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Zannat, K., Watling, D., Wang, J. et al. (Accepted: 2026) Evaluating the Joint Impact of Parental Decision to Drive and Traffic Control Measures on Children's Exposure to Traffic-Related Pollutants During School Commutes. International Journal of Sustainable Transportation. ISSN: 1556-8318 (In Press)

Evaluating the Joint Impact of Parental Decision to Drive and Traffic Control Measures on Children's Exposure to Traffic-Related Pollutants During School Commutes

Abstract

The relationship between traffic around schools and children's exposure to pollution is well established. Few studies investigated the extent to which parental decisions to drive or walk to school shape children's exposure to traffic emissions, as well as the moderating role of traffic-control conditions. In this study, considering different traffic control scenarios, we examined the relationship between traffic emissions resulting from children being driven to school and the pollutant dose experienced by the children walking to school. A simulation-based framework was used to quantify the combined effects of parents' mode choice (either walk or drive) and traffic control measures (e.g., speed limit, and delay-based actuated signal controls) on traffic related pollutant concentration and the dose experienced by children walking to school. The combined impact assessment showed that the effectiveness of emission reduction strategies around the school was found to vary depending on school location (high and low background traffic scenario), proportion of children driven to school, and traffic control condition. Results revealed the gross inequality of the impacts of high car use, as the dose per child walking to school is significantly higher than that for a child driven to school. For both school locations, reducing school car and controlling speed were found to result in decrease in PM_x doses experienced by walkers. The results from this study provide key insights into school travel plan management strategies in different school locations.

Keywords: Traffic control measures, PM_x doses, Traffic-related pollutants, Walking to school, Active school travel (AST), Modal shift, School commute.

1. Introduction

Urban air pollution is one of the major public health concerns, contributing to a wide range of adverse health outcomes [1]. Each year, 4.2 million people die from illnesses related to ambient air pollution exposure [2]. Children are one of the most vulnerable groups facing heightened susceptibility to the harmful effect of air pollution because of their developing immune systems, breathing rates, physical growth patterns, and different metabolic capacities [3, 4, 5, 6, 7, 8]. Children's exposure to air pollution, including particulate matter (PM_x) and oxides of nitrogen (NO_x) has a significant impact on their lung function and cognitive development, contributing to the progression of neurological disorders, autism, and learning deficiencies, with potential ramifications across their entire life course [9, 10, 11]. Children are particularly vulnerable during school hours when air pollution from traffic is at its peak [12] due to prolonged exposure in the case of schools located near busy streets [13, 14]. Children's higher levels of outdoor activity, both at school and in their neighbourhoods [15, 16], as well as while moving through various micro-environments including travel to and from school [17, 18, 19, 20], further increase their risk. In one study it was shown that children received up to 20% of their daily black carbon exposure during their short commute duration [21]. On average, children's exposure to black carbon (BC) is 42% higher at school compared to at home [22].

Studies have identified several factors affecting air pollution levels at or near school premises and along the routes students take in their commute to school [13]. One of the main sources of air pollution around school premises and commuter routes is emissions from road traffic [23]. Research has demonstrated associations between macroscopic traffic conditions [24], including average vehicle speed, traffic density [25], flow (school and non-school) [26, 27, 28], and pollutant concentrations around schools and along commuting routes. Findings from these studies has reinforced the impact of traffic movements on children's exposure to traffic related pollutants and the dose they experience. The relationship between the emissions from traffic (in terms of their consequences for concentration of pollutants and dose for children) and the contribution from queuing and congestion have also been described using these macroscopic parameters [29]. However, this macroscopic approach ignores other microscopic aspects, such as the impact of acceleration, car-following and lane-changing patterns, and driving style, in understanding the link between children's exposure to pollutants and traffic-related factors [30]. In addition to traffic-related factors, studies have highlighted the impact of roadway design, including bottlenecks, intersections, signals, roadway width, and proximity of schools to nearby roads [23, 28], as key urban design factors that influence pollutant concentrations and thereby the dose for school children. Furthermore, built environmental factors and their substantial impact on increased pollutant concentrations, such as whether a school is located in an urban, suburban or rural area [31], the orientation of playgrounds at schools [28], the condition of travel routes [27], and building density [23], have all been highlighted in the literature. Along with traffic and urban-design related factors, individual decisions such as mode choice [30], and route choice [20, 32] significantly affect children's exposure to emissions while commuting from home to school and back. For example, parents' decisions to use a car for school trips leads to increased traffic flows and more drop-offs and idling vehicles around the school area, and these result in frequent delays, queuing, stop-and-go movements, and deceleration and acceleration events, all of which increase emissions [33]. Therefore, the issue of children's exposure to traffic related pollutants, both at school and during school-related commuting, is complex and multidimensional, necessitating both targeted interventions and comprehensive risk-mitigation strategies to effectively protect children from traffic pollution.

Children's overall exposure to harmful traffic related pollutants can be reduced by mitigating pollution exposure at major hotspots such as schools, drop-off and pickup points, and the routes children take (e.g, home to school and back home, travel to tuition, after school club routes, etc.). To reduce emissions and the concentrations of traffic related pollutants at school, near the school precinct, and along the commuting route to school, different strategic interventions have been adopted by local and national governments globally. These include, for example, encouraging short-distance school commuters to walk, cycle or join a walking school bus (WSB) [34, 35], as well as enhancing public transport services [36, 37] and introducing school bus services for school children travelling a longer distance [38]. These widely-implemented interventions all have the potential to reduce emission from local traffic around schools and commuting routes. Other interventions include urban greening [39], green infrastructure [40], green route information intervention [16], as well as implementing standard rules for school locations, classroom design and playground orientation [13]. On the other hand, traffic control measures such as school streets road closures, and low emission zones in areas around schools [37] aim to reduce the number of cars around schools, targeting both school-related and non-school-related traffic. While many interventions explicitly or implicitly aim to reduce car usage around schools, any successful strategy must address both school-related traffic and non-school traffic. To reduce school traffic, understanding the dynamics of parental decisions and influencing factors with respect to switching from car-use to active modes of transportation is crucial. Additionally, the mode choice for children's school travel is significantly influenced by the neighbourhood environment faced by an individual, including the distance to school, access to public transport, street connectivity, land use mix, urban density, the built environment and traffic conditions (traffic density, driving pattern) around the school precinct, and the availability of suitable walking routes to school [41, 42, 43, 44, 45, 46, 47, 48].

While extensive research has been conducted on understanding pollution from local traffic and exposure of school children around the school area, several critical areas remain under-explored:

- The majority of studies on parents' mode choice for children's school travel have highlighted the benefits of active transport, particularly its positive effects on children's physical activity, mental health, and cognitive development [42]. Although the number of children walking to school directly affects the volume of school-related car traffic, few studies have examined how parental decisions to use cars influence children's exposure to local traffic emissions during school commutes [49]. Moreover, while differences in in exposure among school-going children using various travel modes have been documented [27, 20, 36], the extent to which one group's travel decisions may affect the exposure of others remains unexplored.

- Different studies have explored the impact of different control measures to reduce traffic emissions [50, 51, 52]. However, no studies have examined how these measures might moderate school-going children's exposure to traffic-related emissions across different modal split scenarios, such as when the majority of children either walk to school or are driven, which is commonly observed in the UK.

- Although studies have noted the impact of urban built-environmental factors on pollutant concentrations around schools, there is a lack of detailed research on how these design elements influence the microscopic traffic attributes — such as vehicle speed, and acceleration patterns — that directly affect emissions. This gap is critical in exposure estimation, as these microscopic traffic-related factors contribute to higher pollutant concentrations [53], increasing school children's exposure and potentially impacting their health due to prolonged exposure to high doses of pollutants.

- The relationship between children being driven or walking to school and their resulting exposure to local traffic emission has only been investigated using a macroscopic theoretical model [54]. A detailed microscopic investigation of this relationship, including its application for strategic planning to reduce pollutant concentrations and exposure for school children, is absent in the literature.

Therefore, the aim of this study is to investigate the relationship between traffic emissions caused by children being driven to school and the pollutant dose (PM_x) experienced by children walking to school, under varying traffic movement and local traffic control conditions around schools. The contributions of this article to school travel research are threefold. Firstly, the study proposes a simulation-based modelling approach that integrates the effects of parental decision either to drive or walk to school, along with relevant control measures, to enumerate emissions from traffic and the pollutant doses experienced by different groups of school travellers. To the best of our knowledge, this is the first study to jointly assess the impact of parental decisions and control measures within a unified framework on children's exposure to local traffic emission during school commutes. Secondly, the simulation results go beyond quantifying the amount of traffic-related pollutant (PM_x) reduced due to control measures (targeting school and non-school traffic), extending to evaluate their impact on PM_x dose and inequalities across different modal split scenarios and school locations. Finally, the study provides policy recommendations to encourage walking to school, tailored to schools with varying proportions of children walking versus being driven.

2. Simulation based modelling approach

To investigate the relationship between parents' decisions to walk or drive their children to school and the corresponding emissions, and pollutant doses experienced by the school going children, this study adopted a simulation-based approach. For the micro-simulation, Shipley C.E. Primary School, located in the Bradford District, United Kingdom, was selected as the case study. This selection was based on its strategic positioning along Otley Road, a thoroughfare characterised by the higher vehicular flow that crosses the neighbourhood and interfaces with Bradford Road (Figure 1). Additionally, the school does not have a school bus provision. As a result, children living in the catchment area must rely on either cars or walking to school, given the limited public transport coverage and lack of cycling facilities. Due to the dominance of these two major commuting modes, we investigated the impact of pollutant dose from local traffic on children walking or being driven to school.

The traffic data used in this study is conveniently accessible on the official website of the Department for Transport [55]. A summary of the existing traffic flow data obtained from two traffic counters is presented in Figure 3.

To carry out the simulation, the traffic network data for Otley Road was extracted from OpenStreetMap. The signal phase description and duration data were extracted from the Bradford SATURN network model (details of signal timing are presented in the supplementary documents Figure S1). The current speed limit for Otley Road is 30 mph. The traffic simulation encompassed the time frame from 7:00 AM to 10:00 AM. Notably, the influx of school-related traffic commenced between 8:30 AM and 9:00 AM, aligning with the scheduled opening time of the school gate from 8:45 AM to 9:00 AM. Furthermore, considering the school's current capacity, set at 220 children, the simulation was constrained to encompass a maximum of 220 school cars. This assumption is grounded in the premise that each child is transported to school by an individual car as assumed in the bi-modal experiment by Dirks et al. (2024) [54]. To carry out the experiment for a low background traffic scenario, instead of selecting a new school, we used the same network without non-school traffic. This approach has been taken for two particular reasons - (1) to allow for estimates to be made of the relative amount of traffic related pollutants (PM_x) that children may be exposed to depending on where the school is located with similar student populations, and (2) to assess the effectiveness of control measures for schools where every other variable (e.g., the number of school children, the speed limit on road, location of traffic signal etc.) remain the same except for the school location. It is also important to note that, in this study, school locations were classified based on the level of non-school traffic, which is referred to throughout the article as background traffic. Accordingly, schools with high background traffic were those exposed to a high volume of non-school vehicles.

