by the institutional review boards of Peking University and McGill University.

Personal Measurement Recruitment 4.1.3

In each village, up to 20 households were randomly selected to participate in personal exposure monitoring. One eligible adult (aged 40 years or older) from each household was recruited for personal air quality sampling. During the initial wave, 10 of the 20 participants in each village were randomly chosen to wear personal air samplers that collected 24-hour $PM_{2.5}$ filter samples. In subsequent waves, efforts were made to monitor the same participants. If a participant dropped out or declined further participation, another adult from the same household was attempted to be recruited. If no replacement was available within the household, another participant from an enrolled household in the same village was selected.[3]

Indoor Measurement Recruitment 4.1.4

Starting in the second wave of the study, six households per village were randomly selected to undergo indoor air quality monitoring. Wave 1 was not funded for indoor air quality monitoring. A low-cost sensor (PMS7003, Plantower, Zefan Inc.) was deployed in each selected household to continuously measure $PM_{2.5}$ concentrations at one-minute intervals. During the fourth wave, efforts were made to monitor the same households that participated in the second wave. If a household withdrew from the study or declined continued participation, another household already enrolled in the project was recruited as a replacement.

Study Location 4.2

The study was conducted across 50 villages situated in four rural and mountainous administrative districts of Beijing: Fangshan, Huairou, Mentougou, and Miyun. These areas were selected based on their eligibility for Coal-to-Clean Energy Policy (CCEP), which facilitated varying levels of participation. This allowed for meaningful comparisons between villages adopting clean heating technologies and those who continued to rely on solid fuels as well as those who adopted the program and those that did not. The geographic characteristics of the

selected districts, located about 40 km (about 25 miles) from Beijing's urban center, were largely rural with limited external pollution sources. This created a setting well-suited for isolating the local effects of residential heating practices on indoor air quality.

The study included 11 villages in Fangshan, 18 in Huairou, 9 in Mentougou, and 12 in Miyun. Understanding the geographic context was essential for assessing the broader demographic and socioeconomic characteristics that shape heating practices and air quality outcomes in the study area. The map (Figure 1) illustrates the locations and distribution of participant home coordinates across these districts. This research emphasizes indoor and personal pollution exposure, reflecting household heating choices and the corresponding environmental impacts for three winter seasons.

Figure 1. Map displaying the home locations of study participants across four districts in rural Beijing—Huairou in blue (337 participants), Miyun in purple (230 participants), Mentougou in green (147 participants), and Fangshan in red (182 participants). The scale bar represents 50 km (31 mi), and the Beijing city center is marked for reference.

Data Collection and Exposure Measurements 4.3

Data Collection 4.3.1

A detailed questionnaire was administered to each participating household by trained field staff to gather detailed information on household demographics, home coordinates, stove and fuel use patterns, as well as behaviors that are associated with air pollution exposure, such as smoking habits. The questionnaire was designed to capture key household and individual characteristics that could influence air quality and exposure patterns. While the questionnaire included a comprehensive set of questions, this section focuses on the most relevant aspects for

the analysis. In addition to smoking status, the questionnaire recorded gender, education level, occupation, and village of residence. These demographic variables provided important contextual information for exposure assessment and model development.

Gender was recorded as either male or female. Education level was categorized into four groups: Primary school, Secondary or high school, Higher education, and No school attended. However, education was later grouped into two broader classifications: Primary school or below and Secondary or high school and above. Occupation was initially recorded under ten categories: Agriculture and related workers, Factory worker, Government worker, Professional/technical workers, Sales and service workers, Retired, Housewife/husband, Self-employed, Unemployed, and Other or not stated. For analysis, these were consolidated into four broader groups: agriculture or related workers, indoor workers, unemployed, and other/not stated. This reclassification allowed for a more robust analysis while preserving meaningful distinctions between occupational categories. For each participant, the village of residence was recorded, which also allowed for classification into one of the districts included in the study. The treatment status of the policy intervention (solid fuel ban) was determined at this time as well. This classification was essential for assessing the intervention's impact on personal exposures.

Socioeconomic status was also included as a variable of interest and an independent variable with the models. A composite wealth index was developed to assess the relative socioeconomic status of participants using principal component analysis (PCA). This index was constructed from data on household assets, property ownership, and land value to serve as a proxy for long-term affluence. Income data was collected through surveys, which included questions on wages, business earnings, agricultural income, remittances, and government subsidies. Due to potential misreporting and participant reluctance, these self-reported values

were supplemented with a PCA-based wealth index. This approach integrated household assets (such as vehicles and appliances), the number of rooms in the household, house value (calculated using reported house area and estimated rental values), and agricultural and forest land values (estimated by multiplying land area by average agricultural income in each village) as indicators of economic standing. Validation was performed by comparing mean values of wealth-related indicators across different wealth index groups, revealing consistent trends that confirmed the reliability of the constructed index. Further details on this approach can be found in previous literature.[45]

The data was collected through home visits conducted by trained enumerators working usually in pairs. One enumerator typically administered the questionnaire while the other conducted a separate health survey, which included biometric measurements. A component of the data collection process was recording home coordinates to spatially link exposure data. However, due to occasional tablet malfunctions or weak satellite reception, obtaining a location was sometimes difficult, therefore GPS coordinates were attempted to be collected at both the beginning and end of the questionnaire survey.

If both the initial and final GPS attempts were successful, the coordinates were averaged to provide a more stable home location estimate. If only one valid GPS point was recorded, that single point was used. If no GPS coordinates were obtained during the questionnaire survey, the health survey conducted at the same home visit provided an alternative source for the home location. Since health surveys were typically conducted inside the participant's home, their GPS coordinates were considered a valid proxy for home location. If a participant completed their health survey at a clinic rather than at home and on a different day, their GPS coordinate was not considered for home coordinate assignment.

In rare cases where both the questionnaire and health survey failed to record a GPS location, the home coordinate was missing. This occurred for 12 participants who did not have a home coordinate logged at the start or end of the questionnaire survey, nor a health survey coordinate recorded at the beginning or end of the survey on the same day.

The combination of questionnaire responses and GPS data provided a robust dataset for analyzing the impact of the policy intervention on personal air pollution exposures.

Personal $PM_{2.5}$ Measurement 4.3.2

Personal exposure was measured using ultrasonic personal air samplers (UPAS, Access Sensor Technologies, Fort Collins, CO, USA), which actively sampled air at a flow rate of 1.0 L/min. The UPAS units contained 37 mm polytetrafluoroethylene (PTFE) filters (VWR, 2.0 μm pore size) and were equipped with cyclone inlets with a 2.5 μm cut point to capture fine particulate matter. Participants were instructed to wear the personal samplers for a 24-hour period as they went about their daily routines. These measurements provided insight into individual-level exposure to $PM_{2.5}$, supplementing indoor air quality measurements taken at the household level.

All sensors were co-located with a reference-grade $PM_{2.5}$ instrument (Model 5030 SHARP, Thermo Fisher Scientific) on the rooftop of Peking University for 7–10 days before and after the field campaign. The sensor-measured $PM_{2.5}$ concentrations exhibited strong correlations with those obtained from the reference instrument. The sensor-based measurements were adjusted using linear regression models using filter-based $PM_{2.5}$ as the reference. More information on this process can be found in previous literature.[32,45]

Indoor $PM_{2.5}$ Measurement 4.3.3

The indoor $PM_{2.5}$ sensors were strategically placed in living spaces to capture real-time air quality, minimizing potential measurement biases (PMS7003 Plantower, Zefan, Inc.). This method provided consistent data on indoor $PM_{2.5}$ variations during the heating season. Sensors were deployed between late November and mid-January, and measurements continued until late April, when the sensors were recollected. This deployment schedule was designed to capture air quality variations during the heating season.

To further validate the indoor sensor data, co-located $PM_{2.5}$ filter samples were collected in three of the six monitored households per village. These co-located samples were taken during the first 24 hours of indoor sensor deployment, providing an additional reference point for data quality and accuracy. In each wave, field blank filters were collected for 10% of the samples for both personal and indoor filters.

Outdoor $PM_{2.5}$ Measurement 4.3.4

For outdoor $PM_{2.5}$ monitoring, one to three real-time sensors (PMS7003 Plantower, Zefan, Inc.) per village were deployed, typically two, positioned within an environmental enclosure. One sensor was placed centrally, while additional sensors were located at least 500m away. Sensors were installed at least 1.5 m above ground and away from $PM_{2.5}$ sources. For verification, real-time sensors were co-located with UPAS devices (UPAS, Access Sensor Technologies, Fort Collins, CO, USA) that collected filter-based $PM_{2.5}$ samples at 1.0 L/min, which were replaced weekly. If multiple outdoor measurements were taken within a village, they were averaged over the duration of personal exposure sampling for each participant to ensure consistency in exposure assessment.

Sample Analysis 4.4

Runtime Sensitivity Analysis 4.4.1

To ensure the representativeness of the personal air pollution sampling period and the population, data inclusion was evaluated based on two runtime thresholds – 80% and 90% of the total 24-hour sampling period (equivalent to 19.2 hours for 80% and 21.6 hours for 90%). Data below 90% was excluded, as it accounted for less than 21.6 hours of sampling, which was considered insufficient to reflect a full day. The objective was to maximize data inclusion while maintaining proximity to the full 24-hour period to enhance the reliability of the findings. A sensitivity analysis comparing the 80% and 90% thresholds was conducted, assessing average time at home across gender.

Exclusion Criteria 4.4.2

Our exclusionary criteria included for personal sampling was: 1. Only UPAS files were used, as personal files collected with other sampling devices were not included in this study; 2. Participants were required to have recorded home coordinates; 3. UPAS files that were either not initiated correctly, lost, or improperly recorded were excluded; 4. Sampling durations exceeding 26 hours were removed, as these were not considered personal files but rather indoor or outdoor which were not used in this data processing step; and 5. Files with durations less than 21.6 hours (90% of the target 24-hour runtime) were excluded based on the 90% runtime exclusion criterion. 52 files across all waves were excluded due to unresolved merging issues of unknown origin. These files were omitted from the analysis as time constraints limited the opportunity for further investigation.

A total of 600 indoor sensors were deployed in the field, of which 440 were successfully returned. This attrition was due to incomplete data collection related to power failures or broken or lost sensors. Among these, 426 sensors were found to have operated for more than 90% of the designated sampling period and the remaining sensors were therefore excluded from the analysis.

Of the 426 included sensors, 400 contained adequate data for further analysis: Some sensors were nonfunctional due to field-related damages or other sensor malfunctions.

17 indoor files spanning all waves were excluded from the dataset due to unresolved merging discrepancies of unknown origin. These files were omitted from the analysis due to time constraints that prevented an in-depth investigation of the underlying issues. The remaining 383 files were subsequently integrated with the personal UPAS datasets described earlier. Within this subset, only 252 participants possessed concurrent personal and indoor measurements. This arose as some participants either did not receive personal monitoring equipment simultaneously with indoor monitors or did not receive personal monitoring equipment at all.

A total of 383 indoor $PM_{2.5}$ sensor measurements and 896 personal exposure measurements were collected across different study waves. Wave 1 did not include any indoor $PM_{2.5}$ measurements but recorded 193 personal exposure measurements. Wave 2 accounted for 129 indoor observations and 370 personal exposure measurements, while Wave 4 recorded 123 indoor and 333 personal measurements. Wave 3 was not considered due to COVID-19 limitations. After applying these criteria, the remaining eligible observations formed the foundation for subsequent descriptive analyses of personal $PM_{2.5}$ and black carbon exposures, contributing to the analysis of indoor air pollution and personal exposure patterns.

There were 252 observations that had both indoor and personal $PM_{2.5}$ measurements that this study was able to utilize, as shown in Figure 2. Not shown, is the number of participants who had valid personal $PM_{2.5}$ but not valid black carbon concentrations; Seven (2.7%) participants who had personal $PM_{2.5}$ measurements, did not have black carbon measurements. This could have arisen due to optical measurement issues or filter handling.

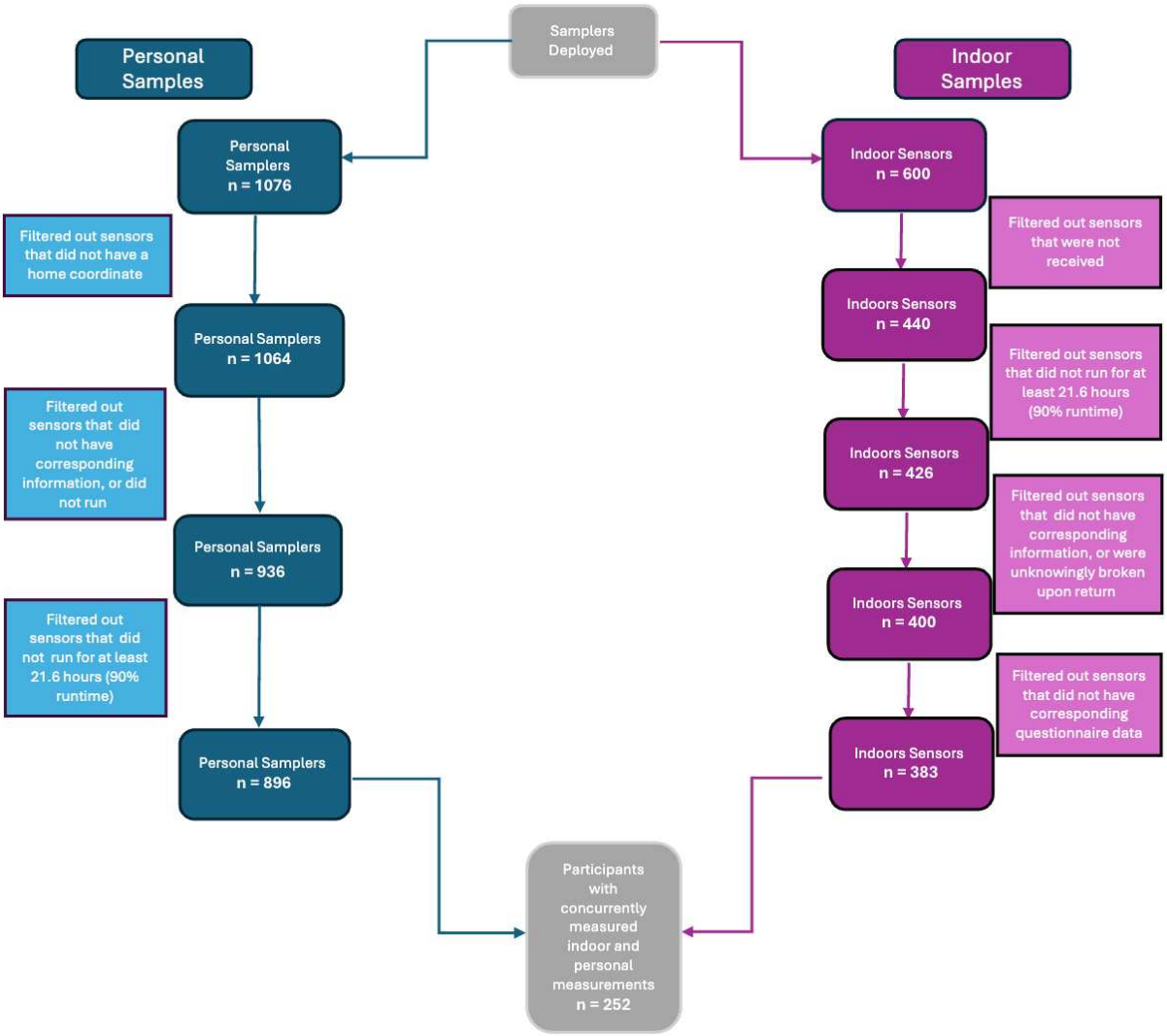

Figure 2. Flowchart illustrating the filtering process for personal filters (blue) and indoor sensors (purple), detailing the number of sensors at each step of data cleaning, leading to 252 participants with concurrently measured indoor and personal $PM_{2.5}$ measurements.

Filter Analysis 4.4.3

Filter samples were collected and stored at 21–22 °C and 30–34% relative humidity (RH) for at least 24 hours. They were pre- and post- weighed after sampling on a microbalance (Mettler Toledo Inc., XS3DU, USA). Filters were then analyzed for black carbon (BC) using an optical transmissometer (SootScan OT21; Magee Scientific, Berkeley, CA, USA). All filter

analysis was conducted at Colorado State University. Procedures for sample collection, filter preparation, and gravimetric and black carbon analysis have been described in previous studies.[45] The SootScan provided a raw value representing the degree of light (infrared) attenuation (ATN IR). To translate this value into a black carbon concentration, a calibration equation was applied. This equation relates the measured optical signal to an empirically derived black carbon mass concentration, accounting for the specific filter material and wavelength of light used in the device. The equation used to identify the black carbon mass concentration is below:

$$\mathrm{BC} = \frac{[(\text{ATN IR Post} - \text{ATN IR Pre}) - \text{median}(\text{Blank ATN IR Post} - \text{Blank ATN IR Pre})] \times \text{Area}}{16.6 \times \text{Volume}} \quad \text{(Eq. 1)}$$

where the UPAS blank median was –1.01, the UPAS filter area was 8.6 cm^2 while 16.6 is a mass absorption cross section. More information on this process has been described in previous literature.[45]

Black carbon blank corrected values that were negative (BC: n = 25, 10.2%) were replaced by randomly assigning a value between zero and half the limit of detection (LOD). The LOD was calculated as the mean added to three times the standard deviation of the blank values. The LOD was 5.8 ug/m^3, therefore half of that is 2.9 ug/m^3. This was performed similar to how previous studies have dealt with such data.[51]

Geofencing Technique 4.6

As discussed, a geofencing technique was applied to participants' GPS coordinates around their home coordinate to classify time spent at home versus away. This method allowed for the identification of time spent in each microenvironment and the assignment of indoor $PM_{2.5}$

exposure accordingly. To achieve this, a geofence radius was defined to capture stationary behavior while minimizing GPS noise and classification errors.

This method of defining the radius involved identifying a radius that encompassed clusters of GPS points indicative of stationary behavior, thereby distinguishing between time spent at home and away from home. If a participant was within the “at-home’ threshold, they would be considered at home, and if they were outside of it, they were classified to be away from home.

To identify the “at-home” threshold, a random selection process was employed to choose 5% of the total personal dataset, equating to 40 personal samples. This 5% was found to be representative of the total dataset. This ensured representation across a spectrum of data completeness, minimizing selection bias.

For all participants, including the 5% subset, the home coordinates were derived from survey responses. To calculate the distance between each GPS location and the home coordinate, the Haversine formula was applied to determine the great-circle distance between two points on the Earth's surface. The Haversine equation is given by:

$$\text{Distance} = 2R \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1) \cdot \cos(\varphi_2) \cdot \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \quad \text{(Eq. 2)}$$

where φ_1, φ_2 are the latitudes, λ_1, λ_2 are the longitudes, and R is the Earth's radius (WGS84 standard: 6,378,137 meters). The WGS84 reference system and China’s official coordinate system, GRS80, have identical earth radii, therefore using WGS84 was justified. For the 5% subset, clustering of GPS points around the subsets home coordinates was visually interpreted to identify "at home" locations and a radius was identified visually for each participant in which

encompassed the “at-home” cluster. Figure S1 highlights four sample home locations and personal GPS coordinates during sampling.

As described in previous research, noise, especially in indoor locations from GPS measurement devices could be substantial.[55] To assess GPS noise for the personal UPAS, stationary indoor and outdoor UPASs were analyzed. Noise occurs when there is poor satellite connection, and on top of stationary points, dilution of precision (DOP) of points was also assessed.

To further improve the accuracy of the geofencing classification, a smoothing parameter was then applied to account for potential noise in the GPS data. If a participant was assigned a location away from home for less than two minutes, they were still classified as being at home. This adjustment accounts for momentary GPS drift from noise or brief location changes that are unlikely to represent meaningful departures from home. Such an approach has been implemented in previous research to enhance the reliability of geospatial classifications.[65] The two-minute threshold was selected to balance sensitivity and specificity—long enough to filter out short, insignificant movements while ensuring that genuine time spent away from home was still captured accurately.

