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TRAVELLERS' PERCEPTION ABOUT VEHICULAR EMISSIONS' AND ITS IMPACT ON PEDESTRIAN TRAVEL BEHAVIOUR

Md Zabiulla¹, B Raghuram Kadali²

¹ Former Post-Graduate Student, Department of Civil Engineering, NIT Warangal
Warangal, Telangana, India-506004
zabi_ce19603@student.nitw.ac.in

² National Institution of Technology Warangal
Warangal, Telangana, India

*Corresponding Author: brkadali@nitw.ac.in

Vehicular emissions have many impacts on human health and travel behaviour. A lot of evidence on the health effects of vehicular emissions is available but very few studies have looked at the impacts on travel behaviour. The current study attempts to fill this research gap by analysing the factors that influence pedestrian travel behaviour concerning vehicle emissions based on travellers' perceptions in the Indian context. For this, a stated preference questionnaire survey was conducted and a factor-based regression followed by a mediation analysis was used to analyse the responses. Results showed that a person's perceived impacts about vehicular emissions had a greater impact on their travel behaviour. Public concern and environmental attitude lead to direct changes in travel behaviour whereas vehicle technology and negligent attitude had significant indirect effects. The present study findings are useful to the urban planning policymakers in reducing the impact of vehicular emissions on pedestrians by implementing strategies that lessen human exposure to transport emissions.

Keywords: Pedestrian, Vehicle Emissions, Travel Behaviour, Perceived Impacts, Attitudes

1. Introduction

Air pollution is one of the global problems that many countries are facing for the past few decades. An estimated seven million people are perishing due to air pollution and of them, 4.2 million deaths are happening due to human exposure to ambient (outdoor) pollution every year worldwide (WHO 2018). Of all the sources of air pollution, the transport sector is the one with a significant contribution to ambient air pollution due to vehicular emissions. The tremendous growth in combustion engine type of vehicular population and traffic congestion on roads resulted in higher levels of outdoor air pollution in urban areas (Ito *et al.*, 2004). The noxious emissions that are released into the air from a vehicle's tailpipe have many negative effects on human health and the environment. Human diseases like asthma, lung cancer, bronchitis, headache and fatigue, eye and skin irritation, cardiovascular and respiratory problems may occur by getting into contact with vehicular emissions (Kim *et al.*, 2017). Incomplete combustion of fuels at high pressure and temperature produce hazardous pollutants such as carbon monoxide, sulphur oxides, nitrogen oxides, carbon dioxide, and particulate matter. Also, there are non-exhaust emissions such as road dust, wear and tear emissions of vehicle tyres, volatile organic compounds (that are evaporated directly into the air from fuel tanks), etc, which cause on-road air pollution. Pollution from roadside soil and plants can pose a high risk of lead-related health problems among children (Ahmad *et al.*, 2019). Roadside vendors, road construction workers, pedestrians, bicyclists, drivers, passengers are exposed to on-road air pollution (Kim *et al.*, 2017).

India is the fifth most polluted country in the world according World Air Quality Report, (WAQ, 2019). Out of the 30 worst polluted cities in the world, 21 cities are from India. Delhi, Mumbai and Bengaluru are consistently placed in the world's top 10 most congested cities for traffic. Generally, traffic congestion and interruption events result in high vehicular emissions in urban areas (Choudhary and Gokhale, 2019). Around 70% of total environmental pollution in India is from the transport sector (Shrivastava *et al.*, 2013). Previous studies conducted in India examined the effects of traffic emissions on human health and ambient air quality in urban areas (Witek and Schachter, 1983; Ghose *et al.*, 2004; Sharma *et al.*, 2017). Analysing the on-road vehicular emissions in developing countries like India is a complex task due to the mixed traffic conditions, varied fuels, diverse travel patterns, mixed technologies and mixed user attitudes (Goel *et al.*, 2015).

Moreover, pedestrians and bicyclists are directly exposed to vehicular emissions as compared to commuters from other modes of transport (Shekarizfard *et al.*, 2020; Singh *et al.*, 2021). Pedestrians often find it difficult to walk in the vicinity of areas having high proportions of vehicular emissions. They inhale toxic pollutants due to their proximity to traffic and higher breathing rates while walking (Luo *et al.*, 2018). Even though walking and bicycling as physical exercise are good for health, the inhalation of toxic pollutants while travelling in highly polluted areas can cause serious health problems. The respiration rates are higher for a bicyclist and so their inhalation doses of pollutants than that of passengers from other motorized transport modes (Bigazzi and Figliozzi, 2014). Further, exposure to vehicular emissions has an impact not only on human health but also on pedestrian travel patterns and behaviour. To avoid this risk of exposure, pedestrians may adopt some changes in their travel behaviour such as reduced walking and bicycling activity during peak traffic hours, avoiding the paths having high emissions (route choices), higher walking speeds, crossing at mid-blocks, shifting from one mode to other, using bicycles and e-bikes for shorter trips, shifting residences to better air quality areas (Cui *et al.*, 2019; Singh *et al.*, 2021).