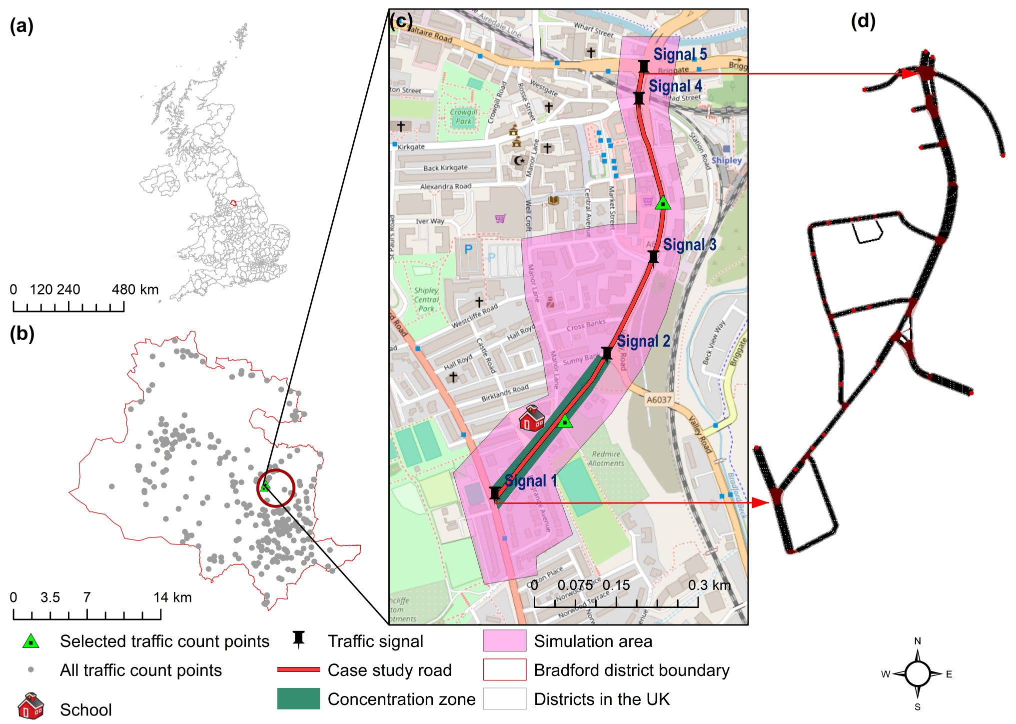

Figure 1: Example road and school location for traffic simulation - a) Bradford District within the UK boundary, b) School location within the Bradford district boundary, c) Shipley C.E. Primary School and Otley Road, d) Sumo simulation network

In terms of simulating scenarios with different modal splits between walking and being driven to school, an iterative approach was devised. In the initial iteration, all of the school children ($n = 220$) were driven to school. Then, a small number ($w = 2$) of children who had previously been driven to school were switched to walking in the following iteration, and this process continues, through $n, n - w, n - 2w, ...$ until no children were driven.

The reason for follow this approach was to minimise Monte Carlo noise in comparisons across different modal split scenarios, and in particular, in the random departure times at which vehicles were generated. By first generating departure times for the maximum pool of n potential vehicles, w vehicles are then randomly chosen for deletion and the pool reduced to $n-w$, importantly with these remaining vehicles maintaining the same departure times they were assigned in the scenario with n vehicles, and this process continues with the next step deleting a further w vehicles from the remaining pool of $n-w$. This process allows us to better exemplify systematic patterns in the model results.

To model the vehicular dynamics, a local area traffic model was developed, and an emission model was utilised to compute emissions from the detailed spatio-temporal traffic profiles. The concentration of traffic related pollutants in front of the school gate was measured using the emission that was computed from the traffic flow. PM_x doses for the children who were being driven and walking to school were computed based on the measured concentration. In this study, in-vehicle pollutant concentrations were assumed to be equivalent to roadside concentrations. This assumption was adopted because in-vehicle concentrations are strongly influenced by vehicle-specific characteristics such as vehicle type and age, cabin air filtration efficiency, and ventilation or recirculation settings [56, 57], which vary widely and require detailed, vehicle-level data that were not available. Incorporating these factors would substantially increase model complexity and was therefore considered to be beyond the scope of the present analysis.

The next subsection includes further information about these four processes, and Figure 2 illustrates the general methodological framework.

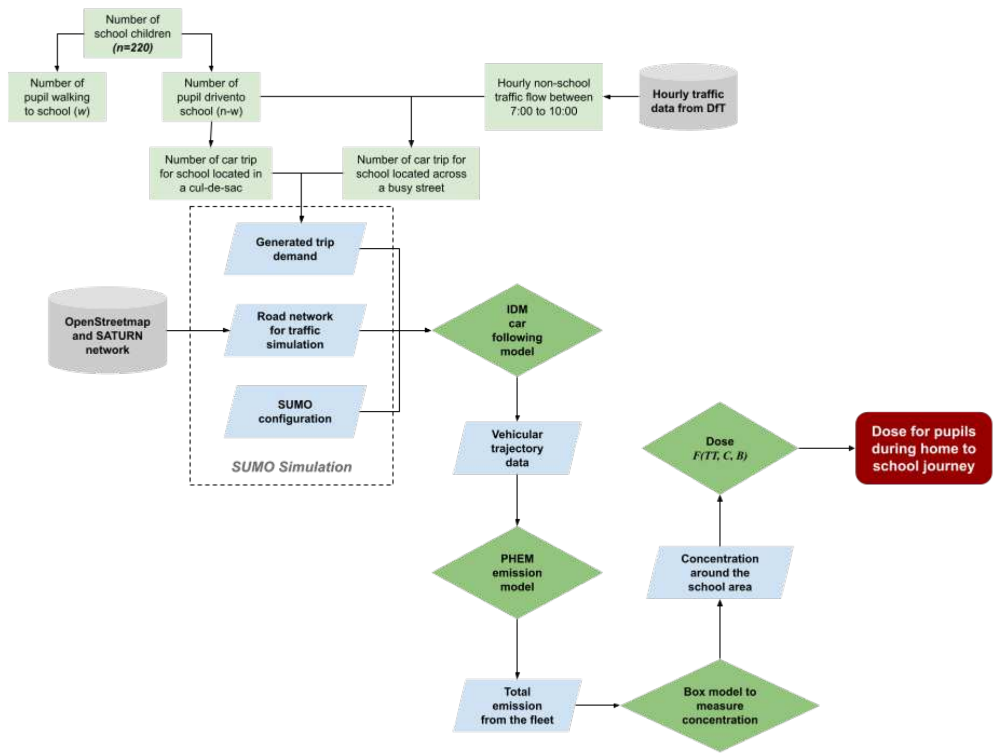

Figure 2: Simulation framework

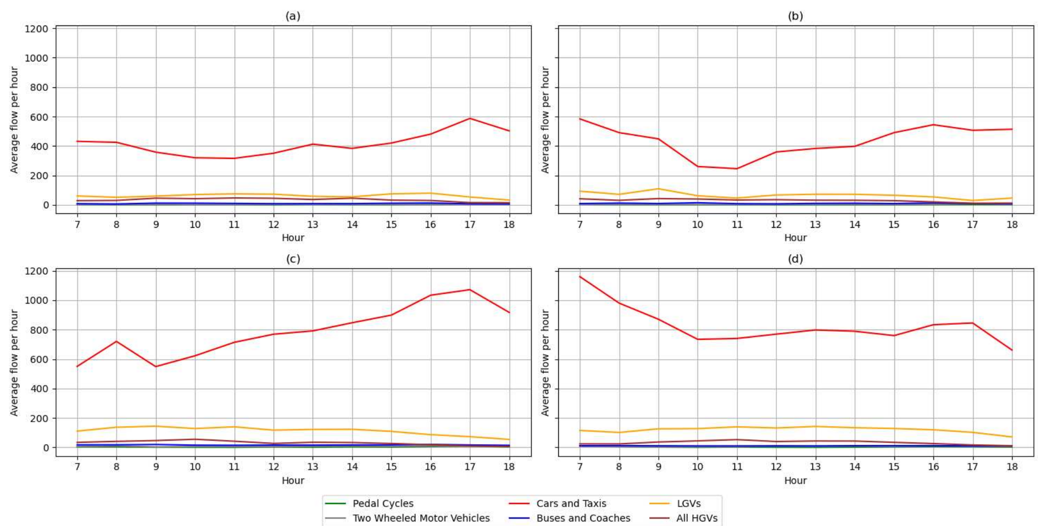

Figure 3: Existing traffic flow conditions, (a) Average hourly traffic count (counter ID=37845): direction North, (b) Average hourly traffic count (counter ID=37845): direction South,(c) Average hourly traffic count (counter ID=7734): direction North, (d) Average hourly traffic count (counter ID=7734): direction South

2.1. Local area traffic model

The traffic model captures the vehicular dynamics which is directly linked to the emission estimation. While macroscopic traffic flow models are recommended for highway flow modelling [58, 59], studies have highlighted the importance and application of microscopic traffic simulations to understand urban local area traffic movement. In this study, a car-following model (CFC) was utilised to simulate the vehicles' longitudinal behaviour and interactions with vehicles in the same lane. Based on the sensitivity test of different car following models by Zannat et al. (2025)[60], we selected the Intelligent Driver Model (IDM) for the micro-simulation. To ensure a smooth transition between free-flow and car-following states, the IDM takes into account the interplay between the desired speed and the interaction with the leading vehicle. Using IDM, the acceleration of the following vehicle $a_{f(t)}$ at time t can be determined using the following Eqn 1:

$$a_{f(t)} = a_{max}\left[1 - \left(\frac{v_{f(t)}}{v_{des}}\right)^{\delta} - \left(\frac{g_{des}}{g(t)}\right)^{2}\right] \tag{1}$$

where, a_{max} is the maximum acceleration, $v_f(t)$ is the current velocity of the following vehicle, $v_{des}$is the desired velocity, δ is the acceleration exponent, $g(t)$ is the actual gap between the leading and the following vehicle, and g_{des} is the desired gap. The position of the following vehicle $x_f(t + \Delta t)$ at time $t + \Delta t$ is updated using the following kinematic Eqn 2:

$$x_f(t + \Delta t) = x_f(t) + v_f \Delta t + \frac{1}{2} a_f (\Delta t)^2 \tag{2}$$

The gap $g(t)$ between the follower and the leader is defined as Eqn 3:

$$g(t) = x_l(t) - x_f(t) - l_f \tag{3}$$

where, $x_l(t)$ is the position of the leading vehicle, $x_f(t)$ is the position of the following vehicle, l_f is the length of the following vehicle. The desired gap g_{des} is given by Eqn 4:

$$g_{des} = g_0 + max\left(v_f T + \frac{v_f(t) - v_l(t)}{2\sqrt{a_{max} b}}, 0\right) \tag{4}$$

where, g_0, is the minimum gap (jam distance) when the vehicle is at a standstill, T is the desired time headway, representing the time the following vehicle wishes to maintain behind the leading vehicle, and b is the comfortable deceleration (positive value). Using the IDM model, we were able to generate vehicle trajectories which were used as inputs to the emissions model. The simulation was run from 7:00 am till 10:00 am. The warm-up and cooling times were 7:00 to 8:00 and 9:00 to 10:00, respectively. The traffic flow between 8:00 and 9:00, which is the typical time for school traffic, had school vehicles added in a iterative manner, as described earlier. For the simulation, we used the SUMO (Simulation of Urban MObility) version 1.20.0 micro-simulation platform.