Once a participant’s location classification was established for each time frame of indoor sampling, their indoor $PM_{2.5}$ concentrations were calculated in relation to time spent at home. Specifically, $PM_{2.5}$ levels were averaged separately for the periods when the participant was classified as being at home as well as across the entire sampling duration, providing two separate indoor $PM_{2.5}$ levels: indoor $PM_{2.5}$ during the entire sampling period referred in this study as Whole Indoor $PM_{2.5}$, and indoor $PM_{2.5}$ averaged during only the duration the participant was at home referred to as Partial Indoor $PM_{2.5}$. This approach not only allowed for a more precise

assessment of indoor air quality exposure under different conditions but also facilitated the calculation of the total time each participant spent at home versus away.

However, a total of 17 participants (2%) who had personal exposure measurements had incorrect home coordinates, as indicated by their recorded time at home being equal to zero seconds. For participants with both personal and indoor exposure measurements, there were five participants with incorrect home coordinates (2%). This was an unrealistic outcome, given that indoor air quality sampling was initiated within the home, meaning participants would have had at least 30 seconds of recorded data, even if they had left immediately. This strongly suggested that their designated home coordinates were incorrect rather than an issue with sampling. The errors did not follow any identifiable pattern related to gender, district, or study wave, indicating that they were likely random occurrences rather than systematic biases.

To address these inaccuracies, a mean imputation approach was applied to the personal dataset to replace the inaccurate time-at-home values. The arithmetic mean was calculated using the entire dataset, ensuring consistency across participants. Additionally, the total sample duration was adjusted accordingly, and the time-away-from-home variable was recalculated based on the total sample duration, which was not impacted by the incorrect home coordinate. The indoor $PM_{2.5}$ concentrations, which were previously averaged based on time spent at home, were also imputed using the mean of those values. A sensitivity analysis removing these participants was performed. The imputed values were checked against the broader dataset to ensure their reasonableness, and the corrected data were analyzed in the same manner as the rest of the dataset. The arithmetic means and the median, as well as the 95% confidence intervals were calculated for the total time spent and home and the total time spent away from home for both the datasets included in this study, 1. Personal measurement only, and 2. Concurrent

personal and indoor measurements. Then, for only the personal and indoor measurements, their indoor $PM_{2.5}$ values were also analyzed with the arithmetic mean, 95% confidence intervals, and the medians.

Descriptive Analysis 4.7

Descriptive statistics were computed to summarize key characteristics of the study population and personal exposure measurements. Given the right skewed distribution of outdoor, personal, and indoor $PM_{2.5,}$ as well as personal BC, geometric means are reported in Table 3, accompanied by interquartile ranges (IQR) which can be found in Figure S2. Arithmetic means were also computed and included in the appendix (Table S1). Log transformations were applied to these variables, with an additional constant of +1 for black carbon to account for near zero values. Log transformations were applied to account for non-normal distributions. Given that black carbon concentrations included near zero values, a log(x+1) transformation was applied (the log function used in R was log1p, to add precision and accuracy). This approach retained small concentration values while ensuring mathematical feasibility. Negative black carbon values were randomly replaced with values between zero and half of the limit of detection (n = 25). Given the nature of black carbon measurements, these negative values could arise from instrument detection limits, background corrections, or measurement variability. However, since the $PM_{2.5}$ data associated with these observations remained valid and filters functioned as expected, these values were retained in the dataset.

Categorical variables, including gender, education level, occupation, smoking status, treatment status, study wave, and district, were summarized using counts and percentages accompanied by their groups geometric mean personal $PM_{2.5}$ and black carbon values.

Continuous variables were summarized using the count and percent. Missing values were excluded from models but were retained in descriptive analyses.

Statistical comparisons were conducted to assess differences in exposure levels across participant characteristics. Independent t-tests were used to compare mean $PM_{2.5}$ and black carbon concentrations between two-group categorical variables (e.g., gender, education level, wave). One-way analysis of variance (ANOVA) was performed for categorical variables with more than two groups (e.g., occupation, smoking status, district, and treatment status). Normality was assumed for these tests, and no post-hoc analyses were conducted. All statistical analyses were conducted using R.

Statistical Analysis 4.8

A series of generalized linear models (GLMs) were developed, incrementally adding variables to assess their influence on exposure variability. The statistical approach focused on determining how different independent variables contributed to explaining exposure differences among individuals.

Variables Selected 4.8.1

The variables included in this study can be categorized based on their temporal characteristics: time-invariant variables, time-varying but not time-resolved variables, and time-varying, time-resolved variables. This classification allows for a structured examination of how different factors contribute to personal exposure variability.

Time-invariant variables include gender, occupation, wealth index, education, village, district, and smoking status. Gender was included to assess its role in the specific regional context. Occupation was considered due to the notable variability in exposure and time spent at home observed in this study, which aligned with findings from other studies.[59] Wealth index was

incorporated because existing research indicated that socioeconomic factors impacted exposure through behaviors such as fuel choice and time spent in polluted environments. Education level was also included, as prior work suggested it could influence exposure through factors such as awareness, fuel choice, and time spent in polluted environments.[57,59] Geographic variables, including village and district, have been included to capture spatial differences in exposure. Smoking status has been considered a time invariant variable in this study, as for the exception of 24 participants with only personal exposures and two participants with both indoor and personal exposures, their smoking habits did not change. Smoking status, however, was not explicitly modeled in this study, as indoor $PM_{2.5}$ levels during the sampling period already reflected smoking's influence on exposure, as shown in Figure 9. The inclusion of village and district as variables was based on the observed variability in personal $PM_{2.5}$ exposure and time spent at home across different locations. These factors were incorporated to account for spatial differences and ensure a comprehensive understanding of exposure patterns in the final model.

In addition to these stable factors, certain variables changed over time but did not have precise temporal resolution. These time-varying but not time-resolved variables included wave, treatment status, and age. Wave was included to account for temporal differences across study periods. Treatment status under the coal-to-clean energy policy was examined due to its relevance in prior studies and observed changes in personal $PM_{2.5}$ exposures following policy implementation.[3] This study has explored exposure reductions in both treated and untreated villages to determine the extent to which changes can be attributed to the policy. This study required participants to be over the age of 40. As a result, it could not capture variability between significantly different age demographics, such as much younger and more elderly individuals, which could affect the generalizability of findings across broader age ranges.

Unlike these broader temporal variables, outdoor $PM_{2.5}$ varied continuously. Outdoor $PM_{2.5}$ concentrations was incorporated by averaging data over the 24-hour personal sampling period, aligning with previous studies that have found outdoor $PM_{2.5}$ to be a strong predictor of personal exposure variance.[3,45] As previously discussed, two indoor $PM_{2.5}$ metrics were computed: Whole Indoor $PM_{2.5}$ and Partial Indoor $PM_{2.5}$. To determine the most suitable variable for inclusion in future research, these metrics were analyzed in separate models to avoid multicollinearity and ensure independent assessment.

In summary, this study included variables such as outdoor $PM_{2.5}$ concentrations, two separate indoor $PM_{2.5}$ concentrations, gender, education, income, occupation, geographic and temporal factors (village, district, and wave), and treatment status, to understand their contributions to personal exposure variability. While variables like in-transit durations, stove use characteristics, and ventilation were also considered, they were excluded due to data limitations or feasibility constraints. This selection ensures a focus on key determinants while addressing practical challenges.

Data Transformations Prior to Model Development 4.8.2

Summary statistics were calculated across key demographic and environmental variables, including season, district, gender, etc. Exposure data exhibited non-normal distributions (see Figure 7), and therefore, natural log transformations were applied to $PM_{2.5}$ concentrations. black carbon values contained some negative values and some very small measurements, so when log transforming, a constant value of one was added before applying the natural logarithm for near zero values, and a random assignment of a value between zero and 2.91 accounted for negative values. A comparison understanding the impact of the replacement method of negative black carbon values was performed and will be discussed later. The three methods were to 1. remove

all negative black carbon values, 2. replace negative black carbon values with the square root of the limit of detection divided by two and 3. replace negative black carbon values with a random value between zero and the limit of detection divided by two. The geometric mean was compared for black carbon values for the three different negative replacement methods. This approach ensured values remained within the valid domain of the logarithm function while maintaining interpretability.

Modeling Approach and Selection 4.8.3

Generalized linear models (GLMs) with a Gaussian family distribution were used to assess the relationship between personal $PM_{2.5}$ and black carbon exposures with the independent variables mentioned previously. Given the dataset's structure, mixed-effects modeling was unsuitable due to a significant proportion of non-repeated measures. Although a subset of participants had multiple exposure measurements, the majority had only one measurement. A distribution analysis showed that 73% of participants had a single measurement, making mixed effects modeling impractical. Therefore, a GLM approach was chosen to retain as much data as possible. A structured GLM framework was used, incorporating both Whole- and Partial- indoor $PM_{2.5}$ exposure data. Four base models were analyzed, considering two different dependent variables (Personal $PM_{2.5}$ and Personal BC) and comparing Indoor $PM_{2.5}$ only while the participant was at home, as well as the indoor $PM_{2.5}$ during the whole sampling period, as described in the Geofencing sections.

The following were the four base models:

$PM_{2.5}$ Models:

$$ln(PM2.5) = \beta 0 + log(Whole\ Indoor\ PM2.5) + \varepsilon \qquad (Eq.\ 3)$$

$$ln(PM2.5) = \beta 0 + log(Partial\ Indoor\ PM2.5) + \varepsilon \qquad (Eq.\ 4)$$

Black Carbon Models:

$$ln(BC + 1) = \beta 0 + log(Whole\ Indoor\ PM2.5 + 1) + \varepsilon \quad (Eq.\ 5)$$

$$ln\ (BC + 1) = \beta 0 + log(Partial\ Indoor\ PM2.5 + 1) + \varepsilon \quad (Eq.\ 6)$$

Where β0 was the intercept, and β1 was the associated coefficient for the first variable added. As for, ε, this was the remaining error.

Model Development and Performance Evaluation 4.8.4

Using these base models, a series of models were then developed by adding variables one at a time. Each addition of a variable was added with the addition of a coefficient. These coefficients can be seen in equations three through six in the form of β0 and β1, while additional variables would correspond to β3-10. This can be seen for the first base model in Table 1. Model selection was then informed by assessing model performance using the Akaike Information Criterion (AIC). Evaluation of the proportion of variance of personal $PM_{2.5}$ and black carbon explained by using data exclusively during periods spent at home (Partial Indoor $PM_{2.5}$) and using data across the entire 24-hour period (Whole Indoor $PM_{2.5}$), as well as other variables identified a priori, was performed by comparing the base model to a series of progressively complex models, each incorporating an increasing number of independent variables. The Akaike Information Criterion (AIC) was used to compare model goodness-of-fit while penalizing complexity. R^2 and Adjusted R^2 values were calculated to assess the proportion of variance explained by the independent variables. Root mean square error (RMSE) was used to measure the average magnitude of prediction errors, providing insight into model accuracy. A summary table of model performance metrics is included in the results section. To address potential collinearity among predictors, Spearman Correlation Matrices and Variance Inflation Factor (VIF) values were examined. All VIF values were close to one, indicating no significant

multicollinearity, as seen in Table S2. Initially, village was included as a predictor but was removed due to high correlation with district.

Table 1. Example iteration steps for modeling personal $PM_{2.5}$ exposure explained by Whole Indoor $PM_{2.5}$ which was averaged during the entire personal sampling duration. The table outlines the sequential addition of covariates in a series of generalized linear models, starting with Whole Indoor $PM_{2.5}$ alone and progressively incorporating additional explanatory variables. These include time at home, demographic factors (gender, district, wave, occupation), environmental influences (outdoor $PM_{2.5}$), and socioeconomic indicators (wealth index, education, and treatment status).

Example Iteration Steps for PM2.5 explained by Indoor PM2.5 Whole

Model
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \beta3(\text{Gender}) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \beta3(\text{Gender}) + \beta4(\text{District}) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \beta3(\text{Gender}) + \beta4(\text{District}) + \beta5(\text{Wave}) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \beta3(\text{Gender}) + \beta4(\text{District}) + \beta5(\text{Wave}) + \beta6(ln[\text{Outdoor PM2.5 Whole}]) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \beta3(\text{Gender}) + \beta4(\text{District}) + \beta5(\text{Wave}) + \beta6(ln[\text{Outdoor PM2.5 Whole}]) + \beta7(\text{Occupation}) + \varepsilon$
$ln(\text{Personal PM2.5}) = \beta0 + \beta1(ln[\text{Indoor PM2.5 Whole}]) + \beta2(\text{Time at Home}) + \beta3(\text{Gender}) + \beta4(\text{District}) + \beta5(\text{Wave}) + \beta6(ln[\text{Outdoor PM2.5 Whole}]) + \beta7(\text{Occupation}) + \beta8(\text{Wealth}) + \varepsilon$

Residual plots, including Q-Q plots, residuals versus fitted values, scale-location plots, and leverage plots, were examined to assess assumptions of homoscedasticity and normality, which are shown for the four top performing models in Figure S3. Slight deviations from normality were observed in Q-Q plots, particularly for black carbon models. Outliers were noted but did not significantly impact model fit. Outliers were retained in all models as all values were deemed plausible based on known environmental conditions. The dataset included seven missing

values for BC, which were removed for BC-specific models but retained for $PM_{2.5}$ analyses. All analysis and modeling were performed and conducting using R (R version 4.4.2).

A sensitivity analysis was further conducted to evaluate how varying the geofencing radius used to define home impacted the performance of select models. Eleven different radii ranging from 20 to 150 meters were tested, each applied using the same two-minute temporal buffer used in the base geofencing method. For each radius setting, time spent at home and indoor $PM_{2.5}$ averaged over the duration of time spent at home was recalculated and incorporated into the black carbon exposure models that utilized concurrent indoor $PM_{2.5}$ concentrations. The resulting model outputs were compared using metrics such as R^2 and the Akaike Information Criterion (AIC) to evaluate changes in predictive performance. This analysis allowed for a systematic comparison of how different radius thresholds influenced model accuracy and supported an evaluation of whether finer scale geofencing improved the explanatory power of black carbon exposure predictions.

Interaction Terms and Stepwise Model Checks 4.8.5

Interaction terms were explored to assess potential interactions between time at home and indoor $PM_{2.5}$ exposure (Whole or Partial). These were tested as robustness checks but were not considered primary findings. Stepwise regression models were performed to evaluate whether the order of independent variable inclusion affected model performance. This also allowed identification of any non-essential predictors. This structured modeling approach employed GLMs with log-transformations to normalize exposure data. Model selection was guided by AIC and multicollinearity diagnostics, with additional checks using residual analysis, interaction terms, and stepwise modeling. These models were primarily examined to explore potential modifying effects rather than as central findings. While they provided insight into possible

relationships between time at home and indoor $PM_{2.5}$ exposure, they were not the focus of the primary analysis due to limited statistical significance and interpretability. Additionally, the primary aim was to assess direct associations rather than complex interaction effects, which may require a more targeted study design or larger sample size to robustly evaluate.

RESULTS

Descriptive Statistics 5.1

Sociodemographic Characteristics 5.1.1

The villages in these districts demonstrated considerable demographic diversity. Education levels among the residents varied, with primary school education being the most common across all regions. Most participants in Huairou had primary school education, with fewer advancing to secondary school or higher education. Similar patterns were observed in Miyun and Fangshan, where primary education was the most prevalent, but a smaller number of individuals pursued further schooling. A notable portion of the population in each district reported no formal education. Most participants in Huairou, Miyun, and Fangshan were engaged in agriculture and related work, with housework and homemaking being the next most common occupation across districts. Retirees, unemployed individuals, and factory workers made up a smaller portion of the population, while professional, technical, and government workers represented a minority in the workforce of this studies participants.

The average wealth varied across districts; These economic differences may influence the affordability of and compliance with clean heating technologies, potentially shaping the degree to which villages engaged with energy transition initiatives. Housing sizes reflected the economic and geographic variations across the districts. On average, homes in Huairou were the largest, with an average area of 140 square meters, followed by Miyun at 121 square meters and Fangshan at 117 square meters. Mentougou reported the smallest average home size, at 93 square meters. This difference may be attributable to variations in topography, local development policies, and economic conditions.

Air Pollutant Characteristics 5.1.2

The median personal $PM_{2.5}$ exposure was 56.2 μg/m^3, with a geometric mean value of 52.9 μg/m^3 (standard deviation of 2.8 μg/m^3). For black carbon exposure, the median concentration was 1.6 μg/m^3, while the geometric mean was 1.5 μg/m^3 (standard deviation of 3.3 μg/m^3). Table 2 presents $PM_{2.5}$ and black carbon exposure levels stratified by key participant characteristics. $PM_{2.5}$ and black carbon levels varied across gender, education, occupation, smoking status, treatment status, and wave. Personal $PM_{2.5}$ exposure was highest among current smokers and participants with no treatment ban. Indoor workers had lower $PM_{2.5}$ exposure levels compared to other occupational groups. Participants in Wave 2 had higher $PM_{2.5}$ exposure compared to those in Wave 4. Among all participants with personal exposure measurements, 90.62% had $PM_{2.5}$ levels exceeding the World Health Organization (WHO) Air Quality Guideline (AQG) of 15 μg/m^3. [75] Among all participants with personal exposure measurements, none had black carbon levels exceeding the Occupational Safety and Health Administration (OSHA) threshold of 3.5 mg/m³ (3,500 μg/m^3), which applies in the absence of polycyclic aromatic hydrocarbons (PAHs). Since PAH content was not assessed in this study, the lower OSHA threshold of 0.1 mg/m³ for black carbon including PAHs could not be evaluated.[76] The black carbon levels observed in this study were consistent with previous measurements in this study area, which reported similar concentrations.[77,78] However, the black carbon concentrations in this study were slightly lower than those in previous studies of comparable areas. While most other studies focused on transitions from solid fuel to gas, this study examined a shift to electric, which may contribute to the observed differences.[57,79]

Table 2. Summary statistics for personal $PM_{2.5}$ and black carbon (BC) exposure across key demographic and contextual characteristics. The table presents the number of participants n count (% of total) within each category and their corresponding geometric mean [95% confidence interval] exposure levels for personal $PM_{2.5}$ ($\mu g/m^3$) and BC ($\mu g/m^3$). Geometric means were used to account for the skewed distribution of exposure data.