There are numerous studies conducted on the assessment of vehicular emissions and their impacts on human health and the environment, and the association of vehicular emissions with the traffic management strategies like traffic signal coordination, ramp metering strategies and traffic calming measures. However, there has been relatively little study on the effects of transport emissions on pedestrian travel behaviour. The present study aims to cover this research gap by investigating the factors affecting pedestrian travel behaviour corresponding to vehicular emissions from travellers' perceptions.

The remaining part of the paper is laid as follows: Section 2 presents the overview of relevant literature. Section 3 describes the methodological framework adopted for the current study. Section 4 and section 5 present the results and discussion of the results respectively. Section 6 is about the policy implications of the results of the study. Section 7 concludes the paper with limitations and the future scope of the research.

2. Literature review

Studies conducted in the past analysed the pedestrian's exposure to traffic-related air pollution (TRAP) and determined various detrimental effects of tailpipe emissions on human health. Also, the existing studies analysed the effects of various factors such as vehicle and road characteristics, socio-economic, demographic and household characteristics, traffic calming measures, user travel attitudes, urban morphology, roadside vegetation and meteorological parameters on vehicle emissions and analysed the pedestrian exposure to these emissions (York Bigazzi and Rouleau, 2017; Zavala-Reyes *et al.*, 2019; Song *et al.*, 2020). Ishaque and Noland (2008), found that long signal cycles have increased pedestrian exposure to vehicular emissions. A 10-40% decrease in the concentrations of pollutants was observed due to the introduction of a green wave in signal coordination (De Coensel *et al.*, 2012). The pedestrian exposure is comparatively less on sidewalks than on major road crossings. People (especially children) who breathe at heights near to that of a vehicle's tailpipe have high exposure to vehicle emissions (Buzzard *et al.*, 2009). Fast walking pedestrians had less exposure to emissions than slow walking pedestrians (Zavala-Reyes *et al.*, 2019). Also, fuel consumption and pedestrian exposure were found to increase due to the presence of a hump on the road (Zavala-Reyes *et al.*, 2019). Bigazzi *et al.* (2015) investigated the impacts of traffic congestion on motorists' exposure to vehicular emissions and compared the duration and intensity of exposure of a motorist to vehicle emissions, corresponding to traffic congestion. It was understood from the results that the lesser the duration of travel on congested roads, the lesser will be the exposure of a motorist to vehicular emissions.

Song *et al.* in (2020) carried out a comparative analysis for three models (emission model, pollutant dispersion model and artificial neural network) for the prediction of the pedestrian exposure to traffic particulate matters (PMs) at a signalized intersection in which Motor Vehicle Emission Simulator (MOVES) package was used to evaluate traffic emission inventory. Similarly, Zavala-Reyes *et al.* (2019) carried out a study to analyse the pedestrian exposure to vehicular emissions using an urban mobility simulator package and a computational fluid dynamics model, with inputs as road networks (streets, pedestrian routes) and meteorological conditions (wind speed and direction) respectively. These studies suggest that the spatial-temporal distribution of vehicular emissions and pollutants is a crucial factor for evaluating pedestrian exposure. Recent studies considered the effect of bicyclists' exposure to traffic-related air pollution for bicycle route planning (Luo *et al.*, 2020) and the development of the bikeability index Tran *et al.* (2020) and found it to have a significant impact on them.

Another set of studies looked at comparing the human exposures to air pollution travelling through different modes of transportation. Ramos *et al.* (2015) analysed the exposures and inhalation of users from different modes such as walking, tram, mini-bus, bus, subway and train. A similar study was carried out by Moreno *et al.* (2015) to compare urban air quality for different travel modes by carrying monitoring equipment in backpacks making a trip route. It was found that commuting through tram has the lowest exposure to air pollution than bus and subway. Many studies concluded that commuting through open modes such as walking, bicycling, motorcycles, auto-rickshaws, cars and buses with opened windows have high exposures than closed modes like cars with air-conditioning and metro (Dirks *et al.*, 2012; Goel *et al.*, 2015; Moreno *et al.*, 2015; Qiu *et al.*, 2017; Shen and Gao, 2019; Singh *et al.*, 2021). The other categories of studies discussed the impact of policies or strategies that reduce vehicular emissions such as improving non-motorized transport, public transport, diverting traffic, closing lanes, pricing mechanisms etc. on travel behaviour (Goel *et al.*, 2015; Fernandes *et al.*, 2016; Geng *et al.*, 2018; Baghestani *et al.*, 2020).