2.2. Emission model and vehicle fleet composition

Here, we required a suitable microscopic emission model for evaluating operational improvements at a granular level, such as traffic signals, and speed limit. The Passenger Car and Heavy Duty Emission Model (PHEM) [61] was selected, estimating emissions based on second-by-second data on vehicle speed and acceleration patterns. To calculate the emissions for the vehicle fleet, we used the SUMO PHEMlight emissions model. PHEMlight relies on data files containing the parameters pertinent to the modelled emissions classes. The model itself was formulated through the utilisation of characteristic emission curves, delineating the emission quantity in relation to the actual engine power of the vehicle. These curves were generated through PHEM, utilising representative dynamic real-world driving cycles. Consequently, the emission and fuel consumption outputs for a vehicle during each simulation step were derived by calculating the power required for the vehicle, as in Eqn 5.

$$P_e = (P_{rolling\ resistance} + P_{air\ resistance} + P_{acceleration} + P_{road\ gradient})/\eta_{gearbox} \tag{5}$$

Here,

$P_{rolling\ resistance} = (m_{Vehicle} + m_{Load}) \times g \times (Fr_0 + Fr_1 \times v + Fr_4 + v^4) \times v$

$P_{air\ resistance} = (Cd \times A \times \rho/2) \times v^3$

$P_{acceleration} = (m_{Vehicle} + m_{Rot} + m_{Load}) \times a \times v$

$P_{road\ gradient} = (m_{Vehicle} + m_{Load}) \times Gradient \times 0.01 \times v$

$\eta_{gearbox} = 0.95 \times (average\ efficiency)$

To compute the power demand, the emission factors are selected from the PHEM database, and the coefficients are determined based on the type of vehicle and engine used by the vehicles. In the initial simulations, all vehicles were assumed to be gasoline Euro 4 for both school and non-school traffic. The Euro 4 standard was selected because it remains widely used in many regions and still represents a substantial share of the on-road fleet [62]. Using Euro 4 vehicles, therefore, provides a realistic and internationally applicable reference for school-run traffic across diverse contexts. To illustrate the influence of fleet composition, we also tested a mixed-traffic scenario comprising 50% diesel and 50% gasoline vehicles, given the absence of fuel-type distribution data for the selected school road. Although a similar scenario could be developed with increasing proportions of electric vehicles (EVs), we did not include EV-specific cases, as modelling only reductions in exhaust emissions would underestimate contributions from non-exhaust sources such as brake wear, tyre wear, and road-dust resuspension. Clearly, different mixes of vehicle types would produce different results, but both IDM and PHEM can be readily adapted to such mixed cases.

2.3. Model to measure concentration

To measure the concentration c (mg/m^3) of pollutants for the entire traffic flow f_t between 8:00 and 9:00, including both school and background traffic, we calculated the total emissions, E, by summing the second-by-second interactions of each vehicle along the selected road segment (l). For this study, the experiment was conducted exclusively on the links in front of the school gate (Figure 1). Children approaching the school gate from either side of the road were exposed to emissions from the selected road links used in the concentration calculation. The concentration $C(f_t)$ of the pollutants generated by the entire traffic flow, f_t, was derived following Dirks et al. (2002, 2003) [63, 64] based on a 'box model' of dispersion from a line source given by Eqn 6:

$$C(f_t) = \frac{E_l(f_t(a, v))}{u\Delta z} + C_B \tag{6}$$

Here, u (m/s) is the wind speed and is assumed to be the average morning wind speed, Δz (m) is the box height and assumed to be the morning box height as estimated in Dirks et al. (2002) [63], while C_B is the background pollutant concentration. In Eqn 6 based on our experiment, the concentration of pollutants depends on the total number of vehicles, N_t, and their corresponding dynamics in the entire fleet, f_t, which comprises school traffic, N_s, and background traffic, N_0, as in Eqn 7.

$$N_t = N_s + N_0 \tag{7}$$

The number of school-related traffic, N_s, is influenced by the number of children being driven to school (n_d) and those walking to school (n_w), given the total number of school children, n_t. The relationship can be expressed as Eqn 8:

$$N_s = n_t - n_w \tag{8}$$

For schools located on high-background traffic condition, the number of background vehicles (N_0) depends on traffic flow data obtained from traffic counter. However, for schools situated on low-background traffic condition, N_0 is assumed to be 0. Finally, the flow dynamics of the vehicle fleet, including both school and background traffic, are determined by car-following characteristics such as vehicle velocity (v_{f_t}) and acceleration (a_{f_t}). Therefore, concentration C, v_{f_t}, a_{f_t} were dependent on f_t, which in turn was dependent on N_s, and N_0.

2.4. Dose calculation

For dose calculation, we followed the framework proposed by Dirks et al. (2024) [54]. The air pollution dose, D (mg), that a child would experience either walking or being driven to school was the product of the concentration C to which the child was exposed, the travel time t and the breathing rate, β, is a factor relative to resting rate, as shown in Eqn 9.

$$D = C \times t \times \beta \tag{9}$$

The dose for children walking to school, n_w, is given in Eqn 10, when the traffic flow is f_t:

$$D_w(n_w, C) = C(f_t(a_{f(t)}, v)) \times t_w(l) \times \beta_w \times n_w \tag{10}$$

Similarly, the dose for all children n_d being driven to school under the traffic flow f_t is given in Eqn 11:

$$D_d(n_d, C) = C(f_t(a_{f(t)}, v)) \times t_d(l, v_{(f_t)}, a_{f(t)}) \times \beta_r \times n_d \tag{11}$$

Therefore, the total dose for all children is derived by Eqn 12, 13, and 14:

$$D_t = D_w + D_d \tag{12}$$

$$D_t(n_w, f_t) = C(f_t) \times [t_w(l) \times \beta_w \times n_w + t_d(l, v_{(f_t)}, a_{f(t)}) \times \beta_r \times n_d] \tag{13}$$

$$D_t(n_w, f_t) = C(f_t) \times [t_w(l) \times \beta_w \times n_w + t_d(l, v_{(f_t)}, a_{f(t)}) \times \beta_r \times (n_t - n_w)] \quad (14)$$

The description and list of model parameters are shown in Table 1. In the absence of specific breathing rates for children either walking or being driven to school, several published sources were used to estimate these rates. Fleming et al. [65] summarised breathing rates from birth to 18 years using a systematic literature review, reporting that for children aged 5–11 years, the lower range of respiratory rates varies from 12–18 breaths/min, the upper range from 25–28 breaths/min, and the median from 18–22 breaths/min. Herbert et al. [66] developed percentile charts for awake children aged 1 month to 13 years in clinical settings, reporting mean rates of 17–21 breaths/min (SD 3), lower range from 15–18 and upper range from 25–28 breaths/min for 5–11-year-old. Marks et al. [67] reported a typical respiratory rate of 21 breaths/min (range 15–29) for awake six-year-old seated quietly or reading. Based on these evidence, we selected a lower end resting respiratory rate of 12 breaths/min for children being driven to school. We assumed a uniform resting or low-activity rate for in-car behaviour, consistent with clinical measurements obtained under calm conditions such as sitting quietly, reading, or listening to a story. Moreover, physical activity can increase respiratory rate by 3–4 times the resting value [68], and in the absence of standardised data for walking children, we assumed a walking respiratory rate equal to three times the resting rate (i.e., 36 breaths/min). These assumptions provide a reasonable approximation, based on current knowledge, for children's inhalation behaviour during typical school travel.

Table 1: List of model parameters

Description	Symbol	Value	Unit
Common parameters			
Length of section	l	0.78	km
Walking speed	v_w	4.2	km/h
Maximum speed limit for car	v_c	70	m/s
Resting breathing rate	β_r	12	$/min$
Walking breathing rate	β_w	36	$/min$
Car following model parameter			
Length of follower vehicle	l_f	5	$meter$
Maximum acceleration	a_{max}	2.6	m/s^2
Maximum deceleration	$-a_{max}$	4.5	m/s^2
Minimum gap	g_0	2.5	$metre$
Acceleration exponent	δ	5	
Desired time headway	T	1	sec
Step length		1	
Vehicle type		Passenger car - gasoline & diesel engine (EURO 4)	
Box model parameter			
Box height	Δz	60	$metre$
Wind speed	u	2.1	m/s
Traffic condition			
Traffic flow in a low-background traffic scenario	f_0	0	veh/h
Traffic flow in a high-background traffic scenario	f_0	7:00 - 8:00 = 1802 8:00 - 9:00 = 1791 9:00 - 10:00 = 1492	veh/h

In our analysis, we examined the relationship between changes in the number of school vehicles and their impact on traffic-related emissions, as well as the resulting pollutant dose experienced by children who are driven to school and those who walk under current traffic conditions. To gain a deeper understanding of this relationship, we assessed the moderating effect of two traffic control measures: reducing the speed limit from 30 mph to 20 mph and implementing delay-based actuated traffic signals. Details of the actuated signal timings are given in Table S1.

3. Results

In this section, the results are outlined in a methodical manner to facilitate easy navigation of our simulation results. First, we highlighted the school trip model results under current conditions where the current speed limit and signal timings were maintained throughout the simulation (Section 3.1). Next, we applied the model to evaluate the tested control measures with the goal of reducing the total PM_x dose for children who were driven and walked to school (Section 3.2 and 3.3).

3.1. Total PM_x dose (mg) for children: Existing traffic and control conditions

The results from the simulation of the modal shift experiment - conducted under the current traffic flow and control measures (e.g., 30 mph speed limit and existing static green and red-light timings), assuming all vehicles are gasoline-powered - are presented in Figure 4. Figure 4 (a) and Figure 4 (b) show the total PM_x dose (mg) for children in scenarios while changing the number of children either walking or being driven to school. Figure 4 (c) and Figure 4 (d) show the per child PM_x dose (mg). The total dose is reported separately for children walking to school and those travelling by car, as well as for all children combined, in order to capture the aggregate exposure burden. On the other hand, mode-specific per child dose explicitly show differences in individual level exposure across travel modes highlighting the exposure inequalities. To understand the impact of fleet heterogeneity alongside variations in the number of children walking or being driven to school, additional experiments were conducted under a mixed-traffic scenario comprising 50% diesel and 50% gasoline-powered vehicles. A summary of these findings is provided in Supplementary Figure S2. The relationship between the number of school car and the total PM_x dose — whether walking, being driven, or combined — as well as per-child and average doses, exhibited a similar trend to that observed in the all gasoline powered vehicle scenario. The higher exhaust emissions from diesel vehicles resulted in an upward shift in dose distribution. A downward shift was plausible with EV vehicles. However, for clarity and ease of interpretation, the gasoline-only scenario is noted here and later sections to illustrate the observed effects resulting from the reduction in a particular type of vehicle.

The leftmost part of Figure 4 represents a situation where no child is walking to school, while the rightmost part represents a scenario where all children are walking. This bi-modal trade-off analysis highlights how and to what extent individual parental decisions to either walk or drive their children impact on the health of school-going children as a result of the overall doses of PM_x. The key difference between the two cases is the amount of non-school traffic; as this is decreased from its current level to zero in the high background traffic case, so the high background traffic scenario results would approach the low background traffic scenario results. It is important to note that the doses were measured specifically when children were passing a particular segment of the road located in front of the school gate (Figure

1 (c)), and so our comparison is only for that segment of the journey.