Characteristic	Total Number PM2.5	Personal PM2.5	Total Number BC	Personal BC
	n (%)	Geometric Mean [95% CI]	n (%)	Geometric Mean [95% CI]
Gender				
Female	138 (54.8)	49.1 [41.5, 58.1]	135 (55.1)	2.9 [2.6, 3.3]
Male	114 (45.2)	57.8 [47.8, 69.9]	110 (44.8)	2.8 [2.5, 3.1]
Treatment Status				
Entered in 2019	70 (27.8)	46.2 [36.6, 58.4]	68 (27.8)	3.3 [2.9, 3.8]
Entered in 2020	42 (16.7)	52.2 [37.5, 72.7]	41 (16.7)	2.4 [2.1, 2.7]
Entered in 2021	19 (7.5)	43.7 [27.2, 70.1]	18 (7.3)	2.6 [2.2, 3.2]
No Ban	121 (48)	59.2 [49.5, 70.8]	118 (48.2)	2.7 [2.2, 3.2]
Education				
Primary School or below	230 (91.3)	53.3 [46.6, 60.9]	223 (91.0)	2.9 [2.7, 3.2]
Secondary/high school or above	22 (8.7)	48.9 [33.1, 72.2]	22 (9.0)	2.5 [1.9, 3.4]
Occupation				
Agriculture and related workers	154 (61.1)	56.6 [48.1, 66.5]	149 (60.8)	3.0 [2.7, 3.3]
Indoor Workers	64 (25.4)	44.1 [26.7, 72.9]	18 (7.3)	2.8 [2.4, 3.3]
Unemployed	18 (7.1)	45.6 [35.6,58.3]	62 (25.3)	2.4 [1.7, 3.2]
Other or not stated	11 (4.4)	86.1 [51.7, 143.4]	11 (4.5)	3.2 [2.2, 4.6]
Missing	5 (2)	29.2 [11.8, 72.1]	5 (2.0)	2.0 [1.5, 2.6]
Smoking Status				
Current Smoker	73 (29)	90.3 [73.1, 111.6]	72 (29.4)	2.9 [2.6, 3.3]
Former Smoker	45 (17.9)	34.1 [26.9, 43.3]	42 (17.1)	3.0 [2.6, 3.5]
Never Smoker	134 (53.2)	45.7 [38.5, 54.4]	131 (53.5)	2.4 [2.1, 2.9]
Wave				
Wave 2	129 (51.2)	60.6 [50.3, 72.9]	126 (51.4)	3.1 [2.7, 3.5]
Wave 4	123 (48.8)	45.8 [38.8, 54.2]	119 (48.6)	2.7 [2.4, 3.0]
District				
Huairou	95 (37.7)	55.3 [44.6, 68.5]	93 (38.0)	2.6 [2.4, 2.9]
Miyun	85 (33.7)	42.3 [34.7, 51.5]	83 (33.9)	2.7 [2.4, 3.1]
Mentougou	62 (24.6)	67.6 [52.6, 86.9]	59 (24.1)	3.6 [2.9, 4.5]
Fangshan	10 (4.0)	51.1 [24.9, 105.2]	10 (4.1)	2.7 [2.0, 3.5]

For continuous variables, the geometric mean and standard deviation were calculated, as shown in Table 3. The age distribution ranged from 43 to 85 years, with a median of 63 years, indicating that this study primarily focused on an older population. The wealth index, described earlier, provided a unitless comparison among participants, ranging from -16 to 20. While the

expected mean was zero, the slightly positive mean suggested that this subset had a marginally higher wealth status than the broader study population. Indoor $PM_{2.5}$ concentrations at home (Partial Indoor $PM_{2.5}$) and throughout the entire sampling period (Whole Indoor $PM_{2.5}$) show minimal variation, with less than a 1 $\mu g/m^3$ difference. On average, participants spent 20 hours at home, accounting for 86% of their total time—a pattern consistent with previous research.[43,55,56]

Table 3. Summary statistics of key continuous participant characteristics and exposure metrics. The table presents geometric means and standard deviations (SD) for outdoor $PM_{2.5}$ concentrations, participant age, wealth index, Whole and Partial Indoor $PM_{2.5}$ exposure while at home and over the entire sampling period, and average duration spent at home.

	Geometric Mean (SD)
Outdoor PM2.5 (ug/m3)	24.8 (24.4)
Age (years)	63 (9.0)
Wealth Index	1.7 (3.6)
Partial Indoor PM2.5 - averaged while at home (ug/m3)	104.4 (50.4)
Whole Indoor PM2.5 - averaged during entire sampling period (ug/m3)	103.8 (49.7)
Average Duration at home (hours)	20.2 (3.7)

T-tests and ANOVA statistical tests were performed to assess differences in exposure levels across participant characteristics. Statistical comparisons using t-tests and ANOVA indicated no significant differences in $PM_{2.5}$ or black carbon exposure by gender ($p = 0.1247$ and $p = 0.2457$, respectively) or education level ($p = 0.6064$ and $p = 0.6257$, respectively). However, differences in $PM_{2.5}$ and black carbon exposure were significant across districts ($p = 0.0153$ and $p = 0.0019$, respectively), and smoking status was significantly different for $PM_{2.5}$ exposure ($p < 0.001$) but not for black carbon exposure ($p = 0.3117$). Participants in Wave 2 had significantly

higher $PM_{2.5}$ exposures than those in Wave 4 ($p = 0.01491$), though black carbon exposure did not differ significantly between waves ($p = 0.1394$). This is shown in Table S3 and S4.

Sensitivity Analysis 5.2

Runtime Sensitivity Analysis 5.2.1

Table 4 shows the sensitivity analysis for the difference between utilizing only samples with 80% (19.2 hours) or only 90% (21.6 hours) of the total runtime of 24 hours. Minimal differences were observed between 80% and 90% runtimes for both male and female participants at various radii, with slight variations in average time at home that did not significantly affect the overall results. The average difference across all measured radii was 6.87 minutes, reinforcing the negligible impact of the runtime threshold on the overall findings observed across other districts and waves. The primary distinction was the number of files retained, with 80% runtime including a slightly larger number of observations. The total number of files retained for the 80% runtime was 863, compared to 826 files for the 90% runtime. However, to prioritize data completeness and ensure consistent representation across participants, 90% runtime was selected for this analysis. This decision aligns with the objective of minimizing potential biases while capturing the most accurate depiction of personal $PM_{2.5}$ exposure during daily activities. With few exceptions, women spent marginally more time at home than men across all radii and runtime criteria, indicating possible gender-based differences in exposure due to variations in time spent at home.

Table 4. Average hours spent at home across varying geofence radii (20 m to 150 m) for male and female participants under two runtime conditions: 90% and 80% of 24-hour sampling periods. The results highlight differences in time-at-home estimates by gender and runtime completeness, with increasing geofence radii yielding higher 'at-home' estimates. The data indicates a convergence of time-at-home at the 70m radius, suggesting diminishing returns in additional time capture beyond this threshold.

Average Time at Home				
	80% Runtime		90% Runtime	
Radius	Female (hours)	Male (hours)	Female (hours)	Male (hours)
20 m	14.20	13.74	14.30	13.74
30 m	17.39	16.86	17.52	16.89
40 m	18.87	18.36	18.01	18.41
50 m	19.71	19.26	19.85	19.34
60 m	20.24	19.77	20.39	19.86
70 m	20.58	20.30	20.74	20.40
80 m	20.77	20.47	20.92	20.58
90 m	20.90	20.62	21.05	20.73
100 m	21.03	20.78	21.18	20.89
125 m	21.21	21.07	21.36	21.19
150 m	21.38	21.39	21.53	21.52

Geofencing Results 5.3

The average radius required to fully encompass at-home clusters for the selected 5% subset of personal samples was 67 meters. This value was established through iterative visual inspection, selecting the smallest radius that captured the entire 'home' cluster while excluding extraneous points. For 7 out of the 40 files, the home coordinates exhibited noticeable home

coordinate offsets. The average radius necessary to encompass these offsets was determined to be 61 meters, still within the average radius of the entire subset.

To determine the impact of noise, the indoor and outdoor sensors were analyzed. This random subset of these included 39 outdoor files and 28 indoor files. The analysis revealed that outdoor files required an average radius of 72 meters to encompass all points, while indoor files, which exhibited greater noise likely due to signal reflection, required an average radius of 94 meters. These align with the 67-meter radii identified for home coordinate geofences, reinforcing the appropriateness of using similar values to minimize noise and accurately capture stationary behavior.

Geofencing Sensitivity Analysis 5.3.1

As the indoor samplers' noise seemed to be higher than visually inspected radii, a sensitivity analysis was performed on a series of radii that were tested to evaluate the impact of geofence size on time-at-home estimates. Radii of 20 meters to 150 meters were applied. This broad range was chosen to ensure the inclusion of both noise and behavioral variability. Figure 3 illustrates the relationship between geofencing radius and hours spent at home across districts and survey waves, highlighting the plateau effect at 70 meters.

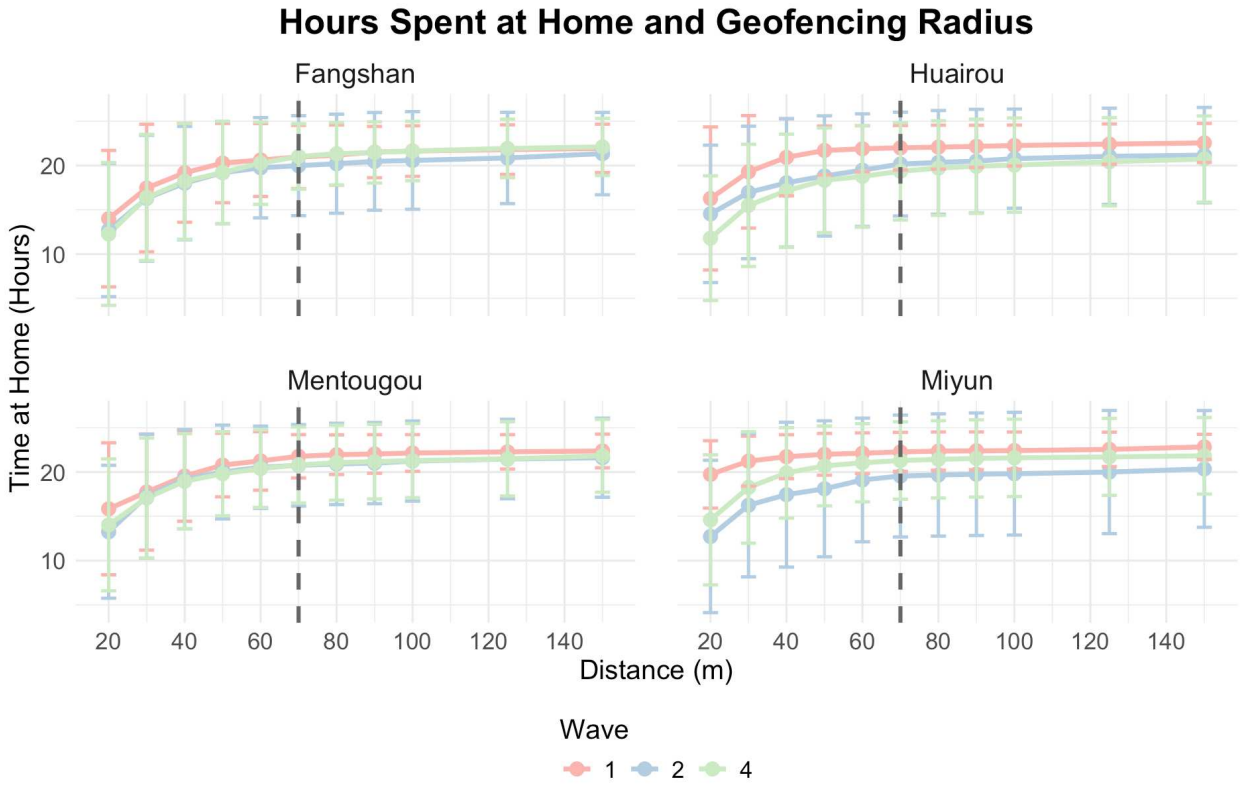

Figure 3. The figure illustrates the relationship between geofencing radius (x-axis), and estimated time spent at home (y-axis) across four districts (Fangshan, Huairou, Mentougou, Miyun). Each panel represents a district, with geofencing radii ranging from 20 to 150 meters. Lines correspond to different survey waves (Wave 1 in red, Wave 2 in blue, and Wave 4 in green), with error bars representing standard deviations. A plateau in time-at-home estimates observed at 70 meters (indicated by the dashed line), suggesting diminishing returns in additional time captured beyond this threshold.

The values of 70 meters and 100 meters were analyzed in greater detail to identify the most appropriate geofence size for time-at-home calculations, focusing on the percentage change in time-at-home for the interval between 70 meters and 100 meters. The results demonstrated minimal increases in time-at-home across all districts and waves, with percentage changes ranging from 2.5% to 6.4%. For the geofencing radius, the plateau effect of time spent at home observed at 70 meters suggested that increasing the radius beyond this threshold captures limited additional data, making 70 meters a reasonable choice for the analysis of time-at-home estimations. Variability in time-at-home was observed across districts and survey waves. For

example, in Wave 1, districts such as Huairou and Miyun exhibited differing time-at-home averages compared to the other waves, while Fangshan demonstrated smaller changes. This likely reflects differences in participant behavior, home layouts, or environmental factors. Overall, this geofencing method provided a robust framework for estimating time-at-home, utilizing a radius of 70 meters as part of the analysis to balance precision and data completeness. Therefore, a geofencing radius of 70 meters was applied to all participants in this study.

Time at Home Results 5.3.2

The mean time spent at home across the personal dataset was 20.0 hours (95% CI: 19.4, 20.7), with a median of 22.4 hours. Similarly, for participants with concurrent personal and indoor measurements, the mean time at home was 20.2 hours (95% CI: 19.3, 21.2), with a median of 22.0 hours as shown by Figure 4.

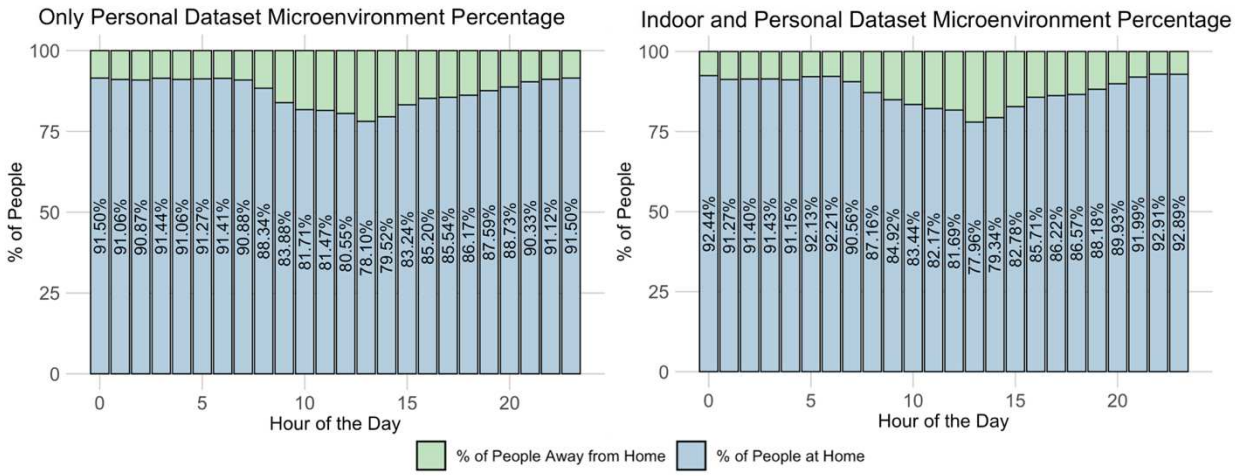

Figure 4. Hourly distribution of time spent at home versus away from home across two datasets. The left panel represents the percentage of participants at home and away from home using only the personal dataset, while the right panel incorporates both the indoor and personal datasets. The x-axis represents the hour of the day, and the y-axis represents the percentage of participants. The stacked bars display the proportion of participants at home (blue) and away from home (green) at each hour, with percentages labeled for clarity. The inclusion of indoor data in the right panel does not adjust the distribution by more than a percent, indicating appropriate representativeness.

Hourly trends in time spent at home were analyzed to determine variations in home presence throughout the day. The proportion of participants at home remained consistently high overnight, with over 90% of participants at home between 12:00 AM and 6:00 AM. The percentage of participants at home gradually declined in the morning, reaching the lowest levels in the afternoon. The lowest percentage of participants at home occurred between 12:00 PM and 3:00 PM, where 78% to 80% of participants remained home in the personal dataset. After this period, the proportion of participants at home increased steadily through the evening and returned to above 90% by 8:00 PM.

These trends were consistent in the subset of participants with both personal and indoor measurements. The percentage of participants at home followed a similar pattern, with a peak presence overnight and a decline in the early afternoon. The lowest percentage of participants at home in this subset occurred at 1:00 PM, with 78% of participants at home.

The time spent at home followed a similar pattern across both datasets, with no significant differences in the overall time at home distribution. The inclusion of indoor exposure data did not substantially alter the observed hourly patterns, as the general trends remained consistent across both groups. These results provided a detailed breakdown of participant behavior across different hours of the day, highlighting daily patterns of time spent at home versus away.

Indoor $PM_{2.5}$ Related to Time Periods at Home 5.3.3

Hourly variations in indoor $PM_{2.5}$ concentrations aligned with participant presence at home, highlighting potential exposure trends. As seen in Figure 5, $PM_{2.5}$ levels exhibited distinct peaks in the early morning and evening hours, corresponding to times when participants were likely engaged in activities before departing and after returning home. The morning peak,

occurring between 6:00 AM and 10:00 AM, coincided with the time period when home presence declines, while the evening peak, occurring between 4:00 PM and 8:00 PM, aligned with the steady increase in home presence observed after work or daily activities. These patterns were consistent with the trends observed in the time-at-home analysis, where participant mobility increased during the day and stabilized during nighttime hours. In contrast, Indoor $PM_{2.5}$ concentrations remained lower during the late-night and early-morning hours, aligning with the hours when over 90% of participants are at home. This trend mirrored the stable overnight home presence recorded in the time-at-home dataset, reinforcing the consistency between movement patterns and indoor air quality variations.

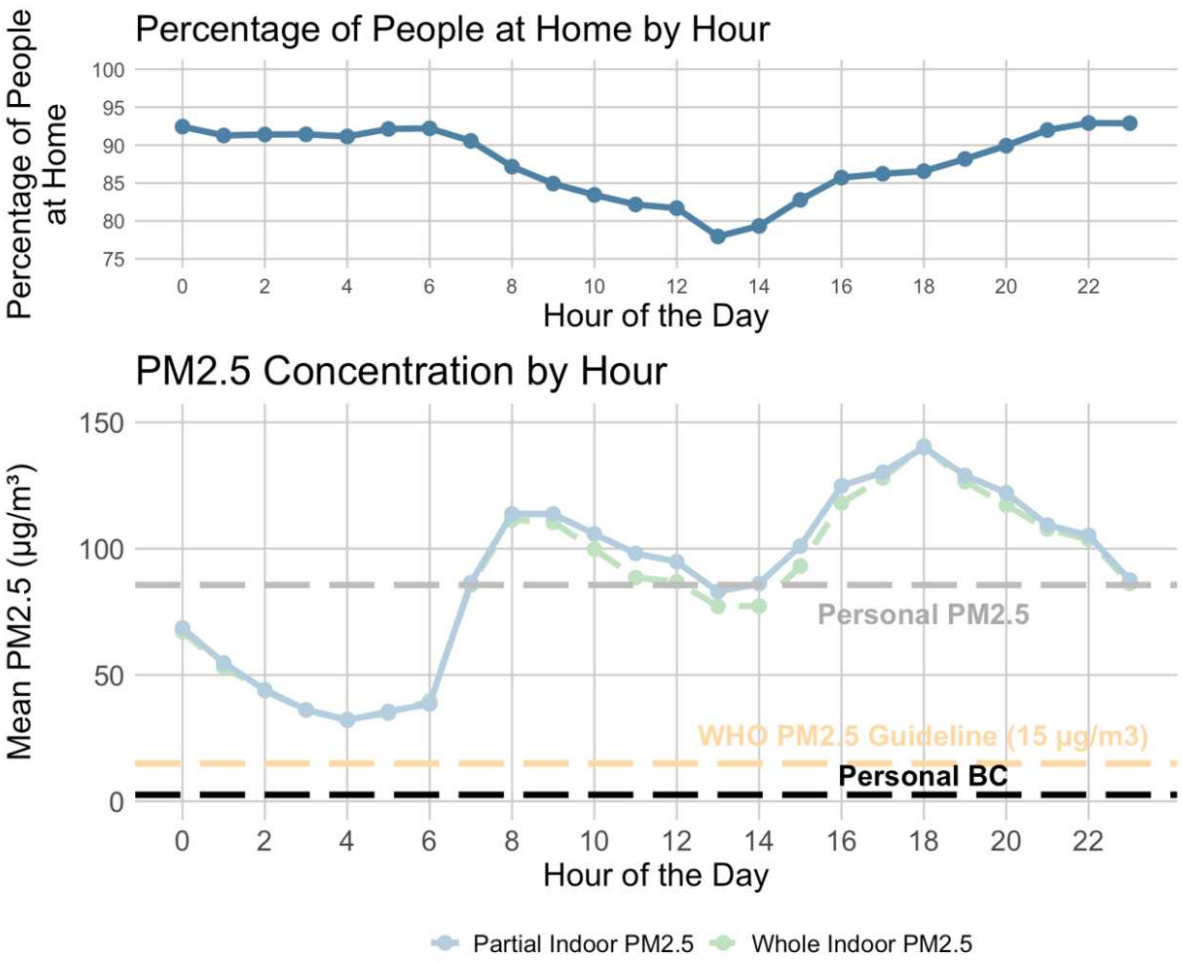

Figure 5. Hourly trends in home occupancy and $PM_{2.5}$ concentrations. The top panel illustrates the percentage of people at home throughout the day with a y- axis scale from 75% to 100%. The bottom panel presents the arithmetic mean $PM_{2.5}$ concentration by hour for the participants with concurrent indoor and personal measurements for both Whole Indoor $PM_{2.5}$ (green) and Partial Indoor $PM_{2.5}$ (blue), alongside reference arithmetic means for personal $PM_{2.5}$ in grey (85.6 µg/m^3), personal BC in black (2.6 µg/m^3) and the 24 hour WHO $PM_{2.5}$ guideline in orange (15 µg/m^3).