In India, studies were carried out to demonstrate the effects of vehicle, traffic and road characteristics on vehicular emissions (Pandian *et al.*, 2009; Gokhale, 2012; Shridhar Bokare and Kumar Maurya, 2013). Ghose *et al.* (2004) carried out a vulnerable analysis and developed a vulnerability index for seven intersections in Kolkata and found that the traffic intersections in Kolkata have poor air quality despite the advanced vehicle technologies. Mishra and Goyal (2014) developed the dynamic emission factors and emission inventories in Delhi, based on vehicle characteristics and controlled emission limits. Maji *et al.* (2021) analysed the personal exposure of travellers to on-road particulate matter concentrations through different travel modes in Delhi. It was inferred from the study that walking and auto rickshaws have high exposures whereas air-conditioned cars and metro have fewer exposures. Singh *et al.*, (2021) explored the travellers' exposure to air pollution and its impact on travel behaviour by a systematic review of 110 studies. Findings showed that there is a change in travel behaviour such as reduced walking and cycling activity, reduced outdoor activity, changing transport modes and altering route choices to avoid exposure to air pollution. Also, it was found that people travelling in open modes (motorcycle, walking and cycling) had high exposures than those in closed modes (car, bus and metro).

Some studies in China revealed that people would not come onto the roads if the outdoor air pollution is severe (Wu and Liao, 2020). A dense network of monitoring stations is required to know real-time information about air pollution. Compared to other developed countries, India has a smaller number of continuous air quality monitoring stations. The pollution monitoring stations available are less than the required number of stations in low and middle-income countries. Hence, studies used various approaches like on-road measurement of vehicle emissions using portable instruments, simulation techniques, emission models, pollutant dispersion models and emission factors for estimating traffic emissions and pedestrian exposure to these emissions. But there is no validated methodology developed for Indian cities to assess the non-quantifiable parameters such as pedestrian activity and driving behaviour (Goel *et al.*, 2015). Moreover, the studies which examined the impacts of human exposure to vehicular emissions, rarely discuss the impact on travel behaviour (Singh *et al.*, 2021). Hence it is essential to understand the public perception about the impact of vehicular emissions and corresponding changes in travel behaviour.

3. Methodology

3.1. Data collection

Two Indian cities namely Warangal and Hyderabad were selected for the present study. A questionnaire survey was conducted in both the cities from January to March of 2021 using an online Google forms tool. In-person surveys were not conducted due to covid-19 restrictions. Online surveys have their own advantages over offline methods such as increased accessibility, respondent convenience, fewer data entry errors and faster data collection in a short period of time (Wardropper *et al.*, 2021). Moreover, considering the present pandemic situation, online surveys prevent the spread of the coronavirus by avoiding physical contact with the respondent. Though there are arguments on online survey methodologies as it generates unreliable, biased and inaccurate data, they can be overcome if they are carried out properly with the utmost care, preparation and documentation (Wardropper *et al.*, 2021).

A probability-based sampling approach (random sampling) is adopted in collecting the data sample from both cities. For the known population and accessible email addresses, email recruiting to a predetermined random sample reduces the errors of sampling and nonresponses to a greater extent (Fielding *et al.*, 2016). Out of 765 random individuals to whom the survey form was sent (through mails

and social media platforms), 513 members responded to the survey (67.05 % response rate). The reasons for the remaining 252 nonresponses may be many such as spam filter (emails may go to the spam folder), wrong email addresses (address not found), deletion before reading, etc. From the 513 responses, 10 responses were found to be missing or incomplete data from a manual screening of the data set. These responses were eliminated for further analysis. Moreover, an outlier analysis was carried out in SPSS version 26 for the data set of 503 samples and 9 responses (outliers) were removed. Further analysis has been carried out for the remaining 494 responses as the final sample size.

3.2. Questionnaire

A stated preference survey was carried out with a self-administered questionnaire through Google forms. The questions were framed following the objectives of the study. A preliminary survey was also carried out among the experts and subsequently, the questionnaire was modified for a better understanding of the participant. The final questionnaire had two sections.

3.2.1. Socio-demographic attributes

In section-1, the socio-demographic variables of the respondents such as age, gender, vehicle ownership (bikes and cars), travel mode, home to work distance, were included. Also, questions related to vehicle condition and exposure time to vehicle emissions were asked in this section.

3.2.2. Observed variables

The questionnaire's second component consisted of seven possible factors relating to the impact of emissions on pedestrians, each containing four to five statements. The statements in this section were measured on a 5-point Likert scale (strongly disagree = 1, neutral = 3, strongly agree = 5).

