

Impact of low-emission driving behavior on brake wear PM emissions: insights from a real-world evaluation[☆]

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ABSTRACT

As vehicle exhaust regulations become more stringent, non-exhaust particulate matter (PM) emissions, particularly from brake wear, which accounts for up to 55% mass of these emissions, have become major contributors to traffic-related PM. However, how low-emission driving behavior influences brake wear PM emissions in real-world conditions remains unclear. In this study, we developed a low-emission driving assistance application and, for the first time, evaluated the real-world impact of low-emission driving behavior (LEDB) on brake wear PM_{2.5} and PM₁₀ emissions. LEDB training was implemented for volunteer drivers in Leeds and Helsinki, resulting in average reductions in brake wear PM_{2.5} emissions by 22.8% and PM₁₀ emissions by 26.1%. Additionally, the promotion strategies for LEDB training are discussed, and the expected emission reduction effects across different implementation scenarios are analyzed. These findings demonstrate that LEDB represents a promising and cost-effective approach that could contribute to reductions in brake wear emissions and improved air quality.

1. Introduction

Road traffic is a major contributor to air pollution, adversely affecting human health, local and regional environments, and the global climate (Emami Javanmard et al., 2023; Fussell et al., 2022; Liu et al., 2024; Shikder et al., 2024). Road traffic-related emissions are mainly categorized into exhaust emissions, arising from incomplete fuel combustion and lubricant volatilization (Chen et al., 2020; Vouitsis et al., 2009), and non-exhaust emissions, generated by brake, tyre, road surface wear, etc. (Liu et al., 2021; Liu et al., 2022b; Liu et al., 2022d). With increasingly stringent controls on exhaust emissions and the promotion of Electric Vehicles (EVs), the relative significance of non-exhaust emissions has risen correspondingly (Amato et al., 2014; Yousuf et al., 2024) and now dominate in

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Particulate Matter (PM) emissions from road traffic (Lawrence et al., 2016; Squizzato et al., 2016). For instance, EVs effectively reduce exhaust emissions, but still generate non-exhaust PM emissions. Due to heavy battery packs, the overall weight of EVs exceeds that of the combustion-engine equivalents, leading to an increase in tyre wear and road wear PM emissions (Men et al., 2022; Timmers and Achten, 2016, 2018). However, brake wear PM emissions are dependent upon the extent of regenerative braking (Beddows and Harrison, 2021). Our previous work (Liu et al., 2022a) summarized the literature on the effect of regenerative braking on brake wear emissions, reporting reductions ranging from a minimum of 25 % to a maximum of 95 %, with an average reduction of 68 %. Recently, Tu et al., 2025 demonstrated that regenerative braking remains highly effective at low speeds, but its mitigating effect diminishes at higher speeds, where mechanical braking is still required. The results from Beji et al. (2020) and Padoan and Amato (2018) show that in urban areas, non-exhaust particle emissions from road traffic play a significant role in contributing to PM pollution. Wang et al. (2023) performed experiments in which vehicles were sealed in a specially designed chamber equipped with a chassis dynamometer to isolate non-exhaust PM emissions from atmospheric and exhaust PM emissions to prevent possible contamination. Their results showed that the total non-exhaust PM could be up to two orders of magnitude higher than the current exhaust PM emission limit. These findings suggest that non-exhaust PM emissions deserve more attention to develop targeted strategies to reduce their impact on air quality.

Since brake-induced wear PM emissions account for up to 55 % of total non-exhaust PM mass from traffic (Acocella et al., 2025; Piscitello et al., 2021), this study focuses on brake-induced wear emissions as a key strategy to reduce overall non-exhaust emissions. Compared to the significant cost and time required for upgrading brake pads and discs, such as those made from lower-emission materials, improving driving behavior is a more cost-effective and efficient method for reducing brake-induced wear emissions (Xia et al., 2023). The results from Feißel et al. (2020) revealed that brake particle emission factors can vary up to by 54 % with different driving behaviors. Similarly, Li et al. (2024) found that aggressive driving significantly increases the generation of 10–23 nm particles in non-exhaust emissions. Furthermore, research has shown that smooth driving can substantially reduce emissions of key air pollutants (Varella et al., 2019).

However, previous studies of driving behaviors have mainly focused on fuel consumption and exhaust emissions (Liu et al., 2025; Ng et al., 2021). Given the difference in the generation mechanisms of exhaust and non-exhaust emissions, adopting more suitable driving behaviors is essential for reducing non-exhaust emissions (Dhital et al., 2021; Huang et al., 2021). Furthermore, greater attention is required to understand how improvement in driving behaviors influence of non-exhaust emissions. This paper has the objective to fill the above research gap by evaluating reductions in non-exhaust PM emissions from brake wear that are possible when adopting the Low-Emission Driving Behaviors (LEDB). As such, the key contributions of our study (as shown in Fig. 1) are as follows:

- Based on the real measurement data, we propose a Brake Wear Emission (BWE) model by applying a traceable machine learning algorithm (Symbolic Regression with Genetic Programming, SR-GP) to estimate real-time PM emissions from the driving behaviors for medium-sized passenger vehicles.
- Based on the BWE model, real-world LEDB training for drivers was evaluated in two European cities, Leeds and Helsinki, and its corresponding effectiveness and applicability were illustrated with evaluation analysis from different road types, driver gender and levels of experience.

The rest of this study is organized as follows. Section 2 presents the experimental setup and analytical methods. Section 3 presents the results and discussion on developing the BWE model, along with the empirical studies on the LEDB. Finally, in section 4, we conclude the paper.

2. Experimental setup and analytical methods

In this section, we first introduce how to obtain real measurement data for our study in Section 2.1. Section 2.2 provides a detailed explanation of how to use the SR-GP algorithm to create the BWE model to estimate the brake wear emissions. Finally, Section 2.3 introduces the implementation and evaluation of the LEDB.

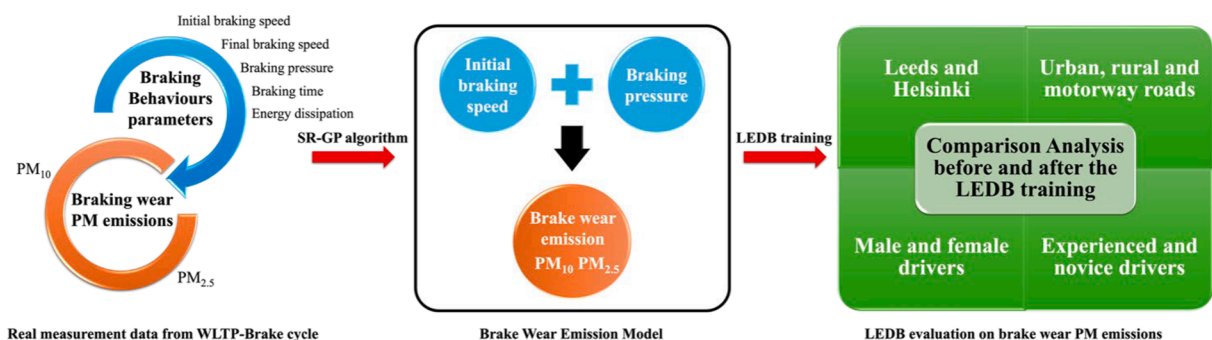


Fig. 1. The framework of this study.

2.1. Test data during the WLTP-Brake cycle

The World Harmonized Light-Duty Vehicle Test Procedure-Brake (WLTP-Brake) cycle has been established as the standard test procedure under the upcoming Euro 7 brake wear emission regulations due to its ability to accurately simulate real-world driving conditions (Liu et al., 2022c; Liu et al., 2022d). This test cycle lasts 4 h and 24 min, covering 192 km across 10 trips. Braking deceleration rates vary between 0.49 and 2.18 m/s², and its corresponding average value is 0.97 m/s², while the average braking speed was 43.7 km/h. In this study, the WLTP-Brake cycle was chosen for experimental testing on the brake dynamometer to more accurately represent the real-world emission characteristics of brake wear PM_{2.5} and PM₁₀. The experimental testing system comprises a brake dynamometer, a wind tunnel, and instrumentation for measuring brake wear emissions. A rotational mass was employed to simulate a moment of inertia of 49.3 kg·m², corresponding to the vehicle's curb weight plus the equivalent mass of 1.5 passengers, based on a front axle brake force distribution of 60 %. To account for parasitic losses within the vehicle, this nominal inertia value (56.7 kg·m²) was reduced by approximately 13 %. The entire braking assembly was enclosed within an oval-shaped chamber, which was continuously supplied with clean air via a high-efficiency particulate air (HEPA H13) filter to minimize background particle contamination. The air carrying brake wear particles was directed from the sealed chamber into a wind tunnel measuring 3.5 m in length and 150 mm in diameter. A sampling probe was positioned within the wind tunnel to collect aerosol samples. Particle measurements were conducted using an Electrical Low-Pressure Impactor (ELPI +) operating at a flow rate of 10 L/min, capable of detecting particles in the size range of 0.004–10 µm. The mass of brake wear generated per braking event was estimated based on measured particle size distributions and number concentrations, under the assumption that all particles were spherical:

$$m_i = \sum_{j=1}^{n_i} (N_j \rho V_j) = \sum_{j=1}^{n_i} \left(N_j \rho \cdot \frac{4}{3} \left(\frac{d_j}{2} \right)^3 \right) = \frac{\pi}{6} \rho \sum_{j=1}^{n_i} N_j d_j^3 \quad (1)$$

where m_i refers to the brake wear particle mass during the i -th braking event. N_j represents the number of particles corresponding to the size d_j , while the particle density ρ was assumed to be 1 g/cm³, following Riva et al. (2019). The particle volume V_j denotes the volume of particles with a diameter of d_j , calculated under the assumption of spherical geometry. Further details regarding the experimental testing system can be found in our previous publication (Liu et al., 2022c; Liu et al., 2022d). The representative results from the tests are presented in Table 1.

2.2. Estimation model for brake wear emission

Based on the test data above, this Section proposes a Brake Wear Emission (BWE) model by using the Symbolic Regression (SR) with Genetic Programming (GP) algorithm to explore the relationship between brake wear PM emissions and driving behaviors.

SR is a rapidly expanding subfield within machine learning that derives symbolic mathematical expressions from data (Koza, 1994). SR methods often employ evolutionary algorithms like GP to search through the space of possible models. GP, an advanced form of Genetic Algorithm (GA), is tailored to evolve symbolic expressions. By simulating natural selection and inheritance processes, it iterates through a population of potential solutions to identify the most optimal ones (Cao et al., 2024). In GP, individuals are typically selected via tournament selection, wherein a subset of the population is evaluated, and the best-performing individual is chosen to pass its traits to subsequent generations. The fundamental differences between GA and GP in the context of SR are 1) GA is fixed-length string for the solution representation while GP is a tree-like structures representing symbolic expressions (as shown in Fig. 2); 2) GA optimize the parameter sets while GP evolving symbolic expressions. GP (SR-GP) has many applications in fields such as science, engineering, and medicine, including curve fitting, data modelling, economic modelling and time series prediction (Guayacán-Carrillo and Sulem, 2024).

There are two advantages for us using the SR-GP in this study. The first advantage is its ability to automatically discover a model without a predefined structure, evolving both the model's structure and parameters instead of relying on fixed mathematical forms, such as linear, exponential and so on. This makes SR-GP significantly different from traditional regression methods (Yamashita et al., 2022). The second advantage of SR-GP is the traceability of its solutions. Unlike typical machine learning methods, SR-GP creates a clear logical relationship between explanatory variables and the response variables. The analytical models it generates come with detailed, interpretable formulas (Elhenawy et al., 2014). To the best of our knowledge, our study is the first to use the SR-GP algorithm to establish the BWE model between brake wear PM emissions and driving behaviors.

In SR-GP, individuals (candidate solutions) in each generation are represented by a tree-like structure composed of nodes/ genes. These tree structures contain two types of nodes/genes: the functional nodes/genes and the terminal nodes/genes. Functional nodes/

Table 1

Representative subset of data collected during the WLTP-Brake cycle (see Supplementary Table S1 for the complete dataset).

Stop number	PM2.5 [mg]	PM10 [mg]	Initial braking Speed [km/h]	Final braking Speed [km/h]	Braking Pressure [MPa]	Braking Time [s]
Stop 1	0.0066	0.020509	20.7	0	0.23	6.0
Stop 2	0.0055	0.014721	23.1	5.58	0.20	7.0
Stop 3	0.0055	0.014229	15.38	4.44	0.24	4.0
...	...	...	...	...	...	...