Across the dataset, the only times when indoor $PM_{2.5}$ concentrations approached the 24-hour averaged threshold set by WHO (24 hour averaged of 15 µg/m^3 for three to four days) were during the early morning hours, particularly between 2:00 AM and 6:00 AM. The peak after this period might indicate a temporal alignment between morning activity levels and increased $PM_{2.5}$ exposure, similar to the observed patterns in home presence where participants were beginning to leave their homes. The rest of the day exhibited relatively lower $PM_{2.5}$ levels, with a gradual

decline following the morning peak and fluctuations corresponding to evening hours when participants returned home and engaged in indoor activities. Whole and Partial Indoor $PM_{2.5}$ measurements remained closely aligned during late-night and early-morning hours when participant presence at home was high. However, as participants began to leave their homes in the morning, the two measurements start to diverge, with Whole Indoor $PM_{2.5}$ remained relatively stable while Partial Indoor $PM_{2.5}$ exhibited a sharper fluctuation. This deviation becomes most noticeable between 12:00 PM and 2:00 PM, where Partial Indoor $PM_{2.5}$ levels exceed Whole Indoor $PM_{2.5}$ by 10-15 $\mu g/m^3$.

Imputed Values Sensitivity Analysis 5.3.4

A total of 17 participants in the personal dataset (2% of the total personal samples) and 5 participants in the dataset with both indoor and personal data combined (2% of the total indoor and personal samples) were identified as having incorrect home coordinates based on their recorded time at home being zero seconds. These participants were evenly distributed across study waves and districts, with no clear patterns related to gender or other demographic characteristics.

After implementing mean imputation, the mean values for time spent at home and time spent away from home remained largely unchanged, with only minimal differences observed. Similarly, the median values exhibited negligible variation, as shown in Table 5. Specifically, the medians for time spent at home did not deviate by more than 0.1 hours (six minutes) in both the personal dataset and the combined personal and indoor dataset. While the arithmetic means and confidence intervals remained stable for the duration categories, slight changes were noted in the indoor $PM_{2.5}$ estimates, mirroring the shifts observed in the median indoor $PM_{2.5}$ values from the personal dataset with the concurrent indoor and personal dataset. However, these variations did

not exceed 4 μg/m^3. These findings suggested that the imputation process had a minimal impact on both $PM_{2.5}$ estimates, and time spent at home.

Table 5. Comparison of time spent at home, time spent away from home, and Indoor $PM_{2.5}$ exposure before and after mean imputation used for time spent at home and Partial Indoor $PM_{2.5}$. The table presents summary statistics for the personal dataset and the combined personal and indoor dataset, showing mean, 95% confidence intervals [CI], and median values. A total of 17 participants (2%) in the personal dataset and 5 participants (2%) in the combined dataset were identified as having incorrect home coordinates.

		Time Spent at Home (hours)		Time Spent Away From Home (hours)	
Personal Dataset Only	Count	Mean [CI]	Median	Mean [CI]	Median
No Imputed Values	**n = 879**	21.1 [20.8, 21.3]	22.4	2.6 [2.4, 2.9]	1.1
Only Imputed values	**n = 17**	21.1 [21.1, 21.1]	21.1	2.5 [2.3, 2.8]	2.8
Both inputed and non inputed values	**n = 896**	21.1 [20.8, 21.4]	22.4	2.6 [2.4, 2.9]	1.2
		Time Spent at Home (hours)		Time Spent Away From Home (hours)	
Personal and Indoor Dataset		Mean [CI]	Median	Mean [CI]	Median
No Imputed Values	**n = 247**	21.0 [20.6, 21.5]	22.1	2.7 [2.2, 3.1]	1.6
Only Imputed values	**n = 5**	21.1 [21.1, 21.1]	21.1	2.6 [2.0, 3.2]	2.9
Both inputed and non inputed values	**n = 252**	21.0 [20.6, 21.5]	22.0	2.6 [2.2, 3.1]	1.6
		Whole Indoor PM2.5 - entire sampling period (ug/m3)		Partial Indoor PM2.5 - while at home (ug/m3)	
Personal and Indoor Dataset		Mean [CI]	Median	Mean [CI]	Median
No Imputed Values	**n = 247**	92.7 [79.5, 105.8]	52.2	92.3 [79.3, 105.3]	50
Only Imputed values	**n = 5**	92.7 [92.7, 92.7]	92.7	64.4 [2.6, 126.2]	42.8
Both inputed and non inputed values	**n = 252**	92.7 [79.8, 105.5]	55.8	91.7 [78.9, 104.6]	49.9

A comparison of distributions across groups showed that the imputed values were reasonably aligned with the overall dataset. The interquartile ranges of time-at-home and time-away-from-home overlapped substantially between imputed and non-imputed participants, supporting the validity of using mean imputation as a robust method. Additionally, $PM_{2.5}$ concentrations in the imputed group fell within the expected range of the broader dataset.

Model Analysis 5.4

Description of Dependent Variables 5.4.1

The primary dependent variables in this analysis were personal $PM_{2.5}$ concentrations and personal black carbon concentrations, both of which represented individual exposure levels.

These variables were continuous and had been log-transformed to improve normality and model performance. Specifically, $PM_{2.5}$ concentrations were log-transformed, while black carbon concentrations underwent a log(x+1) transformation and random negative replacement to account for small and negative values.

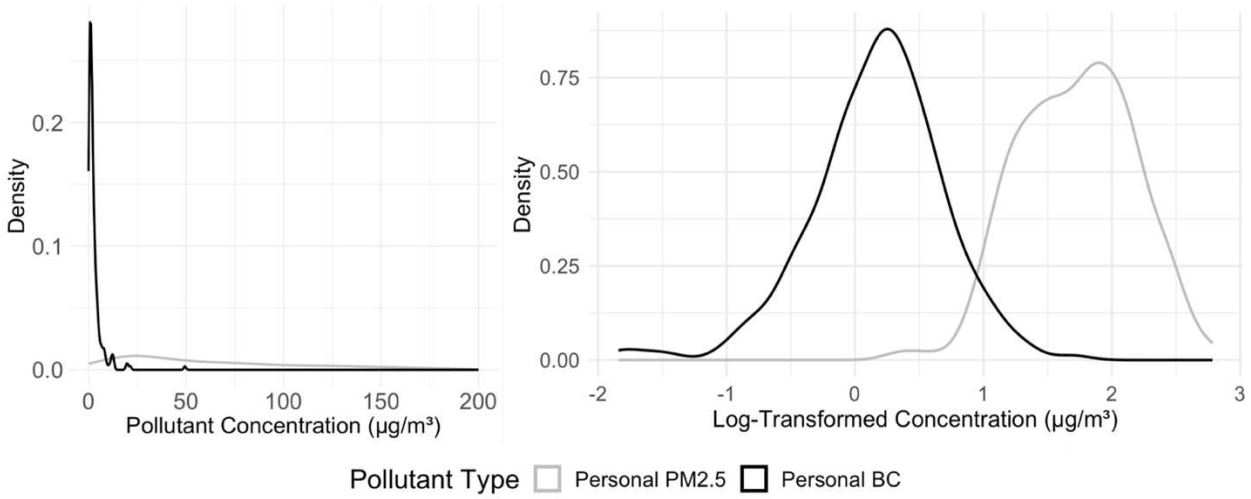

Figure 6. Density distributions of personal $PM_{2.5}$ and black carbon (BC) concentrations before and after log transformation. The left panel illustrates the distribution of raw pollutant concentrations, showing a highly right-skewed distribution for both personal $PM_{2.5}$ (gray) and black carbon (BC) (black). The pollutant concentrations are on the x axis in µg/m^{3}and the density is on the y axis. Both plots have differing y axis scales. The right panel presents the log-transformed values, demonstrating a more normalized distribution.

The untransformed data for both personal $PM_{2.5}$ and black carbon concentrations exhibited substantial right-skewness, with a concentration of values on the lower end and a long tail extending toward higher exposures. Personal $PM_{2.5}$ showed an arithmetic mean of 85.6 µg/m^3 (geometric mean: 52.9 µg/m^3) and a maximum value of 608.94 µg/m^3, while black carbon concentrations had an arithmetic mean of 2.8 µg/m^3 (geometric mean: 1.6 µg/m^3) and a maximum value of 49.4 µg/m^3. These distributions, confirmed by density plots in Figure 6, indicated that a log transformation was necessary to normalize the data and stabilize variance. The density distribution of $PM_{2.5}$ and black carbon before and after log transformation as shown in Figure 6, suggested that extreme values did not disproportionally influence normality.

Comparison of the Impact of Negative Black Carbon Value Replacement Methods 5.4.2

A comparison was conducted to assess the impact of different negative replacement methods for personal black carbon values on geometric mean black carbon exposure estimates across various demographic and contextual factors, as summarized in Table 6. The analysis compared three different approaches: removal of negative values, substitution with the square root of the limit of detection divided by two, and random replacement within the range of zero and half of the limit of detection. The findings indicated that while geometric mean black carbon values remained relatively stable across the different replacement methods, slight variations were observed depending on the chosen approach.

Across categories such as gender, education, and smoking status, the differences in geometric mean black carbon exposure remained within the confidence intervals, suggesting that the choice of negative replacement method did not substantially alter the overall distribution of exposure values. For instance, among male and female participants, geometric mean black carbon values were consistent across all three methods, with only marginal deviations observed when using the random replacement method. Across all three replacement strategies, the relative differences among treatment groups were preserved, indicating that the method used for handling negative values did not significantly alter the comparative trends.

Differences in geometric mean black carbon values were more pronounced across occupation groups, particularly for indoor workers and missing data categories, where the choice of negative replacement method led to slightly larger variations. However, the overall ranking of exposure levels among occupation groups remained unchanged, reinforcing the robustness of the results to different negative value handling techniques.

Given these findings, the use of the random replacement between zero and LOD/2 method was deemed appropriate, as it provided a mathematically consistent approach while preserving the overall exposure distribution. This method allowed for the retention of low black carbon exposure values without introducing excessive variability or altering relative trends among participant groups. As such, it was selected for further analyses to ensure comprehensive data representation and minimize potential biases introduced by exclusion.

Table 6. Comparison of black carbon (BC) exposures evaluating the impact of excluding negative BC values (third column), relating them between replacing them with √(LOD/2) (fourth column) or replacing them with a random value between 0 and LOD/2 (last column). The table presents geometric means with 95% confidence intervals [CI] for all three methods based on descriptive category. A total of 25 out of 245 BC samples were negative.

Characteristic	Total Number	Personal BC	Personal BC	Personal BC
	n (%)	Geometric Mean [95% CI]	Geometric Mean [95% CI]	Geometric Mean [95% CI]
Negative Replacment Method	25 (10.2)	removal	replace with √(LOD/2)	replace with random between 0 & (LOD/2)
Gender				
Female	135 (55.1)	2.7 [2.4, 3.2]	3.1 [2.7, 3.4]	2.9 [2.6, 3.3]
Male	110 (44.8)	2.7 [2.4, 3.0]	2.9 [2.6, 3.2]	2.8 [2.5, 3.1]
Treatment Status				
Entered in 2019	68 (27.8)	2.1 [1.8, 2.5]	3.4 [3.0, 3.9]	3.3 [2.9, 3.8]
Entered in 2020	41 (16.7)	2.6 [2.1, 3.1]	2.5 [2.3, 2.9]	2.4 [2.1, 2.7]
Entered in 2021	18 (7.3)	2.7 [2.1, 3.4]	2.7 [2.2, 3.2]	2.6 [2.2, 3.2]
No Ban	118 (48.2)	3.2 [2.7, 3.7	2.9 [2.5, 3.4]	2.7 [2.2, 3.2]
Education				
Primary School or below	223 (91.0)	2.7 [2.5,3.0]	3.0 [2.8, 3.3]	2.9 [2.7, 3.2]
Secondary/high school or above	22 (9.0)	2.4 [1.7, 3.4]	2.8 [2.2, 3.7]	2.5 [1.9, 3.4]
Occupation				
Agriculture and related workers	149 (60.8)	2.8 [2.4, 3.1]	3.1 [2.8, 3.4]	3.0 [2.7, 3.3]
Indoor Workers	18 (7.3)	2.4 [1.7,3.3]	3.0 [2.6, 3.5]	2.8 [2.4, 3.3]
Unemployed	62 (25.3)	2.7 [2.2, 3.3]	2.4 [1.7, 3.3]	2.4 [1.7, 3.2]
Other or not stated	11 (4.5)	3.2 [2.2, 4.6]	3.2 [2.2, 4.6]	3.2 [2.2, 4.6]
Missing	5 (2.0)	1.4 [0.8, 2.3]	2.1 [1.6, 2.8]	2.0 [1.5, 2.6]
Smoking Status				
Current Smoker	72 (29.4)	2.9 [2.4, 3.4]	3.1 [2.7, 3.4]	2.9 [2.6, 3.3]
Former Smoker	42 (17.1)	2.4 [2.0, 2.9]	3.2 [2.8, 3.6]	3.0 [2.6, 3.5]
Never Smoker	131 (53.5)	2.7 [2.4, 3.2]	2.5 [2.2, 3.0]	2.4 [2.1, 2.9]
Wave				
Wave 2	126 (51.4)	2.9 [2.5, 3.4]	3.2 [2.9, 3.6]	3.1 [2.7, 3.5]
Wave 4	119 (48.6)	2.5 [2.2, 2.8]	2.7 [2.5, 3.0]	2.7 [2.4, 3.0]
District				
Huairou	93 (38.0)	2.5 [2.1, 3.4]	2.7 [2.5, 3.0]	2.6 [2.4, 2.9]
Miyun	83 (33.9)	2.5 [2.1, 3.0]	2.8 [2.5, 3.2]	2.7 [2.4, 3.1]
Mentougou	59 (24.1)	3.4 [2.8, 4.4]	3.7 [3.0, 4.6]	3.6 [2.9, 4.5]
Fangshan	10 (4.1)	2.7 [2.5, 3.3]	2.7 [2.1, 3.6]	2.7 [2.0, 3.5]

Description of Independent Variables 5.4.3

The independent variables in this analysis included gender, education, wave, occupation, smoking status, treatment status, district, and wealth index, as well as outdoor $PM_{2.5}$, Whole Indoor $PM_{2.5}$, and Partial Indoor $PM_{2.5}$. These variables were selected based on their potential influence on personal $PM_{2.5}$ and black carbon exposures, as detailed in previous sections.

Among the continuous independent variables, outdoor $PM_{2.5,}$ Whole Indoor $PM_{2.5,}$ and Partial Indoor $PM_{2.5}$ were log-transformed due to their highly right-skewed distributions, as illustrated in Figure 7. The transformation effectively normalized the data, which ensured more stable variance and improved model interpretability. While their distributions were similar, Partial Indoor $PM_{2.5}$ was slightly higher on average (median = 55.8 μg/m³, mean = 92.7 μg/m³) compared to Whole Indoor $PM_{2.5}$ (median = 49.9 μg/m³, mean = 91.7 μg/m³), reflecting the influence of residential air pollution sources while the participant was at home. The interquartile range for both measures suggested substantial variability across participants, with maximum recorded values exceeding 680 μg/m³.

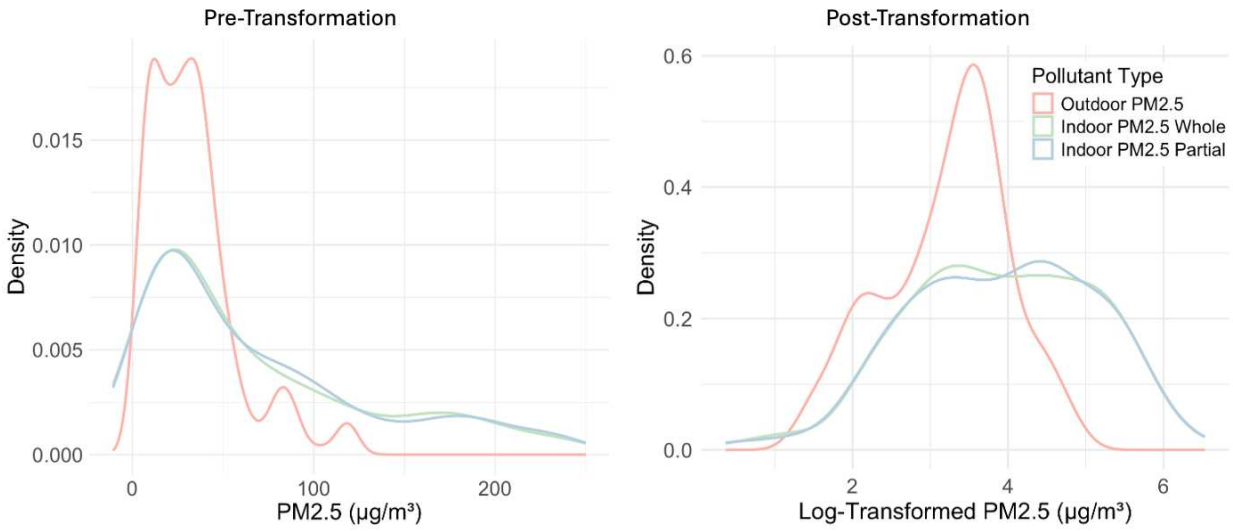

Figure 7. Density distributions of $PM_{2.5}$ concentrations before and after log transformation. The x axis is the $PM_{2.5}$ concentration in µg/m³ and the y axis is density. The left panel illustrates the distribution of raw $PM_{2.5}$ values, showing a right-skewed distribution with extreme values for outdoor $PM_{2.5}$ (red), Whole Indoor $PM_{2.5}$ (green), and Partial Indoor $PM_{2.5}$ (blue). The right panel presents the log-transformed $PM_{2.5}$ values, demonstrating a more normalized distribution across pollutant types.

Categorical variables included in modeling applications comprised of education, occupation, treatment status, wave, district, and gender. Indoor $PM_{2.5}$ levels were analyzed separately for the full sampling period (Whole Indoor $PM_{2.5}$) and only during time spent at home (Partial Indoor $PM_{2.5}$). Variability in indoor $PM_{2.5}$ levels was examined across key independent variables. The cumulative distribution functions (CDFs) in Figure 8 display these variations, with separate panels for each categorical variable.

Gender did not significantly impact indoor $PM_{2.5}$ levels, as distributions for male and female participants were similar for both Whole and Partial Indoor $PM_{2.5}$, however, there might be a slightly higher exposure for males as shown by their higher distributions at higher indoor $PM_{2.5}$ concentrations. Education levels also exhibited minimal differences in indoor $PM_{2.5}$ distributions. Wave 2 had higher indoor $PM_{2.5}$ levels compared to Wave 4, indicating a temporal trend consistent with observed patterns in personal $PM_{2.5}$ exposure. Smoking status had a notable

impact on indoor $PM_{2.5}$ levels, with current smokers experiencing the highest concentrations, followed by former smokers and never smokers. This trend aligned with expectations given smoking as a direct source of indoor particulate matter. However, this will be discussed momentarily, as to why it was not included in the models. Differences in occupational groups suggested variation in work environments and potential sources of exposure, with relatively similar distributions among categories. District variations were observed, with Mentougou exhibiting the highest indoor $PM_{2.5}$ levels, while Miyun, Huairou, and Fangshan had similar yet slightly variable distributions. Treatment status influenced indoor $PM_{2.5}$ concentrations, with some distinctions between intervention years, though distributions remained largely overlapping. Finally, the wealth index is a continuous variable and is represented without categorical separation. The distribution of wealth index values followed a smooth cumulative trend.