From the simulation results, distinct patterns were observed of the relationship between the number of school-going cars and the total PM_x dose for children across the two locations. The total PM_x dose for children followed a concave-down parabolic shape when the school was located in a high background traffic condition (Figure 4 (a)). The total dose, which includes the dose for children who were driven and walked to school, was the highest when approximately 80% (178) of children were walking. Conversely, in cases where a school is situated in a low background traffic condition (Figure 4 (b)), the children's total PM_x dose curve exhibited an inverted parabolic shape, with the highest dose recorded when around 46% (102) children were walking. These results underscore the importance of school location and its potential impact on children's health due to exposure to ambient pollutants. In our case, the only varying factor between the two school locations was the background traffic. Because of the background traffic, the total PM_x dose for children attending the high background traffic school was approximately 76% higher than that of the children attending the school situated in the low background traffic scenario. Moreover, the results highlighted that the number of school cars needing to shift to walking, in order to reduce the total pollutant dose for children walking to school, varied depending on the level of background traffic. Hence, background traffic around the school area not only contributes substantially to local traffic emission but also determines the extent to which school traffic must be reduced to improve air quality in the vicinity. Furthermore, when all children were driven to school, the total PM_x dose was at its lowest for a school situated in a high background traffic condition. But, in such a case, the children who were driven to school experienced the highest pollutant dose (while everyone else migrates to cars) due to the emissions from both the school and background traffic. Therefore, shifting to the car is not an immediate solution for protecting children from vehicular emissions when a school is located across a high background traffic condition. In contrary, when all children walked and the school was situated in a low background traffic condition, the total dose was at its lowest. These results suggested that reducing the number of school cars — often overlooked in the literature as an emission reduction strategy around school areas — is an effective policy for lowering the PM_x dose for children attending a school located in a low background traffic condition.

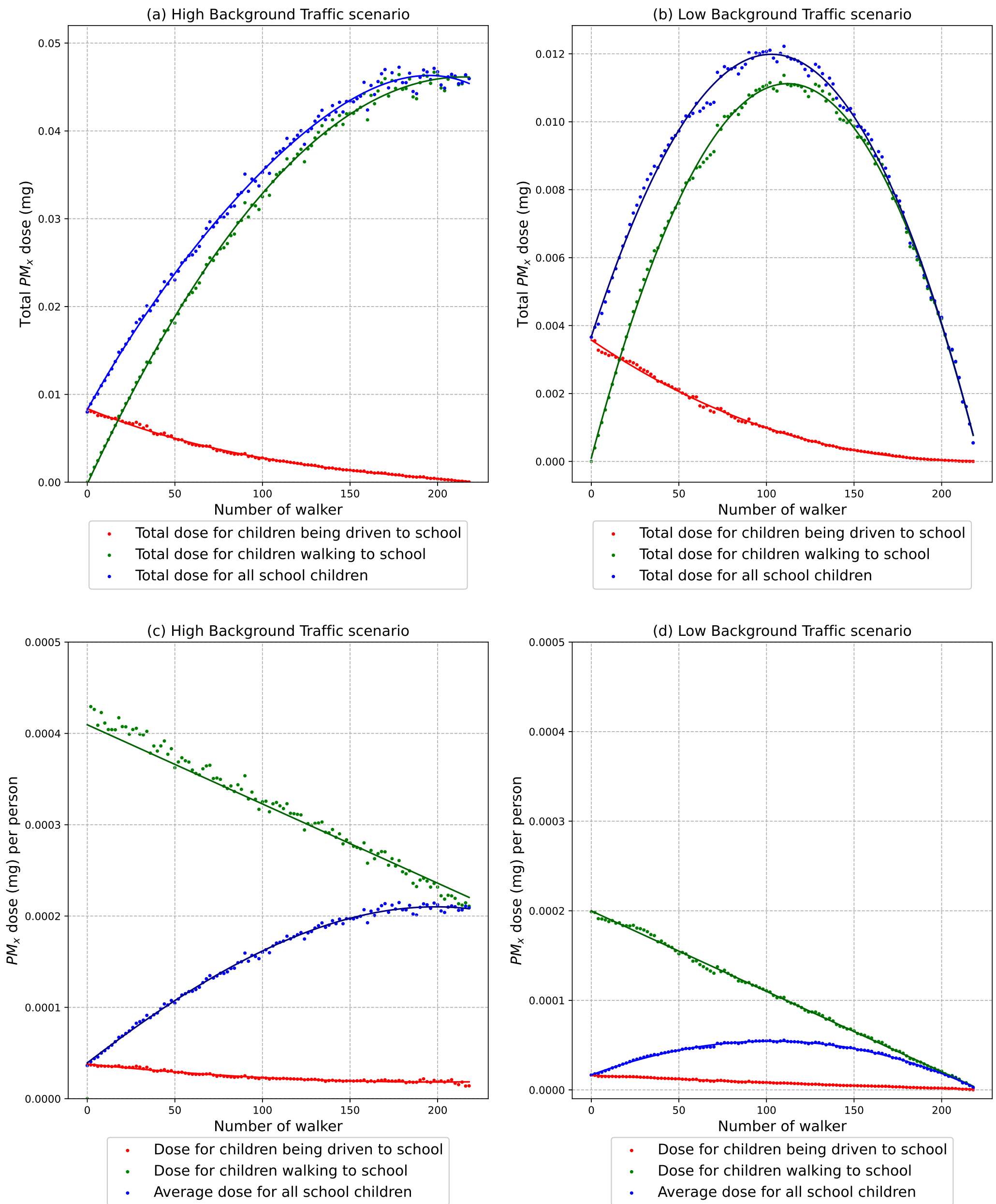

Figure 4: Dose analysis results based on school location (speed limit 30 mph and static signal timing) (a) Total PM_x dose for all school children (school was located in a high background traffic condition),(b) Total PM_x dose for all children (school was located in a low background traffic condition), (c) Per child and average PM_x dose (school was located in a high background traffic condition), (d) Per child and average PM_x dose (school was located in a low background traffic condition)

As with Figure 4 (a) and Figure 4 (b), Figure 4 (c) and Figure 4 (d) show the PM_x dose per child for the school located across a high and low background traffic condition while shifting the number of school going cars to walking. Both figures illustrate the gross inequality of the impacts of high car use, as the dose per child walking to school was significantly higher than that for a child driven to school. This result is plausible because children's respiration rates are higher while walking compared with resting in a car. Moreover, while reduction in traffic emission brought about by changing mode use reduced inequality, it did not disappear except in cases of very low car use (low background traffic case). Regardless of the school's location, the average dose per child walking to school decreased approximately linearly as the number of walking children increased, whereas the average dose for those in the car stayed approximately constant. The average dose per walker decreased by approximately 0.0002 mg in both cases when comparing the no-walker and all-walker cases. This represents a 50% decrease for the high background traffic school relative to the no-walker case and an almost 100% decrease in the low background traffic case. This result indicated that merely lowering school traffic is insufficient for lowering the average PM_x dose per child if the school is located across a high background traffic street. On the other hand, when the school was located in a low background traffic case where more than 102 (46%) children walked to school, every additional child walking to school (instead of being driven) would reduce the overall average dose per person. Therefore, the average PM_x dose per child curve shows a decreasing trend after removing a specific fraction of the school traffic, because there is a minimum amount of background traffic around the school.

Furthermore, to contextualise the pollutant dose measured for the selected road segment, the average daily inhalation rates of children aged 3–11 years (10 m^3/day) was considered [69], together with average roadside urban concentrations (mg/m^3) of $PM_{2.5}$ and PM_{10} [70]. As the simulation focused on a short segment of the school journey rather than the entire trip or total daily exposure, direct comparison with the daily reference values would not accurately reflect the contribution of interventions to reducing traffic-related pollutant exposure. Therefore, a reference exposure corresponding to the time required to traverse the analysed segment was derived. Assuming a typical walking speed for children, the 390m segment was estimated to require approximately six minutes to traverse. The daily average exposure to $PM_{2.5}$ and PM_{10} was scaled to this six-minute duration to provide a comparable reference point. Using this reference, the fractional change in exposure under existing traffic control condition was calculated. The summary of the analysis can be seen in Table 2. Under the high background traffic condition and the gasoline-only scenario, the ratio of the simulated per-child dose to the 6-minute reference average $PM_{2.5}$ dose indicates that as the number of school car decreased, the simulated dose for children walking to school also decreased. When the majority of the children were driven to school, the simulated dose was 37% higher than the typical average roadside $PM_{2.5}$ dose. In contrast, when most children walked to school, the simulated dose represented 74% of the typical roadside exposure. For children driven to school, in the worst case, the simulated dose was only 12% of the typical roadside $PM_{2.5}$ dose. Comparable trends were observed for PM_{10} when comparing simulated doses to typical roadside averages. With an increasing number of diesel-engine vehicles under high background traffic conditions, the simulated dose for the highest school traffic scenario was approximately five times higher than the typical average $PM_{2.5}$ dose and 2.5 times higher for PM_{10}. Conversely, under low background traffic and gasoline-only conditions, the simulated dose was lower than the average roadside $PM_{2.5}$ and PM_{10} doses. However, as the number of gasoline vehicles and school-related cars increased—even under low background traffic—the simulated dose exceeded the typical average $PM_{2.5}$ dose. Overall, these comparisons with typical roadside $PM_{2.5}$ and PM_{10} levels in the UK underscored the critical importance of reducing school-related car traffic to minimise traffic related pollutant dose for children walking to school.

Table 2: Ratio of per-child simulated dose to the 6-minute reference dose under existing traffic and control conditions

Existing traffic and control conditions (high background traffic condition):All vehicles are passenger cars with gasoline engines (EURO 4)											
Number of children		PM_x Dose (mg) per child measured from the simulation		Roadside approximate $PM_{2.5}$ dose (mg) per child in the UK		Ratio of per child dose from the simulation to the 6-minute reference average $PM_{2.5}$ dose		Roadside approximate PM_{10} dose (mg) per child in the UK		Ratio of per child dose from the simulation to the 6-minute reference average PM_{10} dose	
Walking to school	Driven to school	Walking to school	Driven to school	24 hrs	6 min	Walking to school	Driven to school	24 hrs	6 min	Walking to school	Driven to school
2	218	0.000429	0.000037	0.075	0.00031	1.37	0.12	0.147	0.000613	0.701	0.06
100	120	0.000325	0.000023	0.075	0.00031	1.04	0.07	0.147	0.000613	0.531	0.04
150	70	0.000280	0.000020	0.075	0.00031	0.90	0.06	0.147	0.000613	0.457	0.03
200	20	0.000232	0.000019	0.075	0.00031	0.74	0.06	0.147	0.000613	0.378	0.03
Existing traffic and control conditions (high background traffic condition): 50% of the vehicles are passenger car – gasoline engine, and 50% diesel engine (EURO 4)											
2	218	0.001559	0.000147	0.075	0.00031	4.99	0.47	0.147	0.000613	2.54	0.24
100	120	0.001348	0.000102	0.075	0.00031	4.31	0.33	0.147	0.000613	2.20	0.17
150	70	0.001197	0.000087	0.075	0.00031	3.83	0.28	0.147	0.000613	1.95	0.14
200	20	0.001122	0.000081	0.075	0.00031	3.59	0.26	0.147	0.000613	1.83	0.13
Existing traffic and control conditions (low background traffic condition): All vehicles are passenger car – gasoline engine (EURO 4)											
2	218	0.000198	0.000016	0.075	0.00031	0.63	0.05	0.147	0.000613	0.32	0.03
100	120	0.000111	0.000008	0.075	0.00031	0.35	0.03	0.147	0.000613	0.18	0.01
150	70	0.000066	0.000005	0.075	0.00031	0.21	0.02	0.147	0.000613	0.11	0.01
200	20	0.000021	0.000002	0.075	0.00031	0.07	0.01	0.147	0.000613	0.03	0.00
Existing traffic and control conditions (low background traffic condition): 50% of the vehicles are passenger car – gasoline engine, and 50% diesel engine (EURO 4)											
2	218	0.000458	0.000037	0.075	0.00031	1.46	0.12	0.147	0.000613	0.75	0.06
100	120	0.000221	0.000016	0.075	0.00031	0.71	0.05	0.147	0.000613	0.36	0.03
150	70	0.000124	0.000009	0.075	0.00031	0.40	0.03	0.147	0.000613	0.20	0.01
200	20	0.000026	0.000002	0.075	0.00031	0.08	0.01	0.147	0.000613	0.04	0.00

Average roadside concentration of $PM_{2.5}$ in the UK is 0.0075 (mg/m^3), which is 0.0147 (mg/m^3) for PM_{10} [70].