The first factor named pedestrian attitude (ATT) had five statements as (1) I never noticed vehicle emissions while walking on the road (2) I would avoid walking in peak traffic hours (3) I would avoid the routes having high vehicle emissions (4) I would not wait at a bus-stop for a long time (5) I don't bother about vehicle emissions pollution. The second factor named pedestrian behaviour (BEH) included four statements as (1) I walk fast on sidewalks and crossings to avoid vehicle emissions' exposure (2) I cross at mid of the road when there are high vehicle emissions at signals (3) I don't pay attention to vehicle emissions while walking on the road (4) I use the bicycle for short trips instead of walking. Perceived impacts (PIM) was measured on four variables which are (1) Vehicle emissions have adverse effects on human health, (2) Vehicle emissions reduce visibility on road causing accidents, (3) Vehicle emissions have an impact on pedestrian travel behaviour, (4) Vehicle emissions have an impact on climate change. Technology (TEC) factor was measured using four variables as (1) Advanced technologies (e.g., BS-VI) help reduce vehicle emissions, (2) Using electric vehicles would be the best solution to reduce emissions, (3) Old and poorly maintained vehicles emit more emissions, (4) Intelligent Transport Systems (sensors) can help to monitor vehicle emission levels. Environmental attitude (ENA) included five statements as (1) I would wear a mask or helmet to avoid exposure to emissions, (2) Growing trees and vegetation along the roadside would reduce the impact of emissions, (3) Using impure fuel increases vehicle pollution, (4) I prefer public transportation rather than private vehicles. Public concern (PCN) had four statements as (1) I would not use sidewalks when vehicle emissions are less, (2) I would not use sidewalks when vehicle emissions are more, (3) I would like to use e-bikes or e-scooters (4) I would like to use ride-sharing services. Government policies (GPO) was measured on five variables (1) Engines should be turned off at signal stopping, (2) Trucks and heavy-duty vehicles should not enter into urban areas, (3) Public transportation facilities should be improved, (4) Ambient air purifiers should be installed at traffic intersections (5) A toll price should be charged for using old vehicles (i.e. vehicles with low emission standards).

3.3. Model Development

3.3.1. Exploratory Factor Analysis (EFA)

A data reduction and interdependence technique examines the interrelationships among a large number of variables and groups them into certain factors. These factors or components are derived based on their common underlying dimensions of corresponding variables. To extract these factors, a Principal

Component Analysis (PCA) method of extraction is used which derives the factors considering the total variance. To determine the minimum number of factors that account for maximum variance, an Eigen value greater than one criterion was used in PCA. Factors were rotated to make them more meaningful and easier to interpret and also to avoid cross-loadings. For this, the Varimax with Kaiser Normalization method was used which is an orthogonal rotation. To achieve a minimum correlation of 0.5 between factors and their variables, variables with component loadings less than 0.5 were suppressed and deleted. To check the adequacy of the sample size, the Kaiser-Meyer-Olkin (KMO) test (Cerny and Kaiser, 2010) was performed. KMO value closer to 1 (0.8 and above) indicates great sizeable sampling adequacy and less than 0.5 is unacceptable for performing factor analysis. Further, the reliability of variables in the corresponding factors was tested using Cronbach's reliability test (Cronbach, 1951) and unreliable variables were removed subsequently.

3.3.2. Adopted Model

EFA resulted in seven components initially with some of the factors having very little reliability (Cronbach's alpha less than 0.5) and some variables with cross-loadings (difference greater than ± 0.2). Eliminating such variables, five factors were obtained from EFA. These factors have been named according to the common underlying dimension of the corresponding variables. For a factor containing variables with no or less common underlying meaning, the factor is named after the variable having the highest factor loading. The mean scores of these factors were computed and the obtained factors were used as predictors in the multiple regression analysis to estimate the ability to predict the impact of vehicle emissions on pedestrian travel behaviour. The basic assumptions of multiple regressions like normality, multicollinearity and homoscedasticity were tested for the data set and were found satisfying. Further, a mediation analysis was carried out using PROCESS Macro in SPSS to identify the indirect effects of the factors which were found insignificant from the multiple regression analysis.

4. Results

4.1. Descriptive statistics

The descriptive statistics of the collected samples show that most of the respondents were male (78%) and about 72% of total respondents were of age group 18–25 years. This wide variation in gender and age of respondents may be due to the reason that most of the responses were from the educational institutions and employees of Warangal and Hyderabad cities. Forty per cent of the participants have chosen walking as their daily mode of travel and about 30% of respondents showed to use a motorcycle (two-wheeler) for their daily trips as shown in Table 1. About 78% of individuals whose primary mode of travel is walk mode have exposure times more than five minutes. Eight % of respondents whose travel mode is a bus with home to work distance greater than 10 km, had higher exposure times (> 40 min). Less than half of the individuals (38%) claimed that their vehicles are compliant with Bharat Stage VI (BS-VI) emission standards while 33% of respondents selected not applicable (NA).

4.2. Characteristics of Measures

Outlier analysis was carried out in SPSS version 26, to identify the outliers. In univariate analysis, the z score values of the data points falling outside of the threshold -3.29 to $+3.29$ are identified as outliers. The Mahalanobis distance probability is calculated for the data in multivariate analysis. A data point is said to be a multivariate outlier if the Mahalanobis distance probability is less than 0.001. A total of 9 outliers were detected from both methods and are deleted from the total responses. Further analysis is carried out for this data of 494 sample size. From Table 2 it can be observed that the KMO statistic value is 0.846 which is greater than 0.8 indicating very good sample adequacy. Apart from the KMO test, the sampling adequacy can also be justified from the rule of a minimum of 5 to ideally 20 observations per variable (Comrey and Lee, 1992). In the present study questionnaire, there are 29 variables in total. Hence, a minimum of $29 \times 5 = 145$ samples and an ideal of $29 \times 20 = 580$ samples are required. Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identity matrix that has a significance value less than 0.05 indicating that the correlation exists among the variables and the data can be used for factor analysis.