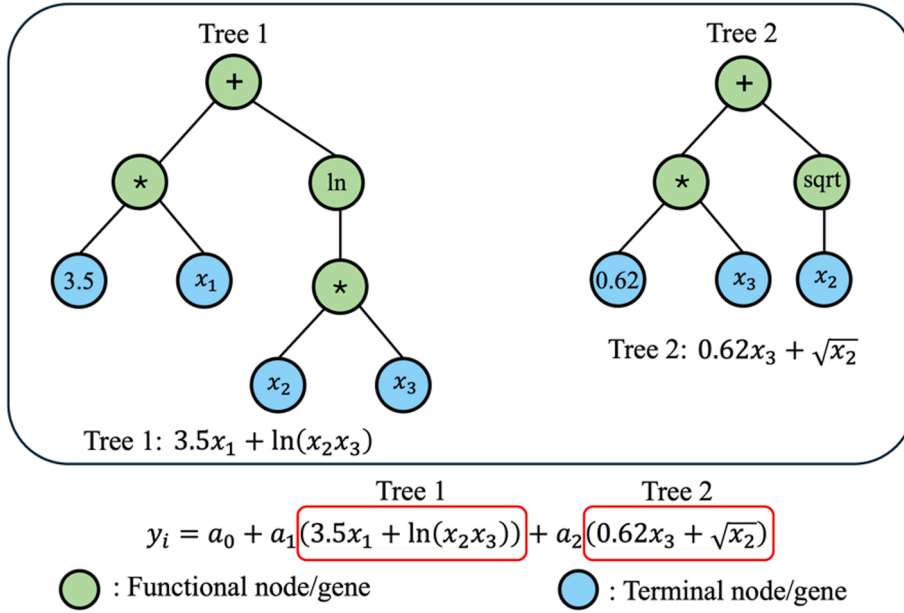


Fig. 2. The structure of the tree in SR-GP.

genes have branches with child arguments, and in our study, include operations such as addition, subtraction, multiplication, division, and other mathematical operations. Terminal nodes/genes contain input data, such as constants or variables, and do not have branches. An individual with two trees is shown in Fig. 2. The relationship between the trees is linear, but each tree can represent any non-linear relationship between variables. Thus, each individual contains multiple trees, and this approach combines the strengths of classical linear regression with the ability to capture non-linear behavior. It eliminates the need to predefine the structure of the non-linear model.

In general, as presented by Marcinkevičs and Vogt (2023) and Guayacán-Carrillo and Sulem (2024) when regressing y on features $\mathbf{x}$, a mathematical expression $g(\mathbf{x})$ could be represent a candidate solution for SR-GP, and then the optimisation problem can be written as:

$$\min_{g \in \mathcal{G}} \frac{1}{n} \sum_{i=1}^n l(g(x_i), y_i) \quad (2)$$

where $\mathcal{G}$ is a set of mathematical expressions and $l(\bullet, \bullet)$ is the fitness function.

The main steps of SR-GP algorithm are generalized as follows:

(1) Generate an initial random population

This process starts by randomly generating a population of symbolic expressions. As mentioned before, the individual for the symbolic expression in the population is represented as a tree structure composed of functional nodes (e.g., addition, subtraction, division, multiplication, natural logarithm, exponential, hyperbolic tangent) and terminal nodes (e.g., variables, constants). The trees can be customized with user-defined constraints on size and/or depth. Each individual is assigned to contain a random number of trees, ranging from 1 to G_{max} , and the depth of each tree is no larger than G_{depth} . G_{max} and G_{depth} are the parameters set by the user.

(2) Conduct a fitness test

Calculate the fitness of each individual in the population by evaluating how well the mathematical expression fits the given data points. In our SR-GP for the evolution loop, the fitness of an individual is assessed using the Root Mean Square Error (RMSE) between the predicted values generated by that individual and the true values (Wei et al., 2023). The RMSE is defined as follows in Eq. (3):

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (f(x_i) - Y_i)^2}{N}} \quad (3)$$

where $f(x_i)$ is the predicted output of SR-GP, $Y_i (i = 1, 2, \dots, N)$ are the real experimental results, and N is the sample size.

Additionally, after the evolution loop, the performance of the models can also be statistically assessed using the coefficient of

determination (goodness of fit) R^2 , as calculated by the following Eq. (4).

$$R^2 = 1 - \frac{\sum_{i=1}^N (f(x_i) - Y_i)^2}{\sum_{i=1}^N (Y_i - \bar{Y})^2} \quad (4)$$

(3) Evolution loop

Evolution occurs over multiple generations, with each new generation of individuals formed through processes like reproduction, crossover, and mutation. Reproduction involves directly copying individuals from the current generation to the next. The percentage of individuals (p_{direct}) copied from the current generation can be set by the user. Crossover aims to create new, potentially better individuals by selecting two existing trees and randomly choosing a crossover node (functional node) to swap parts of the two trees. Mutation introduces variability by randomly altering parts of an individual's expression. This can involve changing an operation, replacing a constant, or modifying a subtree. The crossover and mutation operations are illustrated in Fig. 3.

After evolving the population over several generations, the individual with the highest fitness is typically chosen as the optimal solution to the problem. Based on the above analysis, the SR-GP algorithm can be summarized as the following:

Algorithm 1: Symbolic Regression with Genetic Programming (SR-GP) Algorithm.

Step 0: Initialization.

Set the parameter value of population size pop_{size} ;
 Set the parameter value of the maximum number of generations num_{gen} ;
 Set the parameter value of the maximum number of genes G_{max} per individuals;
 Set the parameter value of the maximum depth G_{depth} for the trees;
 Set the percentage value for crossover p_{cross} , mutation p_{mutate} and direct copying p_{direct} (the sum of p_{cross} , p_{mutate} and p_{direct} must equal 1).

Step 1: Generate an initial random population.

Generate an initial population of random individuals (mathematical expressions).

Step 2: Evaluation.

Using Eq. (3), calculate the fitness of each individual and select the best one in the population.

Step 3: Evolution loop.

For $g = 1$ to num_{gen}
 For $i = 1$ to pop_{size}
 Randomly generate a number r_i between 0 and 1;
 If $0 \leq r_i < p_{cross}$
 Conduct the crossover operation to generate a new individual;
 elseif $p_{cross} \leq r_i < p_{cross} + p_{mutate}$
 Conduct the mutation operation to generate a new individual;
 elseif $p_{cross} + p_{mutate} \leq r_i \leq 1$
 Conduct the reproduction operation to generate a new individual;
 Using Eq. (3), calculate the fitness of the new individual;
 Find the best individual in the population of generation g ;

Step 4: Output.

Return the mathematical expression of the best individual and its corresponding fitness.

In our study, each braking behavior parameter, such as initial braking speed, final braking speed, braking pressure, braking time, and braking energy dissipation, can be regarded as a terminal node/gene. Using the brake wear PM emission data from Section 2.1 as input, the outputs of the SR-GP algorithm is the formula that describe the relationships between braking behavior parameters and its corresponding brake wear PM emissions. These formulas are regarded as the BWE model, which can be applied in the subsequent LEDB training evaluation, in order to estimate brake wear PM emissions from different time-dependent driving behaviors.

2.3. Implementation and evaluation of the LEDB training

Since the WLTP-Brake cycle assesses emissions data based on a light-duty vehicle (Ford Focus), only drivers of light-duty vehicles were invited to participate in our LEDB training to maintain consistency with the WLTP-Brake cycle. The LEDB training consists of two phases: pre-driving and while driving. The pre-driving phase offers advice on low-emission driving behavior and raises environmental awareness through training videos.¹ While driving, the mobile application for LEDB was developed and used to assist drivers throughout their journeys by providing real-time recommendations without interrupting their driving. This mobile application employs a modular approach, allowing for independent development and interaction of components to enhance the driver experience, and is available on both Android and IOS operating systems. As illustrated in Fig. 4, this application consists of three modules: 1) a data collection module, where data is gathered directly from OBD dongles connected to the smartphone via Bluetooth; 2) a scoring module that evaluates driving behavior in real-time; and 3) a recommendation module that provides real-time feedback to help drivers reduce

¹ Driving Tips, <https://modales-project.eu/driving-tips-en/>.

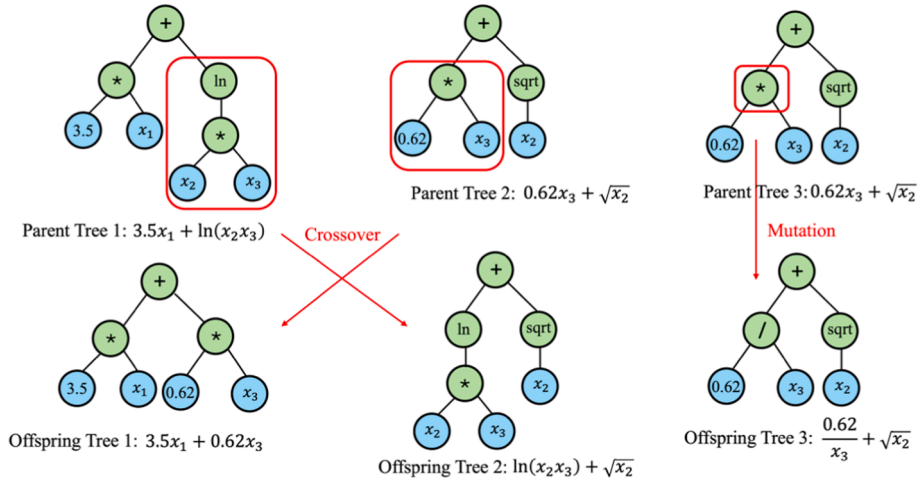


Fig. 3. The genetic operations in SR-GP.

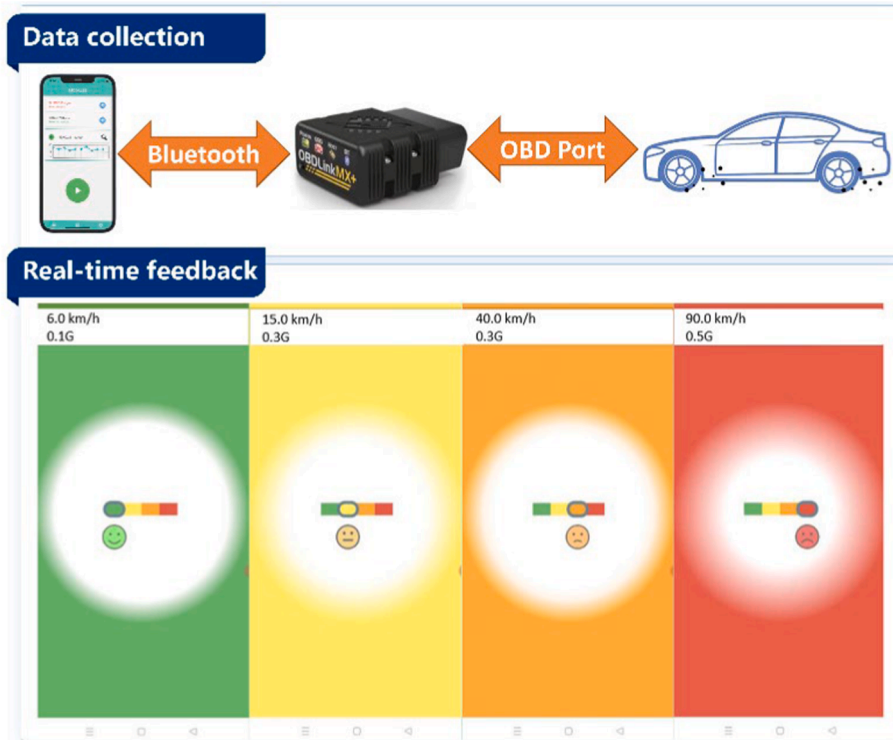


Fig. 4. Schematic diagrams of the data collection and recommendation modules.

emissions. Further details on the mobile application for LEDB can be found in Deliverable 5.3 of our MODALES project.²

The OBD system recorded vehicle speed and longitudinal deceleration during each braking event. To align these measurements with the parameters required in the WLTP-Brake cycle, we performed the following conversions.

The initial speed at the onset of braking was taken directly as v_1 , while the final speed at the end of braking was recorded as v_2 . Braking time t was obtained from the duration between the start and end points of each braking event. Since OBD data does not directly provide brake pressure, we followed the vehicle dynamics-based approach reported in Shi et al. (2021). Specifically, OBD data provided the vehicle's deceleration. Combining vehicle deceleration with vehicle mass and relevant resistance parameters in the literature

² Modales, <https://modales-project.eu/>.

