

Article

Concentration-Dose Decoupling and Nonlinear Health Risks of Dynamic PM_{2.5} Inhaled Doses in Public Transit Microenvironments

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Abstract

Fine particulate matter (PM_{2.5}) exposure in public transport microenvironments has important implications for commuter health, yet concentration-based assessments may not adequately reflect the dose actually inhaled by passengers. This study quantified dynamic PM_{2.5} inhaled doses in Taiyuan, China, using 1 Hz portable monitoring and matched travel surveys across 19 bus and metro routes during summer and winter 2025. After data screening, 1103 valid commuter samples were retained. We combined dose estimation with DML, XGBoost-SHAP, SEM, and Random Forest analysis to examine adjusted associations, explore potential nonlinear patterns, and characterize behavioral responses. Trip-averaged PM_{2.5} concentrations exceeded the WHO 24 h guideline on most monitored routes when interpreted as a health-based reference benchmark for short commuting exposures rather than as a direct regulatory exceedance metric. More importantly, a clear concentration-dose decoupling pattern was observed: 6.6% of trips fell into a low-concentration but high-dose category, indicating that prolonged in-vehicle exposure could substantially elevate inhaled dose even when PM_{2.5} concentrations remained below the sample median. The mean inhaled dose in the longer observed-duration group (top 20% by observed in-vehicle duration) reached 612.26 ± 412.21 µg, which was 7.2 times that of the remaining trips (84.87 ± 115.71 µg). DML results showed that inhaled dose, rather than PM_{2.5} concentration alone, was significantly associated with psychological distress. SHAP analysis suggested an exploratory threshold-like pattern at approximately 300 µg per trip, above which health-risk attribution increased rapidly. SEM results indicated that inhaled dose was associated with higher self-reported somatic burden, whereas PM_{2.5} concentration mainly influenced health indirectly through risk perception. These findings suggest that public transport exposure assessment should move beyond static concentration metrics and incorporate dynamic inhaled dose to better identify high-risk commuting scenarios and support more targeted health-oriented transit management.



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1. Introduction

Fine particulate matter (PM_{2.5}) is a major urban health stressor because it can remain suspended for long periods, carry multiple toxic constituents, penetrate deep into the respiratory tract, and eventually enter systemic circulation. Its adverse effects on respiratory,

cardiovascular, and metabolic health are well established [1,2]. Yet the translation from ambient concentration to actual health burden is not one-to-one. At the individual level, risk is shaped by dynamic exposure profiles involving concentration, duration, activity pattern, and ventilation rate rather than by static pollution levels alone. Although commuting occupies only a limited share of the day, it frequently occurs in high-emission transport microenvironments and can therefore contribute disproportionately to daily exposure.

Public transport is essential for low-carbon mobility, but its environmental benefits do not automatically translate into exposure safety. Studies consistently show substantial PM_{2.5} differences across commuting modes and across routes, seasons, crowding conditions, ventilation settings, and surrounding traffic environments [2–4]. Transit microenvironments should therefore be understood as dynamic exposure settings produced by the interaction of transport operations, cabin conditions, and local emissions rather than as simple reflections of background air quality. This is also why fixed-site monitoring, while valuable for city-scale assessment, remains an imperfect proxy for the exposure actually experienced by commuters in transit [1,5].

Recent advances in portable monitoring have improved the temporal resolution of transport exposure research and have gradually shifted the field from static concentration description to dynamic exposure observation [5,6]. Low-cost sensors have further made real-time measurement and trip-level inhaled-dose estimation increasingly feasible in public transport settings [7]. Even so, much of the literature still focuses on questions such as which mode or route has higher concentrations, while giving less attention to how short-term pollution variability is translated into individual-level health burden [2].

From the standpoint of risk identification, this limitation is closely related to the underuse of inhaled dose. Ambient concentration describes external pollution conditions, but inhaled dose is more directly linked to the mass of particles that actually enters the body. As emphasized in systematic reviews, inhaled dose depends on the joint action of ambient concentration, exposure duration, and pulmonary ventilation rate [8]. In transit microenvironments, a trip with only moderate concentrations can still produce a high dose when the travel time is long or breathing intensity is elevated. Put differently, concentration and dose do not always vary synchronously in commuting contexts [3,9]. This concentration-dose decoupling is especially important for environmental inequality because repeated trips and unequal commute durations can redistribute exposure burdens toward long-distance commuters [10].

The global response to transport-related PM_{2.5} exposure highlights a universal need to shift toward dose-oriented assessments, albeit with regional specificities. In high-income regions, while strict emission standards and low-emission zones have reduced ambient concentrations [11,12], the ‘internalized’ exposure within enclosed microenvironments—such as underground metros—remains a critical yet under-addressed challenge [1,5,9,13]. Conversely, in developing regions characterized by informal paratransit systems, high personal exposure makes real-time dose characterization a vital necessity [14–17]. These contrasting contexts indicate that regardless of the development stage, concentration-based metrics alone are insufficient; assessing actual exposure requires understanding microenvironment-specific doses. Chinese resource-based and old-industrial cities like Taiyuan occupy an intermediate but pivotal position. They combine the challenges of rapidly expanding transit systems with persistent background pollution, long cross-district commuting, and heterogeneous cabin ventilation dynamics. This unique setting underscores the urgency of examining concentration-dose decoupling [10] and microenvironment-specific exposure burdens in transitioning urban contexts.

Another limitation of the current literature concerns mechanism identification. Because exposure processes in transit settings are highly dynamic, analyses based only on

mean comparison, simple correlation, or conventional linear models remain limited in their ability to detect threshold behavior, nonlinear marginal effects, and multi-factor interactions [2,4]. At the same time, exposure, somatic discomfort, risk perception, and protective behavior are often examined separately rather than as linked parts of a single explanatory chain. However, air pollution acts not only as an objective physical stressor but also as an environmental cue through which passengers interpret air quality, crowding, and travel comfort. Previous studies show that objective exposure and subjective appraisal do not always align, yet this gap can substantially shape coping behavior and support for environmental intervention [16,17]. Accordingly, PM_{2.5} risk in public transport is better understood as a multifactor process involving dose accumulation, physiological burden, psychological perception, and behavioral response [18–21].

These unresolved issues are especially relevant in China. Existing transport microenvironment studies have concentrated mainly on large metropolitan areas, while evidence from resource-based and old-industrial cities remains relatively limited. This matters because such cities often combine elevated background pollution with long cross-district commuting and heterogeneous transit conditions. Taiyuan is a representative case: as a resource-based old industrial city, it exhibits persistent particulate pollution characteristics, and prior local research has already linked particulate exposure and co-pollutants to inhalation burden and health risk [22]. Within this context, public transit commuting offers a particularly suitable setting for exposure research because it captures both surface and underground microenvironments. Surface buses are especially dynamic because, compared with relatively stable rail systems, they are more strongly affected by congestion, frequent door opening, changing passenger density, and variable cabin ventilation [2,4,5]. Metro routes were retained in the sample as a complementary contrast rather than excluded from the analysis.

To address these gaps, this study examines Taiyuan's public transit system by combining portable AirBeam monitoring with travel surveys to estimate high-frequency dynamic PM_{2.5} inhaled doses during daily commutes. Rather than treating static ambient concentration as the main risk metric, we focus on inhaled mass and thereby shift the unit of analysis from external concentration to internal exposure burden. Methodologically, we integrate Double Machine Learning (DML), XGBoost-SHAP, Structural Equation Modeling (SEM), and Random Forest models to isolate net effects, identify nonlinear thresholds, trace the pathways linking dose accumulation to physiological burden, psychological distress, and risk perception, and compare the predictor structures of immediate protective behavior and longer-term intervention preferences.

The knowledge gap addressed by this study is not the measurement of PM_{2.5} concentration alone, but the insufficient understanding of how concentration, observed exposure duration, and passenger-specific inhalation rate jointly translate into trip-level inhaled dose in public-transit microenvironments. Existing studies have often examined concentration differences across modes, routes, or cities, whereas fewer studies have linked concentration-dose decoupling with short-term self-reported somatic stress, risk perception, and behavioral response within one field-based framework. Accordingly, this study contributes in three ways. First, it clarifies the concentration-dose decoupling phenomenon in transit microenvironments by centering dynamic inhaled dose rather than static concentration. Second, it explores potential nonlinear dose-related patterns and heterogeneous responses using interpretable machine-learning methods, while treating these results as exploratory rather than confirmatory. Third, it builds a complementary analytical framework linking objective exposure, subjective perception, and behavioral response through related but distinct modeling modules. Compared with our previous work on inhaled-dose risks during daily activities in Guangzhou [23], the present study narrows the focus to public-transit microenvironments in Taiyuan and extends the analysis from dose estimation

alone to concentration-dose decoupling, perception-mediated pathways, and passenger behavioral adaptation.

2. Materials and Methods

2.1. Study Area and Field Campaign

The study was conducted in Taiyuan, a representative resource-based old industrial city in northern China. To capture variation in $PM_{2.5}$ across public transit microenvironments, we monitored 19 bus and metro routes selected to represent major urban functional settings. These routes covered dense commercial districts, residential corridors, suburban commuting lines, and underground rail segments, allowing the sample to reflect differences in traffic intensity, passenger density, and ventilation conditions.

Most surveyed routes passed through busy transport corridors and station areas and can therefore be characterized as moderate-to-heavy traffic transit settings with frequent stop-and-go operation during routine commuting periods. Although source apportionment was beyond the scope of this study, commuters were likely exposed to a mixture of traffic exhaust, resuspended road dust, nearby construction emissions, and seasonal combustion sources. For metro trips, additional particulate inputs may arise from outdoor infiltration at station entrances and from mechanically generated particles within the rail system.

Real-time $PM_{2.5}$ was measured with AirBeam portable monitors (HabitatMap, 34A St Marks Avenue, Brooklyn, NY 11217, USA), which record mass concentrations at 1 s intervals using light-scattering detection. During fieldwork, the devices were carried by investigators and operated in a standardized manner inside the vehicle, with the inlet held close to the passenger breathing zone (nose-mouth height) to improve comparability across trips. Before deployment, all sensors were colocated for 24 h with reference instruments at local national monitoring stations. Device clocks were synchronized before each survey day and cross-checked against the questionnaire time records to support the subsequent time-anchor matching procedure. After calibration and error correction, the sensors achieved $R^2 > 0.90$, indicating acceptable performance under dynamic transit conditions.

A structured questionnaire was administered in parallel with environmental monitoring to collect the information needed for dose estimation and behavioral analysis. The survey recorded demographic characteristics, travel behavior, in-vehicle posture, boarding time, interview completion time, and mask use. These variables were later used to define the observed exposure window, assign inhalation rates, and identify protective responses.

2.2. Sampling Design and Data Collection Procedures

Field surveys were conducted under the theme “Low-carbon Travel and Resident Health” during summer (16–18 June 2025) and winter (29–30 December 2025) across Taiyuan’s municipal districts. The two survey periods were selected to represent two short-term field campaigns under contrasting summer and winter meteorological and operational conditions. Because each campaign covered only a limited number of days, the comparison should be interpreted as a campaign-period comparison rather than as a full characterization of seasonal variability (Figure 1).

