
RESEARCH ARTICLE

Health Modelling of Transport in Low- and Middle-Income Countries—a Case Study of New Delhi, India

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Transportation impacts population health through air pollution, traffic injuries and physical activity. In the cities of low- and middle-income countries, where travel patterns are rapidly changing, the understanding of these impacts on health is limited. We estimate the health loss among adults (≥ 15 years) that can be attributed to motorised transportation systems and health benefits attributed to active travel in New Delhi in the year 2014. We show that under baseline transport patterns, health loss is dominated by road traffic injuries (170,000 disability-adjusted life years, DALYs), which is about three times the burden due to traffic-related fine particulate matter (PM_{2.5}) pollution (~64,000 DALYs). Baseline use of active travel, on the other hand, *prevents* health burden (~90,000 DALYs), which is as large as 40% of the combined health loss due to injuries and vehicular air pollution. Next, we estimate the effect of changing Delhi's travel modal shares to that of London, New York City and Amsterdam. For these scenarios, we limited to the impact on injuries and physical activity. In all scenarios, there is additional health burden due to traffic injuries and reduced physical activity, and the former exceeds the latter. Greater motorisation in the future is likely to result in large burden of health due to injuries and reduced physical activity. Small reductions in active travel have the potential to negate health benefits from large reductions in traffic emissions. There is an urgent need to develop an alternative pathway of development that is not based on greater use of private motor vehicles.

Keywords: transport; health; injuries; physical activity; pm2.5; india; NCD

Introduction

Transport impacts human health through multiple pathways. The latest review by Glazener et al. (2021) highlighted fourteen such pathways. These include four with beneficial effects (green spaces and aesthetics, physical activity, access and mobility independence) and ten with detrimental health effects (air pollution, road travel injuries, noise, stress, urban heat islands, contamination, climate change, community severance, restricted green space, blue

space and aesthetics). Some of these pathways are better recognised and researched and have stronger evidence. Most health impact studies of transport have studied the three pathways of traffic injuries, air pollution and physical activity (Mueller et al., 2015), which are also the focus of this study.

With increasing income levels and urbanisation in many low- and middle-income countries (LMICs), populations are moving towards sedentary lifestyles. Growth in the use of private motorised modes has reduced travel-related physical activity and is projected to reduce further over the next decade of 2020–30 (Ng and Popkin, 2012). In Latin America and South Asia, physical activity levels are significantly lower than the global average (Guthold et al., 2018). Unmanaged growth in the transport sector and rapidly changing travel patterns have resulted in road death rates in LMICs that are three times higher than high-income countries and contribute 93% of the global road deaths (WHO, 2018). Emissions are increasing rapidly in many LMICs compared to Europe or the United States, where emissions have stabilised or are decreasing (Crippa et al., 2018). As expected, fine particulate matter (PM_{2.5}) levels in East Asia, South Asia and parts of Sub-Saharan Africa have increased markedly over the past decades and are currently the highest in the world (Apte et al., 2018; Burnett and Cohen, 2020). These levels of pollution combined with a large population size result in the disproportionate share of premature mortality due to cardiovascular and respiratory diseases in LMICs (Burnett and Cohen, 2020). New evidence on the impact of PM_{2.5} pollution on infant mortality (Heft-Neal et al., 2018) and diabetes (Bowe et al., 2018), now included in the global burden of disease (GBD) estimates (Stanaway et al., 2018), have added to the health burden of PM_{2.5}.

Thus, the transportation sector, through the pathways of physical activity, traffic injuries and air pollution, is likely a major contributor to rapidly increasing health burden in many LMICs. However, our understanding of this relationship is limited in the context of LMICs. A recent systematic review of studies that evaluated the health impact of transport interventions reported a scarcity of such studies in LMICs (Stankov et al., 2020). Another review of health impact assessment studies in LMICs found that most included air pollution as the only pathway, and few included other pathways, such as injuries and physical activity (Thondoo et al., 2021). In the past few years, there has been a growing interest in LMICs for health impact modelling that accounts for multiple exposure pathways, such as in Sao Paulo, Brazil (Sá et al., 2017), Accra, Ghana (Garcia et al., 2021), and Port Louis, Mauritius (Thondoo et al., 2020). Woodcock et al. (2009) produced one of the earliest such modelling studies for London, UK, and Delhi, India.