Table 1. Socio-demographic attributes

Attributes	Frequency	Percentage
Gender		
Male	383	78
Female	111	22
Age		
<18	4	1
18-25	355	72
26-40	97	19
41-60	33	7
>60	5	1
Home to work distance		
<2 km	104	21
2 – 5 km	119	24
5 – 10 km	83	17
10 – 20 km	57	11
>20 km	38	8
NA	93	19
Travel Mode		
Walk	198	40
Bicycle	18	4
Motor Cycle	151	30
Auto-rickshaw	19	4
Car	55	11
Bus	40	8
Metro	17	3
Exposure time		
< 5 min	80	16
5 – 20 min	172	35
20 – 40 min	133	27
40 – 60 min	51	10
> 60 min	58	12
Bharat stage VI		
Yes	188	38
No	141	29
NA	165	33

Table 2. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.846
Bartlett's Test of Sphericity	Approx. Chi-Square	3173.357
	df	325
	Sig.	0.000

Communality (shared variance) is the amount of variance a variable shares with all the other variables being considered. The variables with low communalities (less than 0.4) can be dropped for better results in further analysis. The EFA gives a rotated component matrix that has the components and their corresponding variables with factor loadings. If any cross-loadings are present in the rotated component matrix with a difference greater than ± 0.2 , they are removed one after another and the factor analysis is run again. Each factor should contain a minimum of three variables for a better explanation of the factor. Table 3 shows the rotated component matrix with mean and factor loadings and also the total variance explained (TVE) and Cronbach's α value for each component. All the variables have factor loadings greater than 0.5. Table 4 shows the factor correlation matrix that explains the correlations among the factors of EFA. A significant positive correlation can be seen among all the EFA factors. Perceived impacts (PIM) has a strong (0.603) positive correlation with technology (TEC) but a very weak (0.038) correlation with attitude (ATT) as seen from Table 4.

Table 3. Rotated Component Matrix

Latent variables		Mean	Loadings
Technology (TEC) (TVE = 12.75, Cronbach's α = 0.761)			
TEC1	Old and poorly maintained vehicles emit more emissions	4.25	0.692
TEC2	Intelligent Transport Systems can help reducing vehicle emissions		0.670
TEC3	I would like to use e-bikes or e-scooters		0.594
TEC4	Advanced technologies help to reduce the vehicle emissions		0.570
TEC5	Using electric vehicles would be the best solution to reduce emissions		0.557
TEC6	Using impure fuel increases vehicle pollution		0.554
Perceived Impacts (PIM) (TVE = 12.30, Cronbach's α = 0.754)			
PIM1	Vehicle emissions reduce visibility on road causing accidents	4.44	0.715
PIM2	Vehicle emissions have an adverse effect on human health		0.633
PIM3	Growing trees along the roadside would reduce the impact of emissions		0.625
PIM4	Public transportation facilities should be improved		0.616
PIM5	Pollution monitoring stations should be installed at traffic junctions		0.570
PIM6	Engines should be turned off at signal stopping		0.535
Attitude (ATT) (Cronbach's α = 0.691, TVE = 9.70)			
ATT1	I don't care about vehicle emissions pollution	2.80	0.805
ATT2	I don't pay attention to vehicle emissions while walking on the road		0.704
ATT3	I never noticed vehicle emissions while walking on the road		0.674
ATT4	I would not use sidewalks when vehicle emissions are less		0.627
Public Concern (PCN) (Cronbach's α = 0.588, TVE = 8.8)			
PCN1	I prefer public transportation rather than private vehicles	3.63	0.729
PCN2	A toll price should be charged for using old vehicles		0.603
PCN3	I would like to use ride-sharing services		0.579
PCN4	I use the bicycle for short trips instead of walking		0.554
Environmental Attitude (ENA) (Cronbach's α = 0.687, TVE = 8.87)			
ENA1	I would avoid the routes having high vehicle emissions	3.76	0.818
ENA2	I would avoid walking in peak traffic hours		0.812
ENA3	I would not wait at a bus stop for a long time		0.625

Table 4. Factor correlation matrix (N = 494)

	TEC	PIM	ATT	PCN	ENA
TEC	1				
PIM	.603**	1			
ATT	.097*	0.038	1		
PCN	.397**	.337**	.235**	1	
ENA	.283**	.218**	.427**	.150**	1
Note: ** indicates p -value ≤ 0.01 at 99% significance level and * indicates p -value ≤ 0.05 at 95% significance level.					
TEC: Technology; PIM: Perceived Impacts; ATT: Attitude; PCN: Public concern; ENA: Environmental Attitude.					