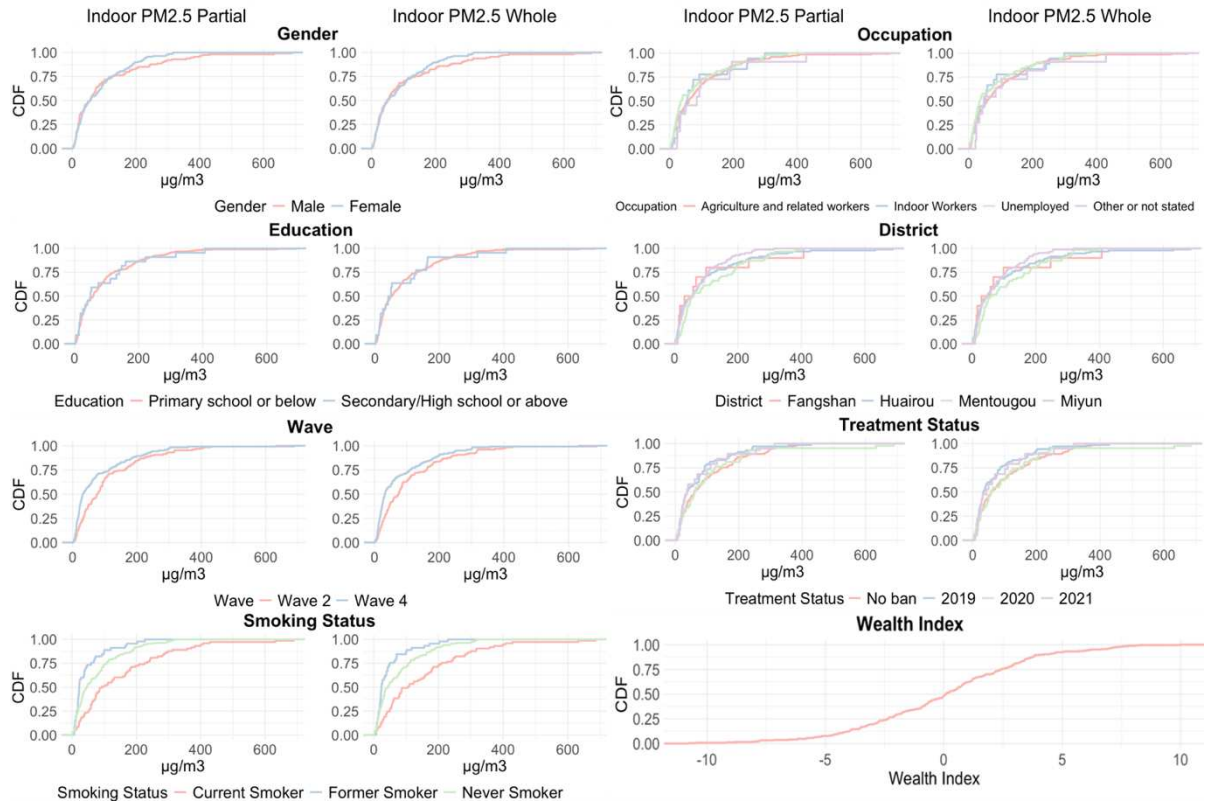

Figure 8. Cumulative distribution functions (CDF) of Partial Indoor $PM_{2.5}$ on the left sides and Whole Indoor $PM_{2.5}$ on the right sides, with concentrations across key variables. Each panel compares the distribution of indoor $PM_{2.5}$ exposure (Partial and Whole sampling periods) by gender, occupation, education, district, survey wave, treatment status, and smoking status. The x-axis represents $PM_{2.5}$ concentration ($\mu g/m^3$), while the y-axis represents the cumulative probability. The wealth index panel demonstrates a distinct distribution, reflecting its continuous nature and the broader socioeconomic variability in the study population, not based on categorical grouping or indoor $PM_{2.5}$.

Smoking status was a notable factor influencing indoor $PM_{2.5}$ concentrations, with current smokers exhibiting significantly higher levels compared to non-smokers and former smokers, as illustrated in Figure 9. However, this variable was excluded from models due to indoor $PM_{2.5}$ already capturing the contribution of smoking-related pollution, thereby minimizing redundancy in the analysis, as depicted in Figure 9.

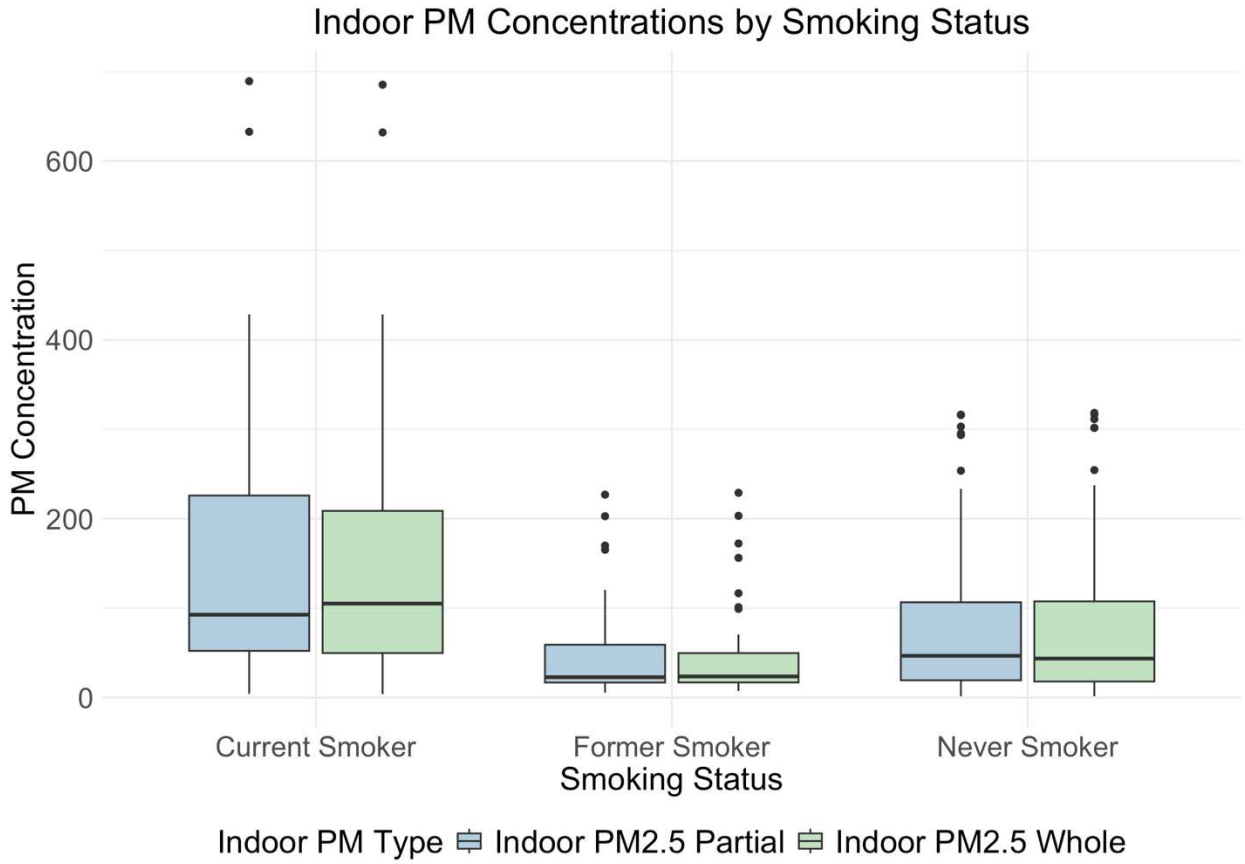

Figure 9. Distribution of indoor $PM_{2.5}$ (Whole and Partial) concentrations by smoking status. The box plots compare indoor $PM_{2.5}$ concentrations during the entire personal sampling period (Whole Indoor $PM_{2.5}$) and while participants were at home (Partial Indoor $PM_{2.5}$) across three smoking categories: current smokers, former smokers, and never smokers. The x-axis represents smoking status, while the y-axis represents $PM_{2.5}$ concentration ($\mu g/m^3$). The boxplots display the median (central line), interquartile range (IQR, the box), and whiskers representing 1.5 times the IQR. Points beyond the whiskers represent outliers.

Overall, these findings highlighted the variability in indoor $PM_{2.5}$ exposure across participant characteristics. Differences in exposure levels across demographic, environmental, and behavioral factors suggested that multiple influences shape indoor air pollution levels. The observed trends provided valuable insights into how these independent variables relate to indoor $PM_{2.5}$ levels, laying the groundwork for further interpretation in subsequent sections.

Correlation Analysis 5.4.4

Spearman correlation matrices, shown in Figure 10, were used to examine potential multicollinearity in the relationships between personal exposure and various environmental and demographic variables. The strongest correlation observed in the matrices was between dependent personal measurements and independent indoor $PM_{2.5}$. However, time spent at home showed minimal correlation with personal $PM_{2.5}$. Outdoor $PM_{2.5}$ displayed a weaker correlation with personal exposure levels, which indicated that outdoor air pollution had a less direct influence on personal $PM_{2.5}$ concentrations than indoor sources.

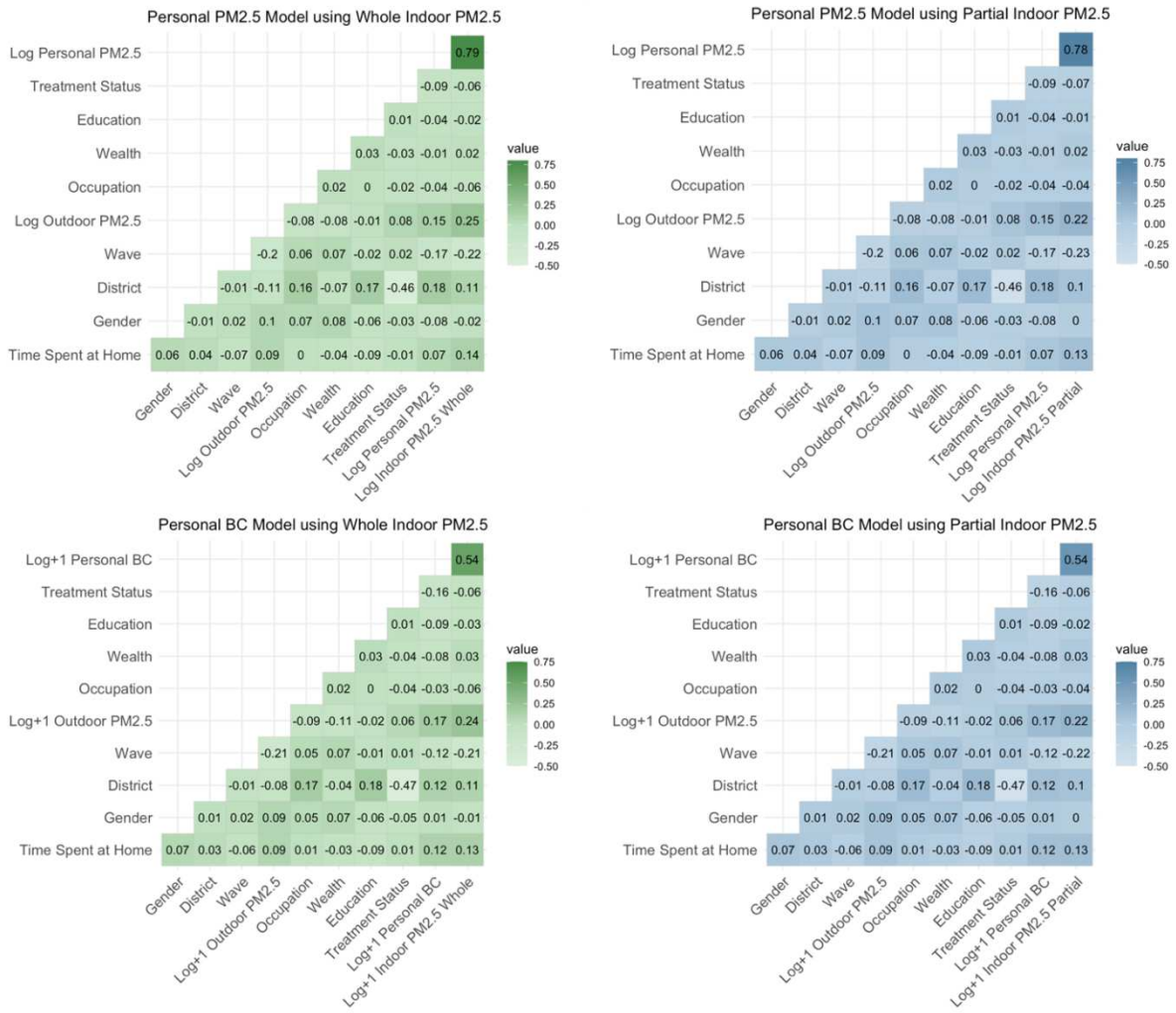

Figure 10. Correlation matrices for personal $PM_{2.5}$ and black carbon (BC) models using Whole and Partial Indoor $PM_{2.5}$ data. Each panel represents a correlation heatmap for a different model specification: personal $PM_{2.5}$ using Whole Indoor $PM_{2.5}$ (top left), personal $PM_{2.5}$ using Partial Indoor $PM_{2.5}$ (top right), personal BC using Whole Indoor $PM_{2.5}$ (bottom left), and personal BC using Partial Indoor $PM_{2.5}$ (bottom right). The values indicate correlation coefficients between predictor variables, with color gradients from -0.50 to 0.75, reflecting the strength and direction of the relationships. Strong positive correlations are shaded darker, while weaker or negative correlations appear lighter. Partial Indoor $PM_{2.5}$ models are represented in blue, while

For black carbon, a similar trend was observed, with personal black carbon exposure showing the strongest correlation with indoor $PM_{2.5}$. However, the correlation between indoor $PM_{2.5}$ and personal black carbon exposure was notably weaker than its relationship with personal $PM_{2.5}$, which indicated that other factors might play a larger role in black carbon exposure. The

difference between the Whole Indoor $PM_{2.5}$ and Partial Indoor $PM_{2.5}$ categories followed the same pattern as $PM_{2.5}$, with Whole Indoor $PM_{2.5}$ displaying a slightly stronger correlation with personal black carbon exposure. The relationship between personal black carbon and outdoor $PM_{2.5}$ was also weaker than the indoor correlations. Time spent at home exhibited minimal correlation with personal black carbon exposure, which mirrored the findings for $PM_{2.5}$. Among the demographic and policy-related variables for both dependent variables, district and treatment status were found to be minimally correlated. Other demographic variables, such as occupation, wealth, and education, displayed relatively weak correlations with personal air pollution exposures.

Overall, the correlation matrices highlighted that indoor air pollution sources played a dominant role in personal exposure levels, while outdoor pollution and time spent at home show weaker associations. These matrices showed little to no multicollinearity, justifying the inclusion of these variables in the models. This suggested that each variable could contributed unique information to the analysis without excessive redundancy, which ensured a more robust and interpretable modeling framework.

Model fit and Performance 5.4.5

The regression models that evaluated personal $PM_{2.5}$ and black carbon exposure provided key insights into the factors influencing individual air pollution exposure levels. Across all models, indoor $PM_{2.5}$ consistently emerged as the strongest predictor of personal $PM_{2.5}$ and black carbon exposure, while time spent at home showed minimal association with either pollutant. The inclusion of Whole versus Partial Indoor $PM_{2.5}$ slightly impacted model fit, with Whole Indoor $PM_{2.5}$ yielding marginally better results for $PM_{2.5}$ models, while Partial Indoor $PM_{2.5}$ performed better for black carbon models.

The top models, as presented in Table 7, indicated that the best-performing model for personal $PM_{2.5}$ included Whole Indoor $PM_{2.5}$, time spent at home, gender, and district. This model achieved an Akaike Information Criterion (AIC) of 489.06, with an R^2 of 0.60 and an adjusted R^2 of 0.59, indicating a relatively strong model fit. In contrast, the model using Partial Indoor $PM_{2.5}$ had a slightly lower R^2 of 0.56 and a higher AIC of 515.16, suggesting that Whole Indoor $PM_{2.5}$ captured exposure variance more effectively. Given that the AIC difference between these models is 26.1, there is overwhelming evidence in favor of the model with the lower AIC.[80]

For black carbon, the models exhibited lower explanatory power, with R^2 values of 0.26 and 0.25 for Whole and Partial Indoor $PM_{2.5}$ models, respectively. The best-performing black carbon model included only Partial Indoor $PM_{2.5}$ yielding an AIC of 407.59. Notably, the model using Whole Indoor $PM_{2.5}$ had a higher AIC of 408.12, indicating that Partial Indoor $PM_{2.5}$ captured personal black carbon exposure variance more effectively than Whole Indoor $PM_{2.5}$. In contrast, these models AIC differ by less than one, suggesting that there is little evidence favoring one over the other, and thus, no meaningful difference between the two.[80] The Spearman correlation values reinforced these trends, with a correlation of 0.80 and 0.78 for personal $PM_{2.5}$ levels in the Whole and Partial Indoor $PM_{2.5}$ models, respectively, while black carbon models had weaker correlations of 0.54 and 0.57. RMSE values indicated that $PM_{2.5}$

models had slightly higher error margins compared to black carbon models, but both exhibited similar levels of predictive uncertainty.

Table 7. Summary of top regression model performance for personal $PM_{2.5}$ and black carbon (BC). The table presents the model specifications, including predictor variables and key performance metrics: Akaike Information Criterion (AIC), R-squared (R^2), adjusted R-squared (Adj R^2), root mean square error (RMSE), and Spearman correlation coefficients. Two models are presented for each dependent variable/pollutant, one using Whole Indoor $PM_{2.5}$ and the other using Partial Indoor $PM_{2.5}$. The equations describe the variables included in each model that was the best performing out of the four base models.

#	Type	Model	AIC	R2	Adj R2	RMSE	Spearman Correlation
1	PM2.5	$ln(Personal\ PM2.5) = \beta0 + \beta1(ln[Indoor\ PM2.5\ Whole]) + \beta2(Time\ at\ Home) + \beta3(Gender) + \beta4(District) + \varepsilon$	489.06	0.60	0.59	0.64	0.80
2	PM2.5	$ln(Personal\ PM2.5) = \beta0 + \beta1(ln[Indoor\ PM2.5\ Partial]) + \beta2(Time\ at\ Home) + \beta3(Gender) + \beta4(District) + \varepsilon$	515.16	0.56	0.55	0.68	0.78
3	BC	$ln(Personal\ BC+1) = \beta0 + \beta1(ln[Indoor\ PM2.5\ Whole+1]) + \varepsilon$	408.12	0.26	0.26	0.57	0.54
4	BC	$ln(Personal\ BC+1) = \beta0 + \beta1(ln[Indoor\ PM2.5\ Partial+1]) + \varepsilon$	407.59	0.25	0.25	0.57	0.57

The sequential addition of demographic and environmental variables showed that occupation and wealth provided some improvements in model fit, but the overall explanatory power remained lower than in $PM_{2.5}$ models, which can be seen in Table S5-S8. The iterative model selection process also demonstrated that adding time at home and outdoor $PM_{2.5}$ did not meaningfully improve model performance, further reinforcing the dominant role of indoor pollution sources. Additionally, the R^2 and adjusted R^2 values did not show substantial improvement with the inclusion of certain variables, indicating that while some demographic and environmental factors slightly enhanced model fit, they did not drastically change the explanatory power of the models. This was particularly evident for variables like time at home

and outdoor $PM_{2.5}$, where their inclusion resulted in negligible increases in R^2, reinforcing their limited role in personal exposure prediction.

Table 8 presents the percent change and confidence intervals for each predictor, highlighting the relative contributions of demographic, temporal, and environmental factors. Indoor $PM_{2.5}$ was the strongest predictor in all the top performing models, with consistently large effect sizes and confidence intervals that did not cross zero. Indoor $PM_{2.5}$ estimates ranged from 90.8% (95% CI: 77.9, 104.6) to 32.8% (95% CI: 24.7, 41.4) for black carbon, highlighting the dominant role of indoor air pollution in shaping personal exposure levels. For every 1 $\mu g/m^3$ increase in indoor $PM_{2.5}$, personal $PM_{2.5}$ increased by 0.9 $\mu g/m^3$ for both Whole and Partial Indoor $PM_{2.5}$ models. Similarly, for black carbon, for every 1 $\mu g/m^3$ increase in indoor $PM_{2.5}$, personal black carbon increased by 0.3 $\mu g/m^3$ for both Whole and Partial Indoor $PM_{2.5}$ models. The coefficient for time spent at home remained at -0.0% (95% CI: -0.0, 0.0) across all models, reinforcing the observation that time spent at home did not drive exposure differences.