Because public transit passengers move through dynamic “flow spaces” that do not have a fixed sampling frame, we adopted a multi-stage spatiotemporal stratified design combined with systematic interception. Routes were first stratified by urban function to ensure spatial coverage, then surveys were distributed across the surveyed weekdays and across peak and off-peak periods to capture temporal variation in crowding and ventilation. Within vehicles and stations, respondents were approached at fixed intervals or in boarding order to reduce interviewer selection bias.

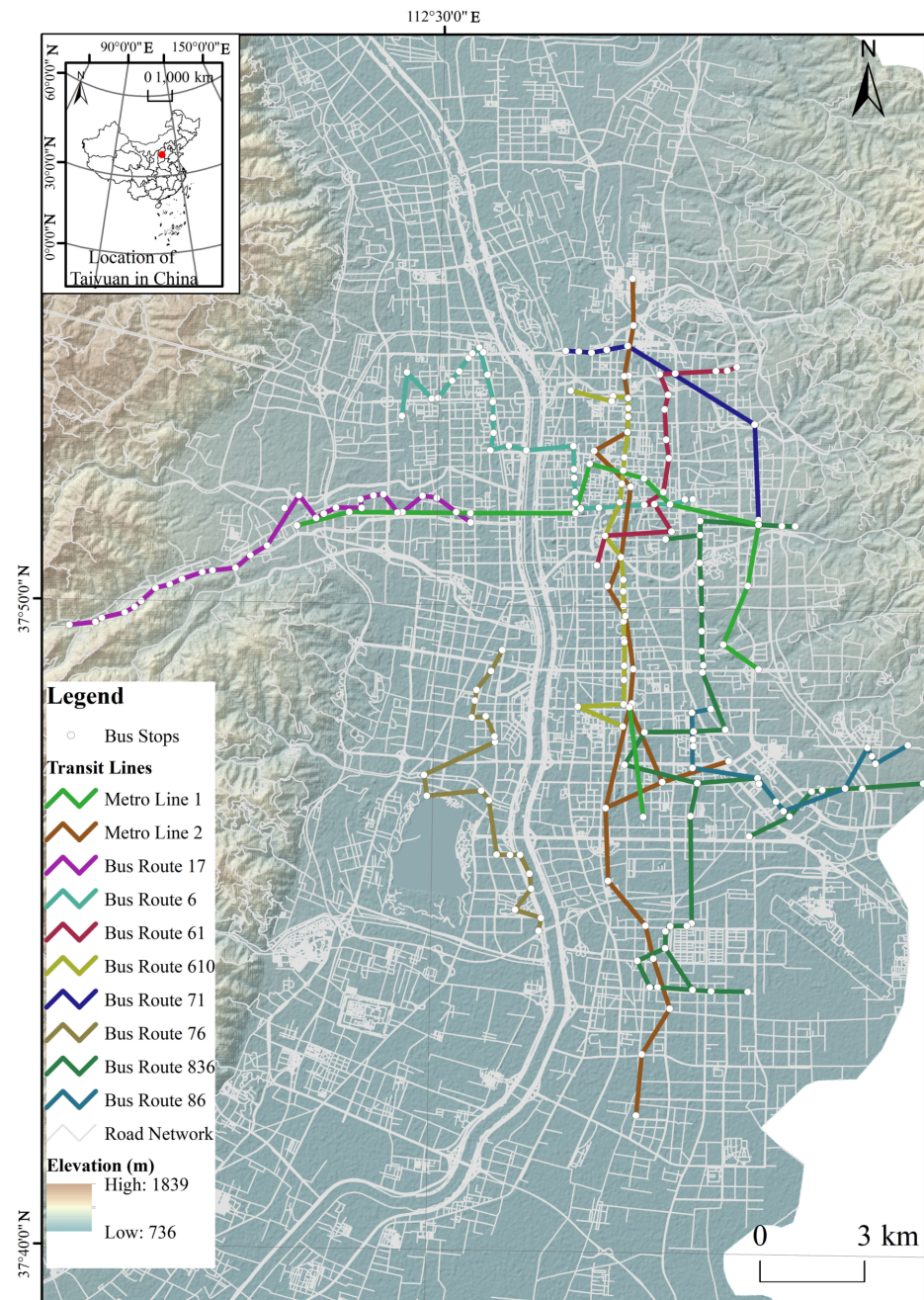


Figure 1. Spatial distribution of surveyed transit lines and stop-level measurement locations in Taiwan, China.

Route selection followed three principles. First, high-mobility corridors such as Route 610 were included to capture intense urban travel. Second, arterial lines linking residential, industrial, and educational areas were used to represent diverse commuter groups. Third, routes spanning the urban–suburban gradient, such as Route 17, were included to reflect differences between short inner-city trips and longer peripheral commutes.

The questionnaire covered five domains: socio-demographic characteristics, commuting behavior, perceived microenvironmental conditions (including noise, odor, and crowding), protective behavior, and self-rated physical and psychological health. To improve response quality, trained investigators conducted standardized face-to-face interviews rather than self-administered surveys. This rigorous face-to-face administration ensured that questions were clearly understood, thereby substantially increasing the accuracy and reliability of the individual survey data. In total, 1200 questionnaires were completed.

During data cleaning, we applied a minimum exposure criterion to retain trips with meaningful in-vehicle exposure. Journeys lasting fewer than three stops were excluded because such trips were unlikely to generate sufficient exposure for reliable assessment. After consistency checks and removal of questionnaires with logical contradictions or missing core variables, 1103 valid observations remained, including 500 summer trips and 603 winter trips, corresponding to an effective response rate of 91.9%. A pilot survey conducted before the main study indicated good instrument quality, with Cronbach's alpha = 0.89 and exploratory factor analysis explaining 73% of total variance (Table 1). For descriptive subgroup comparison, the longer observed-duration group was defined as trips in the top 20% of the observed in-vehicle duration distribution.

Table 1. Descriptive statistics and analytical purposes of core variables.

Variable Category and Name	Descriptive Statistics	Analytical Purpose
I. Individual Demographic Variables		
Gender	Male 489 (44.33%) Female 614 (55.67%)	Basic demographic control variable
Age (years)	38.64 ± 13.58	Used to identify the age distribution of susceptible populations
Education	Below College /Bachelor's 494 (44.79%) College/Bachelor's 478 (43.34%) Above Bachelor's 131 (11.88%)	Proxy variable for environmental justice and cognitive level
Annual Income	2.58 ± 1.62	Economic indicator measuring the individual's capacity to bear commuting costs
Respiratory History	With history 44 (3.99%) Without history 1059 (96.01%)	Used to identify sensitive groups with pre-existing health risks
II. Commuting Characteristics		
Observed in-vehicle duration	14.47 ± 7.72	Core weighting factor for calculating the inhaled dose
Transit Frequency	2.81 ± 1.18	Measures the long-term cumulative exposure frequency
In-cabin Posture	Sitting/Seated 989 (89.66%) Standing/Unseated 114 (10.34%)	Key behavioral variable determining the ventilation rate
III. Objective Exposure Variables		
Average PM _{2.5} Concentration (PM _{2.5} _Avg, µg/m ³)	23.59 ± 11.88	Static baseline illustrating the in-cabin pollution exposure level
Inhaled Dose (Inhaled_Dose, µg)	337.24 ± 951.23	Core innovative indicator and key outcome variable
Temperature (°C)	32.00 ± 8.78	Covariate of micro-environmental exposure conditions
Humidity (%)	76.60 ± 14.39	Covariate of micro-environmental exposure conditions
IV. Subjective Perception and Behavioral Indicators		
Air Quality Rating	4.14 ± 0.89	Direct measurement of subjective air quality perception
Somatic Discomfort	4.06 ± 1.06	Self-rated indicator of physiological burden, a core variable in SEM
Commuting Anxiety	4.22 ± 1.03	Transmissive indicator representing the psychological perception phase
Protective Intention	3.12 ± 1.57	Final outcome variable in the behavioral response stage

Note: Values are descriptive statistics based on the cleaned sample of 1103 valid observations. Categorical variables are presented as *n* (%), and continuous variables are presented as mean ± standard deviation. PM_{2.5} concentration, temperature, and humidity were obtained from portable monitoring; inhaled dose was calculated from matched monitoring and questionnaire data.

Table 1 summarizes the descriptive statistics of the cleaned analytical sample. The table does not report model-estimation results; rather, it provides the statistical profile of the variables used in the subsequent exposure, dose, health-risk, and behavioral analyses. Demographic, commuting, perception, health, and behavioral variables were obtained from the standardized questionnaire. Objective PM_{2.5} concentration, temperature, and humidity were obtained from portable monitoring records. Observed in-vehicle duration was calculated from the recorded boarding and interview-completion times, and inhaled dose was derived by combining trip-specific PM_{2.5} concentration, observed duration, and assigned inhalation rate. Categorical variables are reported as frequencies and percentages, whereas continuous variables are reported as mean $\pm$ standard deviation. To improve transparency and reproducibility, an English version of the questionnaire used in the field survey is provided as a Supplementary Supporting File (Supplementary File S1).

2.3. Data Integration and Inhaled Dose Estimation

Continuous PM_{2.5} measurements were linked to individual trips using a time-anchored matching procedure. Before matching, the monitor timestamps and questionnaire records were synchronized to the same survey-time reference. This stringent time-anchoring procedure effectively grounded the subjective questionnaire records to objective 1 Hz environmental measurements, minimizing temporal recall errors and ensuring precise alignment between actual exposure and self-reported conditions. The start of each observation window was defined by the recorded boarding time, and the end of the analyzed in-vehicle interval was defined by the on-board interview completion time. The 1 s concentration series within this passenger-specific window was extracted and summarized for dose estimation. Short interruptions caused by temporary device disconnection were filled by linear interpolation when the gap exceeded 5 s. Observations with more than 15% missing data within the matched window were removed to maintain data quality.

For each matched trip, the trip-specific mean PM_{2.5} concentration (C) was calculated from the retained 1 s records, and inhaled dose was then estimated using a standard exposure framework that combines concentration, exposure duration, and inhalation rate. This formulation shifts the analysis from external concentration alone to the amount of particulate matter that actually enters the body during the observed commuting interval.

$$D_{in} = C \times IR \times T$$

where D_{in} represents the inhaled PM_{2.5} dose during the observed commuting interval (μg); C is the trip-specific mean PM_{2.5} concentration within the matched 1 s time window ($\mu\text{g}/\text{m}^3$); IR is the assigned inhalation rate (m^3/min); and T is the observed in-vehicle duration (min).

Exposure duration (T) was calculated from the recorded timestamps and was defined as the interval between boarding and interview completion. Because the questionnaire was administered on board, T represents the observed in-vehicle portion of the trip captured in this study rather than the passenger's full origin-destination journey.

$$T = T_{\text{end}} - T_{\text{board}}$$

Accordingly, T was computed as $T = T_{\text{end}} - T_{\text{board}}$, where T_{board} denotes the recorded boarding time and T_{end} denotes the interview completion time. The same passenger-specific interval was used both to extract the 1 s PM_{2.5} series and to estimate inhaled dose, ensuring temporal consistency between monitoring and questionnaire data.