For the factors obtained from the principal component analysis, a multiple linear regression analysis was carried out. The dependent variable is taken as 'impact of vehicle emissions on pedestrian behaviour' and the predictor variables as the factor mean scores and some demographic variables like age, to see their effect on the dependent variable. The hypothesis is that all the predictor variables have a significant positive effect on pedestrian behaviour. Pedestrian behaviour in this study refers to the travel behaviour of pedestrians. From the ANOVA test results as seen in Table 5, it can be observed that the model is identified to be significant (F value = 26.27) and can explain the impact on pedestrian travel behaviour. The R square value obtained is 0.328 and the adjusted R square is 0.316. It was observed from the results of multiple linear regression analysis (refer to Table 6) that the factors Perceived Impacts (PIM), Public Concern (PCN) and Environmental Attitude (ENA) are significant and other factors were

not significant enough to predict the impact on pedestrian behaviour. Among these three factors, Perceived Impacts had a higher effect on pedestrian behaviour. It can be said that the pedestrians who are aware of the impacts of vehicular emissions are supposed to have changes in their travel behaviour. Factors such as technology and attitude had no direct effects but can have indirect effects on pedestrian travel behaviour due to vehicular emissions. To understand the indirect effect, mediation analysis is carried out with perceived impacts and environmental attitude as mediators.

Table 5. ANOVA test results

Model		Sum of Squares	Degrees of freedom	Mean Square	F - statistic	Significance
	Regression	108.848	9	12.094	26.268	.000 ^b
	Residual	222.845	484	0.460		
	Total	331.692	493			

Table 6. Impact on pedestrian travel behaviour results

Model		Unstandardized coefficient (B)	Std. Error	t-value	p-value
	(Constant)	-0.150	0.365	-0.412	0.680
	Technology	-0.045	0.079	-0.567	0.571
	Perceived Impacts	0.813	0.081	10.073	0.000**
	Attitude	-0.071	0.050	-1.429	0.154
	Public Concern	0.181	0.047	3.863	0.000**
	Environmental Attitude	0.122	0.044	2.764	0.006**
	Age group	-0.048	0.049	-0.978	0.329
	Gender	0.061	0.075	0.810	0.418
	Home to work distance	-0.001	0.021	-0.064	0.949
	Exposure time	0.033	0.027	1.233	0.218

Note: Dependent variable: Vehicular emissions have impact on pedestrian travel behaviour; ** indicates p -value ≤ 0.01 at 99% significance level; R square value: 0.328; RMSE: 0.678.

4.3. Mediation Analysis

Mediation analysis was carried out using PROCESS Macro in SPSS to identify the indirect effects of the factors, Technology (TE) and Attitude (ATT) separately, on Impact on pedestrian behaviour (IPB). The factors Public Concern (PC) and Environmental Attitude (ENA) are assumed to mediate the effect between Technology and Pedestrian Behaviour and also between Attitude and Pedestrian Behaviour. Results showed that a partial mediation exists between the predictor and dependent variables in both cases.

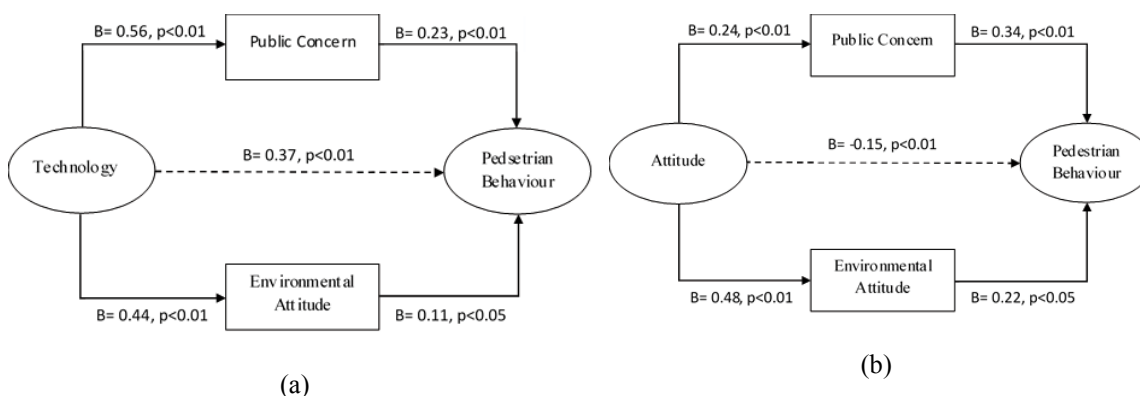


Figure 1. Mediation analysis for factors (a) Technology and (b) Attitude

Table 7. Mediation analysis results

(a) Indirect effect(s) of Technology on Pedestrian behaviour					
	Effect		BootLLCI		BootULCI
Total	0.176		0.099		0.261
PCN	0.127		0.065		0.200
ENA	0.048		0.009		0.097
(b) Indirect effect(s) of Attitude on Pedestrian behaviour					
	Effect		BootLLCI		BootULCI
Total	0.189		0.129		0.250
PCN	0.084		0.048		0.123
ENA	0.105		0.058		0.155
Note: PCN: Public Concern; ENA: Environmental Attitude; BootLLCI: Bootstrapped lower level confidence interval; BootULCI: Bootstrapped upper level confidence interval.					