3.2. Concentration of pollutant and PM_x dose: changes in speed limit

We applied the modal shift experiment for investigating the impact of different speed limits on reducing the traffic-related pollutant dose for children walking to school. Some studies suggest that a lower speed limit can reduce the acceleration rate, leading to decreased emissions and lower pollutant doses [71, 72]. Moreover, in response to efforts to reduce air pollution, many areas across the UK have adopted a 20 mph speed limit [72]. Hence, in this study, we compared the concentration of traffic-related pollutants and resulting dose at the current speed limit with a lower speed limit. To adopt a reduced speed limit, we drew on the low-speed limit strategies already implemented in the UK. Figure 5 shows findings from the simulation carried out with gasoline only passenger car vehicles, considering the current (30 mph) and reduced speed limit (20 mph). The simulation was done for both schools, located in a high and low background traffic condition.

The results from the simulation under different speed limits highlighted varying levels of PM_x concentration, depending on the number of school cars allowed around the school area. Figure 5 (a) shows that for the school located in a high background traffic condition, due to the lower speed limit, the overall PM_X concentrations around the school area were reduced by 52% between 8:00 AM and 9:00 AM when there were no school cars. In the same school, despite an increase in school traffic, the speed reduction resulted in a 58% decrease in PM_x concentrations around the school. However, for a school located in a low background traffic case when all children walked to school, a change in speed limit was not necessary due to no/limited background traffic. In this location, speed reduction substantially reduced PM_x concentrations (approximately 68% when all children were driven to school) while there was an increase in the number of school cars (Figure 5 (b)). Therefore, the application of different modal share experiment, either walking or driven to school, to study the effects of speed restrictions offered insights into how traffic related pollutant concentration can be reduced under different speed limits while allowing for a particular number of school cars around the school area. For instance, to reduce the concentration of pollutants it is possible to calculate how many school cars must be reduced under various speed limit conditions using statistics from Figure 5 (a) and Figure 5 (b). This experimental analysis also highlighted how to reduce the concentration of traffic related pollutants by a certain percentage through the implementation of speed limit control measures; however, this may necessitate further research using a wider area network model in order to ascertain the overall picture of emissions reduction as a result of the application of local area speed control measures.

In addition to the overall concentration of traffic related pollutants, the investigation also provided detailed statistics on the PM_x dose that children would inhale, whether walking or being driven to school, under different speed limit scenarios. Figures 5 (c) and 5 (d) show the total PM_x dose for children being driven to school and Figures 5 (e) and 5 (f) for those walking to school while changing the number of school cars at the two speed limit conditions. The results revealed that for both school locations, when majority of the children were walking to school, speed limit reductions did not substantially affect the dose for those driven to school (Figures 5 (c) and 5 (d)). However, for the school on a high background traffic condition, reducing the speed limit decreased the dose for children who were walking to school. In such a case, while all children were walking to school, the total dose was reduced by 50% for a 20 mph speed limit compared to a 30 mph speed limit, despite the total PM_x dose for the pupils walking to school being the highest (5 (e)). However, Figure 6 (a) and Figure 6 (c) show that with every additional shift from walking to driving, the PM_x dose per child either walking or being driven to school increased, with a steeper rate experienced at 30 mph compared to 20 mph. The last child walking to school would receive the highest pollutant dose from other cars, with the worst situation occurring at a 30 mph speed limit.

In contrast, for a school located in a low background traffic case where no background vehicles were present, the speed limit reduction did not contribute to a dose reduction for children walking to school when everyone was walking to school (5 (f)). This is because with limited or no traffic in a low traffic case, there will be the lowest or no PM_x dose for children when everyone walked to school. In such a school, the ideal situation was either everyone walking or no one walking to school, as at these two extremes the PM_x dose for children walking to school was the lowest. However, in the low background traffic school case, implementation of the lower speed limit eventually resulted in a flatter total PM_x curve than the higher speed limit condition (Figure 5 (f)). The results from the analysis of each child's dose for walking to school under various speed limit regulations confirmed this finding as well (Figure 6 (d)). Moreover, as with the school located in a high background traffic condition, the trend of increased dose for children walking to school with each additional shift from walking to driving was similar, with a higher rate at a 30 mph speed limit (Figure 6 (d)). Conversely, when all children were driven to school, the speed reduction significantly reduced the dose for children being driven to school—by 50% for the high background traffic and 63% for the low background traffic scenario (Figure 5 (c) and Figure 5 (d)). Figure 6 (a) and Figure 6 (b) show that while every child was being driven to school, the PM_x dose per child driven to school was the highest. The analysis result eventually brought to light the rate of PM_x dose variation for children who choose to walk or ride in a car to school while speed control measures were in place. This analysis also showed how the effectiveness of speed control measures is dependent on parents' decisions to choose walking versus driving for their children's school travel plan.

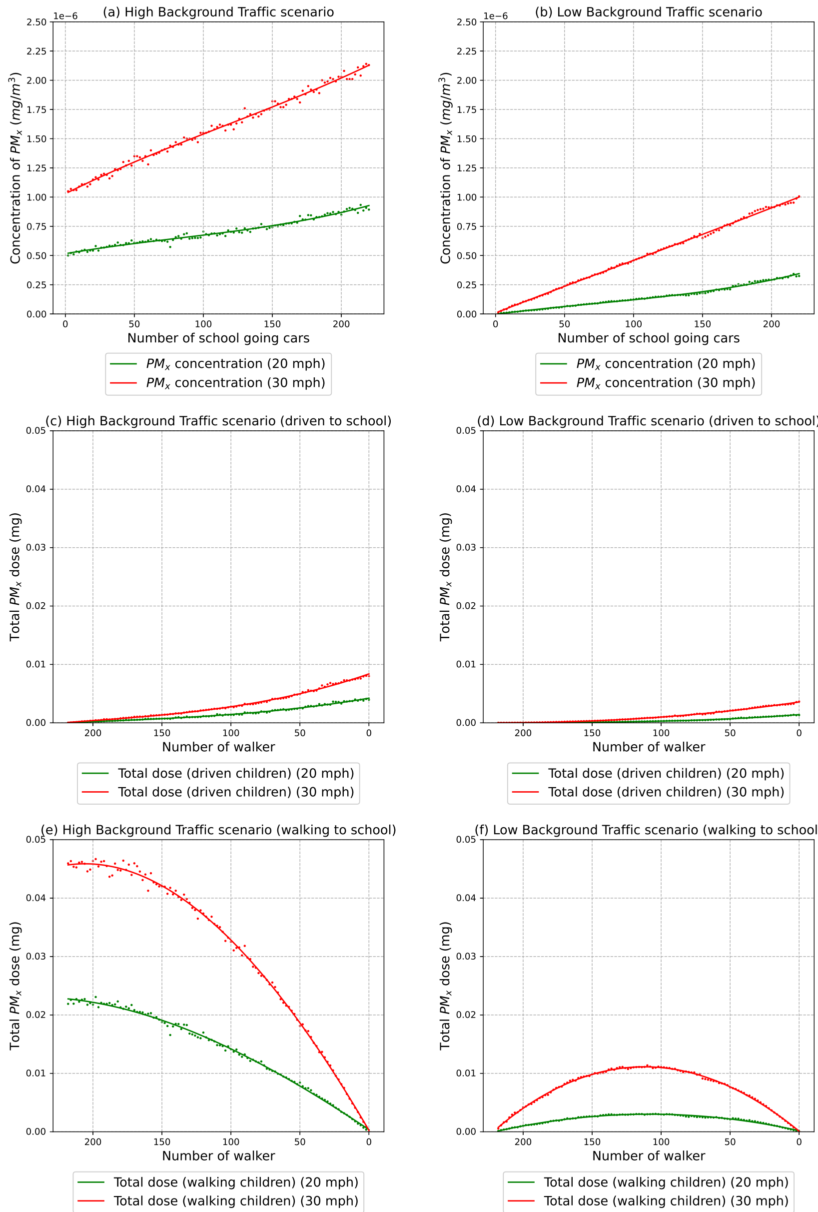

Figure 5: Simulation results showing the impact of speed limit (reduced from 30 mph to 20 mph) on traffic related pollutant concentration and dose - (a) Average concentration of PM_x between 8:00 am to 9:00 am (high background traffic condition), (b) Average concentration of PM_x between 8:00 am to 9:00 (low background traffic condition), (c) Total PM_x dose for children being driven to school while traversing the specific road segment in-front of school (high background traffic condition), (d) Total PM_x dose for children being driven to school while traversing the specific road segment in-front of school (low background traffic condition), (e) Total PM_x dose for children walking to school while traversing the specific road segment in-front of school (high background traffic condition), (f) Total PM_x dose for children walking to school while traversing the specific road segment in-front of school (low background traffic condition)

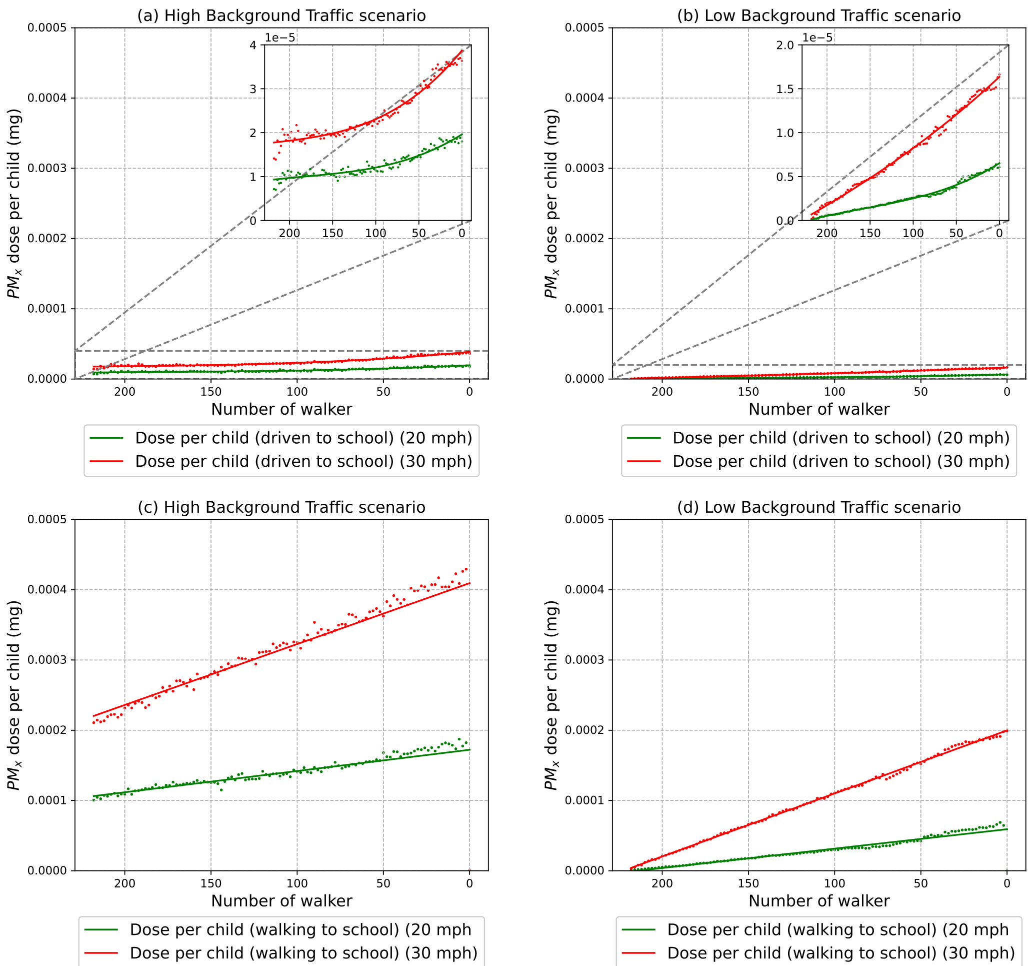

Figure 6: Simulation results showing the impact of speed limit on traffic related pollutant dose per child (a) Per child PM_x dose while being driven to school (high background traffic condition) , (b) Per child PM_x dose while being driven to school (low background traffic condition), (c) Per child PM_x dose while walking to school (high background traffic condition) , (d) Per child PM_x dose while walking to school (low background traffic condition)