Table 8. Percent change in personal $PM_{2.5}$ and black carbon (BC) exposure by model specification, two models for personal $PM_{2.5}$ and two for BC, one using Partial Indoor $PM_{2.5}$ and one using Whole Indoor $PM_{2.5}$. The table presents the estimated percent change in personal $PM_{2.5}$ and BC exposure across different covariates, comparing models using Whole and Partial Indoor $PM_{2.5}$. The results are reported as percentage changes with 95% confidence intervals (CI), allowing for an assessment of the relative impact of demographic, occupational, spatial, and environmental factors on personal air pollution exposure. Reference categories are specified for categorical variables, against which other group estimates are compared against. The table highlights key predictors such as occupation, wave, district, wealth, and outdoor $PM_{2.5}$, and indoor $PM_{2.5}$ Whole and Partial. Asterisks (*) highlight variables that were significant.

Percent Change in Personal PM2.5 and BC Exposure by Model

	Personal PM2.5		Personal BC	
	Using Indoor PM2.5 Whole	Using Indoor PM2.5 Partial	Using Indoor PM2.5 Whole	Using Indoor PM2.5 Partial
	% (95% CI)	% (95% CI)	% (95% CI)	% (95% CI)
Indoor PM2.5 (whole or partial)	90.8 (77.9, 104.6)***	85.8 (72.6, 100.1)***	33.8 (25.6, 42.5)***	32.8 (24.7, 41.4)***
Gender				
Male	ref	ref	ref	ref
Female	-9.6 (-23.7, 7.0)	-12.3 (-26.7, 4.8)	NA	NA
District				
Fangshan	ref	ref	ref	ref
Miyun	-19.5 (-47.6, 23.7)	-20.5 (-49.5, 25.1)	NA	NA
Mentougou	8.8 (-29.8, 68.5)	9.6 (-30.9, 74.0)	NA	NA
Huairou	8.5 (-29.2, 66.4)	6.7 (-32.0, 67.5)	NA	NA
Average Duration at home (hours)	-0.0 (-0.0, 0.0)	-0.0 (-0.0, 0.0)	NA	NA

Exposure levels varied by district, though confidence intervals were wide. Participants in Miyun had statistically insignificantly lower personal exposures compared to Fangshan, while those in Mentougou and Huairou exhibited higher personal exposures, which suggested potential localized pollution sources. Females had lower personal $PM_{2.5}$ exposure compared to males for the $PM_{2.5}$ models, though not statistically significant.

Figure 11 presents the regression estimates and their 95% confidence intervals, allowing for a visual comparison of predictor effects across models. The intercept estimates in the $PM_{2.5}$ plots were notably large, reflecting the baseline levels of exposure when all other predictor variables were held at their reference values. This suggested that a significant portion of exposure was not fully explained by the included variables, which indicated the presence of additional unmeasured factors. Figure 11 highlights that indoor $PM_{2.5}$ remained the most significant predictor, with strong positive associations for both models utilizing Whole and Partial Indoor $PM_{2.5}$. Notably, predictors gender and district smaller effect sizes, all of which cross zero, suggesting weaker or more variable associations with exposure. These visual insights complemented the numerical findings, emphasizing the primary role of indoor pollution sources.

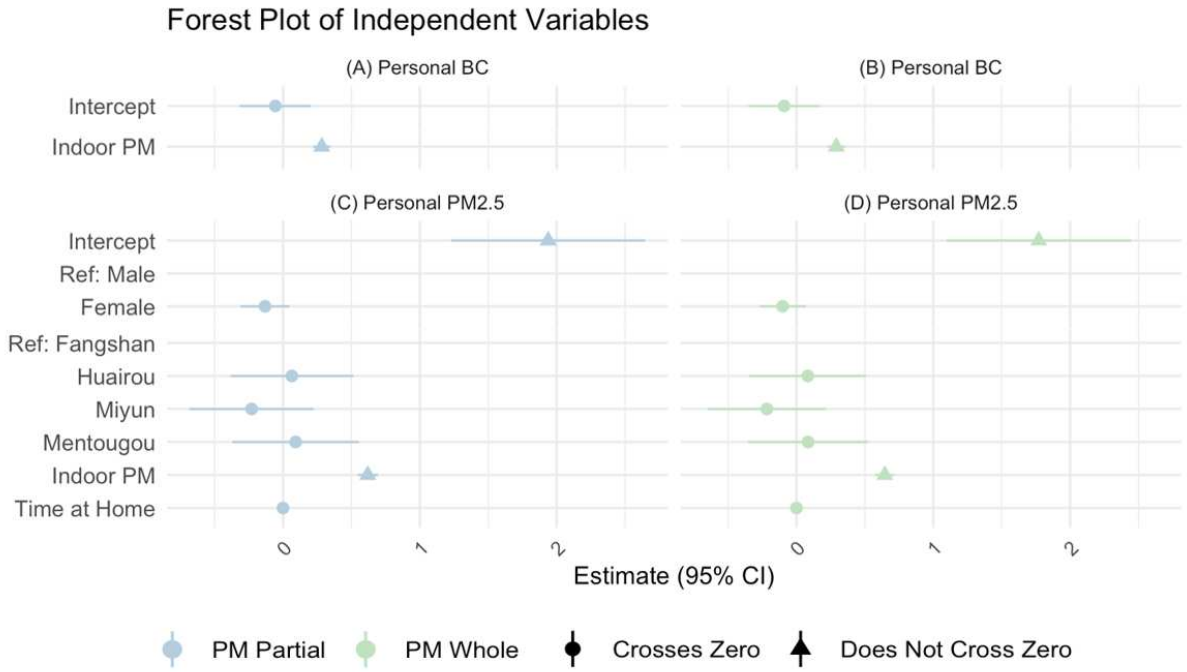

Figure 11. Forest plot of coefficients for independent variables for personal $PM_{2.5}$ and black carbon (BC) models. The figure presents estimated regression coefficients and 95% confidence intervals for key independent variables across four model specifications: (A) and (B) for personal BC, and (C) and (D) for personal $PM_{2.5}$. The models distinguish between Whole Indoor $PM_{2.5}$ (green) and Partial Indoor $PM_{2.5}$ (blue), with markers indicating whether the confidence interval crosses zero (circles) or does not cross zero (triangles). The x-axis represents the estimated effect sizes, while the y-axis lists the independent variables.

Overall, results identify that indoor $PM_{2.5}$ was one of the primary determinants of personal exposure. Time at home showed negligible effects on exposure for $PM_{2.5}$, which indicated that pollutant concentrations rather than time indoors played a more significant role.

Radii Selection Sensitivity Analysis on Modeling 5.4.6

To assess the impact of home radius size on modeling, especially to black carbon (BC) model performance, a sensitivity analysis was conducted across eleven radii ranging from 20 to 150 meters. Changes in radius size compared to the chosen 70-meter radius, did not substantially improve model fit. Changes in R^2 values were minimal, with a maximum improvement of approximately 1%. Akaike Information Criterion (AIC) scores showed similarly small variations,

suggesting that refining the radius alone did not significantly influence model predictive power. Results indicated that time spent at home—whether derived from full or partial classifications—had minimal effect on black carbon model outcomes. Thus, while geofencing remains a useful tool for broad classification, more detailed microenvironment data or multiple personal exposure measures may be required to explain remaining variability in black carbon and $PM_{2.5}$ exposure. Adjusting the radius within the tested range did not appear to offer a practical advantage under the current modeling framework.

Stepwise Modeling Analysis 5.4.7

Stepwise regression models were developed for both $PM_{2.5}$ and black carbon (BC) exposures and were compared to the previously identified top-performing non-stepwise models. For the $PM_{2.5}$ models, stepwise selection retained indoor $PM_{2.5}$ and district as key variables, consistent with prior models, but excluded time at home due to its limited contribution to model performance. Instead, ban status was included in the modeling incorporating Whole Indoor $PM_{2.5}$, and gender was selected for the modeling incorporating Partial Indoor $PM_{2.5}$. These additions suggest that policy implementation and demographic characteristics may play a role in personal $PM_{2.5}$ exposure. These can be seen in Table S9.

For black carbon models, stepwise selection expanded the variable set to include ban status, wealth, and outdoor $PM_{2.5}$, in addition to indoor $PM_{2.5}$. These variables were included in varying orders for the whole and partial samples. Notably, R^2 values improved by approximately 2–4%, and Akaike Information Criterion (AIC) values were slightly lower, indicating either no meaningful improvements, or marginally improved model fit. Compared to the original top-performing models, stepwise models demonstrated slightly better performance while identifying a broader set of explanatory variables. These results show that stepwise modeling effectively

identifies influential variables and improves model fit. However, it may not capture the full value of variables excluded during selection. Iterative modeling remains useful for understanding each variable's specific contribution to model complexity and explanatory power.

DISCUSSION

The effectiveness of household energy transition policies, such as the Coal-to-Clean Energy Policy implemented in China, has been well-documented in terms of reducing indoor air pollution. However, the extent to which these reductions translated into lower personal exposures to fine particulate matter ($PM_{2.5}$) and black carbon remained uncertain.[3,81] On average, participants spent 20 hours at home, accounting for 86% of their total time—a pattern consistent with previous research. This study sought to explore why variability persisted in personal exposure levels despite observed decreases in indoor pollution. While it was expected that individuals who spent more time at home would experience lower personal $PM_{2.5}$ exposures due to reductions in indoor concentrations, the findings indicated that personal exposure variability was not fully explained by time spent at home or indoor $PM_{2.5}$ levels alone. A novel aspect of this study was leveraging time-resolved indoor $PM_{2.5}$ data, aligned with GPS-tracked participant locations, to assess personal exposure when individuals were at home. Despite expectations, the findings have suggested that personal exposure variability did not decrease as anticipated under the Coal-to-Clean Energy Policy (CCEP) intervention, indicating that additional factors beyond indoor $PM_{2.5}$ pollution reductions may be influencing exposure dynamics. This highlights the need for further investigation into the length of personal sampling duration, behavioral patterns, outdoor pollution contributions, and microenvironmental influences on personal exposure levels.

Indoor $PM_{2.5}$ has been a consistently significant predictor of personal $PM_{2.5}$ exposure, reinforcing the strong association between indoor and personal pollution levels. Additionally, models using Whole Indoor $PM_{2.5}$ (Indoor $PM_{2.5}$ averaged during the whole personal sampling period) performed better than those incorporating only the time-resolved indoor fraction (Partial

Indoor $PM_{2.5}$) for the personal $PM_{2.5}$ models, but not for the personal black carbon models, as indicated by superior AIC values. Partial Indoor $PM_{2.5}$ contributed to better performing models for the black carbon models. Notably, time spent at home did not significantly impact personal exposure, suggesting that indoor air pollution levels played a more substantial role than occupancy patterns alone. The black carbon models, while demonstrating a better model fit per AIC values, explained significantly less variability in personal black carbon exposure (25-26%) compared to personal $PM_{2.5}$ models (56-60%), implying that key sources of black carbon exposure may originate outside the home or are not being picked up by indoor measurements. This suggested that black carbon exposure may be driven by different sources, which were not fully captured in the study.

The influence of time-of-day trends on personal $PM_{2.5}$ exposure further suggested that household activities such as cooking and cleaning contributed to indoor $PM_{2.5}$ peaks, aligned with patterns of participant occupancy. These findings indicated that exposure to indoor-generated $PM_{2.5}$ may vary depending on individual behavior patterns, including meal preparation times, home heating times, ventilation practices, and seasonal changes in household activities. This understanding is important for designing more effective indoor air quality interventions that account for human behavior and activity schedules. Moreover, while the approach of using Whole and Partial Indoor $PM_{2.5}$ has explained a substantial portion of personal $PM_{2.5}$ exposure, it has not clarified why personal exposure reductions did not match indoor air pollution declines under the Coal-to-Clean Energy Policy (CCEP) intervention. This discrepancy has highlighted the potential role of other exposure pathways, such as exposure to outdoor pollution, residual indoor pollution from previous exposures, or exposure during transit between locations. The influence of time-of-day trends on personal $PM_{2.5}$ exposure further suggested that household

activities such as cooking and cleaning may have contributed to indoor $PM_{2.5}$ peaks, aligned with patterns of participant occupancy. These findings have provided insight into when and how individuals were exposed, emphasizing that while indoor $PM_{2.5}$ was a primary driver of personal $PM_{2.5}$ exposure, additional sources and behaviors must be considered to fully understand personal black carbon exposure variability.

The Beijing Household Energy Transition (BHET) study has provided insights into the impact of the Coal-to-Clean Energy Policy (CCEP) on indoor air quality and human health. Prior research within this larger study has established that indoor $PM_{2.5}$ levels have declined following policy implementation. However, these studies have also highlighted a persistent gap; Despite reductions in indoor air pollution, personal exposures to $PM_{2.5}$ and black carbon have not decreased as expected, though coal exposures did reduce even if total $PM_{2.5}$ exposure did not.[3] These studies have also identified that there have been beneficial health impacts from the policy implementation, even though 24-hour personal exposures have not been shown to have reduced because of the policy.[82]

Previous research in the larger study has shown that while long-duration indoor air sampling captured notable decreases in $PM_{2.5}$ concentrations, shorter-duration indoor samples did not always show such reductions.[42,81] Additionally, previous analyses within the study examined personal exposure variability in relation to stove use metrics, demonstrating that stove type and fuel choice significantly influenced indoor air quality and, consequently, personal exposure levels.[45] These findings reinforced the need to understand exposure through a multifaceted lens that accounts for personal behavior, indoor air pollution contributions, and microenvironmental influences.

Unlike prior research in the larger study, which had focused on indoor pollution levels and stove use, this study uniquely integrates GPS-tracked time-at-home data with time-resolved indoor $PM_{2.5}$ measurements. This approach provided a new perspective on why personal exposure variability persists despite indoor pollution reductions. While previous studies have established that stove use impacts exposure, this study further expands on that understanding by integrating mobility patterns and time-of-day trends to assess their influence on personal pollution levels. By incorporating these variables, this study offers a refined understanding of the determinants of personal exposure, demonstrating that while indoor $PM_{2.5}$ remained a strong predictor of personal exposure, time spent at home did not significantly influence personal $PM_{2.5}$ levels. Instead, personal exposure variability appeared to be influenced by time-of-day trends and behavioral activity patterns. However, discrepancies suggests that factors beyond household air pollution may be contributing to personal exposure levels.

Consistent with previous findings, this study has confirmed that at-home indoor $PM_{2.5}$ remains a primary determinant of personal $PM_{2.5}$ exposure.[51] However, it also challenged the hypothesis that time spent at home significantly impacts personal exposures. This contradicts expectations that reduced indoor air pollution would directly translate to lower personal $PM_{2.5}$ exposure for individuals who spend more time indoors. The lack of correlation suggested that other factors, such as outdoor pollution sources, larger behavioral activity patterns, and other indoor environments, may play a more significant role than previously considered.

This study highlighted the role personal activity patterns had in shaping exposure outcomes. While knowing the indoor $PM_{2.5}$ exposure during the time that the participant was at home was hypothesized to impact personal exposure, it did not have significant impacts as expected. These insights suggested that future research should prioritize collecting more detailed

behavioral data and account for longer personal exposure sampling durations. Additionally, these findings indicated that interventions targeting indoor air quality alone may be insufficient in fully addressing personal exposure disparities. Overall, this study builds upon the existing research by refining the understanding of personal exposure variability and identifying gaps that require further investigation in subsequent studies.

Beyond its contributions to the larger study, this research has broader implications for the wider field of air pollution exposure science. By integrating high-resolution behavioral and spatial data with personal air pollution monitoring, this study provided a methodological framework that can be adapted and added upon for exposure assessments in diverse environmental and policy contexts. The approach used here highlights the importance of capturing dynamic exposure patterns rather than relying solely on static measurements, which may not fully reflect individual experiences. Additionally, these findings reinforce the necessity of multi-source exposure assessments, incorporating other factors like outdoor pollution contributions, further refined time activity trends (e.g. time spent in other indoor locations, time spent in transit, etc.), and household characteristics, to develop a more comprehensive understanding of exposure variability.

Strengths and Limitations 6.1

Strengths 6.1.1

A primary strength of this study is the scale of its dataset, making it one of the largest studies of its kind to integrate time-activity patterns into exposure modeling. The substantial sample size provided a more comprehensive representation of exposure trends compared to smaller-scale studies. Most household energy intervention studies have assessed a single air pollution metric; however, this study incorporated multiple metrics, specifically both indoor and

personal exposure. While some studies focused solely on GPS data or pair it with a single pollution metric, this study integrated both GPS data and multiple exposure measurements, providing a more comprehensive assessment. The use of time-activity data within a study of this magnitude was rare, contributing valuable insights into exposure variability that may not be observable in more limited investigations.

Another notable strength was the rigorous modeling approach, which incorporated multiple covariates to refine exposure assessment and mitigate potential confounding effects. While geofencing methodologies could be further improved, the studies incorporation of detailed time-activity data enhanced its applicability and strengthened its capacity to evaluate real-world exposure dynamics.

A significant contribution of this research was its integration of time spent at home within exposure models, a methodological element that had not been widely applied in prior studies assessing the China Clean Energy Policy (CCEP). Although the collection of time-activity data itself was not novel, its explicit inclusion in exposure models for this specific policy intervention represents a relatively unique contribution to the literature. This study demonstrated the importance of incorporating behavioral patterns into exposure assessments, particularly in regions undergoing energy transitions.

From an analytical perspective, this study benefits from minimal multicollinearity, as confirmed by low variance inflation factor (VIF) values. Furthermore, the study enhanced understanding of exposure variability by identifying time periods in which personal exposure may be disproportionately affected, particularly through the evaluation of time spent at home.

In terms of policy relevance, the findings provided valuable insights for policymakers and public health professionals. If the goal of energy interventions such as the Coal-to-Clean

Energy Policy (CCEP) was to reduce personal $PM_{2.5}$ exposure, this study highlighted the necessity of incorporating behavioral factors into policy assessments. While these findings were not directly generalizable beyond the study population, they hold relevance for other regions where solid fuel combustion remains prevalent.

Limitations 6.1.2

While this study provided valuable insights into personal $PM_{2.5}$ exposures and time-activity patterns, several limitations must be considered. These limitations primarily relate to data completeness, selection bias, and generalizability. However, in most cases, these constraints are unlikely to meaningfully alter the study's core findings.

One of the primary limitations was data incompleteness, which stemmed from several factors, including participant attrition, device malfunctions, and data processing exclusions. Several files were either not initiated correctly, lost, or improperly recorded. While data attrition is an inherent challenge in longitudinal environmental exposure studies, the distribution of time spent at home in the retained dataset remained stable, suggesting that additional data would not have significantly altered the observed trends. It is important to note that while the completeness of personal exposure measurements could have provided further insight into participants' behaviors, particularly in terms of distinguishing specific time-activity patterns while at home or away, the overall assessment of time spent at home would be unlikely to change with additional data. Longer duration monitoring could have provided greater insight into participants' time-activity patterns, even if the overall time spent at home remained largely unchanged. Understanding how participants allocated their time at home and away would have offered a more nuanced view of their exposure behaviors. However, given the limitations in personal exposure data collection, the recorded time-activity patterns may not fully capture daily

behavioral variations, potentially leading to an underrepresentation of certain exposure scenarios. The exclusion of some self-reported and GPS-tracked data further contributed to potential gaps in understanding individual exposure contexts, though the overall consistency of home-time estimates suggested that key findings remain robust.

Beyond data incompleteness, selection bias presented another potential limitation, as the dataset may not be fully representative of the broader population. The distribution of participants across districts was somewhat imbalanced, with Fangshan having only ten participants, and data from Wave 3 being entirely absent due to COVID-19-related disruptions. However, demographic variables were relatively balanced, and the occupation distribution was consistent across Huairou, Miyun, Mentougou, and Fangshan, with agriculture and housework being the predominant employment categories. The consistency of time-at-home distributions between Waves 2 and 4 further supports the representativeness of the sample despite the missing wave.