The inhalation rate (IR) was assigned using values from the U.S. EPA Exposure Factors Handbook and adjusted to match the activity conditions observed during transit. Because

inhalation rate varies with sex and physical activity, these two characteristics were used to parameterize the dose model [24].

In the questionnaire, seated passengers were treated as engaging in sedentary activity, whereas standing passengers were classified as light activity because maintaining balance requires continuous low-intensity muscular effort. The corresponding inhalation-rate values are listed in Table 2.

Table 2. Assigned values for inhalation rate (IR) across diverse passenger characteristics (m³/min).

Gender	Communing Posture	Activity Intensity Classification	IR
Male	Seated	Sedentary	0.0075
	Standing	Light activity	0.0140
Female	Seated	Sedentary	0.0065
	Standing	Light activity	0.0110

For descriptive comparison, subgroup analyses by sex, posture, and observed in-vehicle duration were conducted using the cleaned sample, with the longer observed-duration group defined as the upper 20% of the observed in-vehicle duration distribution.

2.4. Construction of Subjective Health-Risk Indicators

To maintain consistency across the descriptive analysis, adjusted association analysis, interpretable machine learning, and SEM components, transit-related health-related stress was operationalized with questionnaire-based indicators covering somatic burden, mental distress, and risk perception. All health-related items were measured on a five-point Likert scale. Items originally coded so that higher values indicated better conditions or lower discomfort were reverse-coded, so that higher scores consistently represented greater discomfort, distress, or perceived risk.

Somatic burden was measured with two symptom items reported during the trip: physical discomfort (such as dizziness, headache, chest tightness, or nausea) and drowsiness or fatigue. Mental distress was measured with a separate item asking whether the respondent experienced depressive, suppressed, irritable, or emotionally dysphoric feelings during the journey. Risk perception was captured by one general appraisal item on whether air pollution increases personal health risk and by four in-cabin cue-based items covering haze visibility, abnormal odor, perceived cabin air quality, and concern about cabin air quality.

To improve reproducibility, all item scores were directionally harmonized before aggregation. Somatic_Burden was calculated as the mean of the reverse-coded physical discomfort and drowsiness/fatigue items, Mental_Distress was represented by the reverse-coded emotional item, and Risk_Perception was calculated as the mean of the five perception-related items after directional alignment. The three first-order questionnaire-based dimensions were then defined as follows:

$$\text{Somatic_Burden}_i = \frac{(6 - \text{AD}_i) + (6 - \text{AE}_i)}{2}$$

$$\text{Mental_Distress}_i = 6 - \text{AF}_i$$

$$\text{Risk perception}_i = \frac{\text{AP}_i + (6 - \text{AU}_i) + (6 - \text{AV}_i) + (6 - \text{AW}_i) + (6 - \text{AX}_i)}{5}$$

Here, AD and AE denote self-reported physical discomfort and drowsiness or fatigue, respectively; AF denotes negative emotional states during commuting; AP denotes perceived personal health risk from air pollution; and AU, AV, AW, and AX denote perceived

haze visibility, abnormal odor, perceived cabin air quality, and concern about cabin air quality, respectively.

The Health_Risk_Index was used as an exploratory questionnaire-based indicator rather than as a clinically validated disease-risk scale. Equal weighting was adopted to avoid imposing unverified clinical weights on heterogeneous self-reported symptoms and perceptions. To examine whether the results depended on this aggregation rule, sensitivity analyses were conducted using item-equal, PCA-based, and symptom-only indices. Based on these three first-order dimensions, the overall Health_Risk_Index was constructed as the arithmetic mean of Somatic_Burden, Mental_Distress, and Risk_Perception:

$$\text{Health_Risk_Index}_i = \frac{\text{Somatic_Burden}_i + \text{Mental_Distress}_i + \text{Risk_Perception}_i}{3}$$

Equal weighting was used as a transparent baseline aggregation strategy because no externally validated weighting scheme is available for combining somatic burden, mental distress, and risk perception in the present public-transit microenvironment context. Therefore, the Health_Risk_Index should be interpreted as an exploratory questionnaire-based indicator rather than as a clinically validated disease-risk scale. To assess whether the findings depended on this equal-weighting rule, we conducted sensitivity analyses using three alternative aggregation schemes: an item-equal index based on all eight harmonized questionnaire items, a PCA-based index using the first principal component of the eight items, and a symptom-only index excluding risk perception. These alternative indicators were compared with the baseline equal-dimension Health_Risk_Index in terms of rank correlation, dose-related association, and XGBoost-SHAP feature ranking.

All indices ranged from 1 to 5, with higher values indicating greater integrated health stress during the commute. This design kept the health-risk outcome conceptually distinct from objective exposure variables such as PM_{2.5} concentration, inhaled dose, temperature, humidity, and noise, which were treated as explanatory factors rather than being mechanically embedded in the dependent variable.

For DML, Somatic_Burden and Mental_Distress were modeled separately as outcome variables. For the XGBoost-SHAP analysis, the composite Health_Risk_Index was used as the dependent variable to identify the multidimensional drivers of transit-related health risk. For the SEM, the item-level indicators were retained in the measurement layer: the two symptom items represented self-reported somatic burden, the psychological distress item was modeled as a single-indicator mental-health construct, and the five perception-related items represented the risk-perception dimension. This design ensured consistency across the descriptive statistics, the prediction task, and the mechanism analysis.

The health-related questionnaire items were designed to capture short-term self-reported somatic discomfort, fatigue, emotional distress, and risk perception during the observed trip. These variables should not be interpreted as clinical physiological outcomes or as health conditions caused exclusively by PM_{2.5} exposure during public transport. Rather, they represent acute subjective health-related stress reported within the monitored in-vehicle microenvironment.

2.5. Machine Learning and Statistical Framework

2.5.1. Double Machine Learning for De-Biased Net-Effect Estimation

To estimate the de-biased net effects of key exposure metrics on short-term health-related outcomes while reducing confounding bias, we used a Double Machine Learning (DML)-style residualization framework. Separate models were estimated for Somatic_Burden and Mental_Distress, with trip-level PM_{2.5} concentration and inhaled dose entered as focal treatments in separate specifications. The control set comprised the ob-

served demographic, travel-behavior, and microenvironment covariates summarized in Table 1, excluding the focal treatment variable in the corresponding model.

Following the standard residualization strategy, Random Forest nuisance models were first fitted for both the outcome and the treatment. Let Y_i denote one of the health outcomes, T_i denote the focal treatment variable, and X_i denote the observed covariate vector. In this study, the DML procedure was implemented as a machine-learning-assisted residualization strategy on the analytical sample, with the same observed covariate vector entered into both first-stage models.

The resulting DML coefficients are therefore interpreted as de-biased net effects conditional on the observed covariates, rather than as definitive causal effects under all possible unmeasured sources of confounding.

$$\begin{aligned} Y_i &= g(X_i) + \zeta_i \\ T_i &= m(X_i) + v_i \end{aligned}$$

In the second stage, residuals were computed for both the outcome and treatment variables by subtracting the fitted values from the observed values.

$$\tilde{Y}_i = Y_i - \hat{g}(X_i) \text{ and } \tilde{T}_i = T_i - \hat{m}(X_i)$$

In the final stage, the residualized outcome was regressed on the residualized treatment to obtain the de-biased net-effect estimate.

$$\tilde{Y}_i = \theta \tilde{T}_i + \varepsilon_i$$

where β represents the de-biased net-effect coefficient; Y_i and T_i denote the residualized components of the outcome variable Y_i and the treatment variable T_i , respectively. Both $\hat{g}(X_i)$ and $\hat{m}(X_i)$ are non-linear nuisance functions estimated in the first stage, and ε_i is the stochastic error term. Because the data are cross-sectional and observational, β is interpreted as an adjusted net association after residualization rather than as an experimental average treatment effect.

2.5.2. XGBoost-SHAP Exploratory Analysis

To explore potential nonlinear relationships and feature interactions, we used eXtreme Gradient Boosting (XGBoost 3.1.0) as a supplementary explanatory model for the Health_Risk_Index. The modeling feature set contained 10 variables: temperature, age, humidity, PM_{2.5} concentration, inhaled dose, trip duration, noise, posture, medical history, and gender. Duration was mildly trimmed at the extreme tails to reduce timestamp artifacts, and missing predictor values were median-imputed before model fitting. The cleaned dataset was randomly split into 80% training and 20% testing subsets using `random_state = 42`.

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f(x) \in \mathcal{F}$$

where $\mathcal{F}$ denotes the space of all possible regression trees, and $f_k(x_i)$ represents the prediction of the k -th tree for passenger observation i . To mitigate overfitting within complex transit micro-environments, XGBoost incorporates a regularization penalty into its objective function:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f(x) \in \mathcal{F}$$

In the implementation used for this study, the XGBoost regressor was specified with objective = reg: squarederror, n_estimators = 420, max_depth = 3, learning_rate = 0.035, subsample = 0.85, colsample_bytree = 0.85, min_child_weight = 3, reg_alpha = 0.15, reg_lambda = 1.2, and random_state = 42. Predictive performance was checked on the held-out test set ($R^2 = 0.183$, RMSE = 0.607), after which the model was refit on the full cleaned dataset for final SHAP interpretation.

SHAP analysis was used for two complementary purposes. At the global level, mean absolute SHAP values were used to rank the relative importance of predictors. At the individual level, SHAP dependence patterns were examined to identify how inhaled dose and its interaction with other features changed the predicted level of health risk across different exposure conditions.

Global Importance and Interactions: Features are ranked using SHAP summary plots based on their mean absolute SHAP values to identify key drivers and interaction effects. For a feature subset $S \subseteq F$ (where F is the complete feature set), the SHAP value ϕ_j represents the marginal contribution of feature j to the change in model expectation, calculated as follows:

$$\phi_j(x) = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [v(S \cup \{j\}) - v(S)]$$

In this formulation, $|F|$ denotes the total number of input features, and $|S|$ represents the cardinality of a feature subset excluding the target feature j . The function $v(S)$ signifies the expected model prediction for the health risk index when conditioned only on the features within subset S . The difference $v(S \cup \{j\}) - v(S)$ quantifies the marginal contribution of feature j to the predicted health risk index. The weighting coefficient, $\frac{|S|!(|F|-|S|-1)!}{|F|!}$, accounts for all possible permutations of feature combinations, thereby ensuring the mathematical uniqueness and fairness of the attribution.

In this way, the nonlinear predictions from XGBoost can be decomposed into an overall baseline and the contribution of each feature for a given observation, making it possible to identify both dominant risk factors and potential threshold effects.

$$g(x) = \phi_0 + \sum_{j=1}^M \phi_j$$

where ϕ_0 is the base value, representing the sample mean of the health risk index across the entire dataset, and ϕ_j denotes the SHAP attribution value for the j -th feature.

2.5.3. Structural Equation Modeling of the Dual-Pathway Mechanism

To examine how objective exposure is translated into perceived risk, discomfort, and protective behavior, we estimated a structural equation model (SEM). The SEM contained two observed exposure inputs, PM_{2.5} concentration and inhaled dose, and three health-related latent or quasi-latent outcomes: physiological burden, risk perception, and psychological distress. This framework allowed the simultaneous assessment of linked pathways while accounting for measurement error in the multi-item constructs.