(rolling resistance and aerodynamic drag), the net braking force can be calculated. The braking pressure is then calculated by Eq. (5).

$$p = \frac{ma + F_{res}}{k\mu} \quad (5)$$

where m is vehicle mass, a is the vehicle deceleration, F_{res} is the longitudinal resistance force, k is the brake system transmission coefficient, and μ is the brake lining friction coefficient.

Through this integration, OBD-derived deceleration serves as input to reconstruct braking pressure p , which is then applied to the brake wear model. These procedures enabled us to map OBD-derived variables (v_1 , v_2 , t , and p) into the WLTP-Brake cycle framework and estimate brake-wear PM emissions based on real-world driving behavior.

A total of 59 volunteer drivers were recruited from Leeds in the UK and Helsinki in Finland. In Leeds, 33 volunteer drivers participated, while Helsinki had 26 drivers. The gender distribution was consistent across both cities, with 73 % of the participants being male and 27 % female. The data collection in Leeds and Helsinki, from July 2022 to January 2023, was divided into two phases. During the first four months (before training), the drivers involved continued their regular driving behavior without the LEDB training. In contrast, during the last three months (after training), the drivers involved adopted the LEDB training and used its corresponding mobile application, which offered real-time feedback and recommendations to modify their driving behavior. The driving data during before and after training for each user was transmitted to a server and handled anonymously, fully adhering to the General Data Protection Regulation (GDPR). We selected the trips by matching journeys with the same distance and similar travel times before and after training, ensuring that traffic conditions on the same route are nearly identical. This minimizes the influence of external factors, allowing us to focus on the impact of LEDB on brake wear PM emissions. The extracted data was used as input for the BWE model to evaluate the impact of the LEDB on brake wear $PM_{2.5}$ and PM_{10} emissions.

3. Results and discussion

The results of the SR-GP algorithm, which are regarded as the BWE model, are analyzed and discussed in Section 3.1. Based on the BWE model, the LEDB training designed to reduce brake-induced wear emissions is evaluated, and the details of the corresponding empirical case studies are presented in Section 3.2. Policy implications are discussed in Section 3.3.

3.1. BWE model

For the brake wear $PM_{2.5}$ and PM_{10} emissions data, given the relatively smaller $PM_{2.5}$ and PM_{10} values from individual braking events, we applied a logarithmic transformation, e.g., $\ln(PM_{2.5})$, to transform the data with the aim of better capturing the variations. Here, to avoid duplication of descriptions, we use the brake wear $PM_{2.5}$ as an example for more detailed analysis. The SR-GP algorithm (Algorithm 1) was used to determine the relationship between the logarithm of brake wear $PM_{2.5}$ emissions, $\ln(PM_{2.5})$, and braking behavior parameters, including vehicle initial braking speed (v_1), vehicle final braking speed (v_2), braking pressure (p), braking time (t), and energy dissipation when braking (E) (Woo et al., 2021). To prevent overfitting, 80 % of the data were randomly allocated to the training set, while the remaining 20 % were assigned to the test set (Cao et al., 2024). The parameters for the SR-GP algorithm are set as shown in Table 2.

Fig. 5 shows the changes in objective function values over 3000 generations of iterations. The blue line illustrates the value of the best fitness individual in each generation (1000 individuals). During the initial iterations, the $\log(RMSE)$ value of the best individual decreases rapidly, followed by further improvements around the 500th and 1250th generations, and then it stabilizes. Overall, as iterations proceed, the $\log(RMSE)$ value of the best individual gradually decreases with the increase in generations, reflecting the evolutionary nature of biological populations. The red line shows the average $RMSE$ value of the population at each generation. From it, we can observe that the average $RMSE$ value of each generation fluctuates as the number of iterations increases, indicating that the algorithm attempts to escape local optima and search for a globally optimal solution.

From the results of the SR-GP algorithm, the optimal relationship formula found between the $\ln(PM_{2.5})$ and braking parameters are shown in the following Eq. (5):

$$\ln PM_{2.5} = 33p^{0.437pv_1} - \frac{279}{v_1 + 7.94} + 4.04 \quad (5)$$

where p is the braking pressure with $p \in [0.14, 0.54]$ and v_1 is the initial vehicle braking speed with $v_1 \in [0, 132.49]$.

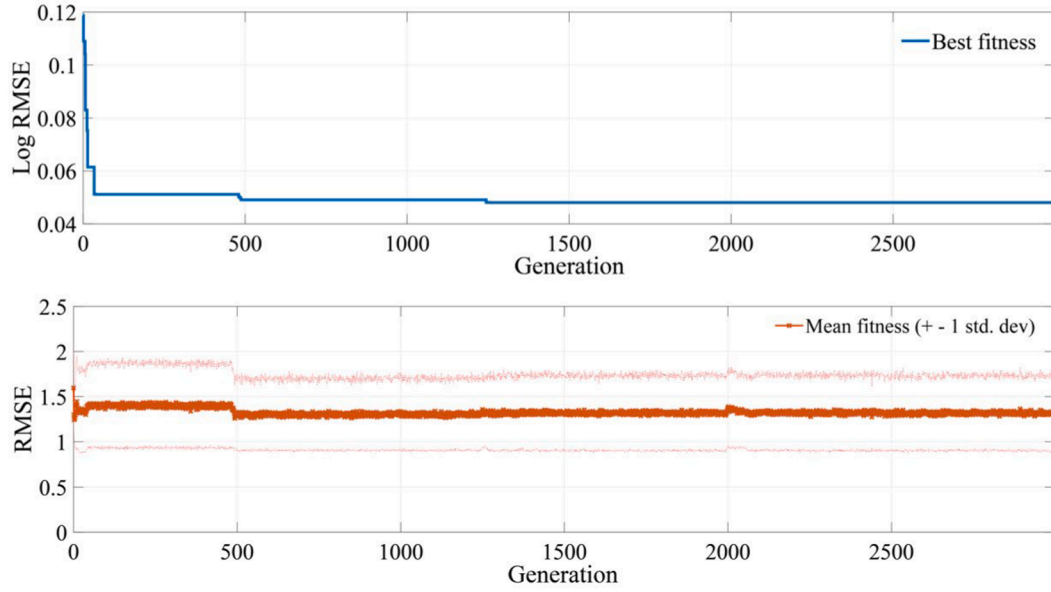
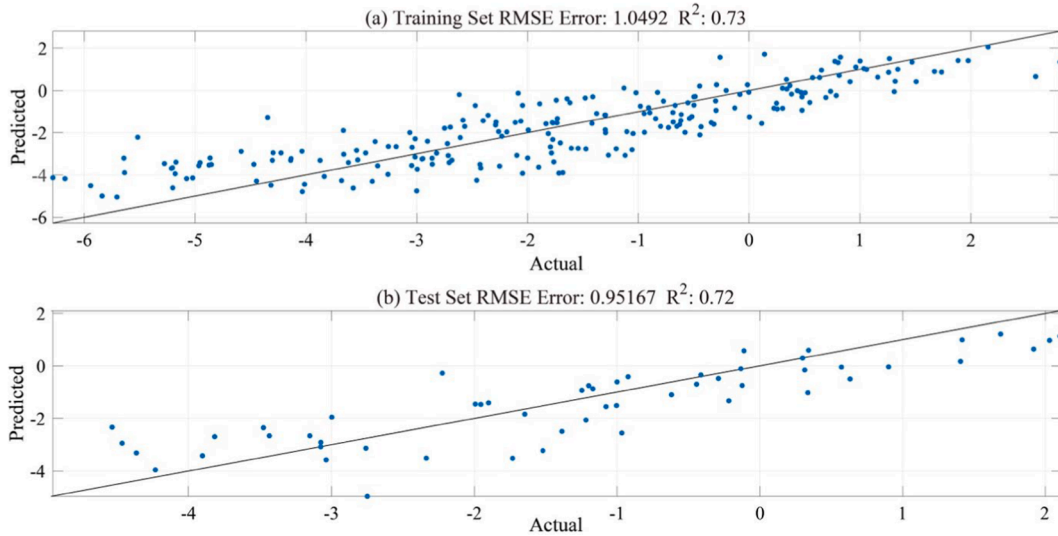
To evaluate the performance of the derived expression, the $RMSE$ and coefficient of determination (R^2) were calculated for both the training and test sets. The obtained results are shown in Fig. 6. The comparison shows that the values of $RMSE$ and R^2 both in the training and test sets are roughly the same, which is indicative of the fact that we have avoided overfitting. In addition, the R^2 values are greater than 0.72 both in the training and test sets, indicating that the mathematical expression obtained through the SR-GP algorithm performs well.

From Eq. (4), it is observed that higher braking pressure ($p > e^{-1} \approx 0.368$) and higher initial braking speed ($v_1 > 0$) are positively correlated with the brake wear $PM_{2.5}$ emissions. In the current study, the braking pressure (p) can be considered as the braking intensity. When the initial braking speed is constant, greater braking pressure (which corresponds to a greater braking acceleration rate) results in higher $PM_{2.5}$ emissions. Similarly, for a constant braking intensity (p), a higher initial braking speed leads to increased $PM_{2.5}$ emissions. Therefore, it can be concluded that aggressive driving behaviors, characterized by greater braking intensity and higher

Table 2

The parameter values for the SR-GP algorithm.

pop_size	num_gen	G_{max}	G_{depth}	P_{cross}	P_{mutate}	P_{direct}
1000	3000	2	3	0.8	0.12	0.08

**Fig. 5.** The convergence of the SR-GP for $\ln PM_{2.5}$.**Fig. 6.** The RMSE and R^2 of training and test sets for $\ln PM_{2.5}$.

initial braking speed lead to increased brake wear $PM_{2.5}$ emissions.

In parallel, the SR-GP algorithm was employed to derive the formula between $\ln(PM_{10})$ and braking parameters, with the result presented in Eq. (6). From this, it can be observed that a similar functional form was obtained, indicating that the brake wear $\ln(PM_{10})$ emissions are correlated with p and v_1 .

$$\ln PM_{10} = 25.4p^{0.5pv_1} - 80(0.437v_1)^{\frac{1}{v_1}} + 85.4 \quad (6)$$

where p is the braking pressure with $p \in [0.14, 0.54]$ and v_1 is the initial vehicle braking speed with $v_1 \in [0, 132.49]$.

The results of the SR-GP algorithm, Eq. (5) and Eq. (6), are regarded as the BWE model, and its performance statistics information is shown in Table 3. From this table, it is observed that RMSE and R^2 values for both the training set and test set are very similar, indicating that our BWE model is not overfitted. Additionally, all R^2 values are greater or equal to 0.7 indicate that the brake-induced wear emissions ($PM_{2.5}$ and PM_{10}) have a strong correlation with braking intensity and initial braking speed.

To further evaluate the effectiveness of our BWE model, we compared it with linear regression and nonlinear regression (exponential form). Table 4 shows the specific fitting equation results and the coefficient of determination R^2 for each method.

From Table 4, the main factors affecting brake wear $PM_{2.5}$ and PM_{10} emissions in brake operation parameters can be seen as initial braking speed (v_1) and braking pressure (p), and their impact on emissions is nonlinear. The developed BWE model yields a high R^2 values indicating the best-fitting performance among the methods. Specifically, by combining different input variables, we found that the R^2 value for linear regression ranges between 0.44 and 0.56, which means a relatively weak linear correlation between brake-induced emissions and driving behaviors.

Our results show that braking pressure (brake intensity) has a positive correlation with PM emissions, which is consistent with the findings of many previous studies (Beji et al., 2020; Hesse et al., 2019), i.e., stronger braking behaviors lead to higher generation of PM emissions. It is also noted that our study focuses on the impacts of drivers' behavioral characteristics (e.g., braking speed, intensity) rather than the impacts of the external environment such as temperature (Jiang and Li, 2016; Woo et al., 2021). This is because in most vehicle designs, drivers are unable to monitor the real-time temperature of the brake discs and pads during braking. Such calibrated behavioral characteristics will provide better direct information for controlling and optimizing braking maneuvers for large-scale implementations (e.g., drivers' training, automated braking). In addition, while existing studies (Woo et al., 2021; zum Hagen et al., 2019) mainly focus on calibrating parameters assuming a given formula (e.g., exponential form), the developed SR-GP in our study can optimize and calibrate both the symbolic formulas and parameters, this allowing us to reveal better relationships between the variables (e.g., linear, non-linear or mixed).

In addition, similar to the studies by Woo et al. (2021); zum Hagen et al. (2019), only a single vehicle model (the Ford focus) was used to obtain the experimental data for the WLTP-brake cycle in this study. Given the wide variety and continuous evolution of vehicles on the market, it is impractical to test every model. To maintain consistency, efforts were made to select light vehicles similar to the experimental model when conducting LEDB training. Future research could consider a broader range of vehicle types, prioritizing those with higher market share, to enhance the generalizability of the results.