Although selection bias could theoretically influence results, the relatively uniform trends across districts and waves suggested that the core exposure patterns observed in this study remained valid. However, the wide range of observed personal $PM_{2.5}$ exposures (2.1 μg/m^3 to 608.9 μg/m³) suggested significant day-to-day fluctuations. Extending the duration of personal sampling, such as conducting multi-day continuous monitoring, would provide a more stable representation of exposure patterns and improve the ability to account for daily behavioral shifts.

A potential concern in time-activity studies is the Hawthorne effect, where participants alter their behavior due to awareness of being observed. In this study, however, there is little evidence to suggest that this significantly impacted results. Given that most participants spent most of their time at home, it is unlikely that observation awareness meaningfully changed their

behavior. If the Hawthorne effect were a major factor, one would expect participants to spend more time away from home to avoid observation, yet this was not the case. While the possibility of minor behavioral changes cannot be entirely ruled out, the stability of time-at-home estimates across participants and waves suggested that this effect did not substantially bias the findings.

The generalizability of these findings is inherently constrained by the study's geographic and socio-economic context. The study population primarily consisted of rural households reliant on solid fuel combustion, and while the results offered meaningful insights for similar communities, they may not be directly transferable to urban environments or populations that do not rely on solid fuels for heating or cooking. However, within the context of northern China and similar rural regions, the findings were likely broadly applicable. Time-activity patterns were highly location-dependent, and while this study provided valuable regional insights, caution should be exercised when extrapolating results to dissimilar settings.

Overall, while limitations related to data incompleteness, selection bias, and generalizability exist, their impact on the studies core conclusions was minimal. The observed trends in time-at-home distributions remained consistent across waves and districts, suggesting that additional data would primarily refine behavioral insights. The representativeness of the dataset, coupled with the stability of exposure estimates, supported the reliability of the results, making them relevant for policy considerations in similar rural environments.

Future Research Directions 6.2

Future research should address the temporal limitations of exposure monitoring by extending personal $PM_{2.5}$ sampling beyond 24-hour periods. Conducting multi-day exposure assessments would improve the ability to capture intra-individual variability and provide a more representative view of long-term exposure trends. Additionally, examining exposure trends

during key behavioral transition periods—such as 6:00 AM - 10:00 AM (when home presence declines) and 4:00 PM - 8:00 PM (when home presence increases)—may offer valuable insights into exposure drivers and potential intervention points.

Another priority for future research should be improving geofencing accuracy through the integration of more diverse environmental and behavioral data, with the goal of enabling more refined classification of microenvironments. As geofencing methods become more precise, future work should also focus on expanding the number and specificity of microenvironments that can be identified. This would allow researchers to move beyond broad categories such as "at home" and "away from home" to include distinctions like being inside versus outside the home, in transit, at the workplace, or in other frequented settings, thereby deepening the understanding of exposure contexts.

The integration of time-resolved, continuous monitoring of personal exposure with GPS tracking would offer a more precise understanding of when and where individuals are exposed to the highest levels of pollution. To enhance microenvironment classification, future studies should also incorporate additional sensor data—such as light intensity, noise, accelerometer readings, temperature, humidity, and GPS-derived speed—to better distinguish between nuanced indoor and outdoor settings. This is particularly relevant for identifying environments such as at home–indoors versus at home–outdoors, as well as workplaces and transit settings. These improvements would deepen insights into exposure patterns in the context of both location and activity type.

Initial efforts were made in this study to refine geofencing classification methods by incorporating environmental indicators such as temperature change and speed. These exploratory analyses aimed to evaluate whether such additions could improve the accuracy of determining

when a participant was indoors or outdoors. For temperature, a threshold of ±1°C over one minute was tested, following methods outlined in previous research.[64] While this approach improved classification in some instances, limitations became apparent. In certain cases, the method produced high—though not entirely implausible—estimates of outdoor time (e.g., up to nine hours outdoors while still within the home boundary), likely caused by uncorrected one-way temperature drops. Inaccurate assumptions about indoor versus outdoor temperature patterns may have further complicated results. These findings suggest that while temperature change is a promising refinement tool, it requires careful calibration and validation before it can be reliably incorporated into future studies. Additional research should explore its integration with other environmental indicators and assess its utility through controlled sensitivity analyses and ground truth validation.

Speed data were also explored as a supplementary indicator. Various thresholds (0.5 to 6 m/s) and smoothing windows (1 to 5 minutes) were tested based on previous research. While higher speeds generally suggested transit or outdoor activity, lower thresholds risked misclassifying slow indoor movement as being away from home. The combination of a 4 m/s threshold and a five-minute smoothing window appeared to offer a reasonable trade-off, identifying periods of sustained movement without excessive reclassification. Nonetheless, speed-based refinements introduced additional classification error and did not lead to substantially improved accuracy in the absence of validated ground truth data. As a result, the method was applied only in a limited capacity. These early-stage analyses helped identify both the potential and the constraints of integrating environmental signals into geofencing classification.

Another major area for future research involves expanding the number and specificity of identifiable microenvironments. Future research could build on these exploratory methods through more rigorous testing and validation. In particular, machine learning approaches—including supervised learning algorithms—could be employed to integrate multiple data streams and improve the accuracy of microenvironment classification, especially in complex and transitional settings. Combining location-based information with temperature, relative humidity, light, speed, and accelerometer data could allow for more granular microenvironment classification and facilitate the identification of behavioral patterns, such as room-level movements, household proximity, or compliance with monitoring protocols. This level of temporal and spatial resolution would enable more robust exposure modeling, especially when paired with time-activity logs for cross-referencing. Including such logs or diaries could improve classification accuracy and provide a reference for quality control, helping to resolve misclassifications that sensor data alone cannot correct.

To fully operationalize these methods in future studies, a systematic sensitivity analysis and development of standard quality control procedures would be required. Further testing is necessary before these methods could be deployed in large-scale epidemiological studies. While a combination of methods will likely offer the most accurate classification, in resource-limited settings, even single-method approaches—if properly calibrated—may be sufficient. Ultimately, continued development and validation of these tools will be essential for advancing personal exposure assessment and understanding the real-world impact of air quality interventions.

From a policy perspective, this study highlighted the importance of incorporating longer-term personal exposure assessments and time-activity patterns into energy intervention evaluations. Policymakers should consider how behavioral factors influence exposure trends, as

well as how extended monitoring periods could refine intervention impact assessments. One promising avenue for future research involves the integration of source apportionment findings within exposure models. Prior research[42] suggested that while the Coal-to-Clean Energy Policy (CCEP) successfully reduced coal-derived contributions to personal $PM_{2.5}$ exposure, overall $PM_{2.5}$ levels did not decline, indicating the need for additional mitigation strategies beyond coal reduction alone, if the sampling duration accurately depicts and captures personal variability to $PM_{2.5}$ and BC.

Ultimately, future studies should prioritize enhancing geospatial classification methods, extending exposure monitoring durations, and integrating multi-sensor datasets to refine personal air pollution exposure assessments. These improvements would provide a stronger foundation for both scientific research and evidence-based policymaking in air quality management.

CONCLUSION

This study assessed the variability in personal $PM_{2.5}$ and black carbon exposures in rural Beijing following the implementation of the Coal-to-Clean Energy Policy (CCEP). By integrating time-activity patterns and geofencing techniques, this work aimed to determine whether refined exposure classifications would explain the unexpected persistence of high personal exposure levels.

The findings demonstrated that indoor $PM_{2.5}$ concentrations significantly influenced personal exposure, but time spent at home was not a significant predictor in the models. This challenged the expectation that participants spending more time at home would experience lower personal exposure, given the reductions in indoor $PM_{2.5}$ following the policy intervention. The results could suggest that factors beyond the ones included here, contributed to personal exposure variability. Furthermore, incorporating Partial Indoor $PM_{2.5}$, rather than using full-duration indoor $PM_{2.5}$ data, did not improve model performance for personal $PM_{2.5}$, but did for personal BC, which suggested that current exposure frameworks may not fully capture the nuances of personal exposure patterns or that another aspect of exposure was not being considered here.

The findings highlighted key methodological considerations for future studies. The lack of a clear reduction in personal exposure levels despite policy-driven improvements in indoor air quality suggested that 24-hour personal exposure sampling may be insufficient to capture long-term exposure trends. Future research should prioritize extended-duration personal monitoring to better account for temporal variability. Additionally, outdoor exposure and transit-related contributions remain underexplored, and incorporating source apportionment into the modeling

framework could be included to quantify their influence on personal $PM_{2.5}$ and black carbon levels. An improved geofencing methodology, incorporating additional metrics, could refine exposure classification and provide greater insight into microenvironmental impacts.

An implication of this study is the need for longer-duration personal exposure assessments to improve the accuracy of air pollution exposure modeling. While indoor $PM_{2.5}$ remained a dominant factor in personal exposure, the inability to explain remaining variability underscores the complexity of exposure dynamics. Future interventions should integrate more sophisticated geofencing, outdoor exposure assessments, and longer-duration personal monitoring to improve exposure prediction and better inform air quality policy.

The work presented in this thesis provided a foundation for refining personal exposure assessment methodologies in air pollution research. The same modeling framework could be expanded to incorporate additional microenvironmental factors and longer sampling durations, further advancing the field's understanding of personal exposure variability. Future research should explore how different modeling approaches, including enhanced geofencing and extended monitoring, impact the accuracy of exposure assessments and contribute to improved air quality interventions. Addressing these gaps is important for designing effective strategies that accurately reflect real-world exposure patterns and their associated health outcomes.

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APPENDICES

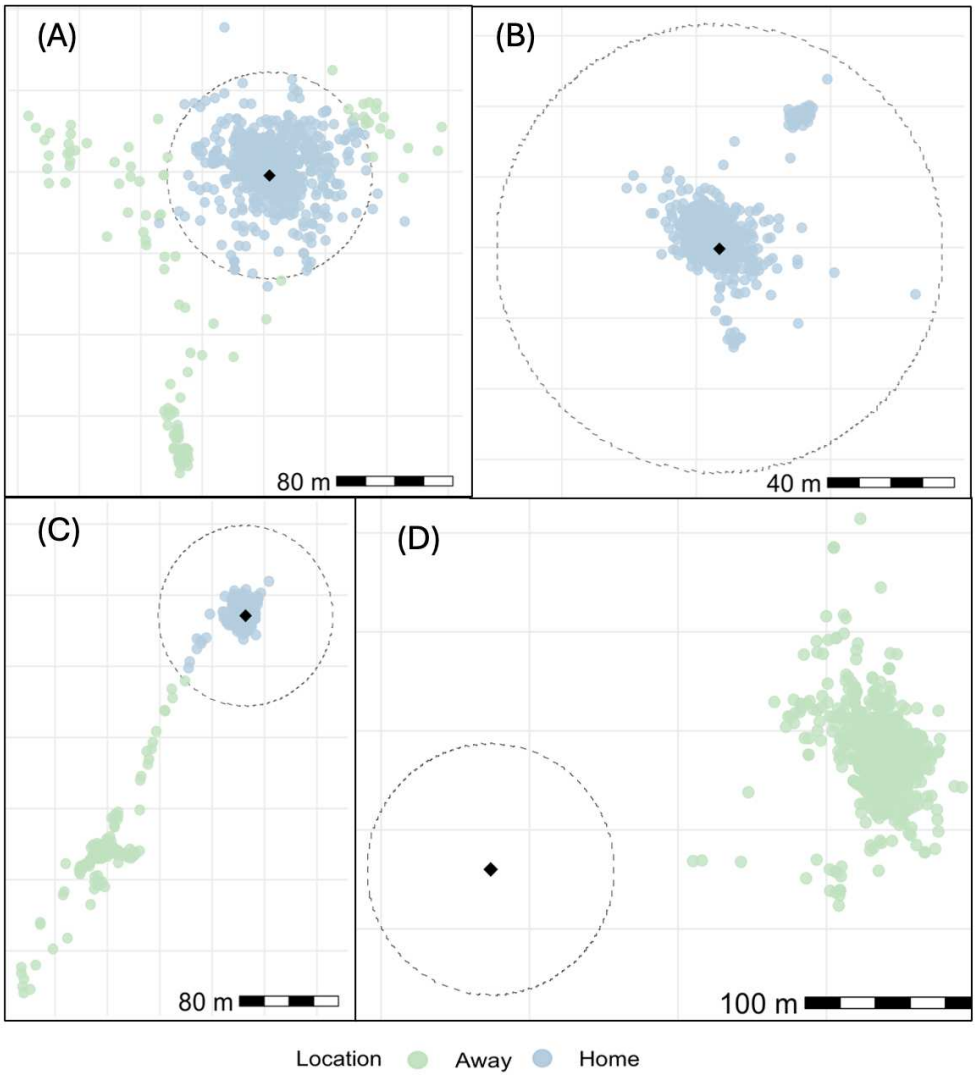

Figure S1. Spatial distributions of participant GPS locations over the sampling period, with each point representing an individual recorded location. The home coordinate is shown by the black diamond, and the dashed circle represents the 70 m mark around the home coordinate, which was chosen as the geofencing radius. The colors indicate how the geofencing method classified each individual point: home or away from home. Scale bars provide distance references for each subplot. (A) illustrates a participant with distinct noise. (B) shows a participant who spent the entire sampling period at home. (C) illustrates a participant who has traveled along distinct travel paths. (D) shows a participant whose recorded home coordinate appears slightly offset, who's time at home and Partial Indoor $PM_{2.5}$ would be imputed.

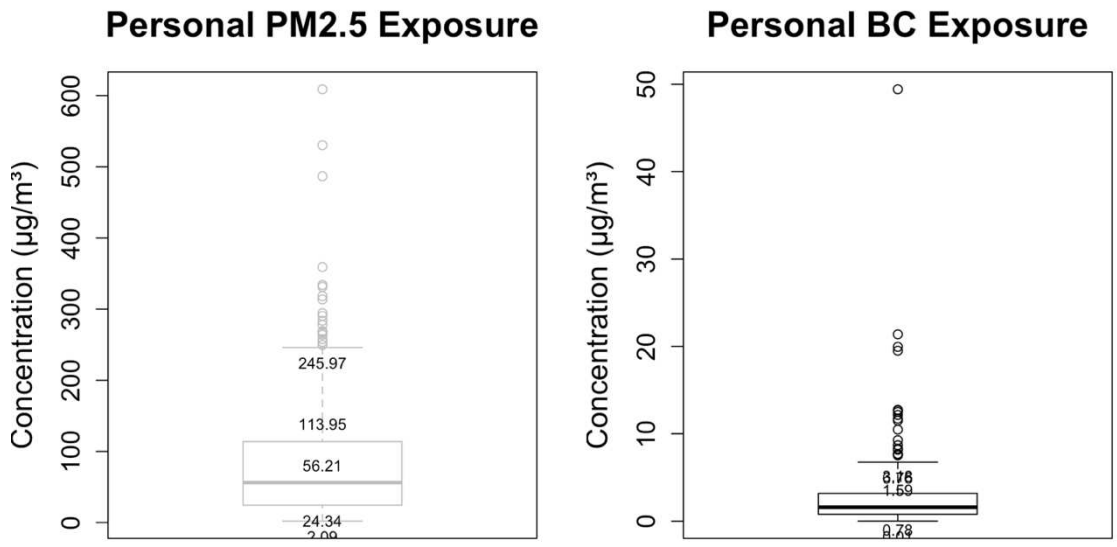

Figure S2. Boxplots of personal $PM_{2.5}$ and black carbon (BC) exposure concentrations (µg/m^3). The left panel represents $PM_{2.5}$ exposure (grey), while the right panel represents BC exposure (black). The boxplots display the median, interquartile range, and outliers for each pollutant, with numerical labels indicating key statistical values. The labeled values correspond to key statistical measures, including the minimum, first quartile, median, third quartile, and upper whisker limit. The whiskers of the boxplots extend to the most extreme values, while the dots above them represent individual data points that are considered outliers.

Table S1. Summary of participant characteristics, including gender, treatment status, education, occupation, smoking status, wave, and district. The table displays the total number of participants in each category along with their arithmetic mean personal $PM_{2.5}$ and black carbon (BC) exposure concentrations ($\mu g/m^3$), with corresponding 95% confidence intervals [CI].

Characteristic	Total Number PM2.5	Personal PM2.5	Total Number BC	Personal BC
	n (%)	Arithmetic Mean [95% CI]	n (%)	Arithmetic Mean [95% CI]
Gender				
Female	138 (54.8)	77.6 [64.5, 90.8]	135 (55.1)	3.1 [2.2, 4.0]
Male	114 (45.2)	95.3 [76.4, 114.0]	110 (44.8)	2.4 [1.9, 3.0]
Treatment Status				
Entered in 2019	70 (27.8)	72.8 [55.8, 89.8]	68 (27.8)	3.6 [2.6, 4.7]
Entered in 2020	42 (16.7)	93.0 [57.8, 128.0]	41 (16.7)	1.8 [1.4, 2.3]
Entered in 2021	19 (7.5)	70.6 [38.6, 102.0]	18 (7.3)	2.3 [1.5, 3.2]
No Ban	121 (48)	92.9 [76.4, 109.0]	118 (48.2)	1.9 [1.3, 2.6]
Education				
Primary School or below	230 (91.3)	86.5 [74.7, 98.4]	223 (91.0)	2.8 [2.3, 3.4]
Secondary/high school or above	22 (8.7)	76.1 [41.3, 111.0]	22 (9.0)	2.4 [1.0, 3.7]
Occupation				
Agriculture and related workers	154 (61.1)	92.3 [76.5, 108.0]	149 (60.8)	3.0 [2.2, 3.7]
Indoor Workers	64 (25.4)	66.1 [41.8, 90.4]	18 (7.3)	2.6 [1.8, 3.5]
Unemployed	18 (7.1)	73.4 [54.8, 91.9]	62 (25.3)	2.3 [0.2, 4.3]
Other or not stated	11 (4.4)	116.0 [64.0, 168.0]	11 (4.5)	2.8 [1.5, 4.1]
Missing	5 (2)	41.6 [13.8, 69.3]	5 (2.0)	1.1 [0.5, 1.6]
Smoking Status				
Current Smoker	73 (29)	130.0 [104.0, 156.0]	72 (29.4)	3.1 [2.2, 4.0]
Former Smoker	45 (17.9)	47.2 [35.0, 59.4]	42 (17.1)	2.7 [2.0, 3.4]
Never Smoker	134 (53.2)	130.0 [104.0, 156.0]	131 (53.5)	1.9 [1.3, 2.6]
Wave				
Wave 2	129 (51.2)	99.2 [81.7, 117.0]	126 (51.4)	3.2 [2.3, 4.1]
Wave 4	123 (48.8)	71.4 [58.0, 84.9]	119 (48.6)	2.4 [1.8, 2.9]
District				
Huairou	95 (37.7)	91.9 [72.0, 111.8]	93 (38.0)	2.1 [1.7, 2.5]
Miyun	85 (33.7)	61.6 [50.5, 72.7]	83 (33.9)	2.3 [1.8, 2.8]
Mentougou	62 (24.6)	108.2 [80.8, 135.6]	59 (24.1)	4.7 [2.8, 6.6]
Fangshan	10 (4.0%)	90.1 [27.5, 152.8]	10 (4.1)	1.9 [1.1, 2.8]

Table S2. This table presents the Variance Inflation Factor (VIF) values for four models assessing the relationships between personal $PM_{2.5}$ and black carbon (BC) exposure with various covariates. Each model is built incrementally, starting with a base model that includes only "Time at Home" and sequentially adding gender, district, wave, outdoor $PM_{2.5}$, occupation, wealth, education, and treatment status. The table is divided into four sections: (1) Personal $PM_{2.5}$ Model Using Whole Indoor $PM_{2.5}$; (2) Personal $PM_{2.5}$ Model Using Partial Indoor $PM_{2.5}$; (3) Personal BC Model Using Whole Indoor $PM_{2.5}$; and (4) Personal BC Model Using Partial Indoor $PM_{2.5}$.