In the measurement layer, physiological burden was indicated by physical discomfort and drowsiness/fatigue; risk perception was indicated by the five perception-related questionnaire items; and psychological distress was represented as a single-indicator construct based on the emotional-distress item.

$$\begin{aligned} x &= \Lambda_x \xi + \delta \\ y &= \Lambda_y \eta + \epsilon \end{aligned}$$

where x and y are vectors of observed indicators for exogenous and endogenous latent variables, respectively. In the present specification, the exogenous side represents the objective exposure inputs, whereas the endogenous side contains physiological burden, risk perception, and psychological distress. The loading matrices link each latent construct to its corresponding questionnaire indicators, and the measurement error vectors capture item-specific unexplained variance, which explicitly absorbs non-systematic subjective noise from the self-reported items. This structural design ensures that the core pathway estimations remain robust against individual reporting biases.

The structural model specified a dual-pathway mechanism in which inhaled dose was allowed to affect physiological burden directly, $PM_{2.5}$ concentration was allowed to influence risk perception, and risk perception was allowed to transmit effects further to both physiological burden and psychological distress.

$$\eta = B\eta + \Gamma\zeta + \zeta$$

In this framework, B is the coefficient matrix for the relations among endogenous constructs, Γ represents the effects of the observed exposure variables on those constructs, and ζ is the vector of structural residuals. The retained paths correspond to the hypothesized exposure-perception-impairment cascade evaluated in Section 3.3.

Model parameters were estimated by maximum likelihood. Model adequacy was evaluated using the Comparative Fit Index (CFI > 0.90), Tucker–Lewis Index (TLI > 0.90), and Root Mean Square Error of Approximation (RMSEA < 0.08). Standardized path coefficients were then used to interpret the relative strength of the physiological and perception-mediated pathways.

2.5.4. Random Forest Models for Behavioral Responses

To compare the determinants of immediate protective behavior and longer-term intervention preference, we fitted RandomForestRegressor models for mask-wearing frequency and willingness to pay (WTP). Both outcomes were analyzed as five-point ordered questionnaire scores, and a common predictor set was used: humidity, observed in-vehicle duration, $PM_{2.5}$ concentration, temperature, risk perception, inhaled dose, gender, standing/seated posture, medical history, and education.

Models were estimated for the overall sample (Summer + Winter) and separately for the Summer and Winter subsamples. For each target, observations with complete data on the outcome and predictors were retained, a 75%/25% train-test split was implemented with random_state = 42, and a Random Forest regressor with n_estimators = 1000 was fitted. Test-set R^2 values were 0.134, 0.062, and −0.004 for mask-wearing in the overall, summer, and winter models, respectively, and 0.086, 0.201, and 0.011 for WTP. Because predictive accuracy was modest, interpretation focused primarily on relative feature importance across seasons rather than on point prediction alone.

To make the full workflow easier to follow, Figure 2 summarizes the study design from route selection and synchronized monitoring to dose reconstruction and the linked DML, XGBoost-SHAP, SEM, and Random Forest analyses.

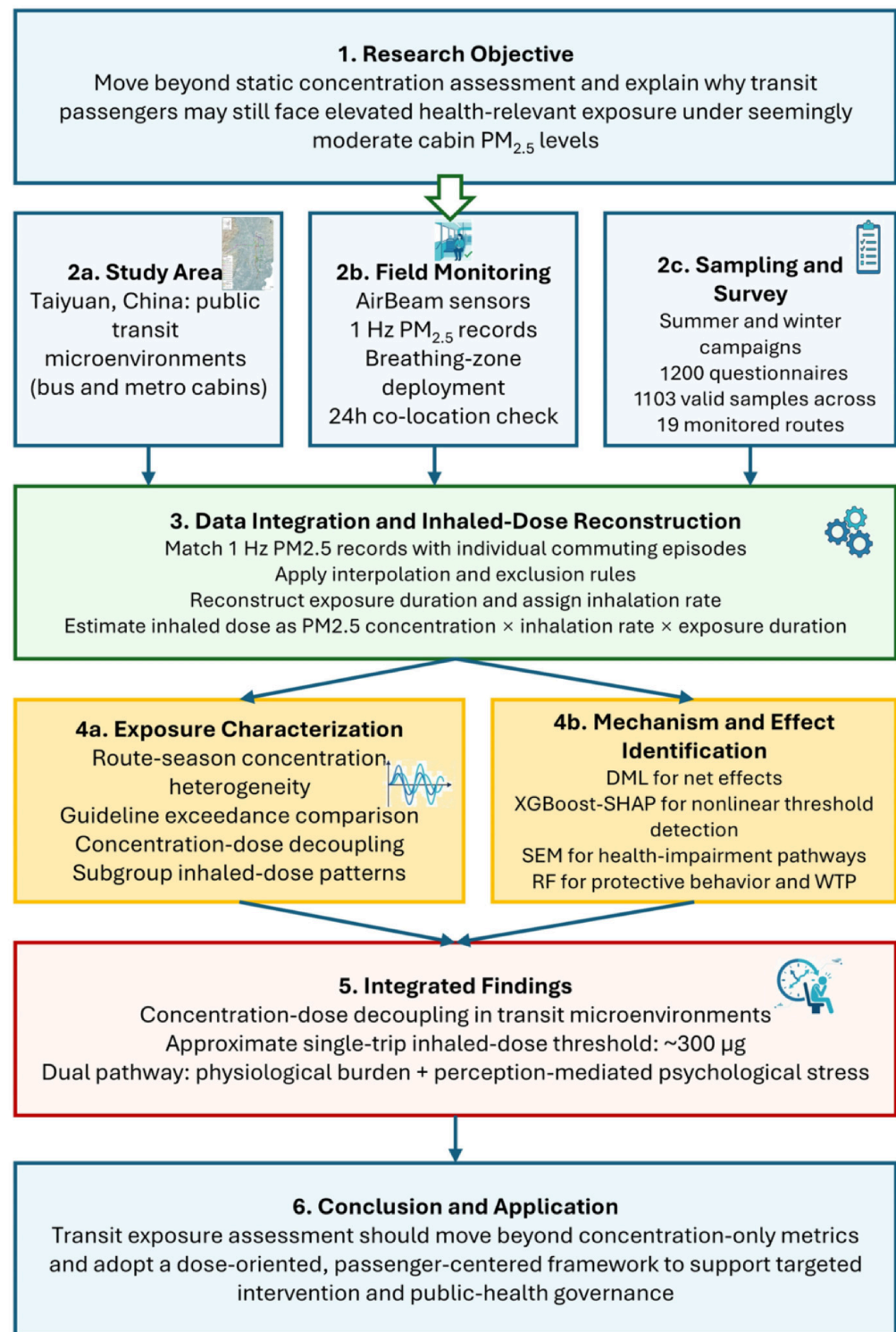


Figure 2. Technical roadmap of the full study, from route selection and synchronized monitoring to dose reconstruction and integrated multi-model analysis.

3. Results

3.1. Spatiotemporal Heterogeneity and Concentration-Dose Decoupling

Figure 3 shows marked route-specific and summer-winter campaign-period difference in in-cabin PM_{2.5} concentrations across matched transit routes. Overall, PM_{2.5} levels were generally higher in winter than in summer for most routes, although this pattern was not uniform. Route 610 showed the most pronounced summer anomaly, with the highest mean

concentration in summer ($43.5 \mu\text{g}/\text{m}^3$) compared with $19.8 \mu\text{g}/\text{m}^3$ in winter. It should be noted that this value represents the trip-averaged concentration. Route 86 also remained relatively polluted in both seasons, reaching $33.6 \mu\text{g}/\text{m}^3$ in summer and $28.2 \mu\text{g}/\text{m}^3$ in winter, whereas Metro Line 1 exhibited a typical winter-dominant pattern (20.4 vs. $35.2 \mu\text{g}/\text{m}^3$). Similar winter-elevated patterns were observed on Route 61, Route 17, and Route 836, while Route 6, Route 76, and Route 71 remained comparatively low in both seasons.

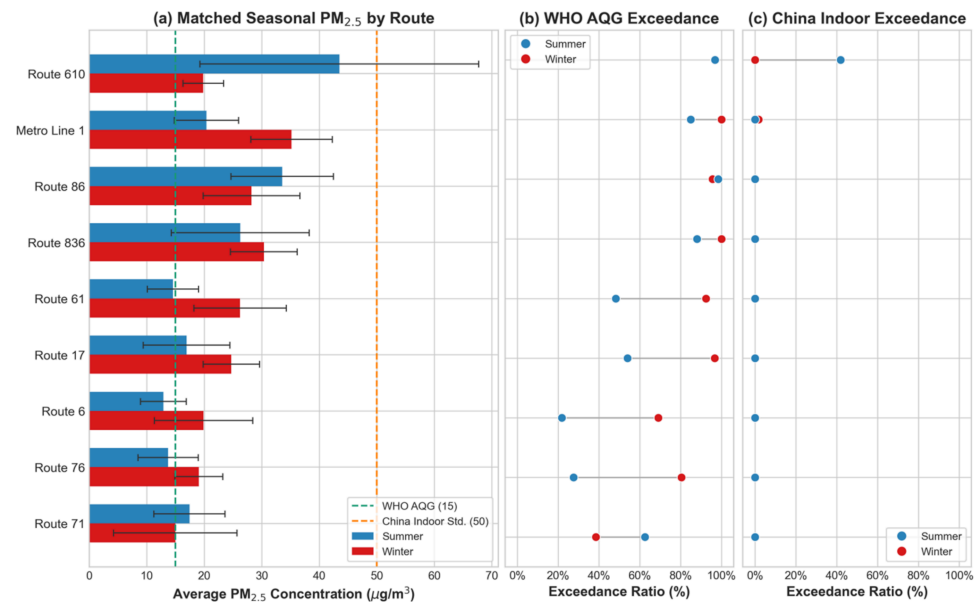


Figure 3. Integrated summer-winter comparison of in-cabin PM_{2.5} exposure across matched transit routes.

Although exposure duration in transit microenvironments is relatively short, the trip-level average concentration remains relevant for assessing short-term inhalation burden and was therefore compared with established 24 h health-based reference values as a precautionary benchmark. Exceedance analysis showed that the WHO 24 h air quality guideline ($15 \mu\text{g}/\text{m}^3$) was exceeded on most matched routes in both seasons. In winter, exceedance reached 100% on Route 836 and Metro Line 1 and remained above 90% on Route 610, Route 17, Route 86, and Route 61. In summer, exceedance was still extremely high on Route 86 (98.4%) and Route 610 (96.8%). By contrast, exceedance of the Chinese indoor PM_{2.5} standard ($50 \mu\text{g}/\text{m}^3$) was uncommon and was observed mainly on Route 610 in summer (41.9%), with only marginal exceedance on Metro Line 1 in winter (1.7%). These results indicate that, although most routes remained below the national indoor threshold, substantial health-relevant exposure risks persisted when evaluated against the more stringent WHO guideline. Accordingly, PM_{2.5} in transit microenvironments was interpreted primarily against the WHO guideline, while the Chinese indoor standard was used as a supplementary national reference.