3.3. Concentration of pollutant and PM_x dose: changes in signal conditions

The impact of traffic signal controls on vehicular emission is well-established, as it affects different parameters such as vehicle waiting time at signals, acceleration and deceleration, queue length, and manoeuvrability. Along with the speed limit, we investigated how signal control affects the pollutant exposure of children walking and being driven to school. The chosen school, located in a high background traffic condition, has its traffic regulated by four major signals. We examined the contribution of these signals to traffic emissions under both static[1] and delay-based actuated traffic signalling[2]. To assess the impact of signals for a low background traffic school, we used the same signal timings but without background traffic. All phases and duration of the current and actuated signal timings are included in the supplementary Figure S1 and Table S1.

The results from the simulation experiment (Figure 7 and Figure 8) indicated that compared to changing the speed limit, actuated signals did not show a substantial reduction in emissions and concentrations from traffic flow, either with or without school traffic (Figure 7 (a) and (b)). When all of the children were walking to school and the school was located in a high background traffic school, the delay-based signal reduced the concentration of PM_x around the school by 17%. The reduction in concentrations was less than 5% when there was an increase in school-going traffic. The effect of signal timings on reducing emissions and concentrations in-front of school was not discernible when the school was located in a low background traffic (Figure 7 (b)). Similarly, as signals did not reduce emissions in the low

[1]Fixed phase duration

[2]Actuation is based on vehicular delay

background traffic school, their effect on reducing exposure and dose of PM_x for children walking or being driven to school was not noticeable (Figure 7 (d) and Figure 7 (f)). Conversely, with fewer school-going cars and the school located in a high background traffic case, delay-based signals showed a reduced dose for children walking to school (Figure 7 (e)). However, they did not substantially influence exposure for children being driven to school, whether the school was located in a high or low background traffic condition (Figure 7 (c) and Figure 7 (d)). Nevertheless, for a school located in a low background traffic with increased vehicular flow, delay-based signals reduced the average exposure for children being driven to school more effectively than for a school located in a high background traffic condition. This was achieved by potentially reducing their delay at the signals and thus decreasing their travel time in the car (Figure 8 (a) and Figure 8 (b)). As the concentration due to delay-based signals was not significantly reduced, they could not substantially decrease the average dose per child walking to school for either school location. Instead, the results highlighted a sharp increase in average dose with the rise in school traffic (Figure 8 (c) and Figure 8 (d)). Overall, the results showed how the number of children walking or being driven to school could influence the effectiveness of signal control strategies in reducing exposure for school-going children.

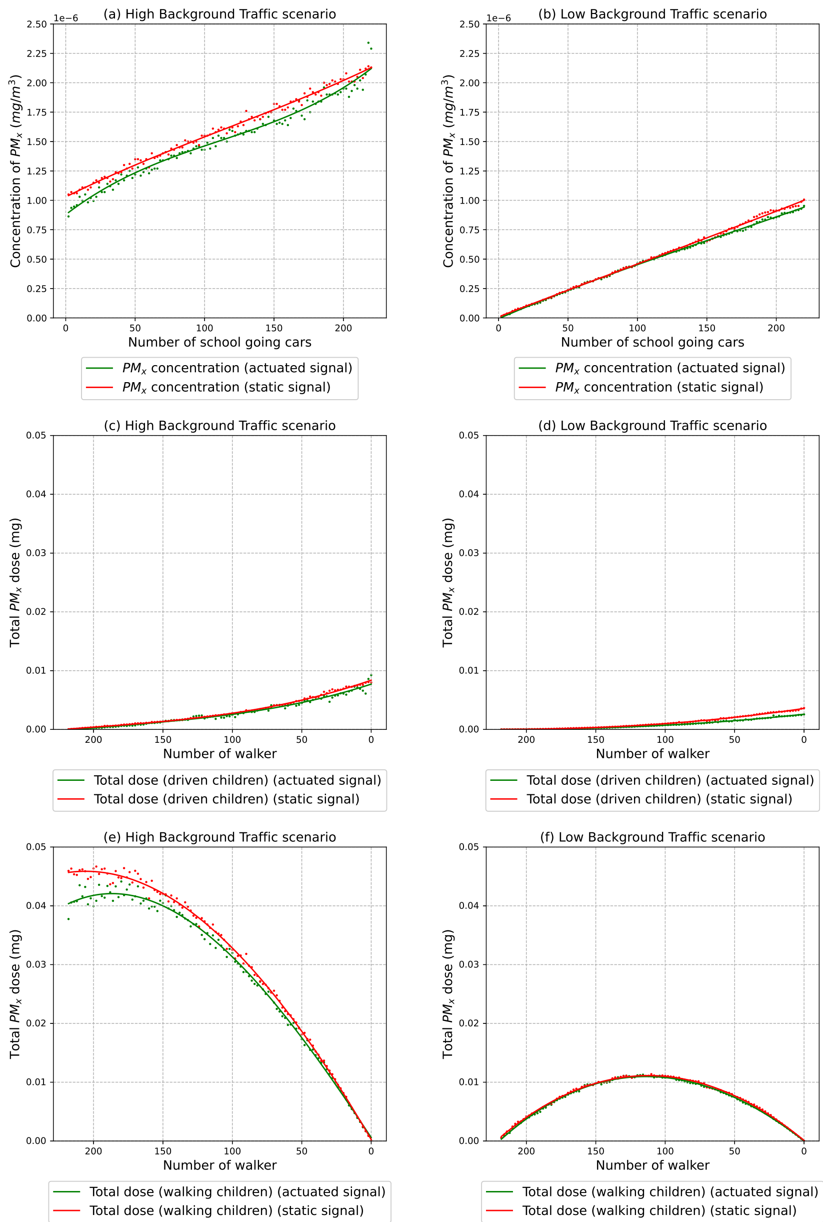

Figure 7: Simulation results showing the impact of static signal and delay based actuated signal on traffic related pollutant concentration and dose (a) Average concentration of PM_x between 8:00 am to 9:00 am (high background traffic condition), (b) Average concentration of PM_x between 8:00 am to 9:00 (low background traffic condition), (c) Total PM_x dose for children being driven to school while traversing the specific road segment in-front of school (high background traffic condition), (d) Total PM_x dose for children being driven to school while traversing the specific road segment in-front of school (low background traffic condition), (e) Total PM_x dose for children walking to school while traversing the specific road segment in-front of school (high background traffic condition), (f) Total PM_x dose for children walking to school while traversing the specific road segment in-front of school (low background traffic condition)

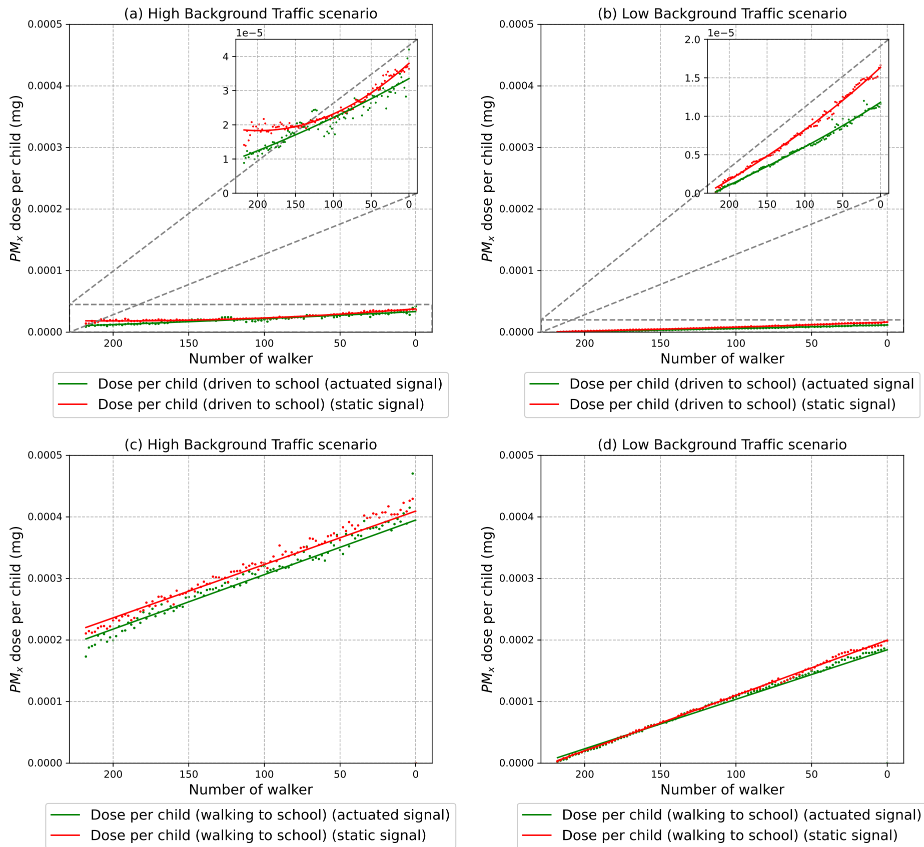

Figure 8: Simulation results showing the impact of static signal and delay based actuated signal on per child pollutant dose (a) Per child PM_x dose while driven to school (high background traffic condition) , (b) Per child PM_x dose while driven to school (low background traffic condition), (c) Per child PM_x dose while walking to school (high background traffic condition) , (d) Per child PM_x dose while walking to school (low background traffic condition)

4. Discussion

The aim of child health initiatives (CHI) is to ensure safe and healthy travel to school in order to lower emissions from vehicles and hence exposure to air pollution [73]. To achieve this, the initiative emphasises promoting walking to school and reducing car traffic in school areas. However, the relationship between children's travel mode to school — whether being driven or walking — under varying traffic flow and traffic control scenarios, and its potential impact on pollutant dose for both dominant school travel groups remains under explored. In this study, we proposed a simulation-based framework that integrated a microscopic car-following model with an emissions model to assess the health and environmental impacts driven primarily by reductions in school-related vehicle emissions. Specifically, we examined pollutant dose exposure for children who were either being driven or walking to school. Furthermore, this study extended the investigation by evaluating the moderating effects of traffic control measures on reducing traffic related pollutant dose for school-going children under two distinct background traffic flow conditions: high-flow and low-flow scenarios. The findings provided key insights for developing effective school travel management strategies tailored to different school locations.