In this paper, we aim to fill this gap in the literature. We present a health impact model of transport for the megacity Delhi. We present the baseline health burden due to transport through the three exposure pathways of PM_{2.5} pollution, traffic injuries and physical activity for people 15 years or older. We also present physical activity and injury impacts resulting from future scenarios of travel patterns. The work presented in this paper was done as part of a doctoral thesis at Transportation Research and Injury Prevention Programme (now TRIP Centre), Indian Institute of Technology Delhi (Goel, 2017).

Data and methods

Case study city—Delhi

In 2011, Delhi had a population of 16.7 million and, along with its contiguous cities (see **Figure 1**), forms an agglomeration of 22.5 million, with a population density of 240 person per hectare (Goel and Guttikunda, 2015). In 2014, the annual average PM_{2.5} concentration was 146 ug/m³ (median: 111 ug/m³ and interquartile range: 66–374 ug/m³ (Goel, Gani et al., 2015)) and contributed to by multiple sectors (Guttikunda and Calori, 2013). With these concentration levels, Delhi is one of the most polluted cities in the world. In 2011, 21% of

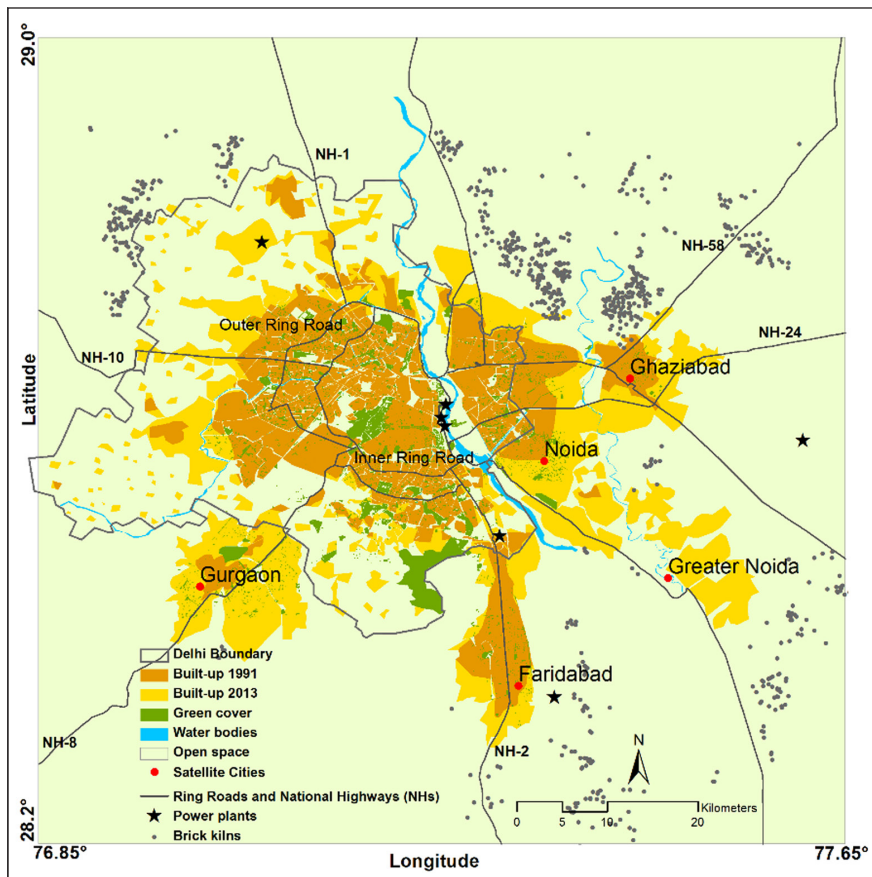


Figure 1: Delhi and its neighbouring cities.