Figure 4 presents the overall distribution of cumulative inhaled dose across passengers, and Figure 5 shows how this variability changes when the cleaned sample is stratified by demographic and behavioral attributes. Likely due to differences in basal metabolic rate and ventilation, the average inhaled dose among male passengers ($208.76 \pm 319.58 \mu\text{g}$, $n = 489$) was significantly higher than that among female passengers ($175.29 \pm 279.59 \mu\text{g}$, $n = 614$) (Mann–Whitney U test, $p < 0.05$). Second, passengers maintaining a standing posture in the cabin experienced a markedly higher average inhaled dose ($300.57 \pm 398.32 \mu\text{g}$, $n = 114$) than seated passengers ($177.62 \pm 282.33 \mu\text{g}$, $n = 989$, $p < 0.001$). In addition, the standing group showed a wider interquartile range and more extreme values, indicating greater

exposure instability within the transit microenvironment. Most notably, observed in-vehicle duration exerted a strong amplifying effect on dose accumulation. The average inhaled dose for the longer observed-duration group (top 20% by observed in-vehicle duration) reached $612.26 \pm 412.21 \mu\text{g}$ ($n = 213$), which was 7.2 times that of the remaining trips ($84.87 \pm 115.71 \mu\text{g}$, $n = 890$). Together, these results suggest that inhaled dose is shaped not only by pollutant concentration, but also by the way the dose model incorporates passenger-specific inhalation rate and observed travel behavior, especially posture and observed in-vehicle duration. Accordingly, these subgroup contrasts should be interpreted as differences in estimated internal burden rather than as entirely independent sources of concentration variability.

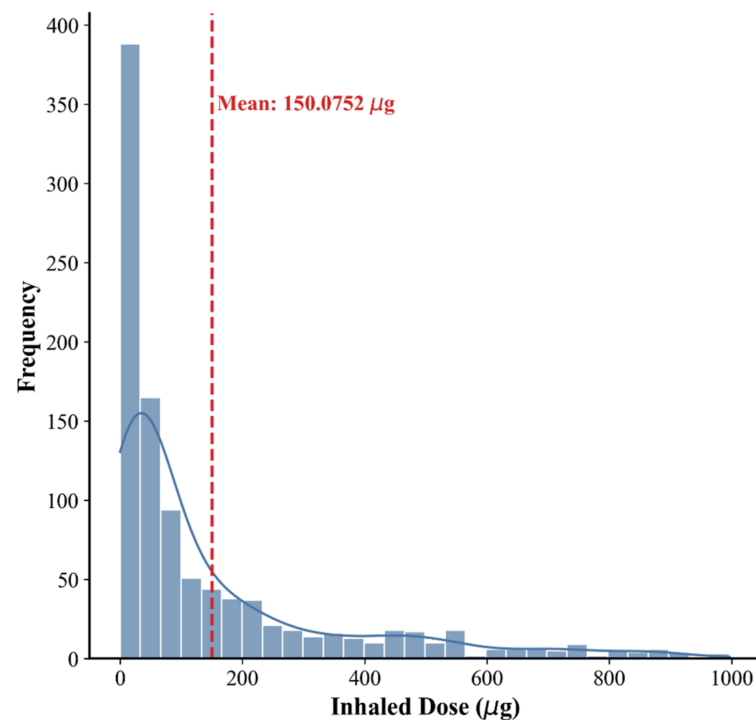


Figure 4. Frequency distribution and comparative analysis of cumulative PM_{2.5} inhaled doses among all passengers.

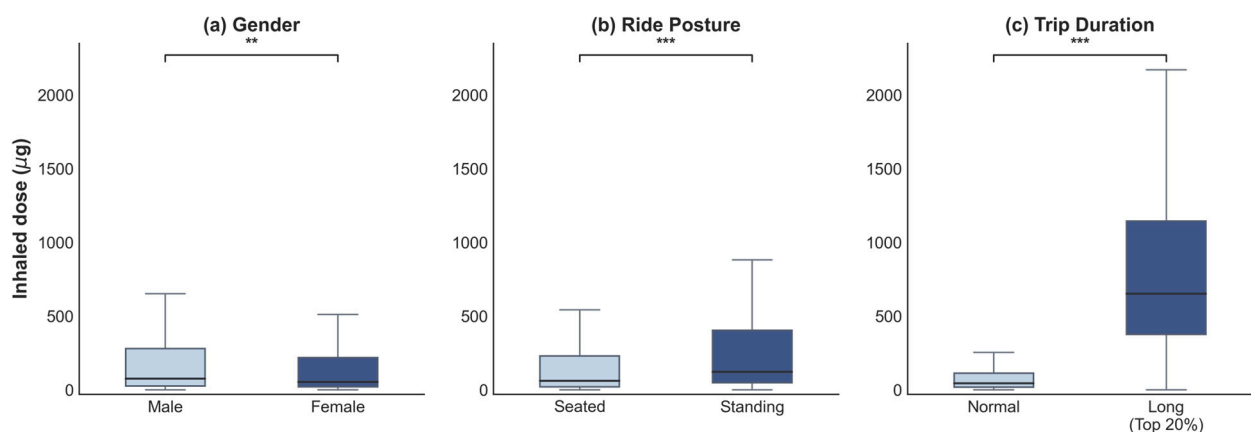


Figure 5. Comparative analysis of individual inhaled doses across different demographic and behavioral attributes. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 6 further reveals a clear concentration-dose decoupling pattern in the public transit microenvironment. Most short observed-duration trips clustered in the low-

concentration, low-dose region, whereas a distinct low-concentration, high-dose zone was still observed. Although this subgroup accounted for only 6.6% of the cleaned samples, it was dominated by longer-duration observations, indicating that prolonged in-vehicle exposure can substantially elevate cumulative inhaled dose even when $\text{PM}_{2.5}$ concentrations remain below the sample median ($22.0 \mu\text{g}/\text{m}^3$). At the same time, the high-concentration, high-dose quadrant remained more prevalent, suggesting that dose accumulation was jointly shaped by both concentration level and exposure duration. These findings indicate that assessment frameworks based solely on ambient or in-cabin $\text{PM}_{2.5}$ concentration may underestimate exposure risk under specific commuting conditions and highlight the importance of incorporating inhaled dose alongside concentration when evaluating health-relevant transit exposure.

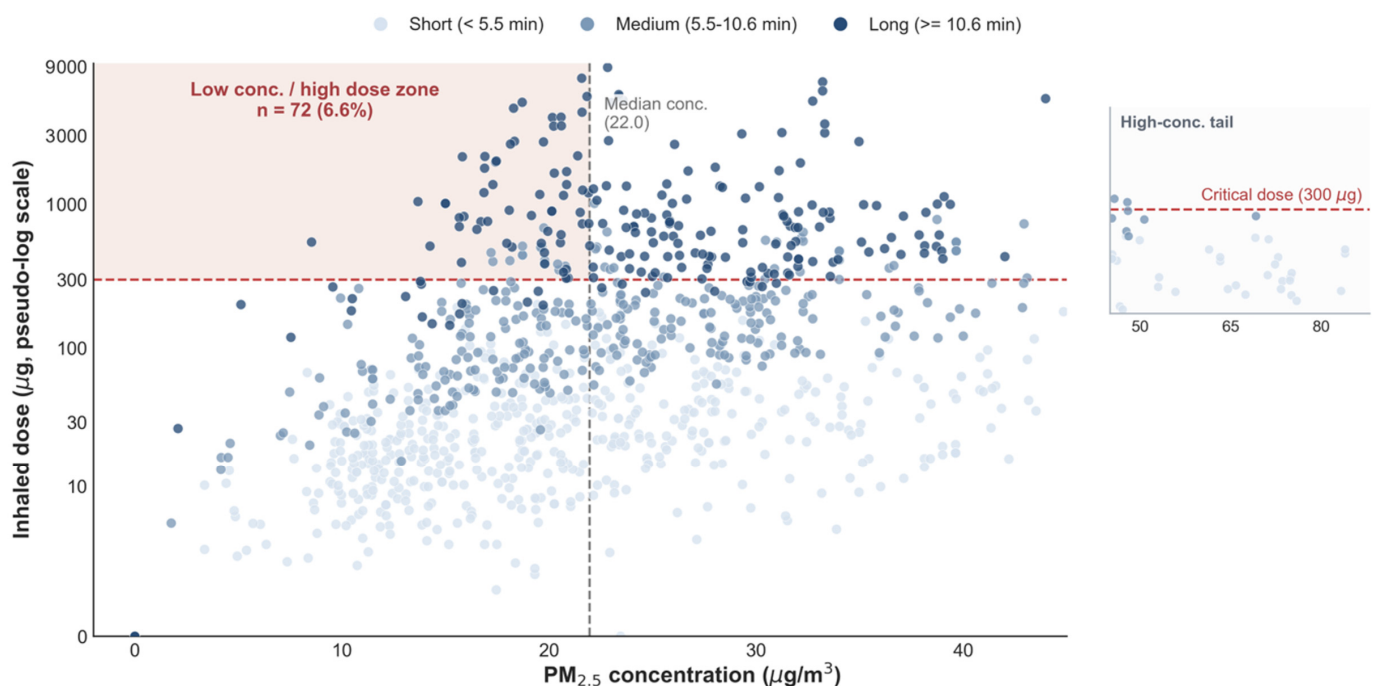


Figure 6. Bivariate distribution and coupling characteristics between $\text{PM}_{2.5}$ concentrations and inhaled doses.

3.2. Adjusted Associations and Exploratory Nonlinear Pattern of Inhaled Dose

Building upon the identification of inhaled dose as the core exposure metric, we next examined its adjusted associations with self-reported health-related outcomes and exploratory nonlinear patterns using the DML and XGBoost-SHAP frameworks. We first estimated the net effects of $\text{PM}_{2.5}$ concentration and inhaled dose using DML, and then used XGBoost-SHAP to characterize the global importance and local threshold behavior of the health risk index. As shown in Table 3, the DML results indicate that $\text{PM}_{2.5}$ concentration alone did not exhibit a statistically significant de-biased net effect on physiological burden or psychological distress. By contrast, cumulative inhaled dose showed a significant positive net association with psychological distress (effect = 1.12×10^{-4} , $p < 0.05$). This result suggests that, compared with concentration alone, the internalized dose accumulated during commuting is more directly linked to psychological distress and may therefore provide a more informative indicator for broader health-risk evaluation.

Table 3. De-biased net-effect estimates for PM_{2.5} concentration and inhaled dose on health outcomes based on the DML framework.