The results from the simulation model showed that if all else being equal, the influence of school cars on the total and average PM_x dose for children who walked to school differed depending on the background traffic flow condition. This result indicated that when a school is located adjacent to a high background traffic condition, the concentrations of traffic related pollutants across the links near the school gate are substantially higher compared to a school situated in a low background traffic condition. The significance of school location and its proximity to nearby busy streets, along with their potential impact on the concentration of NO_x, BC and PM_x, UFP, and CO

have also been highlighted in recent studies [74, 75, 23, 29, 24]. Results from our gasoline only simulation scenarios further revealed that to lower the total traffic-related pollutant dose for children walking to school, more than 80% of school cars must shift to walking, but for a school in a low background traffic case, the percentage is about 46%. Hence, both environments require a substantial reduction in school car traffic to decrease the risk of pollutant exposure for children walking to school. To achieve this, measures to manage school traffic, such as charging a high parking fee or limiting drop-off times [30], may encourage parents to use more environment friendly forms of transportation. Moreover, schools should implement strategies that encourage a shift from driving to walking to school — not limited to infrastructure development, but extending to innovative programs such as WSBs or bicycle trains [35, 27, 76], park-and-stride schemes [77], and awareness-raising campaigns and educational initiatives. Among these programs, the implementation of WSBs has been acknowledged to substantially reduce car use around school areas, which in turn improves local air quality [78].

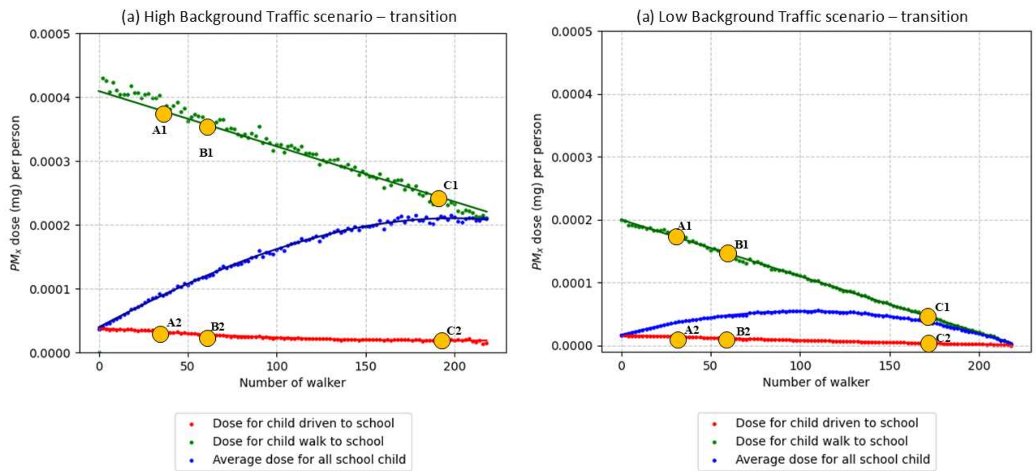

Figure 9: Observation of drive to walk transition across two schools

Furthermore, the results from the simulation could be interpreted as indicating several important transition phases in which significant changes to pollutant dose arise. For example, consider a school in a condition where the majority of the children are driven and few of them are walking, such as the (A1, A2) phase shown in Figure 9. Following the implementation of a nudge policy that modestly increases walking to school ((B1, B2) in Figure 9), the average dose per walker decreases, while the average dose per car user remains nearly constant. However, children who transition from travelling by car to walking experience an increased dose compared to their pre-transition levels, as the average dose following policy implementation is significantly higher than before the transition. Now suppose there is a stronger intervention, such as a ban on all but essential vehicles, resulting in a substantial increase in walking to school ((C1,C2) in Figure 9). In this case, the average dose per walker decreases significantly, while the average dose per car user again remains largely unchanged. For the high background traffic scenario, children transitioning from car to walking still face an increased dose compared to pre-transition levels, as the average dose after the strong intervention (C1) is substantially higher than in the pre-transition phase (A2). In contrast, for the low background traffic scenario, children making the same car-to-walk transition experience only a relatively small increase in dose compared to before the transition, as the average dose after the intervention (C1) is very close to that pre-transition (A2). By examining these distinct impacts of high car use on the exposure of both walkers and car travellers, we can illuminate the inequalities that are not immediately apparent when only considering air quality. Moving forward, such impacts should be incorporated into the economic appraisal of policies and schemes to ensure that the externalities imposed by car users on other societal groups are fully accounted for.

Furthermore, the results showed that in both cases considered, reducing car-use for school journeys was found to approximately linearly decrease the PM_x doses of walkers (i.e. linear in number of walkers). If this is the only consideration, then any kind of policy pathway (whether gradual or a shock) leading to a decrease in car-use is beneficial. However, the average PM_x doses per child did not decrease for a high background traffic school when every child walked to school. This is particularly because of the flow of background traffic during school time [79]. Due to emissions from background traffic, which contributed significantly to the concentration of high background traffic scenario, lowering school traffic will not be sufficient for such a school location for reducing emissions and exposure to traffic related pollutants. In such a case, the most desirable step may be to direct policies at first reducing non-school traffic. An additional concern for such school locations is that reducing school traffic may inadvertently make school routes more attractive to non-school traffic during peak hours. This potential shift further underscores the need for traffic control measures to prevent additional emitting vehicles from entering the school area. On the other hand, average dose per child for a school with minimal background traffic highlighted that a 'nudge' policy could have the unintended consequence of significantly increasing the dose for those transitioning from car to walking. This outcome is undesirable both for the individuals affected and for fostering future transitions to walking. However, this impact might be justified by the numerous other benefits of walking to school, both for individuals—such as improved physical health, socialisation opportunities and educational advantages, as well as for society, including contributions to mitigating climate change. While we did not quantify these broader benefits in this study, they warrant consideration. Alternatively, in such cases, a stronger policy that enforces a rapid and substantial reduction in car use may be preferable, as it prevents those transitioning from car to walking from experiencing negative effects on their dose.

Furthermore, the dose analysis conducted on children who were driven to school revealed that switching to a car was not the best way to protect the children from pollutions. The results from both school locations indicated that when no one was walking, the children who were driven to school had the largest cumulative PM_x dose. These results have two main takeaways: (1) due to an increased number of school cars, the number of cars near schools will increase, and so will the dose for children being driven to school. (2) while pupils are driven to school, they are no longer able to get any physical activity. A study by Westman et al. (2013) [80] also found that children who were driven to school were more likely to have lower levels of activation (a scale between alert and tired) than children who travelled in other modes. Other research has emphasised the health and environmental advantages of walking while also recognising the association between social interaction, learning process development, and the subjective well-being of children who walk to school and find it enjoyable [81, 41, 82]. Moreover, children who walk at a young age not only immediately improve their health and well-being but also learn about their neighbourhood, road safety and other systematic issues (e.g., social equity, sustainability) early on and adopt healthy habits that they can carry into adulthood [83, 84, 85].

The result from this study also demonstrated that, in contrast with previous studies [32, 36, 19], children who were driven to school experienced a comparatively lower overall PM_x dose than children who walked. This finding highlights key differences across various modelling approaches for assessing exposure and dosage levels in children travelling to school by different modes. In this study, we modelled a scenario focusing on a specific section of road, regardless of the entire journey from home to school. The pollutant dose for children — whether driven or walking — was calculated only while traversing the designated road segment in front of the school. In this context, despite both groups being exposed to similar emission levels, the higher breathing rate of children who walk results in a consistently higher dose for them compared to those driven to school. The relationship between breathing rate and higher dose for active travellers has also been highlighted in the study by Dons et al. (2012); Elford and Adams (2019); Zuurbier et al. (2010) [86, 87, 88]. Moreover, Dirks et al. (2018) [27] observed that when route lengths for cars and pedestrians are approximately equal, pedestrians tend to be more exposed to emissions than car users. Car users may encounter higher exposures due to longer routes, increased congestion, increased waiting time at traffic signals, or searching for parking, whereas walkers can often select shorter, low-traffic routes through neighbourhoods or parks, potentially resulting in lower exposure and dose [87].

The investigation of the impact of traffic control measures around the school area highlighted the effectiveness of these measures based on the traffic flow conditions of both non-school and school traffic. For a school located either in high or low background traffic condition, speed reduction performed better than an actuated delay-based signal. A study by Dijkema et al. (2008) [89] also highlighted that a stringent speed limit is effective in reducing exposure and the health impacts of those living near roadways. Beyond speed reduction, the effectiveness of signal control is evident under high background traffic conditions at lower traffic flow rates, although it remains very subtle for schools located in low background traffic case. Furthermore, despite the increased traffic flow due to school cars, which may have slowed the fleet's rate of speeding, the effectiveness of speed reduction in reducing PM_x concentration was evident. With the maximum number of school traffic, the concentration of PM_x dose reduction was 58% at the 20-mph speed limit, which was 50% when there was no school traffic. However, the delay-based actuated signal did not substantially reduce PM_x concentrations, most likely because the timing of the current static signal is designed to minimise traffic delays. A trivial reduction in concentration was evident while there were minimal school cars.

Since a delay-based signal could make the school road the shortest route for non-school traffic, then rather than removing non-school traffic, the resulting concentration of PM_x may not be effectively reduced by this approach. A study by Rouphail et al. (2001) [53] also revealed that traffic measures aimed at reducing the number of stops at intersections provide greater air quality benefits than those focused solely on minimising control delay because vehicle emissions were found to be highest during the acceleration mode rather than during the idle mode. Furthermore, the results from our study indicated that there was reduced efficacy in lowering pollutant concentrations as traffic flow increased, underscoring the ineffectiveness of the delay based signalling strategy in lowering emissions. This necessitates taking into account a variety of indicators such as stop time, waiting time, emission etc. in order to employ signal control as a practical emission reduction technique.

Likewise, the effects of the control measures differed according to whether children were driven or walked to school. This result is evident for both schools located in a high and low background traffic condition. When more children were walking, there was a greater advantage since both speed reduction and actuated signal strategy substantially reduce concentrations and PM_x dose for those who walked to school. Moreover, there was an evident correlation between increasing traffic surrounding the school and the average rise in PM_x dose for children walking to school. However, for children who walked to school, the rate of increase in PM_x dose due to increased flow (the slope of the average dose curve) remained constant for both signal conditions, noting that the slope of the curve for the strict 20 mph speed limit was relatively lower than that of the 30-mph rate. In other words, a higher speed restriction (30 mph) was found to raise the average dose per child walking to school at a higher rate compared to a lower speed limit (20 mph) when there was a rise in the number of school cars around the school area. Additionally, the PM_x dose per individual was found to change substantially with the increasing number of children driven to school for both school locations. Additionally, due to different control measures, such as speed reduction and actuated signal condition, the distinct effect of traffic flow (increasing rate with increased school cars) on the total PM_x dose and average dose for children driven to school was evident.

The results of this study offer key insights for developing school travel management strategies tailored to different school locations. It is clear from the results that for both school locations, the most ideal outcome was to have all children walking to school. However, to be realistic, there will always be some children who can only be dropped off for various reasons, e.g. those with special needs or disability. Nonetheless, since there is only one road leading to the gate, it might be easier to determine what might be the optimal and yet realistic travel plan for the school. For example, in our case study, for the school located in a high background traffic condition, the ideal target was found to be 80% and for a low background traffic case 46%, which will maximise the benefits of walking. A possible way to achieve this target is to introduce permits for children to be dropped off at the gate. These permits might be reserved for those with special needs only. Such an approach will also help reduce car travel to school by parents living nearby who still use cars, as mentioned by McDonald and Aalborg (2009) [33].