3.2. Impact of LEDB on brake wear PM emissions

In this Section, box plots were employed to compare brake wear $PM_{2.5}$ and PM_{10} emissions before and after LEDB training in Leeds and Helsinki, as they effectively display data distributions and simplify comparisons.

Fig. 7 illustrates overall and individual brake wear $PM_{2.5}$ and PM_{10} emissions before and after LEDB training in Leeds and Helsinki. It can be seen that adopting LEDB has a significant positive impact on reducing brake wear emissions. The overall results showed that the mean values of brake wear $PM_{2.5}$ emissions decreased from 4.13 to 3.19 mg/stop after LEDB training, a reduction of 22.8 %. Similarly, brake wear PM_{10} emissions dropped from 9.37 to 6.92 mg/stop, a reduction of 26.1 %. Specifically, in Leeds, the mean values of brake wear $PM_{2.5}$ and PM_{10} emissions decreased from 4.79 to 3.74 mg/stop and from 10.12 to 7.56 mg/stop after the LEDB training, corresponding to reduction rates of 21.9 % and 25.3 %, respectively. In Helsinki, the LEDB resulted in reductions of 25.1 % for brake wear $PM_{2.5}$ and 27.8 % for brake wear PM_{10} emissions. While both cities experienced reductions in brake wear $PM_{2.5}$ and PM_{10} emissions following the LEDB training, Leeds had higher $PM_{2.5}$ and PM_{10} emissions than Helsinki, both before and after the training. This difference is likely attributed to the fact that Leeds, with its hilly terrain featuring a greater number of uphill and downhill sections, requires more intense braking, leading to higher brake wear $PM_{2.5}$ and PM_{10} emissions compared to the relatively flat landscape in Helsinki.³

Furthermore, to validate the reliability of the proposed method, we conducted an additional evaluation of the average emission factors per kilometer before LEDB training in both Leeds and Helsinki, and compared these values with those reported in the literature, as summarized in Table 5. These literature-reported EFs were obtained using various methodologies, including receptor modelling, roadside monitoring, and brake dynamometer tests. Across these studies, brake wear PM_{10} EFs ranged from approximately 1 to 27 mg km⁻¹ veh⁻¹, while $PM_{2.5}$ EFs reached up to 5 mg km⁻¹ veh⁻¹, depending on the measurement technique and study location. However, most values were concentrated in a narrower range, typically between 5 and 9 mg km⁻¹ veh⁻¹ for PM_{10} and 2 to 4 mg km⁻¹ veh⁻¹ for $PM_{2.5}$. The average emission factors obtained in this study, which are 7.64 and 7.05 mg km⁻¹ veh⁻¹ for PM_{10} , and 2.74 and 2.43 mg km⁻¹ veh⁻¹ for $PM_{2.5}$ in Leeds and Helsinki, respectively, fall within these representative ranges. The agreement with previously reported values confirms the robustness and validity of our approach.

In addition, since the emission factor only reflects the cumulative PM emissions per kilometer traveled, we aim to achieve a more precise evaluation of individual braking behaviors. Therefore, we continue to use the metric of milligrams per stop (mg/stop) for our analysis.

³ Topographic map, <https://en-us.topographic-map.com/map-vblv51/Helsinki/>.

Table 3

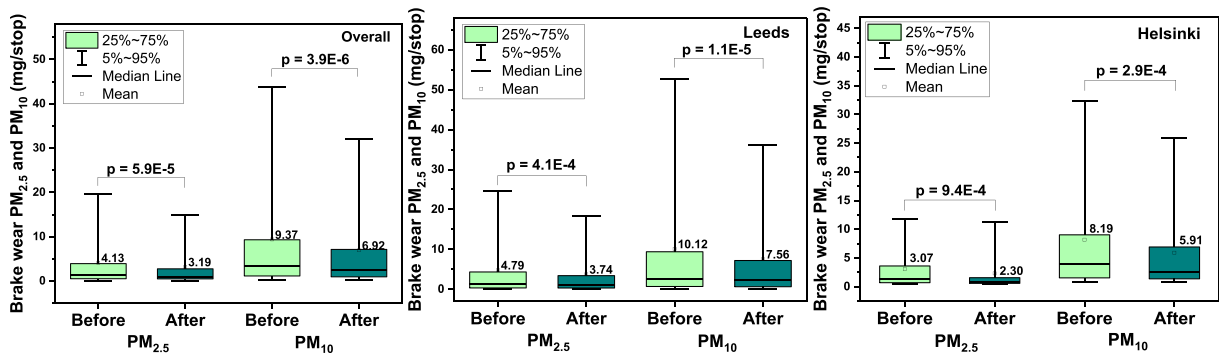
The performance statistics information about the BWE model.

Brake-induced wear emission	Training		Test	
	RMSE	R^2	RMSE	R^2
PM _{2.5}	1.05	0.73	0.95	0.72
PM ₁₀	1.06	0.70	0.99	0.70

Table 4

Statistical information on the results of different methods.

Methods	Input variables x	R^2	Formular	R^2	Formular
Linear regression* $y = a_0 + a_1 \bullet x_1 + a_2 \bullet x_2 + \dots$	v_1, p	0.44	$a_0 = -1.2513$ $a_1 = 0.0575$ $a_2 = -1.3719$	0.52	$a_0 = -2.8936$ $a_1 = 0.1277$ $a_2 = -1.6273$
	v_1, v_2, t, p	0.47	$a_0 = -1.0191$ $a_1 = 0.0722$ $a_2 = -0.0182$ $a_3 = 0.0551$ $a_4 = -4.7276$	0.51	$a_0 = -1.4235$ $a_1 = 0.1976$ $a_2 = -0.0807$ $a_3 = -0.0317$ $a_4 = -12.6149$
	E	0.45	$a_0 = -0.1300$ $a_1 = 0.0007$	0.56	$a_0 = -0.1744$ $a_1 = 0.0017$
	E, v_1	0.51	$a_0 = -1.0356$ $a_1 = 0.0004$ $a_2 = 0.0307$	0.53	$a_0 = -2.0329$ $a_1 = 0.0011$ $a_2 = 0.0629$
			$a_0 = 8.2 \times 10^{-6}$ $a_1 = 1.4829$	0.60	$a_0 = 4.1 \times 10^{-5}$ $a_1 = 1.4061$
Non-linear regression* $y = a_0 \bullet x_1^{a_1}$	E	0.55	$a_0 = 6.4 \times 10^{-6}$ $a_1 = 0.1965$ $a_2 = 12.6494$	0.70	$a_0 = 3.3 \times 10^{-5}$ $a_1 = 0.2738$ $a_2 = 7.9939$
	E, v_1	0.63			
Our method: SR-GP** $y = a_0 + a_1 \bullet T_1 + a_2 \bullet T_2 + \dots$	v_1, v_2, t, p, E	0.72	Eq. (5) in the BWE model	0.70	Eq. (6) in the BWE model

* E : the dissipation energy (Woo et al., 2021).** T_j : tree $j = 1, 2, \dots$ in SR-GP; a_j : the coefficient of T_j in SR-GP.**Fig. 7.** Overall and individual brake wear PM_{2.5} and PM₁₀ emissions before and after LEDB training in both Leeds and Helsinki.

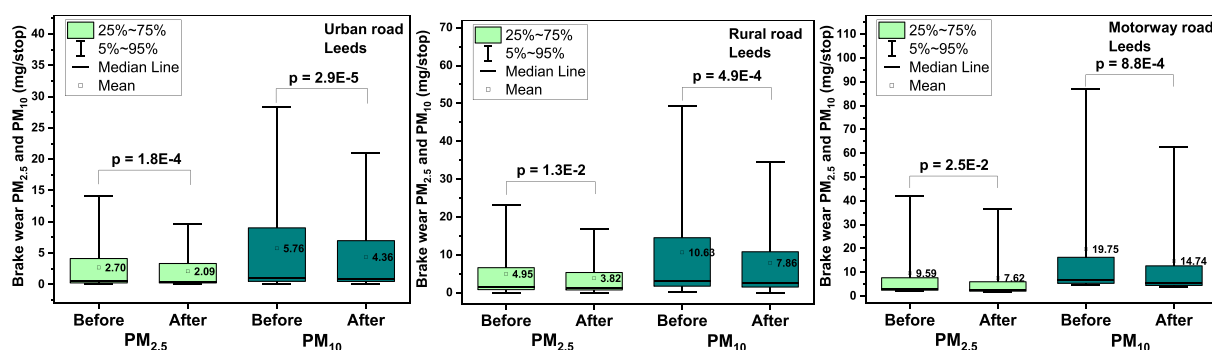
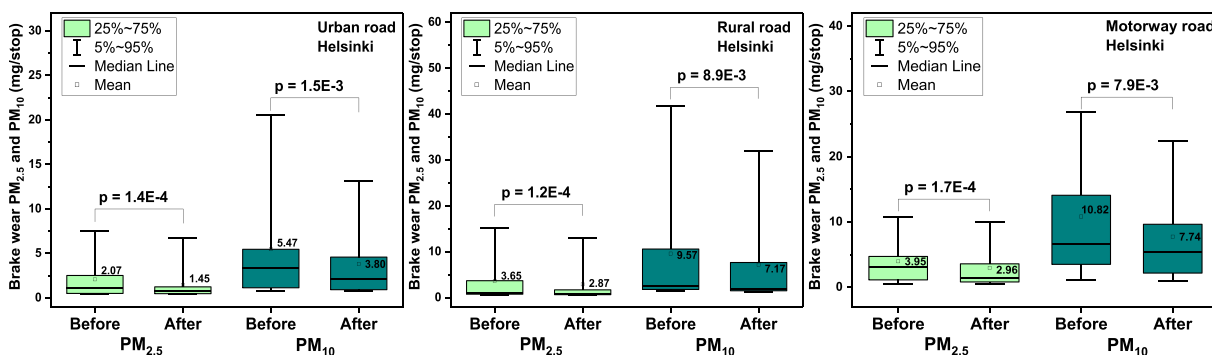
3.2.1. Various road types

Fig. 8 and 9 below demonstrate the evaluation of how road types affect brake wear PM emissions in Leeds and Helsinki respectively. Fig. 8 illustrates PM_{2.5} and PM₁₀ emissions per stop across various road types in Leeds. It is observed that the mean values of these emissions on motorway roads were the highest, followed by rural and urban roads. On urban roads, the mean values of brake wear PM_{2.5} and PM₁₀ emissions were reduced from 2.70 mg/stop and 5.76 mg/stop to 2.09 mg/stop and 4.36 mg/stop, respectively, after the implementation of the LEDB training, corresponding to reductions of 22.6 % and 24.3 % (see Fig. 10). On rural roads, the mean values decreased by 22.8 % (from 4.95 mg/stop to 3.82 mg/stop) and (from 10.63 mg/stop to 7.86 mg/stop) by 26.1 % respectively. On motorway roads, where braking occurs less frequently but at higher speeds, PM_{2.5} emissions were reduced by 20.5 % (from 9.59 mg/stop to 7.62 mg/stop), and PM₁₀ emissions decreased by 25.4 % (from 19.75 mg/stop to 14.74 mg/stop).

As shown in Fig. 9, the patterns of brake wear PM_{2.5} and PM₁₀ per stop across the road types in Helsinki mirrors that of Leeds, with brake wear generating the highest PM emissions on motorways, followed by rural and urban roads. However, compared to Leeds, Helsinki achieved even more significant reductions following the LEDB training.

Table 5Summary of the brake wear PM_{10} and $\text{PM}_{2.5}$ emission factors (EFs) ($\text{mg km}^{-1} \text{ veh}^{-1}$).

PM_{10} EFs	$\text{PM}_{2.5}$ EFs	Data source	City (Country)	Reference
7.64	2.74	Real-world road assessment	Leeds (UK)	Present work
7.05	2.43	Real-world road assessment	Helsinki (Finland)	Present work
6.2	2.47	Receptor modelling	Birmingham (UK)	Beddows and Harrison (2021)
1–18.5		Receptor modelling	Torino (Italy)	Piscitello et al. (2021)
6.72	2.61	Receptor modelling	UK	Liu et al. (2022a)
5.49	3.64	Receptor modelling	Hamburg (Germany)	Samland et al. (2024)
27 ± 4		Receptor modelling	Chengdu (China)	Chen et al. (2025)
15.1 ± 0.1		Brake dynamometer study		Neukirchen et al. (2025)
16.3 ± 0.4				
	0–5	Roadside study	Reno (USA)	Abu-Allaban et al. (2003)
2.9–7.5	1.8–2.8	Brake dynamometer study		Garg et al. (2000)
8.1		Brake dynamometer study		Sanders et al. (2003)
5.8		Brake dynamometer study		Iijima et al. (2008)
8.64	2.92	Brake dynamometer study		Woo et al. (2022)

**Fig. 8.** Brake wear PM emissions on different types of roads before and after LEDB training in Leeds.**Fig. 9.** Brake wear PM emissions on different types of roads before and after LEDB training in Helsinki.