Causal Path	Effect Size (β)	<i>p</i> -Value
PM _{2.5} Concentration → Somatic Discomfort	−0.000147	0.964186
Inhaled Dose → Somatic Discomfort	0.000085	0.185173
PM _{2.5} Concentration → Psychological distress	−0.000441	0.905767
Inhaled Dose → Psychological distress	0.000112	0.034341

To further characterize the multidimensional determinants of integrated health stress, we used the XGBoost-SHAP model to assess the relative importance of the selected predictors of the health risk index. Given the modest held-out predictive performance of the XGBoost model, the SHAP results should be interpreted as exploratory rather than confirmatory. Within this limitation, Figure 7 suggests that variation in the health risk index was associated with a combination of microenvironmental conditions, individual susceptibility, and internal exposure burden. Humidity was the most important predictor (mean $|SHAP| = 0.151$), followed by age (0.123), temperature (0.085), inhaled dose (0.080), and trip duration (0.064). PM_{2.5} concentration (0.057) and noise (0.042) had moderate effects, whereas posture, medical history, and gender contributed only marginally. Notably, both humidity and age ranked above the objective pollution indicators, and inhaled dose showed greater importance than PM_{2.5} concentration, indicating that internalized exposure burden was more informative for explaining transit-related health risk than concentration alone. The SHAP beeswarm plot further revealed substantial heterogeneity in the effects of the leading predictors, especially humidity, age, temperature, and inhaled dose, suggesting that the determinants of transit-related health risk were strongly nonlinear and varied considerably across individuals.

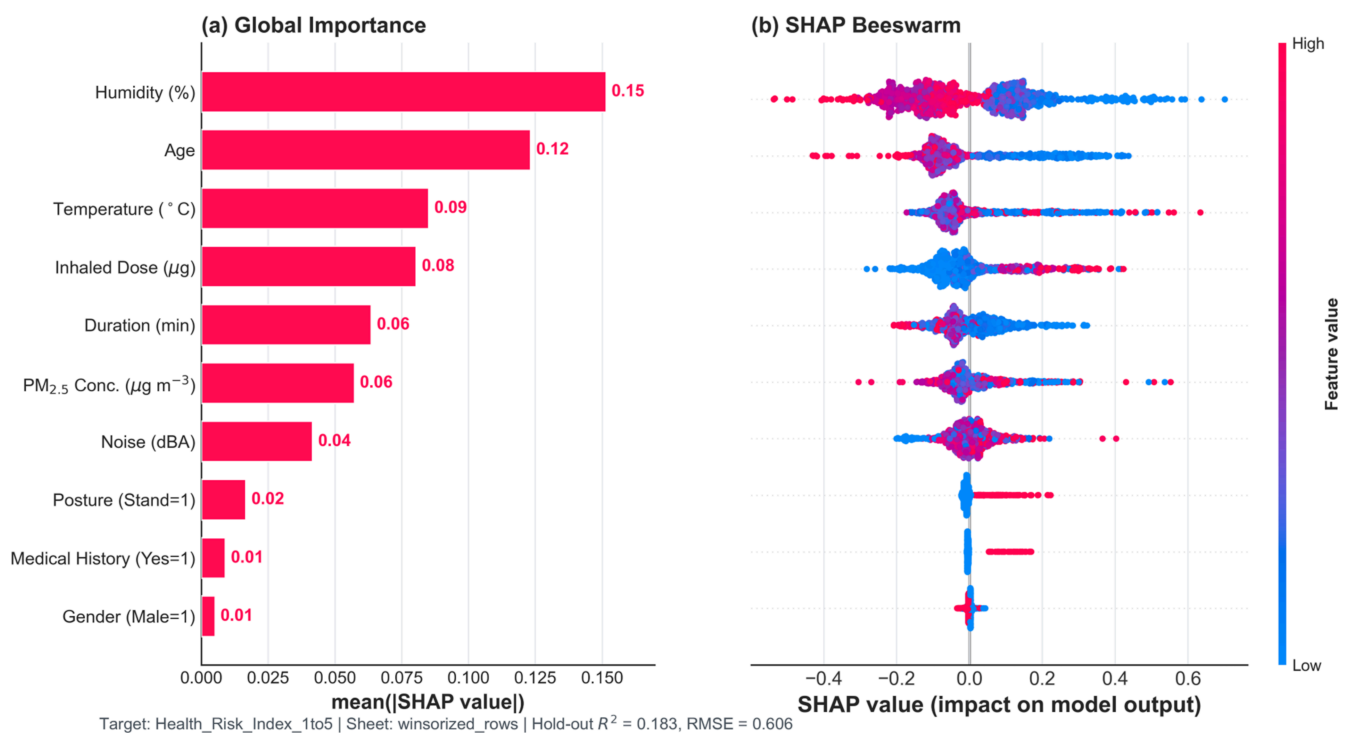
**Figure 7.** Global importance ranking and SHAP beeswarm distribution of the predictors of the health risk index.

Figure 8 further illustrates the nonlinear dependence of the health risk index on inhaled dose. The SHAP dependence plot suggested a threshold-like pattern around approximately 300 μg per trip. However, because the XGBoost model explained only a limited share of the variance in the composite health-risk index, this value should be interpreted as an exploratory, sample-specific marker of elevated integrated health stress rather than as a validated toxicological threshold. The smoothed dependence curve confirms this transition from a near-neutral or weakly negative effect at lower doses to a clearly positive effect at higher doses. Temperature was identified as the strongest interaction feature, implying that thermal conditions may further amplify the health-risk effect associated with high inhaled doses. Taken together, these findings show that the health implications of transit $\text{PM}_{2.5}$ exposure cannot be adequately captured by concentration alone, and that inhaled dose provides a more sensitive basis for identifying nonlinear escalation in commuter health risk.

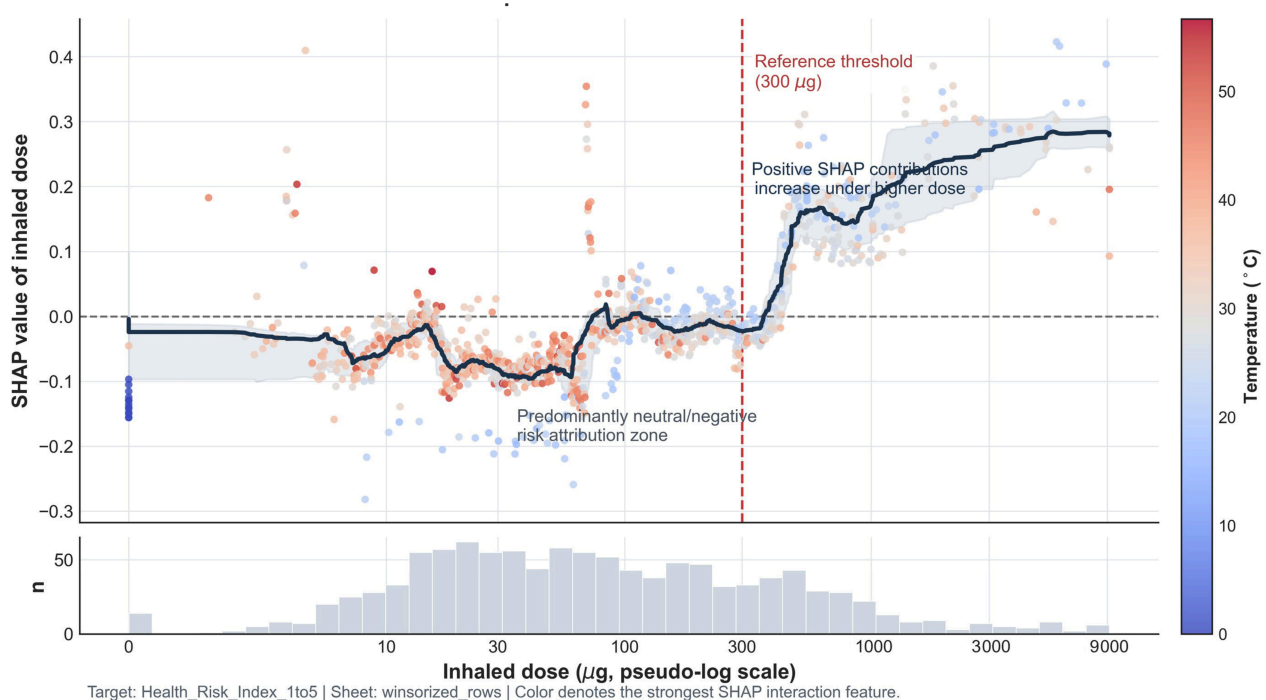


Figure 8. Nonlinear SHAP dependence of inhaled dose on the health risk index.

Sensitivity analysis further examined whether the dose-related pattern depended on the equal-weighting rule used to construct the Health_Risk_Index. The baseline equal-dimension index was compared with three alternative indicators: an item-equal index, a PCA-based index, and a symptom-only index. The alternative indicators were strongly correlated with the baseline index (Spearman $r = 0.913$ – 0.951). The association between log-transformed inhaled dose and the health-related indicator remained positive across all aggregation schemes, although the statistical strength varied across alternative indicators, and inhaled dose ranked consistently among the top four predictors in the XGBoost-SHAP analysis. These results suggest that the main dose-related pattern was not driven solely by the equal-weighting rule. Nevertheless, because the indicator is based on self-reported symptoms and perceptions, it should still be interpreted as an exploratory questionnaire-based measure rather than as a clinically validated health-risk scale.

3.3. Dual Pathways Linking Transit PM_{2.5} Exposure to Self-Reported Health-Related Stress

To further clarify how PM_{2.5} exposure in transit microenvironments affects passenger health, we constructed a structural equation model (SEM) incorporating objective exposure indicators, risk perception, and health outcomes. The model showed a good overall fit (CFI = 0.991, TLI = 0.977, RMSEA = 0.040), indicating that the proposed structure was appropriate for explaining the interrelationships among exposure burden, subjective perception, and health responses.

As shown in Figure 9, the SEM results revealed two distinct but interconnected pathways linking transit PM_{2.5} exposure to self-reported health-related stress. The first was a direct association with self-reported somatic burden. Cumulative inhaled dose had a significant positive direct effect on physiological burden ($\beta = 0.0746$, $p < 0.05$), suggesting that internalized particle accumulation during commuting constituted an immediate physical stressor contributing to acute discomfort symptoms. In contrast, PM_{2.5} concentration did not show a significant direct effect on either physiological burden or psychological distress.

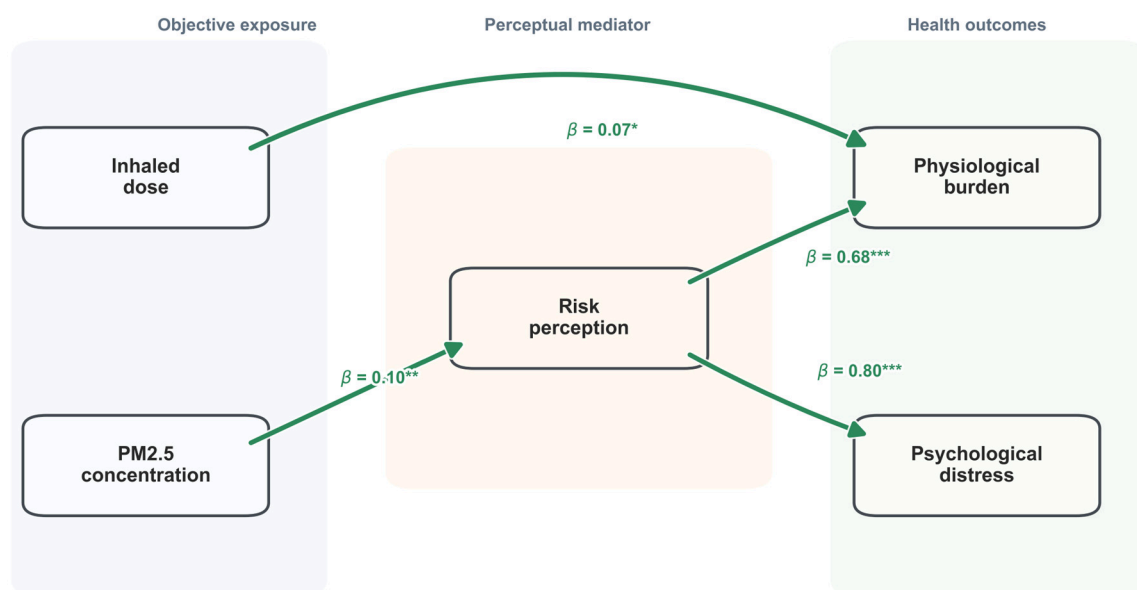


Figure 9. Standardized path coefficients and structural relationships in the SEM linking inhaled dose, PM_{2.5} concentration, risk perception, physiological burden, and psychological distress.