All the direct and indirect effects as seen in Figures 1(a) and 1(b) are significant at a 95% significance interval supporting the hypothesis that a mediation effect exists between Technology and Pedestrian Behaviour. Also, from the correlation analysis (see Table 4), it can be observed that there is no case of multicollinearity as the correlation between mediating variables is less. The indirect effect of Technology on Pedestrian Behaviour through mediator Public concern is obtained by multiplying the direct effects (unstandardized coefficients) of Technology on Public Concern and Public Concern on Pedestrian Behaviour. Similar is the case with Environmental Attitude. The indirect effects are shown in Table 7 with unstandardized coefficients and bootstrap confidence intervals. It was observed that the indirect effect of Technology on Pedestrian behaviour is significant with mediators Public Concern (Unstandardized coefficient = 0.127, BootLLCI = 0.065 and BootULCI = 0.200) and Environmental Attitude (Unstandardized coefficient = 0.048, BootLLCI = 0.009 and BootULCI = 0.097). But the mediator Public Concern has a strong indirect effect compared to that of the mediator Environmental Attitude.

In the second case of mediation analysis, the indirect effect of Attitude on Pedestrian Behaviour is significant with the mediators Public Concern (Unstandardized coefficient = 0.084, BootLLCI = 0.048 and BootULCI = 0.123) and Environmental Attitude (Unstandardized coefficient = 0.105, BootLLCI = 0.058 and BootULCI = 0.155). In this case, the mediator Environmental Attitude was found to have a strong mediating effect than that of the mediator Public Concern. The total effect shown in Table 7 is the sum of the direct and indirect effects.

5. Discussion

In the present study, factors affecting pedestrian travel behaviour due to exposure to vehicular emissions were explored using the factor analysis method. The EFA resulted in five factors as shown in Table 3. The component 'Technology' had a high total variance (12.75%) followed by 'Perceived Impacts' (12.30%). It was found from the multiple regression analysis that the components technology and attitude were not significant enough to predict the impact of vehicular emissions on pedestrian travel behaviour but were found to be significant from the mediation analysis with mediators as Public Concern and Environmental Attitude components. The mediation observed was partial as both the direct and indirect effects were significantly affecting pedestrian travel behaviour. This indicates that vehicle technology and pedestrian attitude can have significant indirect effects on pedestrian travel behaviour for the pedestrians who are concerned about the impacts of air pollution and having an environmental attitude of avoiding exposure to vehicular emissions. From figure 1(b), it can be seen that the component attitude has a direct negative effect ($B = -0.15$) on pedestrian travel behaviour which is the rejection of our null hypothesis that all the predictor variables have a significant positive effect on the pedestrian travel behaviour. The component Attitude measures the ignorant and negligent attitude of the pedestrian towards the vehicular emissions. The negative sign explains the rationale that the pedestrians with negligent and carefree attitudes will have less impact on their travel behaviour. In the present study, from the statistical analysis, it was found that about 6% of the participants jointly agreed that their travel

behaviour is not affected by the vehicular emissions as they neither paid attention (ATT2) (19.2%) to vehicular emissions nor they ever noticed (ATT3) (18.8%) the vehicular emissions during their travel. Whereas, 82% of total individuals have agreed that vehicular emissions have an impact on pedestrian travel behaviour.

The other components such as Perceived Impacts (t-value = 10.073, p-value = 0.000), Public Concern (t-value = 3.863, p-value = 0.000) and Environmental Attitude (t-value = 2.764, p-value = 0.006) have significant positive effects on pedestrian travel behaviour corresponding to vehicular emissions as seen from Table 6. This indicates that the changes in the pedestrian travel behaviour are observed for the persons who are aware of the impacts of vehicular emissions or concerned about the exposure to emissions (and so using public transit, ride-sharing services and bicycles) or having an environmental attitude (avoiding busy routes, changing departure times) towards air pollution (Welch *et al.*, 2005; Saberian *et al.*, 2017; Cui *et al.*, 2019; Song *et al.*, 2019). From the present study, it was found that nearly 15% (collectively) of all the respondents agreed to shift to other modes of travel such as bicycle (for short trips instead of walking) (PCN4) (43%), e-bikes or e-scooters (TEC3) (73%), public transport (PCN1) (61%) and ride-sharing services (PCN3) (68%) to reduce their exposure rate to vehicular emissions. Also, the participants chose the alternate choices of avoiding exposure to vehicle emissions such as avoiding the routes having high emissions (ENA1) (68%) and avoiding walking in peak traffic hours (ENA2) (77%). Existing studies have shown that replacing car trips with public transport, walking and cycling have reduced vehicular emissions and also the exposure to the emissions (Shiftan and Suhrbier, 2002; Tiwari *et al.*, 2016; Geng *et al.*, 2018). It was observed from the statistical analysis that most of the participants were aware of the impacts of vehicular emissions such as health impacts (PIM2) (98%) and vision problems (PIM1) (83%).