Specifically, as shown in Fig. 10, on urban roads, mean brake wear $\text{PM}_{2.5}$ reduced by 30.0 %, from 2.07 mg/stop to 1.45 mg/stop, while PM_{10} dropped by 30.5 %, from 5.47 mg/stop to 3.80 mg/stop. Rural roads also experienced marked reductions, with brake wear $\text{PM}_{2.5}$ decreasing by 21.4 % (from 3.65 mg/stop to 2.87 mg/stop) and PM_{10} by 25.1 % (from 9.57 mg/stop to 7.17 mg/stop). Motorways showed a 25.1 % reduction in $\text{PM}_{2.5}$ from 3.95 mg/stop to 2.96 mg/stop and a 28.5 % reduction in PM_{10} from 10.82 mg/stop to 7.74 mg/stop.

From the results presented, it is evident that all three road types exhibited significant reductions in brake-induced $\text{PM}_{2.5}$ and PM_{10} emissions after the LEDB training. This demonstrates the potential of LEDB initiatives to reduce non-exhaust emissions on road transport, such as brake wear PM emissions, without the need for extensive technological upgrades. In both cities, there were the highest brake wear $\text{PM}_{2.5}$ and PM_{10} emissions per stop on motorway roads compared to urban and rural roads, reflecting the higher average driving speeds on motorways compared to urban and rural roads. Higher initial braking speeds on motorways necessitate more intense braking when required, leading to increased brake wear PM emissions per stop (Mathissen et al., 2018).

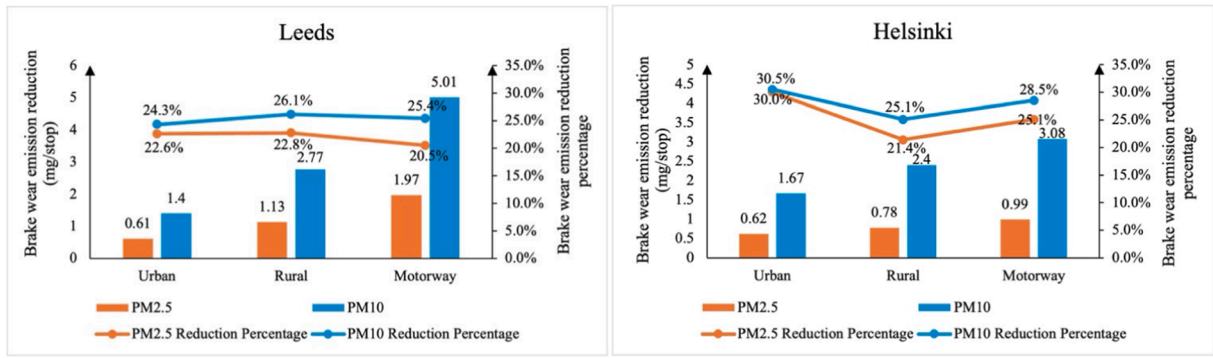


Fig. 10. The reduction in mean brake wear PM emissions across different road types after the LEDB training.

Furthermore, prioritizing LEDB training on urban roads is advantageous. While our results showed that the absolute reduction in brake wear emissions per braking event was highest on motorways, the percentage reductions were generally greater on urban roads. Moreover, Hicks et al. (2023) found that, when ranked by emission factors, urban roads had the highest emissions per kilometer, followed by rural roads and motorways. The emission factor represents the cumulative amount of PM emissions per kilometer travelled. Although urban roads generate lower PM emissions per braking event, the high frequency of braking due to traffic signals and congestion results in greater overall emissions per kilometer. In contrast, motorways, with more intense but less frequent braking, show lower total emissions per kilometer. Consequently, implementing LEDB training on urban roads offers greater potential for reducing brake wear PM emissions.

In addition, as shown in Fig. 10, motorways exhibit the highest reduction in brake wear PM emissions per stop, followed by rural roads, with urban roads showing the lowest reduction after the LEDB training in both cities. However, the percentage reduction demonstrates a different trend across these road types. In most cases (PM_{2.5} in Leeds, and both PM_{2.5} and PM₁₀ in Helsinki), the percentage reduction on motorways is lower than that on urban roads after the LEDB training. This suggests that while motorways have higher brake emissions per stop, the scope for reducing emissions through LEDB is relatively limited due to constraints on adopting higher speeds. In contrast, urban roads, with their lower average speeds, can achieve a higher percentage reduction in brake wear PM emissions after LEDB training, offering greater potential for emission reduction.

3.2.2. Driver gender

Fig. 11 and 12 illustrate the evaluation of how driver gender affects brake wear PM emissions in Leeds and Helsinki respectively. As shown in Fig. 11, the mean values of brake wear PM_{2.5} and PM₁₀ emissions were noticeably higher for male drivers compared to female drivers. Specifically, in Leeds, the brake wear PM_{2.5} emissions from male drivers were 1.52 times than those of female drivers before the LEDB training and 1.47 times afterwards. For PM₁₀ emissions in Leeds, the mean values for male drivers remained 1.50 times those of female drivers, both before and after the LEDB training. It is worth noting that, following the LEDB training in Leeds, male drivers experienced a larger reduction in brake wear PM_{2.5} and PM₁₀ emissions compared to female drivers. The mean values of PM_{2.5} emissions decreased by 22.6 % for male drivers and 19.9 % for female drivers. In terms of PM₁₀ emissions, the mean value for male drivers dropped by 2.80 mg/stop, while that for female drivers dropped by only 1.87 mg/stop (as shown in Fig. 13).

Fig. 12 shows the brake wear PM_{2.5} and PM₁₀ emissions for female and male drivers in Helsinki, before and after the LEDB training. A similar finding was observed for brake wear PM_{2.5} emissions, where mean values for male drivers were 1.27 and 1.25 times those of female drivers before and after the LEDB training. The average PM₁₀ emissions for male drivers were 1.24 times those of female drivers before the LEDB training, slightly decreasing to 1.23 times after the LEDB training. Additionally, both female and male drivers experienced notable reductions in brake wear PM_{2.5} and PM₁₀ emissions following the LEDB training. Female drivers reduced the brake wear PM_{2.5} and PM₁₀ emissions by 24.8 % and 27.2 %, respectively, while male drivers achieved slightly greater reductions of 25.1 % for PM_{2.5} and 28.0 % for PM₁₀ (as shown in Fig. 13).

The results from both cities indicate that LEDB training leads to substantial reductions in brake wear PM emissions for both male and female drivers. The brake wear PM emissions for male drivers were higher than those for female drivers, both before and after the LEDB training, which is likely because male drivers tend to exhibit more aggressive driving behaviors, such as harder braking and higher vehicle speeds, compared to female drivers. This is consistent with findings from other researchers. For example, Warshawsky-Livne and Shinar (2002) highlighted that men tend to drive more aggressively than women. Similarly, Shinar and Compton (2004) found that men are nearly twice as likely to engage in aggressive driving behavior. Lyu et al. (2018) revealed that male drivers generally have higher average speeds than female counterparts. This results in higher initial braking speeds and consequently generates more brake wear PM emissions.

Additionally, as shown in Fig. 13, although male drivers had a higher absolute reduction in brake wear PM emissions after LEDB training, the reduction percentage was nearly the same as for female drivers. This suggests that LEDB training has a similar impact on reducing brake wear PM emissions, in terms of percentage, for both male and female drivers.

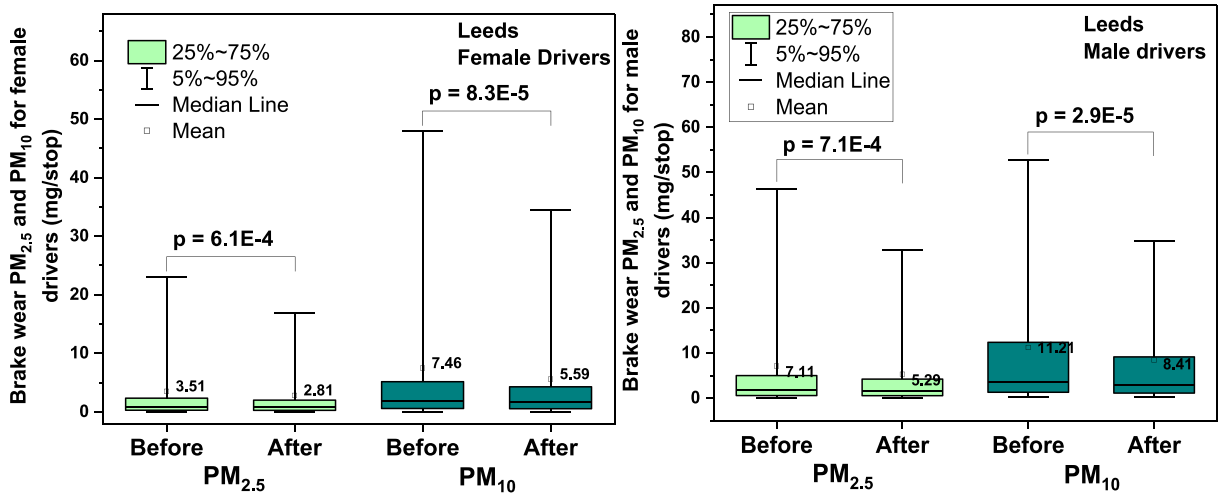


Fig. 11. Effect of driver gender on brake wear PM emissions before and after LEDB training in Leeds.

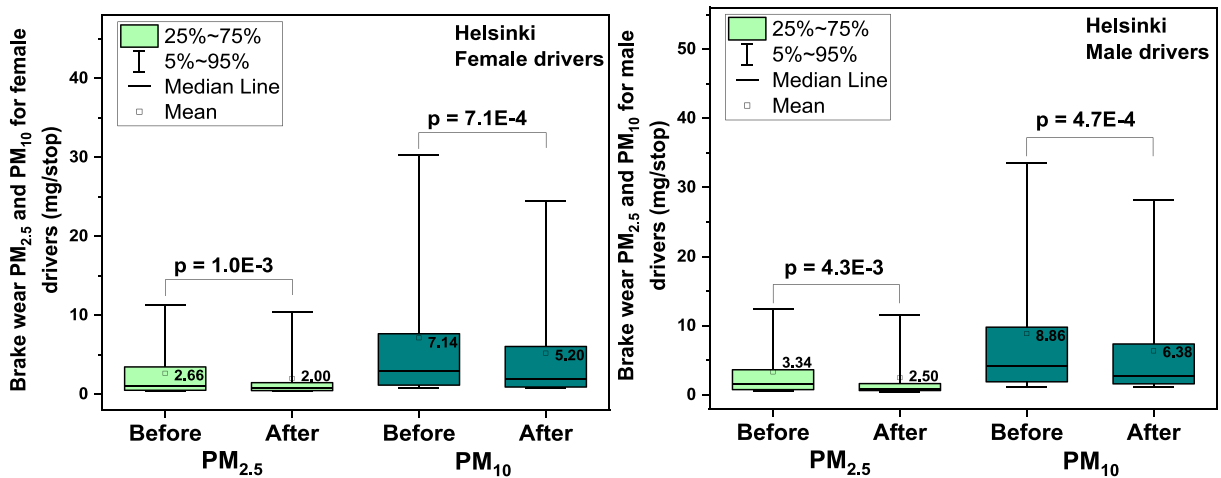


Fig. 12. Effect of driver gender on brake wear emissions before and after LEDB training in Helsinki.