The second pathway operated through subjective perception. PM_{2.5} concentration significantly increased passengers' risk perception ($\beta = 0.0981$, $p = 0.0011$), indicating that instantaneous concentration changes were more likely to function as perceptual environmental cues than as direct physiological stressors. Elevated risk perception, in turn, exerted strong positive effects on both physiological burden ($\beta = 0.6807$, $p < 0.001$) and psychological distress ($\beta = 0.7995$, $p < 0.001$). These results suggest that transit-related self-reported health stress was not associated only with estimated particle intake, but also with a perception-mediated pathway through which pollution signals amplified both somatic and psychological responses.

Overall, the SEM highlights a dual mechanism of health impairment in transit microenvironments: inhaled dose primarily acts through a direct physiological pathway, whereas PM_{2.5} concentration mainly affects health indirectly through risk perception. This distinction further supports the need to evaluate transit exposure using both objective dose-based metrics and perception-related responses when assessing passenger health risk.

3.4. Divergent Determinants of Immediate Protective Behavior and Willingness to Pay

Given the physiological and perception-based pathways identified above, we further examined how transit-related health stress translated into immediate protective behavior and longer-term intervention preferences. As shown in Figure 10, the Random Forest results revealed clear differences in the determinants of mask-wearing and willingness to pay (WTP) for health interventions.

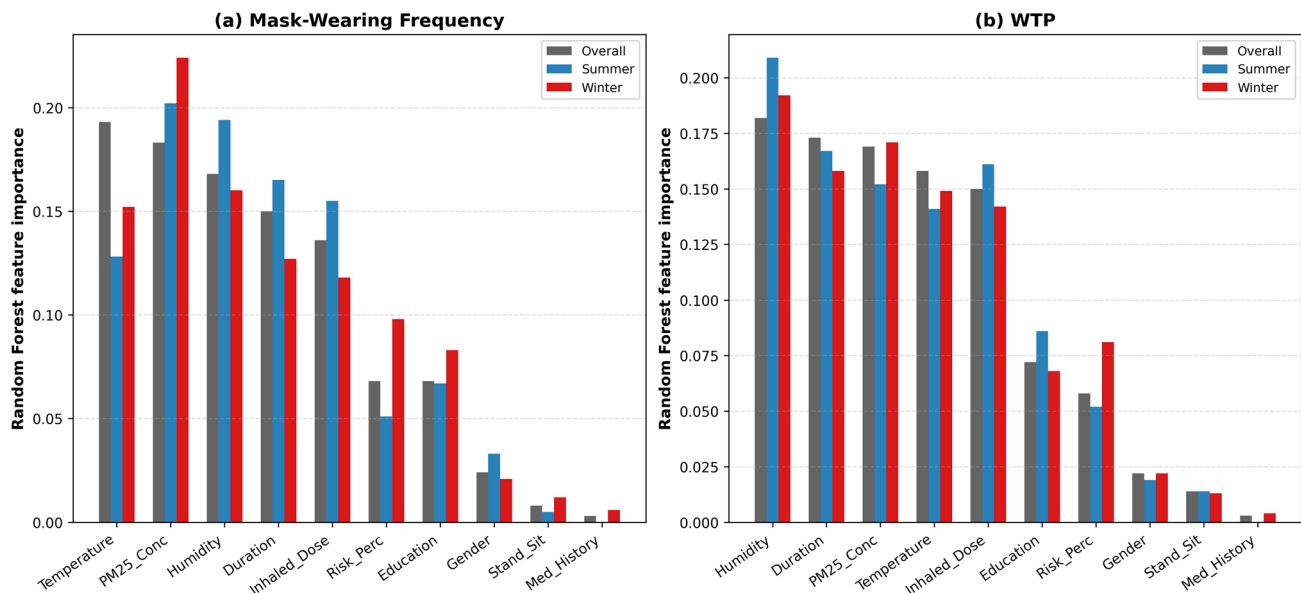


Figure 10. Relative importance of predictors of mask-wearing and willingness to pay (WTP) among transit passengers across the overall, summer, and winter models.

For mask-wearing, the most important predictors in the overall model were temperature (0.193), PM_{2.5} concentration (0.183), humidity (0.168), trip duration (0.150), and inhaled dose (0.136). After seasonal stratification, PM_{2.5} concentration ranked first in both summer (0.202) and winter (0.224), indicating that immediate protective behavior was closely associated with contemporaneous pollution exposure and in-cabin environmental stress. This pattern suggests that mask-wearing mainly reflects an acute behavioral response to the current commuting environment. The broadly consistent but not identical seasonal ranking patterns indicate that the predictor profile of mask-wearing was shaped by a shared set of environmental stressors, while the relative strength of specific predictors still varied under contrasting summer and winter microenvironmental conditions.

For WTP, the leading predictors were humidity (0.182), trip duration (0.173), PM_{2.5} concentration (0.169), temperature (0.158), and inhaled dose (0.150), and the overall ranking pattern remained broadly consistent across summer and winter. Compared with mask-wearing, WTP appeared to be less strongly driven by short-term pollution signals alone and more closely related to the combined influence of environmental conditions and travel burden. In both models, risk perception and education showed only secondary importance, whereas gender, posture, and medical history contributed little to explanatory power. Overall, these findings suggest different predictor structures for immediate protective behavior and longer-term intervention preference: mask-wearing aligns more closely with current exposure conditions, whereas WTP reflects a broader evaluation of recurring commuting-related environmental stress.

4. Discussion

4.1. Rethinking Exposure Metrics in Transit Microenvironments

Although trip-averaged PM_{2.5} concentrations in some monitored public transit vehicles exceeded the WHO 24 h Air Quality Guideline of 15 µg/m³, most observations remained closer to the WHO interim-target range than to severe pollution episodes. Nevertheless, such guideline values should be interpreted with caution in transit microenvironments because passenger exposure is transient, concentrated within a single trip, and strongly modulated by route conditions and ventilation dynamics. In this context, short-term peak exposure may still carry important acute health implications, even when the corresponding daily average is not extreme [25,26].

The most notable finding of this study is the clear decoupling between ambient concentration and personal inhaled dose within the public transit microenvironment. Conventional exposure assessment has long relied on fixed-site monitoring or residence-based ambient concentrations, yet such approaches cannot fully capture the spatiotemporal heterogeneity generated by commuting duration, passenger activity, and route-specific ventilation conditions [20,21]. Our results show that relatively moderate in-cabin PM_{2.5} concentrations do not necessarily correspond to a low personal burden. Once time-amplification effects, respiratory activity, and travel behavior are incorporated, cumulative inhaled dose may increase substantially even under cabins that formally satisfy concentration-based standards. This interpretation is consistent with previous studies showing that inhaled dose is often more representative of actual exposure burden than concentration alone, particularly in transport microenvironments where travel time and microenvironmental dynamics play a decisive role [8,9,22].

The DML results further reinforce this concentration-dose paradox. Ambient PM_{2.5} concentration did not exhibit a significant de-biased net effect on somatic burden or psychological distress, whereas cumulative inhaled dose showed a significant and more sensitive association with psychological distress. This suggests that, within the short timescale of a single commute, concentration itself may be a less informative indicator of acute subjective stress than the integrated dose accumulated in the respiratory system. Taken together, these findings support complementing static concentration evaluation with dynamic dose-oriented assessment in public-transport exposure research.

Another noteworthy result is that summer in-cabin PM_{2.5} concentrations exceeded winter levels on some routes, a pattern that differs from the typical macro-scale seasonal narrative of winter haze in northern China. This apparent inconsistency is plausible when viewed at the street-canyon and cabin scales. Elevated temperature and solar radiation during summer can promote photochemical production of secondary aerosols, while traffic-related non-exhaust emissions and road-dust resuspension continue to contribute to near-road fine particles [23,24]. At the same time, buses on dense urban routes experience frequent door-opening events, which intermittently introduce polluted outdoor air into the cabin. When windows remain closed and air-conditioning operates under recirculation-dominated settings, these introduced particles may be retained rather than effectively diluted. Existing studies likewise show that air exchange rate, recirculation mode, door-opening frequency, and filtration efficiency are key determinants of in-cabin PM_{2.5} variability [25–27]. Therefore, the health effect of “ventilation” in transit cabins is not unidirectional; it reflects the combined outcome of pollutant ingress, pollutant removal, and route-specific operating conditions [28]. Dense urban routes such as Route 610 likely experienced stronger short-interval pollutant ingress because repeated door opening and short stop spacing could outweigh the potential dilution benefit of transient air exchange.

The machine-learning results are consistent with this meteorological interpretation. Figure 7 shows that humidity and temperature remained among the leading predictors in

the XGBoost-SHAP model, and Figure 10 indicates that the season-stratified Random Forest models also assigned substantial importance to humidity, temperature, and trip duration. More directly, the monitored route pattern also supports this interpretation: on Route 610, the mean summer PM_{2.5} concentration reached 43.06 µg/m³ under warmer and more humid in-cabin conditions (35.88 °C; 94.08%) than in winter (19.83 µg/m³; 28.58 °C; 62.97%). Although these observations do not constitute route-specific source apportionment, they are consistent with the view that summer thermal and moisture conditions can modulate in-cabin PM_{2.5} accumulation and passenger stress. Urban relief may also influence the spatial distribution of transit-related PM_{2.5} exposure. Taiyuan is located in the Fenhe River valley and is bounded by surrounding mountainous terrain, which can weaken atmospheric dispersion under stable meteorological conditions. In such basin-like settings, pollutants emitted from traffic, industry, and seasonal heating may accumulate more easily in low-lying urban corridors and poorly ventilated street canyons. This mechanism may partly explain why some surface routes exhibited elevated in-cabin PM_{2.5} concentrations even when city-wide conditions were not extremely polluted. Nevertheless, relief was not explicitly included as a quantitative predictor in the present model because route-level elevation, wind-field, and street-canyon morphology data were not available. Therefore, the possible increase in pollution in lowlands should be interpreted as a plausible topographic mechanism rather than as a directly tested result. Future studies should integrate mobile monitoring with digital elevation models, land-use data, and local meteorological fields to test whether low-lying transit corridors experience systematically higher exposure.