Statements related to strategies that reduce vehicular emissions and pedestrian exposure to emissions such as turning off engines at signal stopping, improving public transit, restricting heavy-duty vehicles entering into the urban areas, charging for using low emission standard vehicles (BS4 or below), installing air pollution monitoring stations at traffic intersections, growing vegetation along the roadside, etc were measured from the questionnaire. But some of these variables were eliminated for further analysis as they were found to be loaded in two or more factors of the EFA and also had factor loadings less than 0.5. Statistical analysis showed that most of the participants agreed to adopt changes in their travel behaviour such as choosing alternate routes (ENA1) (77%), avoiding peak traffic hours (ENA2) (68%), and being willing to accept changes in the policies such as turning off engines at signal stoppings (PIM6) (84%), toll charging for old vehicles (PCN2) (60%), growing trees along the roadside (PIM3) (90%), improving public transport facilities (PIM4) (93%), etc. It can be observed from the regression analysis that all the above measures significantly affect pedestrian travel behaviour.

6. Policy Implications

As air pollution has become a devastating problem across the globe, many studies have been focusing on various strategies to reduce air pollution particularly from the transport sector (Shiftan and Suhrbier, 2002; Frank *et al.*, 2006; de Nazelle *et al.*, 2010; Neves and Brand, 2019; Hulkkonen *et al.*, 2020). However, travellers' exposure to air pollution and its impact on their travel behaviour are rarely discussed in these studies. This is important because reducing transport emissions may not necessarily reduce the exposure to emissions. Emission controlling policies should focus more on reducing human exposure to emissions to minimize the negative impacts of vehicular emissions. Policies such as diverting traffic and closing lanes to reduce vehicle emissions are unproductive sometimes as they increase the emissions on the alternate traffic routes (Fernandes *et al.* 2016). To make such measures effective, the traffic should be diverted to those areas where the pedestrian density is less. The other category of measures is pricing mechanisms. Researchers found that the pricing schemes such as congestion pricing, green tax and emission charging etc were not always effective in reducing the emissions at all the locations (Yin and Lawphongpanich 2006). Also, studies have found that awareness programs and public advisories on reducing air pollution can effectively change the travel behaviour of commuters (Welch *et al.*, 2005; Tribby *et al.*, 2013). Jain *et al.*, 2016, have found that the best alternative policy for megacity Delhi, India to reduce transport emissions is the combination of measures like rigorous emission norms, advanced engine technology, alternative public transport systems and premium parking cost for private vehicles. Introduction of electric vehicles is another best alternative to overcome the problem of transport emissions. Nonetheless, the implementation of these strategies or policies is still a problem in many low and middle-income countries.

7. Conclusions

The present study has explored the factors affecting pedestrian travel behaviour due to the impact of vehicular emissions from the public perceptions. Factors such as Technology, Attitude, Perceived Impacts, Public Concern, Environmental Attitude were derived from the exploratory factor analysis. It can be concluded from the study that the pedestrians who are aware of the impacts of vehicular emissions will adopt changes in their travel behaviour such as shifting to other travel modes and reducing walking and cycling during peak traffic hours. Also, the impact on pedestrian travel behaviour was observed to be significant with the factors Public Concern and Environmental Attitude. Persons who are concerned about their health and environment show a willingness to accept emission controlling policies such as congestion pricing, turning off engines at signal stoppings, pricing for using low emission standard vehicles and improving public transportation facilities. Further, the study results indicated that vehicle technology and negligent attitude of pedestrians towards vehicular emissions had significant indirect effects on pedestrian travel behaviour. Pedestrians who are unaware and ignorant of the impacts of vehicular emissions had fewer or no changes in their travel behaviour. It can be inferred from the current study that travel mode, as well as the home to work distance, can significantly affect pedestrian exposure to vehicular emissions.

There are certain limitations to the present study. The first limitation is that the sample size of the data collected was finite and also, the method of data collection used in this study was internet surveys which may not reflect the characteristics of the population leading to obvious gender bias as in who uses the internet or responds to the survey. An offline survey in the field incorporating the education and income attributes of participants and their attitudinal preferences and behavioural evidence, and on-road pollution measurements might yield better results and support the theoretical concept. However, the findings of the present study can be useful to the transport planners and policymakers by implementing innovative strategies and promoting pedestrian-friendly street designs to reduce vehicular emissions and their impacts on pedestrian health and travel behaviour.

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