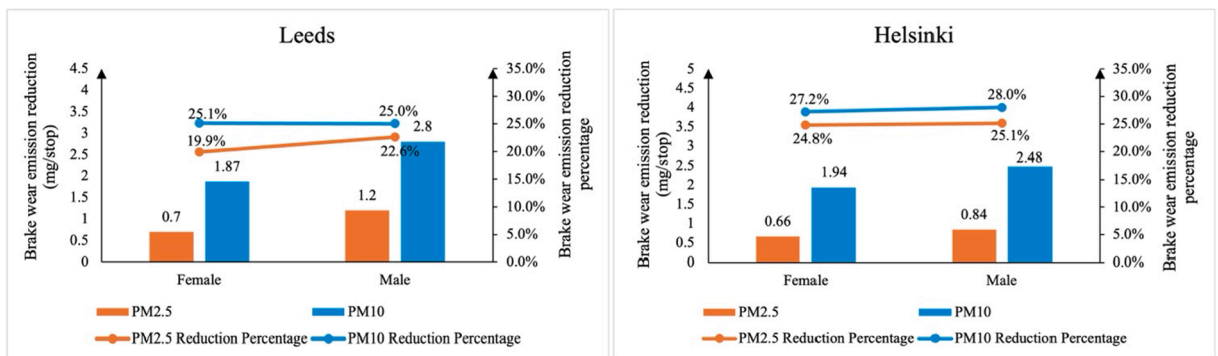


Fig. 13. The reduction in the mean value of brake wear PM emissions for driver gender after the LEDB training.

3.2.3. Driver experience

Fig. 14 and 15 illustrate the evaluation of how driver experience influences brake wear PM emissions in Leeds and Helsinki respectively. In this study, drivers with at least five years of experience were defined as experienced, while those with less were

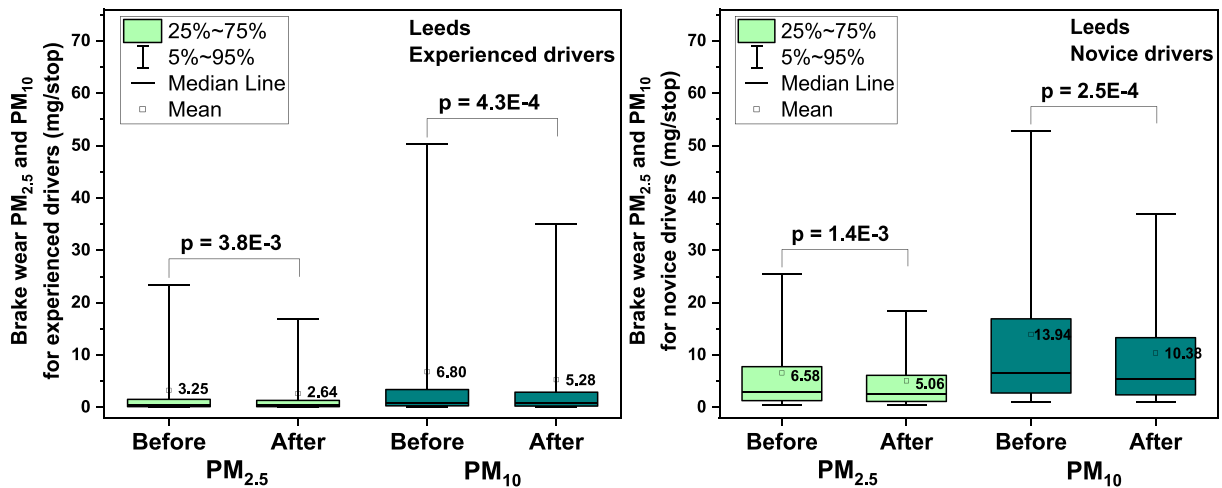


Fig. 14. Effect of driving experience on brake wear PM emissions before and after the LEDB training in Leeds.

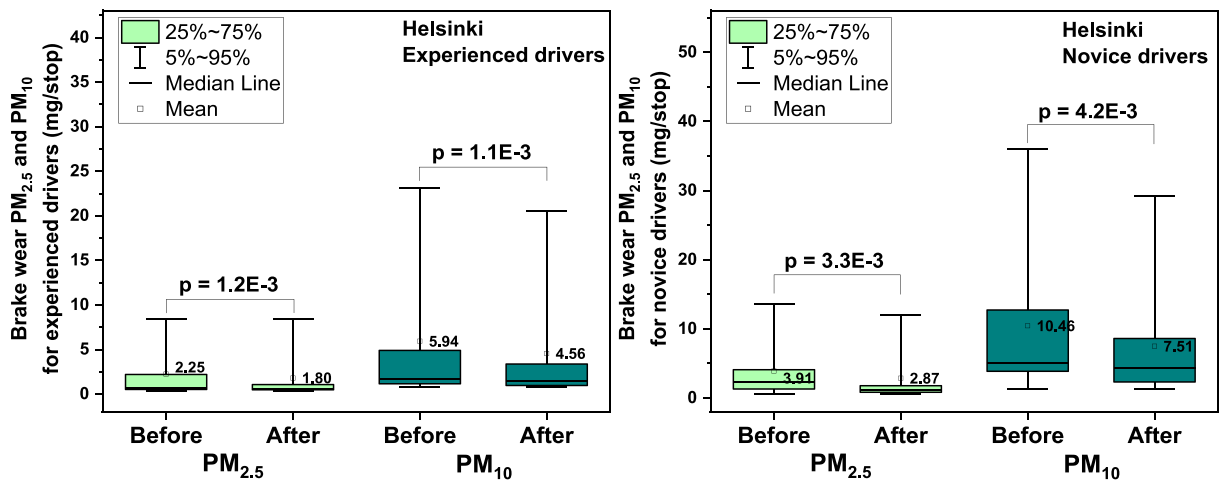


Fig. 15. Effect of driving experience on brake wear PM emissions before and after the LEDB training in Helsinki.

classified as novices. Fig. 14 shows brake wear PM_{2.5} and PM₁₀ emissions for both experienced and novice drivers in Leeds, before and after the LEDB training. It is evident that the average values of brake wear PM emissions for novice drivers were significantly higher, with PM_{2.5} levels being 2.02 and 1.92 times those of experienced drivers before and after the training, respectively. Similarly, for PM₁₀, these differences were also pronounced, with emissions being 2.05 and 1.97 times those of experienced drivers. However, compared to experienced drivers, the LEDB training proved to be more effective for novice drivers, with brake wear PM_{2.5} and PM₁₀ emissions reducing by 23.1 % and 25.5 %, respectively, whereas experienced drivers showed smaller reductions of 18.8 % for PM_{2.5} and 22.4 % for PM₁₀ (as shown in Fig. 16).

Fig. 15 illustrates the impact of driving experience on brake wear PM_{2.5} and PM₁₀ emissions in Helsinki, before and after the LEDB training. Similar to the previous observations for the Leeds results, novice drivers consistently exhibited higher brake wear PM emission levels compared to experienced drivers. Before the LEDB training, the average brake wear PM_{2.5} and PM₁₀ emissions associated with novice drivers were 1.74 and 1.76 times those of experienced drivers, respectively. Following the training, the ratios were 1.59 for PM_{2.5} and 1.65 for PM₁₀. In Helsinki, novice drivers also demonstrated a more marked improvement in reducing brake wear PM emissions following the LEDB training, compared to experienced peers, with decreases of 26.6 % in PM_{2.5} and 28.2 % in PM₁₀, whereas experienced drivers achieved smaller reductions of 20.0 % and 23.2 % for PM_{2.5} and PM₁₀ emissions, respectively (as shown in Fig. 16).

Results from both cities indicate that, despite both novice and experienced drivers achieving reductions in brake wear PM emissions following the LEDB training, novice drivers still exhibited substantially higher overall brake wear emissions compared to experienced counterparts. This disparity is mainly due to novice drivers' tendency for frequent abrupt braking, caused by undeveloped driving skills, as well as their inconsistent driving behavior (Huang et al., 2021; Shinar and Compton, 2004), both of which result in higher brake wear PM emissions. Experienced drivers, on the other hand, possess better peripheral perception abilities (Garay-Vega et al.,

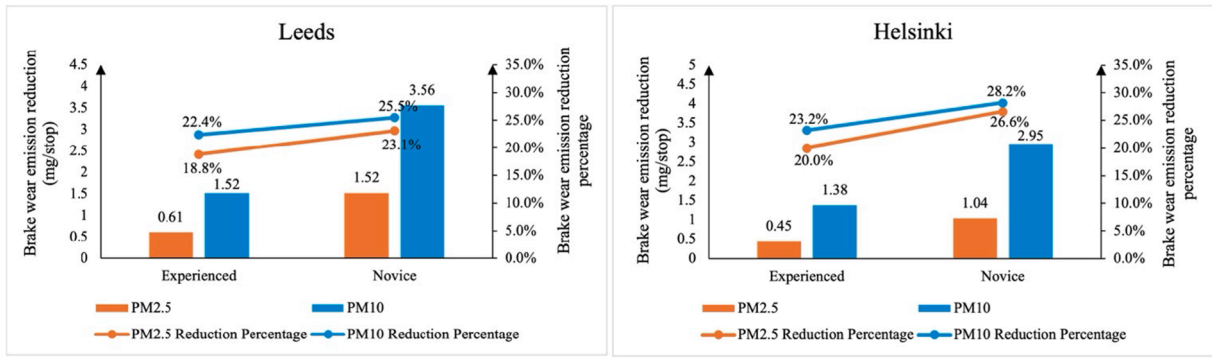


Fig. 16. The reduction in the mean value of brake wear PM emissions for driver experience level after the LEDB training.

2007), enabling them to anticipate situations and brake more smoothly, thereby reducing brake wear PM emissions.

It is found from Fig. 16 that novice drivers achieved greater improvements in reducing brake wear PM emissions, both in absolute reduction and percentage reduction, following LEDB training compared to experienced drivers. This means that tailoring stricter training requirements for novice drivers and incentivizing their participation in low-emission driving programs could yield more substantial emission reductions within this group. Given more room for improvement than experienced drivers, policymakers could develop targeted interventions such as requiring additional LEDB modules in driving schools and integrating LEDB into navigation systems to encourage smoother driving habits. These measures would not only address skill gaps but also promote low-emission driving behavior, ultimately reducing vehicle emissions and improving overall air quality.

3.3. Policy promotion strategy and implications analysis for LEDB training

In this Section, we discuss strategies for promoting LEDB training and analyze the expected emission reduction effects of LEDB training across different promotion implementation scenarios.

3.3.1. Policy promotion strategy

To maximize the effectiveness of the LEDB training intervention, we propose the following promotion strategies, as illustrated in Fig. 17.

- (1) Driver licensing integration. Incorporating LEDB modules into the driving qualification/license exam. This strategy would not only steadily increase the number of LEDB training participants, but also enhance its overall effectiveness. As demonstrated in Section 3.2, novice drivers showed significantly higher reductions in brake wear PM emissions compared to experienced drivers, both in absolute and percentage terms. Policies focusing on novice drivers could therefore effectively reduce brake wear PM emissions and contribute to broader environmental improvements.
- (2) Technology integration. Embedding the BWE model within autonomous technology can further support the promotion of LEDB. While achieving widespread adoption of low-emission driving behavior among all drivers remains challenging, the increasing use of autonomous driving technology offers new possibilities for seamless integration. The model and approach presented in this paper can aid in developing low brake wear emissions for automated braking systems in emerging road transportation vehicles, including electric vehicles, autonomous vehicles, and connected vehicles (Paschalidis et al., 2023). Once autonomous driving models are trained with low brake emission parameters, software updates can be applied to enable widespread LEDB practices at scale (Zhang et al., 2024). This strategy ensures emission reductions independent of driver willingness and enhances the long-term feasibility of LEDB.
- (3) Economic incentives. Broader participation can be encouraged through mechanisms such as emissions-tax discounts or vehicle insurance subsidies for LEDB-trained drivers. Many countries and regions worldwide have implemented some taxes related to

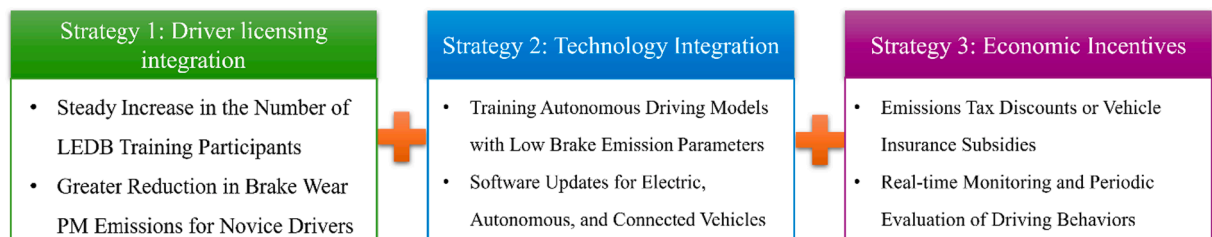


Fig. 17. Policy promotion for LEDB training.

emissions to reduce environmental impact, such as the vehicle emissions tax in the UK⁴ and the carbon tax in Canada.⁵ A similar incentive-based strategy could promote wider adoption of LEDB.