International comparison helps to clarify both the commonality and specificity of our findings. Studies in European and North American cities, such as London, Lisbon, Sacramento, and Hong Kong, have shown that PM_{2.5} exposure in transport microenvironments varies substantially by mode, route, ventilation condition, and surrounding traffic environment [1,4,5,9]. In these contexts, the policy and research focus has often been placed on modal comparison, route-level concentration variability, and the performance of relatively mature transport systems. By contrast, studies from more traffic-intensive settings such as Delhi have reported higher on-road exposure levels, reflecting stronger influences from roadside emissions, congestion, and limited separation between passengers and traffic sources [3]. Compared with these international cases, Taiyuan appears to represent an intermediate but policy-relevant transit exposure context. Its trip-averaged in-cabin PM_{2.5} concentrations were not as extreme as those reported in heavily traffic-dominated systems, but the observed concentration-dose decoupling indicates that moderate concentrations can still generate high personal exposure burden when travel duration, posture-related inhalation rate, and cabin ventilation dynamics are considered. This comparison suggests that cross-regional differences in public-transit exposure cannot be evaluated by concentration alone; the same concentration level may correspond to different inhaled doses depending on travel time, ventilation regime, passenger behavior, and background urban pollution.

4.2. Toxicological and Psychological Interpretations of the 300 µg Threshold and Dual Pathways

The XGBoost-SHAP analysis suggested an exploratory turning point around approximately 300 µg per trip, above which the predicted questionnaire-based health-risk indicator increased more sharply. Because this threshold was derived from a composite outcome that combines somatic burden, mental distress, and risk perception, it should be interpreted as an empirical threshold for elevated integrated health stress within this dataset rather than as a universal toxicological cutoff. It is important to note that the substantial variations in inhaled doses driving these acute symptoms are not primarily caused by minor baseline differences in adult respiratory rates. Rather, they are determined by the massive multiplier effects of in-cabin posture (where standing nearly doubles the inhalation rate due to the

physical effort of maintaining balance) and prolonged travel duration (which generated up to a 7.2-fold difference in cumulative dose in our sample). Even so, the observed nonlinear pattern remains biologically plausible. According to established respiratory deposition models (such as those by the ICRP), fine particles like PM_{2.5} can effectively bypass the upper airways and penetrate deep into the alveolar region. Under relatively low particulate burdens, airway defense systems, including mucociliary clearance and macrophage-mediated removal, may still buffer this particulate intrusion effectively. However, once the cumulative inhaled burden accelerates—driven by the aforementioned posture and duration multipliers—and exceeds a certain threshold (e.g., ~300 µg), retention in the distal respiratory tract increases rapidly. This overwhelms the short-term physiological buffering capacity [27,28], leading to oxidative stress and acute somatic symptoms [29,30].

This interpretation is also consistent with toxicological evidence showing that particulate matter can induce oxidative stress, epithelial injury, and inflammatory activation, thereby contributing to acute pulmonary and systemic responses [29,30]. Accordingly, the sharp increase in SHAP values above 300 µg may reflect a non-linear amplification of biological stress once the inhaled dose surpasses the respiratory system's short-term coping capacity. Because this threshold was derived from a questionnaire-based composite indicator and from an XGBoost model with modest predictive performance, it should be treated as a hypothesis-generating marker rather than as a validated health-risk threshold.

Beyond the physiological pathway, our SEM results indicate a second pathway operating through perception and emotion. In the present study, ambient PM_{2.5} concentration did not directly translate into measurable organic damage, but rapid fluctuations in pollution levels, often accompanied by visible haze, odor, or a sense of stuffiness, likely functioned as salient environmental cues. These cues may heighten risk vigilance and trigger subjective defensive responses, which in turn intensify psychological distress. This interpretation is supported by previous studies showing that perceived pollution and health-risk perception can mediate annoyance and self-reported symptoms even under relatively moderate exposure conditions [31,32]. Real-time evidence also suggests that perceived air quality may diverge considerably from measured pollution in everyday activity spaces, including travel environments [33]. In descriptive terms, among trips with inhaled dose ≥ 300 µg, 33.3% of respondents reported at least mild-to-moderate physical discomfort (item score ≤ 3), 36.6% reported drowsiness or fatigue, and 29.2% reported negative mood symptoms. These indicators reflect acute self-reported stress rather than clinically diagnosed disease. Therefore, health stress in transit microenvironments should not be understood solely as a toxicological process; it is more appropriately viewed as a dual-driving cascade involving both objective physiological burden and subjective psychological appraisal.

4.3. The Evolution of Passenger Behavior Under Microenvironmental Stressors

The divergence between the determinants of mask-wearing and willingness to pay (WTP) further suggests that passengers respond to transit pollution through distinct behavioral response logics rather than through a single uniform mechanism. In our analysis, mask-wearing was more closely associated with contemporaneous PM_{2.5} concentration, temperature, humidity, and observed in-vehicle duration, indicating that immediate self-protective behavior is triggered mainly by current in-cabin environmental stress. Inhaled dose and medical vulnerability still contributed, but they were not the dominant predictors in the overall ranking. By contrast, WTP for long-term improvement of the transit environment was shaped more strongly by observed in-vehicle duration and adverse meteorological conditions, implying a slower and more deliberative evaluation of recurring environmental burden.

This distinction is broadly consistent with international behavioral literature. Studies from different national contexts have shown that adoption of personal protective measures is strongly shaped by health knowledge, perceived barriers, and risk awareness [17], whereas support for broader environmental improvement is more closely linked to perceived health risk, socioeconomic conditions, and daily mobility constraints [34–37]. Our results extend this literature by showing that, in transit microenvironments, these two response patterns are conceptually different and display different predictor profiles: immediate mask-wearing aligns more closely with contemporaneous pollution cues and short-term commuting conditions, whereas willingness to pay reflects a longer-term evaluation of recurrent environmental burden. This cross-national comparison suggests that the general logic of protective behavior is broadly shared, but its specific triggers remain sensitive to local commuting conditions and pollution contexts.

4.4. Strengths and Limitations

The novelty of this study lies in three aspects. First, compared with most previous public-transport exposure studies that mainly characterize PM_{2.5} concentration differences across modes or routes, this study places inhaled dose at the center of the analysis and explicitly identifies concentration-dose decoupling in transit microenvironments. Second, compared with conventional linear or descriptive approaches, we integrate DML, XGBoost-SHAP, SEM, and Random Forest models to examine net exposure effects, nonlinear dose-response patterns, perception-mediated pathways, and behavioral responses within a single analytical framework. Third, compared with our previous work on inhaled-dose risks during daily activities in Guangzhou, the present study focuses specifically on public-transit microenvironments in Taiyuan, a resource-based old-industrial city, and extends the analysis from dose estimation to threshold identification, health-risk perception, and passenger behavioral adaptation. These extensions allow the study to contribute not only to exposure assessment but also to health-oriented transit management.

Several limitations should also be acknowledged. First, PM_{2.5} was treated as a bulk mass indicator, and no source-specific or component-resolved characterization was available. As a result, particles with equal mass may still differ substantially in oxidative potential and toxicity across routes and seasons. Second, the temporal coverage of the field campaign was limited. Measurements were conducted over three summer days and two winter days, which does not allow robust inference about full seasonal variability. Therefore, the summer-winter comparison in this study should be interpreted only as a comparison between two short monitoring campaigns. Future work should include repeated measurements across longer periods, multiple months, different weather conditions, and both weekdays and weekends to evaluate seasonal patterns more rigorously. Third, PM_{2.5} monitors were operated by investigators rather than worn by each passenger, which improved measurement consistency across trips but may not fully represent micro-scale differences in exposure within crowded cabins. A fourth limitation concerns the inherent subjectivity of the questionnaire data and the composite Health_Risk_Index, which relies on self-reported symptoms rather than clinical diagnoses. To mitigate such subjective biases, we employed standardized face-to-face interviews, strict temporal matching with 1 Hz monitors, and noise-resilient models (e.g., SEM measurement error isolation). Furthermore, sensitivity analyses (Spearman $r = 0.913\text{--}0.951$) confirmed that our core findings are robust across alternative aggregation schemes, overcoming the exploratory nature of the baseline equal-weighting method. Nonetheless, future studies should validate this construct using clinical physiological biomarkers. The XGBoost-SHAP model showed modest predictive performance on the held-out test set ($R^2 = 0.183$), indicating that the available predictors captured only part of the variability in self-reported integrated health risk. Therefore,

SHAP-based feature rankings and threshold patterns were used only for exploratory interpretation and require external validation in future studies. In addition, the proposed method is transferable, but the Taiyuan results are not universally representative. Portable monitoring, questionnaire matching, and inhaled-dose estimation can be used in other settings, including small lakeside resort towns. However, route selection, sampling periods, transport modes, meteorological variables, and behavioral groups must be redesigned according to local conditions. Therefore, the method should be locally calibrated and validated before its results are generalized. A further limitation is that the study cannot fully isolate the health influence of PM_{2.5} exposure during public transport from exposures and physiological conditions occurring before or after the trip. Self-reported discomfort, fatigue, and emotional distress may be affected by pre-existing health status, previous daily exposure, sleep quality, work stress, activity before boarding, and other environmental factors outside the public-transport microenvironment. Therefore, the observed associations should be interpreted as short-term trip-level relationships between measured in-vehicle PM_{2.5} exposure and self-reported health-related stress, rather than as evidence of an exclusive causal effect of public-transport PM_{2.5} exposure.

5. Conclusions

This study demonstrates that PM_{2.5} exposure in public transit microenvironments cannot be adequately characterized by concentration alone. Across 19 transit routes in Taiyuan, trip-averaged in-cabin PM_{2.5} concentrations showed clear route-specific and campaign-period heterogeneity and exceeded the WHO 24 h guideline on most routes when interpreted as a health-based benchmark for short commuting exposures, although exceedance of the Chinese indoor standard was comparatively limited. Some urban routes also showed higher summer concentrations, highlighting the importance of meteorological conditions, pollutant infiltration, and route-specific ventilation dynamics.

A key finding is the presence of concentration-dose decoupling, whereby relatively moderate PM_{2.5} concentrations may still produce high personal exposure burden when observed in-vehicle duration is prolonged. The longer observed-duration group (top 20% by observed in-vehicle duration) had a mean inhaled dose 7.2 times that of the remaining trips, and 6.6% of observations fell into a low-concentration but high-dose category. Inhaled dose was more informative than PM_{2.5} concentration for explaining psychological distress and for exploring broader variation in the questionnaire-based composite health-risk indicator. XGBoost-SHAP analysis further suggested an exploratory threshold-like pattern at approximately 300 µg per trip, above which the contribution of inhaled dose to the composite indicator increased.

The results further suggest that transit-related health impairment operates through complementary pathways: inhaled dose primarily increased physiological burden directly, whereas PM_{2.5} concentration mainly acted through risk perception, which then intensified psychological distress. Immediate and longer-term responses also showed different predictor structures, with mask-wearing reflecting sensitivity to contemporaneous commuting conditions and willingness to pay reflecting a broader evaluation of recurring environmental stress. Overall, these findings support a shift from concentration-based assessment toward dose-oriented and passenger-centered evaluation for healthier transit management.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/atmos17060539/s1>, Supplementary Material S1. English Version of the Field Questionnaire.

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