PM2.5 Model Using Whole Indoor PM2.5

VIF Values	Base + time at home	… + Gender	… + District	… + Wave	… + Outdoor PM2.5	… + Occupation	… + Wealth	… + Education	… + Treatment Status
log(Whole Indoor PM2.5)	1.010	1.012	1.020	1.042	1.080	1.085	1.091	1.092	1.102
Time at Home	1.010	1.022	1.024	1.024	1.025	1.029	1.032	1.038	1.041
Gender	1.010	1.012	1.025	1.025	1.030	1.044	1.047	1.049	1.064
District	1.010	1.012	1.009	1.010	1.027	1.039	1.040	1.052	1.166
Wave	1.010	1.022	1.020	1.028	1.054	1.087	1.088	1.089	1.092
log(Outdoor PM2.5)	1.010	1.012	1.024	1.042	1.125	1.126	1.132	1.132	1.148
Occupation	1.010	1.012	1.025	1.024	1.080	1.034	1.036	1.039	1.046
Wealth	1.010	1.022	1.009	1.025	1.025	1.085	1.021	1.023	1.029
Education	1.010	1.012	1.020	1.010	1.030	1.029	1.091	1.047	1.056
Treatment Status	1.010	1.012	1.024	1.028	1.027	1.044	1.032	1.092	1.131

PM2.5 Model Using Partial Indoor PM2.5

VIF Values	Base + time at home	… + Gender	… + District	… + Wave	… + Outdoor PM2.5	… + Occupation	… + Wealth	… + Education	… + Treatment Status
log(Partial Indoor PM2.5)	1.013	1.014	1.022	1.046	1.076	1.081	1.087	1.087	1.094
Time at Home	1.013	1.024	1.027	1.027	1.027	1.032	1.035	1.041	1.044
Gender	1.013	1.011	1.024	1.024	1.028	1.042	1.045	1.047	1.063
District	1.013	1.014	1.008	1.010	1.027	1.038	1.039	1.051	1.170
Wave	1.013	1.024	1.022	1.032	1.058	1.090	1.090	1.092	1.095
log(Outdoor PM2.5)	1.013	1.011	1.027	1.046	1.116	1.118	1.123	1.123	1.167
Occupation	1.013	1.014	1.024	1.027	1.076	1.034	1.036	1.039	1.047
Wealth	1.013	1.024	1.008	1.024	1.027	1.081	1.020	1.022	1.026
Education	1.013	1.011	1.022	1.010	1.028	1.032	1.087	1.047	1.058
Treatment Status	1.013	1.014	1.027	1.032	1.027	1.042	1.035	1.087	1.137

BC Model Using Whole Indoor PM2.5

VIF Values	Base + time at home	… + Gender	… + District	… + Wave	… + Outdoor PM2.5	… + Occupation	… + Wealth	… + Education	… + Treatment Status
log(Whole Indoor PM2.5 +1)	1.010	1.012	1.021	1.043	1.076	1.081	1.088	1.090	1.100
Time at Home	1.010	1.023	1.025	1.025	1.026	1.031	1.034	1.039	1.042
Gender	1.010	1.013	1.025	1.025	1.028	1.041	1.044	1.046	1.062
District	1.010	1.012	1.008	1.010	1.026	1.038	1.039	1.051	1.164
Wave	1.010	1.023	1.021	1.028	1.056	1.087	1.087	1.089	1.093
log(Outdoor PM2.5 +1)	1.010	1.013	1.025	1.043	1.121	1.123	1.130	1.131	1.152
Occupation	1.010	1.012	1.025	1.025	1.076	1.034	1.036	1.038	1.045
Wealth	1.010	1.023	1.008	1.025	1.026	1.081	1.022	1.023	1.028
Education	1.010	1.013	1.021	1.010	1.028	1.031	1.088	1.049	1.059
Treatment Status	1.010	1.012	1.025	1.028	1.026	1.041	1.034	1.090	1.131

BC Model Using Partial Indoor PM2.5

VIF Values	Base + time at home	… + Gender	… + District	… + Wave	… + Outdoor PM2.5	… + Occupation	… + Wealth	… + Education	… + Treatment Status
log(Partial Indoor PM2.5 +1)	1.009	1.009	1.018	1.041	1.066	1.079	1.084	1.085	1.092
Time at Home	1.009	1.019	1.022	1.023	1.024	1.035	1.036	1.042	1.045
Gender	1.009	1.010	1.022	1.022	1.028	1.040	1.042	1.044	1.060
District	1.009	1.009	1.008	1.010	1.025	1.037	1.038	1.050	1.163
Wave	1.009	1.019	1.018	1.030	1.058	1.088	1.090	1.092	1.096
log(Outdoor PM2.5+1)	1.009	1.010	1.022	1.041	1.113	1.112	1.122	1.122	1.143
Occupation	1.009	1.009	1.022	1.023	1.066	1.034	1.036	1.038	1.045
Wealth	1.009	1.019	1.008	1.022	1.024	1.079	1.021	1.022	1.027
Education	1.009	1.010	1.018	1.010	1.028	1.035	1.084	1.049	1.058
Treatment Status	1.009	1.009	1.022	1.030	1.025	1.040	1.036	1.085	1.130

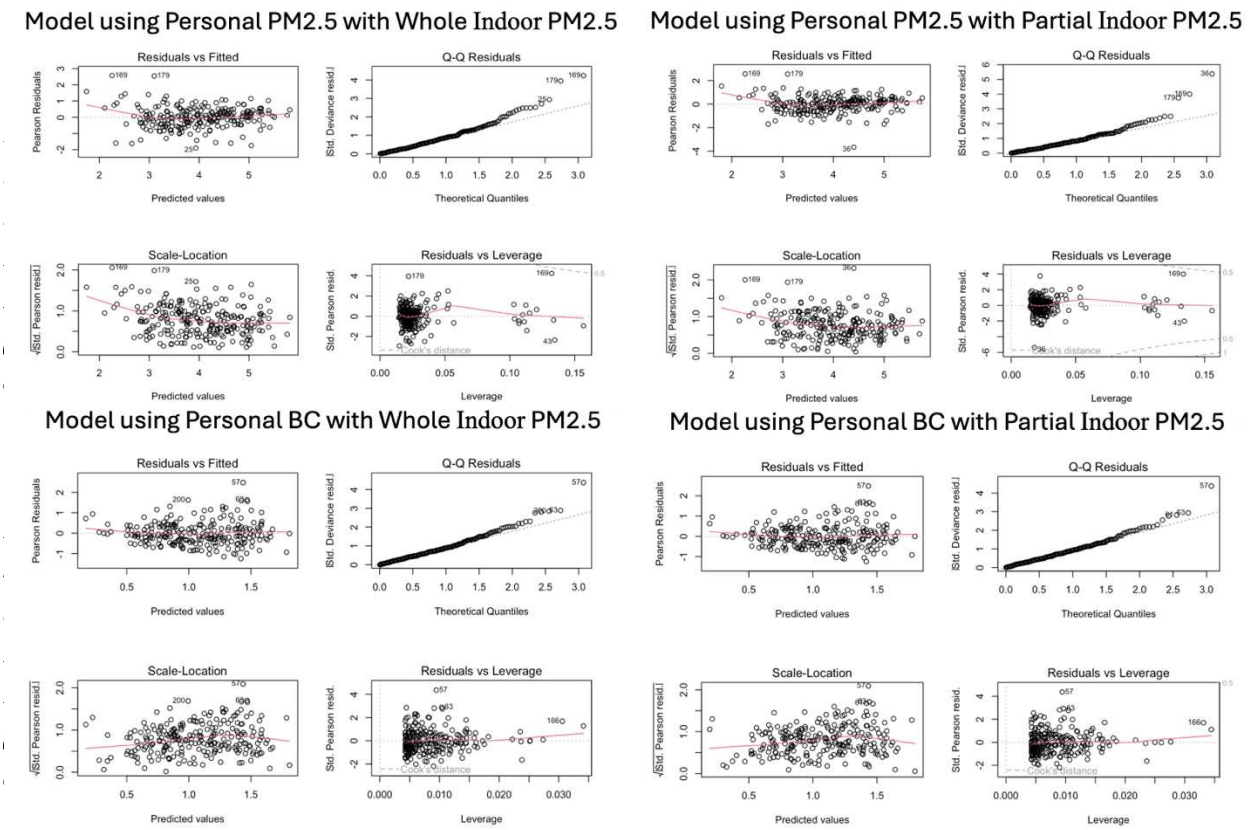

Figure S3. This figure presents diagnostic plots for the four top performing generalized linear models assessing the relationships between personal $PM_{2.5}$ and black carbon (BC) exposure with Whole and Partial Indoor $PM_{2.5}$ concentrations. Each model includes residual diagnostics to evaluate model fit and assumptions. The figure is divided into four sections: (1) Model using Personal $PM_{2.5}$ with Whole Indoor $PM_{2.5}$, (2) Model using Personal $PM_{2.5}$ with Partial Indoor $PM_{2.5}$, (3) Model using Personal BC with Whole Indoor $PM_{2.5}$, and (4) Model using Personal BC with Partial Indoor $PM_{2.5}$. Each section contains four diagnostic plots: Residuals vs. Fitted, which checks for non-linearity and variance homogeneity; Q-Q Residuals, which assesses normality of residuals; Scale-Location, which evaluates homoscedasticity; and Residuals vs. Leverage, which identifies influential points.

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Table S3. Results of ANOVA tests evaluating differences in personal $PM_{2.5}$ and black carbon (BC) levels across different categorical variables: occupation, district, and smoking status. The DF (Group, Residual) column indicates the degrees of freedom associated with between-group and within-group variability. Degrees of freedom (DF) in ANOVA are calculated as follows: subtracting 1 from the total number of groups (k - 1) for the Group DF (Between-Group DF) and subtracting the number of groups from the total number of observations (N - k) for the Residual DF (Within-Group DF). The F-Value represents the ratio of variance explained by the grouping variable to the variance within groups, indicating the extent to which group means differ from each other. The p-Value assesses statistical significance, with values less than 0.05 considered significant. Significant results are bolded and are marked with an asterisk (*), indicating meaningful differences in $PM_{2.5}$ or BC levels across the corresponding grouping variable. The Mean Squares (Group) column represents the variance attributed to the grouping variable and is calculated by dividing the sum of squares for the group by its degrees of freedom. This value provides insight into the magnitude of differences among groups.

ANOVA Results for Personal PM2.5 and BC Across Different Grouping Variables

Variable	Grouping Variable	DF (Group, Residual)	F-Value	p-Value	Mean Squares (Group)
PM2.5	Occupation	(3, 243)	1.333	0.264	11064.644
BC	Occupation	(3, 236)	0.180	0.910	3.515
PM2.5	District	(3, 248)	3.539	**0.015***	28250.116
BC	District	(3, 241)	5.116	**0.002***	92.371
PM2.5	Smoking	(2, 249)	15.294	**0.000***	112912.904
BC	Smoking	(2, 242)	1.171	0.312	22.185

Table S4. This table presents the results of t-tests evaluating differences in personal $PM_{2.5}$ and black carbon (BC) levels across different categorical variables: gender health, education health, and wave. The t-Statistic measures the difference between two group means relative to the variability within the data. The DF (Degrees of Freedom) column represents the number of independent values that can vary in the data. The p-Value assesses statistical significance, with values below 0.05 indicating a significant difference between groups. Significant results are bolded and are marked with an asterisk (*). The 95% Confidence Interval provides the range within which the true mean difference is expected to fall. The Mean Group 1 and Mean Group 2 columns display the average $PM_{2.5}$ or BC levels for each group compared in the t-test.

T-Tests Results for Personal PM2.5 and BC Across Different Grouping Variables

Variable	Grouping Variable	t-Statistic	DF	p-Value	95% CI	Mean Group 1	Mean Group 2
PM2.5	Gender Health	-1.541	250	0.125	-40.2, 4.9	77.644	95.279
BC	Gender Health	1.164	243	0.246	-0.5, 1.8	3.078	2.427
PM2.5	Education Health	0.516	250	0.606	-29.5, 50.4	86.535	76.078
BC	Education Health	0.488	243	0.626	-1.4, 2.4	2.828	2.352
PM2.5	Wave	2.452	250	**0.015***	5.5, 50.0	99.163	71.42
BC	Wave	1.483	243	0.140	-0.3, 1.9	3.185	2.362

Table S5. Model comparison for predicting personal $PM_{2.5}$ exposure using Whole Indoor $PM_{2.5}$ as a primary predictor. The table presents different model specifications with varying covariates, including time at home, gender, district, wave, outdoor $PM_{2.5}$, occupation, wealth, education, and treatment status. Covariates are added one at a time to assess their impact on model performance. Model performance is assessed using AIC, R^2, adjusted R^2, RMSE, and Spearman correlation. The lowest AIC value is indicated with an asterisk (*), representing the best-fitting model among those tested.

Personal PM2.5 Model Using **Whole** Indoor PM2.5

	Model	AIC	R2	Adj R2	RMSE	Spearman Correlation
1	*= Indoor PM2.5 Whole*	493.38	0.58	0.58	0.66	0.79
2	*= Indoor PM2.5 Whole + Time at Home*	494.27	0.58	0.58	0.66	0.79
3	*= Indoor PM2.5 Whole + Time at Home + Gender*	494.08	0.59	0.58	0.66	0.79
4	*= Indoor PM2.5 Whole + Time at Home + Gender + District*	489.06*	0.60	0.59	0.64	0.80
5	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave*	491.03	0.60	0.59	0.64	0.80
6	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole*	492.26	0.61	0.59	0.64	0.80
7	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation*	494.96	0.61	0.59	0.64	0.80
8	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth*	496.75	0.61	0.59	0.64	0.80
9	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education*	498.55	0.61	0.59	0.64	0.80
10	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education + Treatment Status*	498.56	0.62	0.59	0.63	0.80

Table S6. Model comparison for predicting personal $PM_{2.5}$ exposure using Partial Indoor $PM_{2.5}$ as a primary predictor. The table presents different model specifications with varying covariates, including time at home, gender, district, wave, outdoor $PM_{2.5}$, occupation, wealth, education, and treatment status. Covariates are added one at a time to assess their impact on model performance. Model performance is assessed using AIC, R^2, adjusted R^2, RMSE, and Spearman correlation. The lowest AIC value is indicated with an asterisk (*), representing the best-fitting model among those tested.

Personal PM2.5 Model Using **Partial** Indoor PM2.5

	Model	AIC	R2	Adj R2	RMSE	Spearman Correlation
1	*= Indoor PM2.5 Partial*	519.90	0.53	0.53	0.70	0.78
2	*= Indoor PM2.5 Partial + Time at Home*	520.45	0.53	0.53	0.70	0.77
3	*= Indoor PM2.5 Partial + Time at Home + Gender*	519.50	0.54	0.53	0.69	0.78
4	*= Indoor PM2.5 Partial + Time at Home + Gender + District*	515.16*	0.56	0.55	0.68	0.78
5	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave*	517.07	0.56	0.55	0.68	0.78
6	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole*	519.06	0.56	0.54	0.68	0.78
7	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation*	519.82	0.57	0.55	0.67	0.78
8	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth*	521.76	0.57	0.55	0.67	0.78
9	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education*	523.33	0.57	0.54	0.67	0.78
10	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education + Treatment Status*	525.47	0.58	0.55	0.67	0.79

Table S7. Model comparison for predicting personal black carbon (BC) exposure using Whole Indoor $PM_{2.5}$ as a primary predictor. The table presents different model specifications with varying covariates, including time at home, gender, district, wave, outdoor $PM_{2.5}$, occupation, wealth, education, and treatment status. Covariates are added one at a time to assess their impact on model performance. Model performance is assessed using AIC, R^2, adjusted R^2, RMSE, and Spearman correlation. The lowest AIC value is indicated with an asterisk (*), representing the best-fitting model among those tested.

Personal BC Model Using **Whole** Indoor PM2.5

	Model	AIC	R2	Adj R2	RMSE	Spearman Correlation
1	*= Indoor PM2.5 Whole*	408.12*	0.26	0.26	0.57	0.54
2	*= Indoor PM2.5 Whole + Time at Home*	410.08	0.26	0.25	0.57	0.54
3	*= Indoor PM2.5 Whole + Time at Home + Gender*	411.11	0.26	0.25	0.57	0.54
4	*= Indoor PM2.5 Whole + Time at Home + Gender + District*	410.14	0.28	0.27	0.56	0.54
5	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave*	412.12	0.28	0.26	0.56	0.54
6	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole*	414.06	0.28	0.26	0.56	0.54
7	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation*	418.13	0.29	0.26	0.56	0.55
8	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth*	417.97	0.3	0.26	0.55	0.55
9	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education*	418.42	0.3	0.26	0.55	0.56
10	*= Indoor PM2.5 Whole + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education + Treatment Status*	419.61	0.32	0.27	0.55	0.57

Table S8. Model comparison for predicting personal black carbon (BC) exposure using Partial Indoor $PM_{2.5}$ as a primary predictor. The table presents different model specifications with varying covariates, including time at home, gender, district, wave, outdoor $PM_{2.5}$, occupation, wealth, education, and treatment status. Covariates are added one at a time to assess their impact on model performance. Model performance is assessed using AIC, R^2, adjusted R^2, RMSE, and Spearman correlation. The lowest AIC value is indicated with an asterisk (*), representing the best-fitting model among those tested.

Personal BC Model Using **Partial** Indoor PM2.5

	Model	AIC	R2	Adj R2	RMSE	Spearman Correlation
1	*= Indoor PM2.5 Partial*	407.59*	0.25	0.25	0.57	0.52
2	*= Indoor PM2.5 Partial + Time at Home*	408.94	0.26	0.26	0.57	0.54
3	*= Indoor PM2.5 Partial + Time at Home + Gender*	410.22	0.27	0.26	0.57	0.54
4	*= Indoor PM2.5 Partial + Time at Home + Gender + District*	408.90	0.29	0.27	0.56	0.54
5	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave*	410.90	0.29	0.27	0.56	0.54
6	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole*	412.66	0.29	0.26	0.56	0.54
7	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation*	415.56	0.30	0.26	0.55	0.55
8	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth*	415.51	0.30	0.27	0.55	0.56
9	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education*	415.68	0.31	0.27	0.55	0.56
10	*= Indoor PM2.5 Partial + Time at Home + Gender + District + Wave + Outdoor PM2.5 Whole + Occupation + Wealth + Education + Treatment Status*	416.73	0.32	0.27	0.54	0.57

Table S9. Summary of stepwise regression model performance for personal $PM_{2.5}$ and black carbon (BC). The table presents the model specifications, including identified variables and key performance metrics: Akaike Information Criterion (AIC), R-squared (R^2) adjusted R-squared (Adj R^2), root mean square error (RMSE). Two models are presented for each dependent variable/pollutant, one using Whole Indoor $PM_{2.5}$ and the other using Partial Indoor $PM_{2.5}$. The equations describe the variables included in each model that was identified by the stepwise process for the four base models.

#	Type	Model	AIC	R2	Adj R2	RMSE
1	PM2.5	$ln(Personal\ PM2.5) = \beta0 + \beta1(ln[Whole\ Indoor\ PM2.5]) + \beta2(District) + \beta3(Treatment\ Status) + \varepsilon$	487.18	0.61	0.60	0.64
2	PM2.5	$ln(Personal\ PM2.5) = \beta0 + \beta1(ln[Partial\ Indoor\ PM2.5]) + \beta2(District) + \beta3(Gender) + \varepsilon$	514.24	0.56	0.55	0.68
3	BC	$ln(Personal\ BC+1) = \beta0 + \beta1(ln[Indoor\ PM2.5\ Whole+1]) + \beta2(Treatment\ Status) + \beta3(Wealth) + \beta4(Outdoor\ PM2.5) + \varepsilon$	405.08	0.30	0.28	0.55
4	BC	$ln(Personal\ BC+1) = \beta0 + \beta1(ln[Indoor\ PM2.5\ Whole+1]) + \beta2(Treatment\ Status) + \beta3(Outdoor\ PM2.5) + \beta4(Wealth) + \varepsilon$	403.04	0.31	0.29	0.55