Since the benefits of LEDB training may diminish over time, linking incentives (strategy 3) to continuous driving performance would help sustain improvements. For example, driving behavior data could be monitored in real time using on-board devices or smartphone applications, while participants' driving performance could be evaluated periodically (e.g., monthly or quarterly):

- Drivers who maintain smoother, low-emission driving behaviors would qualify for continued or higher incentives in the next evaluation period.
- Drivers who revert to aggressive driving patterns would result in lower incentives or even lose their eligibility in the subsequent evaluation period.

Furthermore, large-scale real-world validation of the proposed strategies is essential. Future work will therefore integrate LEDB training with real-time monitoring and periodic evaluation of driving behavior, combined with economic incentives, to assess adoption rates and the cost-effectiveness of different incentive levels. In addition, we plan to test LEDB training across broader driver populations, vehicle types, and traffic environments. These efforts will help quantify how economic incentives can sustain participation and support long-term reductions in brake-wear emissions.

The LEDB training is designed for routine driving conditions and excludes emergency braking, focusing instead on situations where braking can be anticipated and moderated. As a result, both the frequency and intensity of brake use tend to be reduced, thereby mitigating brake wear emissions. It is important to emphasize that the LEDB training applies only to routine driving conditions, where it promotes smoother and more anticipatory driving behaviors. Emergency braking remains essential for safety and is explicitly outside the scope of behavioral modification.

Moreover, while the promotion of EVs is a cornerstone of EU transport policy and their benefits in reducing exhaust emissions and carbon emissions are well established, challenges remain in addressing non-exhaust emissions. Regenerative braking can reduce brake wear, but does not fully eliminate it (Beddows and Harrison, 2021; Tu et al., 2025). This suggests that promoting EV adoption alone will not fully resolve brake wear emission problems. Furthermore, a complete transition to EVs across the EU will require sustained policy support and substantial investment in infrastructure, fleet renewal, and raw material supply chains. Even under ambitious policy scenarios, large numbers of ICEVs and hybrid vehicles are likely to remain in operation for the foreseeable future. Against this background, LEDB training provides an immediately actionable and relatively cost-effective measure that applies to all vehicle types—ICEVs, hybrids, and EVs. Therefore, LEDB training should be considered a complementary measure alongside EV promotion, providing near-term brake wear emission reductions while supporting the long-term structural transition to electric mobility.

3.3.2. Policy implications

Based on our real-world road calculations, it is expected to reduce average brake wear PM_{2.5} emissions by 22.8 % and PM₁₀ emissions by 26.1 % through the LEDB training. To further examine the policy implications of LEDB training on brake wear PM emissions across the traffic network, we evaluated the annual reductions in brake wear PM emissions from passenger cars on UK road networks under three adoption scenarios: 30 %, 60 %, and 100 % of drivers implementing the LEDB. The evaluation of annual reductions was based on the mean reduction values for brake wear PM emissions following LEDB training, alongside data on the number of passenger cars⁶ and the driving mileage⁷ in the UK in 2023. Details on the calculation of passenger car numbers and driving mileage by vehicle age are provided in our previous work (Liu et al., 2024).

Fig. 18 illustrates the annual reductions in brake wear PM_{2.5} and PM₁₀ emissions across three scenarios. It can be obvious from these results that adopting LEDB for passenger cars can effectively reduce brake wear PM_{2.5} and PM₁₀ emissions by up to 285.8 and 920.4 tonnes per year, respectively, on UK road networks. This finding indicates that improving driving behavior provides a cost-effective means of reducing brake wear PM emissions, thereby enhancing environmental quality.

In addition, regarding policy implications, future research could investigate targeted economic incentives to promote LEDB training. For example, studies may examine which types of discounts or subsidies are most effective in encouraging participation. This would involve the design of incentive schemes that, within limited budgetary or resource constraints, maximize participation or policy impact (Ding et al., 2025).

⁴ Vehicle tax for electric and low emission vehicles. <https://www.gov.uk/guidance/vehicle-tax-for-electric-and-low-emissions-vehicles#:~:text=You%20will%20need%20to%20pay,subject%20to%20change%20for%202025>.

⁵ How carbon pricing works. <https://www.canada.ca/en/environment-climate-change/services/climate-change/pricing-pollution-how-it-will-work/putting-price-on-carbon-pollution.html>.

⁶ Vehicle licensing statistics. <https://www.gov.uk/government/statistics/vehicle-licensing-statistics-april-to-june-2023/vehicle-licensing-statistics-april-to-june-2023#:~:text=At%20the%20end%20of%20June,the%20end%20of%20June%202022>.

⁷ Road traffic estimates in Great Britain: 2023. <https://www.gov.uk/government/statistics/road-traffic-estimates-in-great-britain-2023/road-traffic-estimates-in-great-britain-2023-headline-figures>.

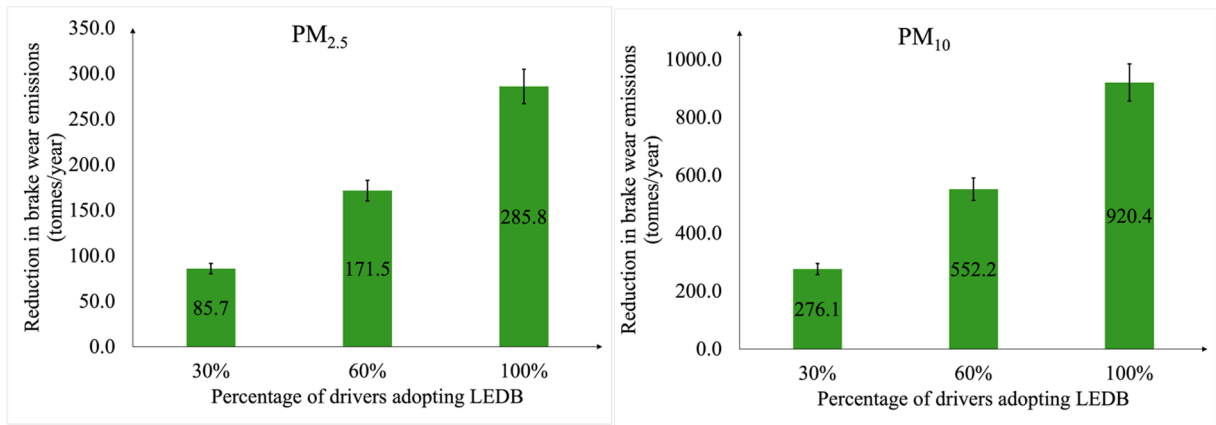


Fig. 18. Annual reductions in brake wear PM emissions across three scenarios.

4. Conclusion

This paper assesses the reduction of brake wear PM_{2.5} and PM₁₀ through the LEDB training. Using real measurement data during WLTP-Brake cycle, the BWE model is proposed by using a traceable machine learning method, the SR-GP algorithm, to estimate the brake wear PM emissions by the driving behaviors. Based on this BWE model, we implemented LEDB training for volunteer drivers in two European cities, Leeds and Helsinki, and evaluated the reduction in brake wear PM emissions through case studies from both locations. The key findings are as follows:

- The BWE model was developed by using the SR-GP algorithm, which provides an explicit and traceable formula linking brake wear PM emissions and braking pressure and initial braking speed, outperforming the existing linear regression or nonlinear regression models.
- Real-world tests conducted in Leeds and Helsinki demonstrated that improving driving behavior is an effective method to reduce brake wear PM emissions, with LEDB training resulting in a reduction of mean brake wear PM_{2.5} emissions per stop by 21.9 %–25.1 % and PM₁₀ emissions by 25.3 %–27.8 % in both cities.
- After LEDB training, there was the greatest reduction in brake wear PM emissions per stop on motorways, following by rural and urban roads.
- LEDB training resulted in a similar percentage reduction in brake wear PM emissions for both male and female drivers, despite male drivers exhibiting more aggressive driving behaviors and achieving a higher absolute reduction.
- Novice drivers achieved greater improvements in reducing brake wear PM emissions, both in absolute reduction and percentage reduction, through LEDB training compared to experienced drivers. It suggests that LEDB training is more effective in reducing emissions among novice drivers.

The above insights support targeted interventions and policy recommendations, such as integrating LEDB training into driver education and incentivizing participation through economic measures. Additionally, by incorporating LEDB training into autonomous driving systems, the approach has the potential to further mitigate non-exhaust emissions, offering a scalable, cost-effective solution to improve air quality and promote sustainable transportation practices.

CRediT authorship contribution statement

Ye Liu: Writing – original draft, Methodology, Data curation, Conceptualization. **Tangjian Wei:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Haibo Chen:** Writing – review & editing, Funding acquisition, Conceptualization. **Sijin Wu:** Software, Data curation, Conceptualization. **Yili (Kelly) Tang:** Funding acquisition, Writing - Review & Editing.. **Zhiyuan Lin:** Writing – review & editing, Visualization, Investigation. **David Watling:** Writing – review & editing, Visualization, Conceptualization. **Jingwen Yao:** Visualization, Validation. **Nansong Yue:** Writing – review & editing, Visualization, Validation. **Chenxi Wang:** Writing – review & editing, Visualization, Validation. **Dingsong Cui:** Writing – review & editing, Validation, Data curation. **Dimitris Margaritis:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

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

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Appendix A. Supplementary data