Also, our simulation identified a notable turning point in a scenario where the school was located in a low background traffic condition. With a very high walking mode share, the dose for children walking was actually lower than for those being driven. However, this turning point is sensitive to other factors, such as the volume of background traffic and implemented control measures. For instance, we did not observe this turning point at a school with high background traffic, where higher exposure persisted for walkers. Therefore, our results highlight the need for drastic, comprehensive actions rather than gradual, incremental adjustments. A mere nudge towards promotion of active transport may create the risk of establishing protracted transitional periods in which walking is promoted but not sufficiently shielded from environmental hazards. To ensure both safety and effectiveness, we must adopt rapid, transformative strategies that establish safe, low-exposure environments for walkers from the outset, avoiding the pitfalls of an incomplete transition and supporting healthier, more sustainable urban mobility.

5. Conclusion

The World Health Organisation (WHO) lists air pollution as one of the greatest environmental health risks and calls for immediate actions to attain safe air quality for citizens. Exposure to air pollution is linked to premature deaths, health impacts, and welfare losses [90]. Hence, mitigating children's exposure to air pollution emerges as a critical objective for public health. In this study, we explored the joint relationship between children being driven to school under different traffic control condition and their potential impact on the exposure to traffic-related pollutants and dose (PM_x) received by those walking through a simulation-based approach, combining a car-following model with an emission model. This allowed us to analyse the association between parental mode choice dynamics while considering other traffic calming measures that influence the microscopic aspects of traffic movement and their combined impact on exposure to traffic-related pollutants for both walking children and those driven to school.

The simulation results showed that, depending on the school location, the number of school and background cars, their interactions, and the traffic control measures in place, the PM_x dose for children varies. Based on our results, switching from being driven to walking is not sufficient to reduce the PM_x dose for pupils walking to school. Other control measures are also needed. The effectiveness of control measures in reducing doses for pupils walking to school also varies based on school location and the number of children driven to school. The benefits of different control measures are at their maximum with a reduced flow of school traffic. However, to ensure that restrictions on school traffic do not inadvertently attract background traffic into the school area, further research is needed to examine how reducing school-related vehicles affects wider traffic movement. Developing a wider-area network model would help identify major origin–destination (O–D) pairs with the potential to divert through school zones and inform control measures to mitigate these diversion risks. A similar investigation with a wider area network model is warranted to evaluate the effectiveness of control measures in reducing pollutant doses for school children, considering the potential diversion impacts on other vulnerable points of interest, such as hospitals.

In this study, we focused on two specific control measures and their potential impact on reducing children's exposure to traffic related pollutants. Future research could expand on this framework to analyse the effectiveness of other control measures, such as implementing school streets or transitioning from petrol to electric cars, and reducing heavy-duty vehicles, while also promoting active travel to school. Additionally, our study measured the dose for children on the road segment in front of the school. Future research could extend the scope of the micro-simulation to calculate the overall dose for children's entire journey, which would help identify a walking route to school less exposed to traffic emissions. Moreover, in this study, in-vehicle concentrations were assumed to be equivalent to roadside concentrations due to the lack of vehicle level details. Future studies should also account for vehicle characteristics (e.g., age, engine type, ventilation mode, window position, cabin air filtration), traffic conditions, and meteorological factors that may influence in-vehicle exposure. Incorporating real-time personal monitoring and high-resolution spatial data would enhance exposure accuracy and reduce uncertainty in transport-mode comparisons. While direct comparison with on-site school air-quality monitoring data would further strengthen model validation, the consistency of the predicted concentrations with measured average roadside data in the UK, provides confidence that the results represent plausible real-world conditions rather than artifacts of specific parameter selections. Ultimately, this study, in its current form, highlights how the detrimental effects of traffic emissions can be mitigated by choosing to switch from car to walking and by implementing location-specific control measures.

6. Supplementary documents

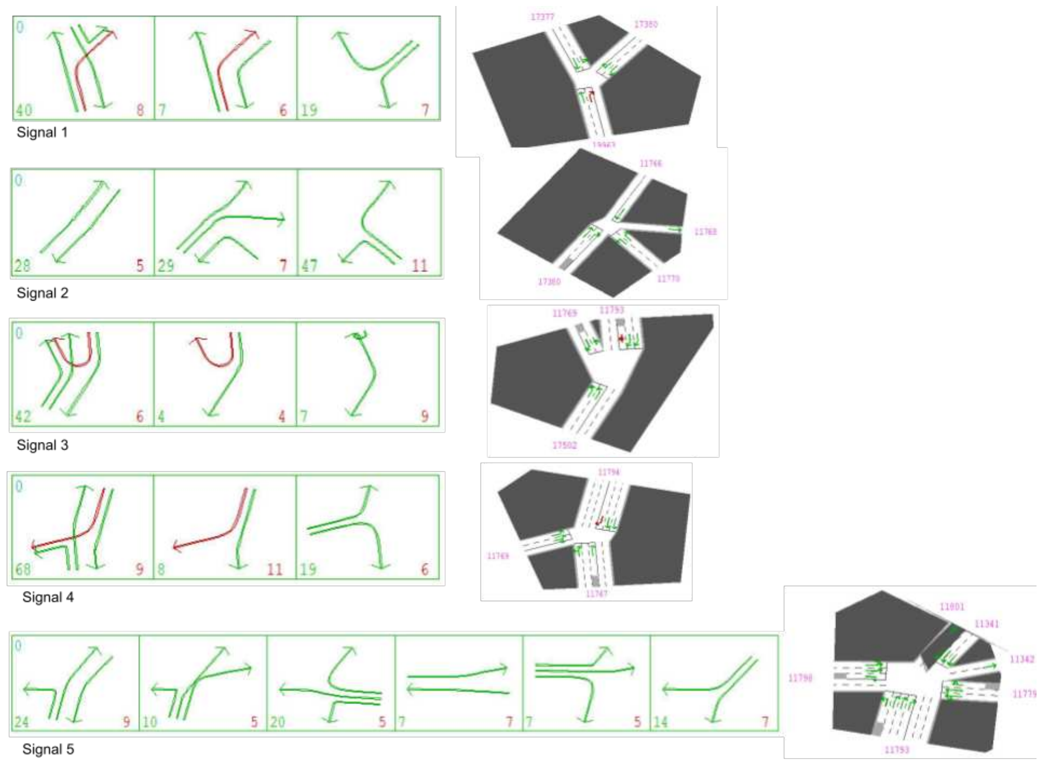

Figure S1: Existing signal phase time

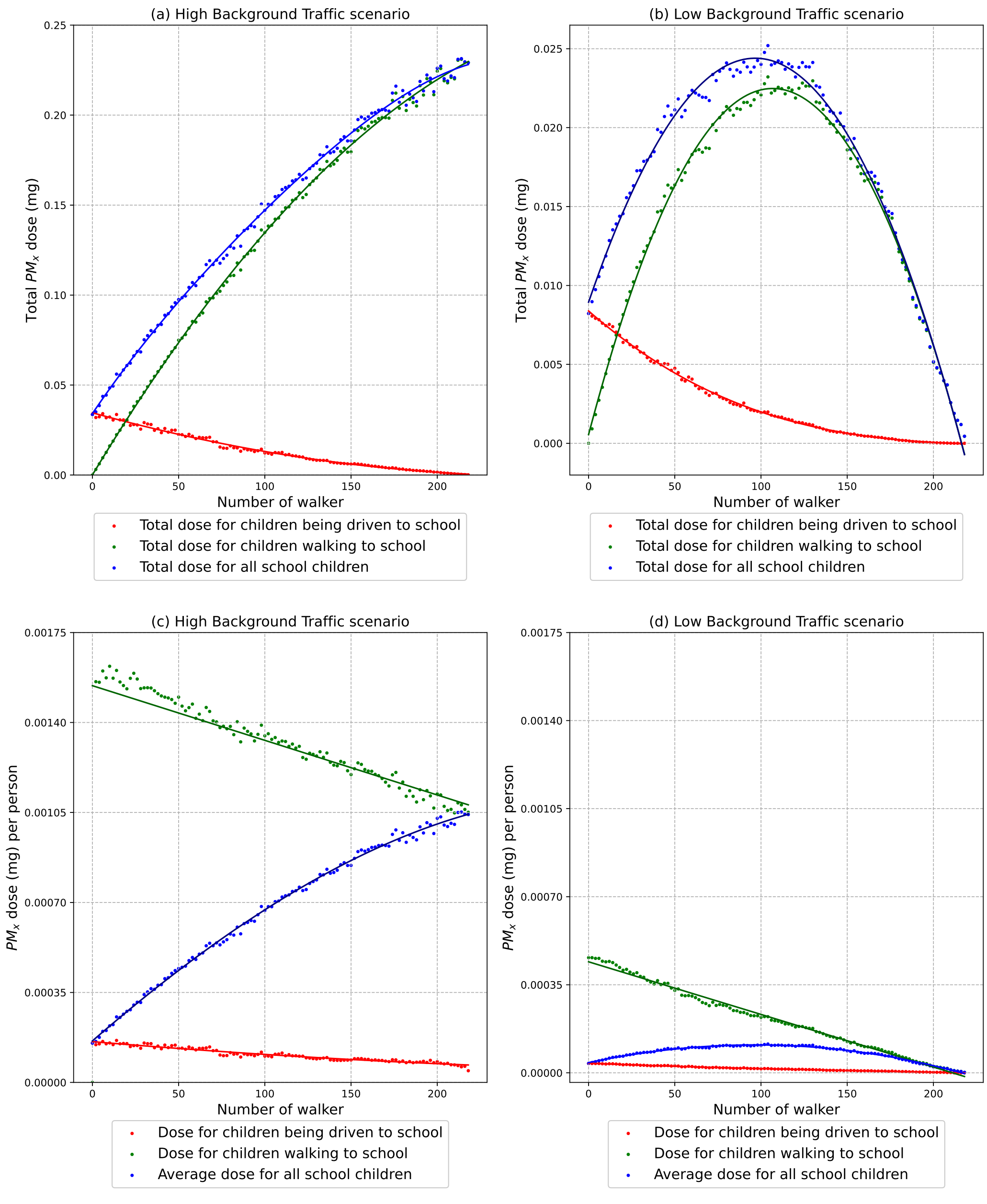

Figure S2: Dose analysis results based on school location (speed limit 30 mph and static signal timing) (a) Total PM_x dose for all school children (school was located in a high background traffic condition),(b) Total PM_x dose for all children (school was located in a low background traffic condition), (c) Per child and average PM_x dose (school was located in a high background traffic condition), (d) Per child and average PM_x dose (school was located in a low background traffic condition)

Signal id	Phase id	Duration
Signal 1	Phase 1	min 5 - max 50
	Phase 2	8
	Phase 3	7
	Phase 4	6
	Phase 5	min 5 - max 50
	Phase 6	Phase 7
Signal 2	Phase 1	min 5 - max 50
	Phase 2	5
	Phase 3	min 5 - max 50
	Phase 4	7
	Phase 5	min 5 - max 50
	Phase 6	11
Signal 2	Phase 1	min 5 - max 50
	Phase 2	6
	Phase 3	4
	Phase 4	4
	Phase 5	7
	Phase 6	9
Signal 2	Phase 1	min 5 - max 70
	Phase 2	9
	Phase 3	8
	Phase 4	11
	Phase 5	min 5 - max 25
	Phase 6	6
Signal 2	Phase 1	min 5 - max 30
	Phase 2	9
	Phase 3	10
	Phase 4	5
	Phase 5	min 5 - max 25
	Phase 6	5
	Phase 7	7
	Phase 8	7
	Phase 9	7
	Phase 10	5
	Phase 11	min 5 - max 20
	Phase 12	7

Table S1: List of signal id, phase and lengthen phase duration for actuated signal

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