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References

- Abu-Allaban, M., Gillies, J.A., Gertler, A.W., Clayton, R., Proffitt, D., 2003. Tailpipe, resuspended road dust, and brake-wear emission factors from on-road vehicles. *Atmos. Environ.* 37 (37), 5283–5293.
- Accocella, M., Bianco, C., Tosco, T., Sethi, R., 2025. Mobility of non-exhaust brake wear dust from road traffic in saturated and unsaturated porous media mimicking subsurface environments. *J. Hazard. Mater.* 491, 137851.
- Amato, F., Cassee, F.R., Denier van der Gon, H.A.C., Gehrig, R., Gustafsson, M., Hafner, W., Harrison, R.M., Jozwicka, M., Kelly, F.J., Moreno, T., Prevot, A.S.H., Schaap, M., Sunyer, J., Querol, X., 2014. Urban air quality: the challenge of traffic non-exhaust emissions. *J. Hazard. Mater.* 275, 31–36.
- Beddows, D.C.S., Harrison, R.M., 2021. PM10 and PM2.5 emission factors for non-exhaust particles from road vehicles: dependence upon vehicle mass and implications for battery electric vehicles. *Atmos. Environ.* 244, 117886.
- Beji, A., Deboudt, K., Khaldi, S., Muresan, B., Flament, P., Fourmentin, M., Lumière, L., 2020. Non-exhaust particle emissions under various driving conditions: implications for sustainable mobility. *Transp. Res. Part D: Transp. Environ.* 81, 102290.
- Cao, W., Sun, X., Chen, X., 2024. Estimation and validation for fatigue properties of steels by symbolic regression. *Int. J. Fatigue* 186, 108416.
- Chen, J., Li, W., Zhang, H., Jiang, W., Li, W., Sui, Y., Song, X., Shibasaki, R., 2020. Mining urban sustainable performance: GPS data-based spatio-temporal analysis on on-road braking emission. *J. Clean. Prod.* 270, 122489.
- Chen, Q., Wang, A., Wang, S., Liu, H., Gong, L., Tu, R., 2025. Modeling urban brake wear particle emissions: a ride-hailing case in Chengdu, China. *Transp. Res. Part D: Transp. Environ.* 139, 104541.
- Dhital, N.B., Wang, S.-X., Lee, C.-H., Su, J., Tsai, M.-Y., Zhou, Y.-J., Yang, H.-H., 2021. Effects of driving behavior on real-world emissions of particulate matter, gaseous pollutants and particle-bound PAHs for diesel trucks. *Environ. Pollut.* 286, 117292.
- Ding, Y., Jian, S., Yu, L., 2025. How to reduce carbon emissions in the urban transportation systems through carbon markets? Balancing the monetary and environmental benefits. *Appl. Energy* 377, 124454.
- Elhenawy, M., Chen, H., Rakha, H.A., 2014. Dynamic travel time prediction using data clustering and genetic programming. *Transp. Res. Part C Emerging Technol.* 42, 82–98.
- Emami Javanmard, M., Tang, Y., Wang, Z., Tontiwachwuthikul, P., 2023. Forecast energy demand, CO2 emissions and energy resource impacts for the transportation sector. *Appl. Energy* 338, 120830.
- Feibel, T., Hesse, D., Augsburg, K., Gramstat, S., 2020. Measurement of vehicle related non-exhaust particle emissions under real driving conditions. FISITA.
- Fussell, J.C., Franklin, M., Green, D.C., Gustafsson, M., Harrison, R.M., Hicks, W., Kelly, F.J., Kishta, F., Miller, M.R., Mudway, I.S., Oroumijeh, F., Selley, L., Wang, M., Zhu, Y., 2022. A review of road traffic-derived non-exhaust particles: emissions, physicochemical characteristics, health risks, and mitigation measures. *Environ. Sci. Technol.* 56 (11), 6813–6835.
- Garay-Vega, L., Fisher, D.L., Pollatsek, A., 2007. Hazard anticipation of novice and experienced drivers: empirical evaluation on a driving simulator in daytime and nighttime conditions. *Transp. Res. Rec.* 2009 (1), 1–7.
- Garg, B.D., Cadle, S.H., Mulawa, P.A., Groblicki, P.J., Laroo, C., Parr, G.A., 2000. Brake wear particulate matter emissions. *Environ. Sci. Technol.* 34 (21), 4463–4469.
- Guayacán-Carrillo, L.-M., Sulem, J., 2024. Symbolic regression based prediction of anisotropic closure in deep tunnels. *Comput. Geotech.* 171, 106355.
- Hesse, D., Augsburg, K., Feibel, T., 2019. Real driving emissions measurement of brake dust particles, In: Pfeffer, P. (Ed.), *9th International Munich Chassis Symposium 2018*. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 663–674.
- Hicks, W., Green, D.C., Bevers, S., 2023. Quantifying the change of brake wear particulate matter emissions through powertrain electrification in passenger vehicles. *Environ. Pollut.* 336, 122400.
- Huang, Y., Ng, E.C.Y., Zhou, J.L., Surawski, N.C., Lu, X., Du, B., Forehead, H., Perez, P., Chan, E.F.C., 2021. Impact of drivers on real-driving fuel consumption and emissions performance. *Sci. Total Environ.* 798, 149297.
- Iijima, A., Sato, K., Yano, K., Kato, M., Kozawa, K., Furuta, N., 2008. Emission factor for antimony in brake abrasion dusts as one of the major atmospheric antimony sources. *Environ. Sci. Technol.* 42 (8), 2937–2942.
- Jiang, J., Li, D., 2016. Theoretical analysis and experimental confirmation of exhaust temperature control for diesel vehicle NOx emissions reduction. *Appl. Energy* 174, 232–244.
- Koza, J.R., 1994. Genetic programming as a means for programming computers by natural selection. *Stat. Comput.* 4 (2), 87–112.
- Lawrence, S., Sokhi, R., Ravindra, K., 2016. Quantification of vehicle fleet PM10 particulate matter emission factors from exhaust and non-exhaust sources using tunnel measurement techniques. *Environ. Pollut.* 210, 419–428.
- Li, J., Ge, Y., Wang, X., Zhang, M., Yang, Z., Zhong, C., Sun, J., Wang, Y., 2024. Non-exhaust gas and particle emissions of light-duty vehicles – Quantification under driving conditions in a sealed cabin. *Atmos. Environ.* 319, 120308.
- Liu, E., Lin, Z., Chen, H., Jia, D., Liu, Y., Guo, J., Li, T., Wei, T., 2025. Multiobjective eco-driving speed optimisation with real-time traffic: Balancing fuel, NOx, and travel time. *Energy* 324, 135793.
- Liu, Y., Chen, H., Gao, J., Li, Y., Dave, K., Chen, J., Federici, M., Perricone, G., 2021. Comparative analysis of non-exhaust airborne particles from electric and internal combustion engine vehicles. *J. Hazard. Mater.* 420, 126626.
- Liu, Y., Chen, H., Jiang, L., Li, T., Guo, J., Wei, T., Crowther, R., 2024. Environmental and health impacts of banning passenger cars with internal combustion engines: a case study of Leeds, UK. *Transp. Res. Part D: Transp. Environ.* 134, 104343.
- Liu, Y., Chen, H., Li, Y., Gao, J., Dave, K., Chen, J., Li, T., Tu, R., 2022a. Exhaust and non-exhaust emissions from conventional and electric vehicles: a comparison of monetary impact values. *J. Clean. Prod.* 331, 129965.
- Liu, Y., Chen, H., Wu, S., Gao, J., Li, Y., An, Z., Mao, B., Tu, R., Li, T., 2022b. Impact of vehicle type, tyre feature and driving behaviour on tyre wear under real-world driving conditions. *Sci. Total Environ.* 842, 156950.
- Liu, Y., Chen, H., Yin, C., Federici, M., Perricone, G., Li, Y., Margaritis, D., Shen, Y., Guo, J., Wei, T., 2022c. PM10 prediction for brake wear of passenger car during different test driving cycles. *Chemosphere* 305, 135481.
- Liu, Y., Wu, S., Chen, H., Federici, M., Perricone, G., Li, Y., Lv, G., Munir, S., Luo, Z., Mao, B., 2022d. Brake wear induced PM10 emissions during the world harmonised light-duty vehicle test procedure-brake cycle. *J. Clean. Prod.* 361, 132278.

- Lyu, N., Cao, Y., Wu, C., Xu, J., Xie, L., 2018. The effect of gender, occupation and experience on behavior while driving on a freeway deceleration lane based on field operational test data. *Accid. Anal. Prev.* 121, 82–93.
- Marcinkevičius, R., Vogt, J.E., 2023. Interpretable and explainable machine learning: a methods-centric overview with concrete examples. *WIREs Data Min. Knowl. Discovery* 13 (3), e1493.
- Mathissen, M., Grochowicz, J., Schmidt, C., Vogt, R., Farwick zum Hagen, F.H., Grabiec, T., Steven, H., Grigoratos, T., 2018. A novel real-world braking cycle for studying brake wear particle emissions. *Wear* 414–415, 219–226.
- Men, Z., Zhang, X., Peng, J., Zhang, J., Fang, T., Guo, Q., Wei, N., Zhang, Q., Wang, T., Wu, L., Mao, H., 2022. Determining factors and parameterization of brake wear particle emission. *J. Hazard. Mater.* 434, 128856.
- Neukirchen, C., Saraji-Bozorgzad, M.R., Mäder, M., Mudan, A.P., Czasch, P., Becker, J., Di Bucchianico, S., Trapp, C., Zimmermann, R., Adam, T., 2025. Comprehensive elemental and physical characterization of vehicle brake wear emissions from two different brake pads following the Global Technical Regulation methodology. *J. Hazard. Mater.* 482, 136609.
- Ng, E.C.Y., Huang, Y., Hong, G., Zhou, J.L., Surawski, N.C., 2021. Reducing vehicle fuel consumption and exhaust emissions from the application of a green-safety device under real driving. *Sci. Total Environ.* 793, 148602.
- Padoan, E., Amato, F., 2018. Chapter 2 - Vehicle Non-Exhaust Emissions: Impact on Air Quality, In: Amato, F. (Ed.), *Non-Exhaust Emissions*. Academic Press, pp. 21–65.
- Paschalidis, E., Zhai, S., Guo, J., Wei, T., Liu, P., Chen, H., 2023. The twofold role of legal liability misattribution on intention to buy automated vehicles: a survey in China. *Int. J. Hum. Comput. Interact.* 1–12.
- Piscitello, A., Bianco, C., Casasso, A., Sethi, R., 2021. Non-exhaust traffic emissions: sources, characterization, and mitigation measures. *Sci. Total Environ.* 766, 144440.
- Riva, G., Valota, G., Perricone, G., Wahlström, J., 2019. An FEA approach to simulate disc brake wear and airborne particle emissions. *Tribol. Int.* 138, 90–98.
- Samland, M., Badeke, R., Grawe, D., Matthias, V., 2024. Variability of aerosol particle concentrations from tyre and brake wear emissions in an urban area. *Atmos. Environ.* X 24, 100304.
- Sanders, P.G., Xu, N., Dalka, T.M., Maricq, M.M., 2003. Airborne brake wear debris: size distributions, composition, and a comparison of dynamometer and vehicle tests. *Environ. Sci. Technol.* 37 (18), 4060–4069.
- Shikder, M.F.H., Tang, Y., Almehdawe, E., Araújo, J.C., 2024. Risk incident analyses in the transportation of anhydrous ammonia as an emerging clean energy resource. *Risk Analysis* n/a(n/a).
- Shinar, D., Compton, R., 2004. Aggressive driving: an observational study of driver, vehicle, and situational variables. *Accid. Anal. Prev.* 36 (3), 429–437.
- Shi, B., Xiong, L., Yu, Z., 2021. Pressure estimation based on vehicle dynamics considering the evolution of the brake linings' coefficient of friction. *Actuators* 10, 76.
- Squizzato, S., Masiol, M., Agostini, C., Visin, F., Formenton, G., Harrison, R.M., Rampazzo, G., 2016. Factors, origin and sources affecting PM1 concentrations and composition at an urban background site. *Atmos. Res.* 180, 262–273.
- Timmers, V.R.J.H., Achten, P.A.J., 2016. Non-exhaust PM emissions from electric vehicles. *Atmos. Environ.* 134, 10–17.
- Timmers, V.R.J.H., Achten, P.A.J., 2018. Chapter 12 - Non-Exhaust PM Emissions From Battery Electric Vehicles, In: Amato, F. (Ed.), *Non-Exhaust Emissions*. Academic Press, pp. 261–287.
- Tu, D., Xie, J., Chai, H., Liu, J., 2025. Non-exhaust emissions of battery electric vehicles and their impact on tunnel ventilation. *Transp. Res. Part D: Transp. Environ.* 147, 104929.
- Varela, R.A., Faria, M.V., Mendoza-Villafuerte, P., Baptista, P.C., Sousa, L., Duarte, G.O., 2019. Assessing the influence of boundary conditions, driving behavior and data analysis methods on real driving CO2 and NOx emissions. *Sci. Total Environ.* 658, 879–894.
- Vouitsis, E., Ntziachristos, L., Pistikopoulos, P., Samaras, Z., Chrysikou, L., Samara, C., Papadimitriou, C., Samaras, P., Sakellariopoulos, G., 2009. An investigation on the physical, chemical and ecotoxicological characteristics of particulate matter emitted from light-duty vehicles. *Environ. Pollut.* 157 (8), 2320–2327.
- Wang, Y., Li, J., Yin, H., Yang, Z., Zhong, C., Sun, J., Hu, Y., Li, Z., Shao, Y., Zhang, L., Du, T., Ge, Y., 2023. A new method to assess vehicle airborne non-exhaust particles: principle, application and emission evaluation. *Appl. Energy* 352, 121942.
- Warshawsky-Livne, L., Shinar, D., 2002. Effects of uncertainty, transmission type, driver age and gender on brake reaction and movement time. *J. Saf. Res.* 33 (1), 117–128.
- Wei, T., Yang, X., Xu, G., Shi, F., 2023. Medium-term forecast method for daily passenger flow of high-speed railway based on DLP-WNN. *China Railway Sci.* 2 (1), 121–139.
- Woo, S.-H., Jang, H., Na, M.Y., Chang, H.J., Lee, S., 2022. Characterization of brake particles emitted from non-asbestos organic and low-metallic brake pads under normal and harsh braking conditions. *Atmos. Environ.* 278, 119089.
- Woo, S.-H., Kim, Y., Lee, S., Choi, Y., Lee, S., 2021. Characteristics of brake wear particle (BWP) emissions under various test driving cycles. *Wear* 480–481, 203936.
- Xia, Y., Liao, C., Chen, X., Zhu, Z., Chen, X., Wang, L., Jiang, R., Stettler, M.E.J., Angeloudis, P., Gao, Z., 2023. Future reductions of China's transport emissions impacted by changing driving behaviour. *Nat. Sustain.*
- Yamashita, G.H., Fogliatto, F.S., Anzanello, M.J., Tortorella, G.L., 2022. Customized prediction of attendance to soccer matches based on symbolic regression and genetic programming. *Expert Syst. Appl.* 187, 115912.
- Yousuf, A.K.M., Wang, Z., Paranjape, R., Tang, Y., 2024. An in-depth exploration of electric vehicle charging station infrastructure: a comprehensive review of challenges, mitigation approaches, and optimization strategies. *IEEE Access* 12, 51570–51589.
- Zhang, Q., Yin, J., Fang, T., Guo, Q., Sun, J., Peng, J., Zhong, C., Wu, L., Mao, H., 2024. Regenerative braking system effectively reduces the formation of brake wear particles. *J. Hazard. Mater.* 465, 133350.
- [AuthorError] et al., 2019 zum Hagen, F.H.F., Mathissen, M., Grabiec, T., Hennicke, T., Rettig, M., Grochowicz, J., Vogt, R., Benter, T., 2019. Study of brake wear particle emissions: impact of braking and cruising conditions. *Environ. Sci. Technol.* 53 (9), 5143–5150.