households owned at least one car, 38% owned at least one powered two-wheeler (PTW) and 30% owned at least one cycle. The ownership of vehicles has been rapidly growing. In the past decade (2009–2018), half a million cars and PTW have been registered every year. Public transportation includes intermediate public transportation (cycle rickshaws, three-wheeled motorised rickshaws (auto rickshaws), mini vans), buses and a metro rail system (Goel and Tiwari, 2016). We present a health impact analysis for 2014 as the baseline year, with a projected population of 18.3 million people 15 years or older.

Travel patterns

We conducted a household travel diary survey in Delhi in 2013 using a face-to-face interview approach. To sample households, we used a stratified (area-level income \times distance from centre \times four quadrants of the city) two-stage random sampling approach using a gridded (1 km \times 1 km) population sampling frame (see Supplementary Information (SI) for details). We used a random walk approach for the final sample of households in the sampled grids. The average response rate was 65%, with significant variation across the sampled grids. We recorded the previous-day trip diary of all members of the households and used proxy responses for young children and those not available in the household at the time of interview. Post cleaning, we retrieved travel diaries from ~1,700 households (6,844 individuals). **Table 1** presents mode share of trips for people aged 15 years or greater, considering only main modes and the gender

Table 1: Mode share of trips for population older than 15 years.

Main mode	Trip share	Mode share by gender		Distribution of trips within each mode	
		Male	Female	Male	Female
Walk	42.5%	32.4%	63.4%	51.3%	48.7%
Cycle	5.6%	8.0%	0.8%	95.4%	4.6%
Powered two-wheelers	13%	17.6%	3.4%	91.0%	9.0%
Car	9.1%	11.2%	4.8%	82.9%	17.1%
Cycle Rickshaw	2.2%	1.5%	3.5%	46.8%	53.2%
Auto Rickshaw	1.7%	1.3%	2.6%	51.0%	49.0%
Shared Auto Rickshaw	1.7%	1.6%	1.9%	64.0%	36.0%
Bus	19.4%	21.9%	14.4%	75.8%	24.2%
Metro	3.5%	3.3%	4.1%	62.4%	37.6%
Train	0.1%	0.1%	0.05%	78.1%	21.9%
Taxi	1.2%	1.2%	1.1%	71.0%	29.0%
All modes	100%	100%	100%	33.0%	67.0%

distribution of trips within each mode. In a trip that involves multiple travel modes, for example, while using public transport, the main mode was the one used for the longest duration. Up to four in ten trips are by walking, and one quarter of all trips were made using various public transport modes—bus, metro, shared auto rickshaw, auto rickshaw and train. There are significant differences across the modes in terms of gender representation. Females contributed 33% of all trips and 19% of all travel distance, even though they comprise half the population. Gender representation has significant variation across the modes of transport. Females are most underrepresented in the use of cycling and PTW. India has one of the highest levels of gender inequality in the world (Black, 2016), and the work participation rate of women is among the lowest (Deshpande and Kabear, 2019). Out-of-home mobility for work and for all travel needs is much lower among females than males (Census-India, 2016; Sanchez et al., 2017).

Physical activity

We express intensity of travel physical activity as metabolic equivalent of task (MET) and the volume of activity as MET-h, which is the product of duration of activity and its corresponding MET value. For walking, we used MET values of 3.5 and 3.7 for females and males, respectively, and for cycling, a value of 6.8 METs was used for both sexes (Ainsworth et al., 2000; Woodcock, Givoni and Morgan, 2013). We included duration of walking and cycling that was done either as a main mode or as one of the stages of the trip, for example, walking to public transport stops. We estimated average weekly active travel time (walking and cycling) as 107 minutes and 156 minutes per capita for males and females, respectively. Most of this time was contributed by walking alone—99% for females and 84% for males. For females, 28% of their walking time was contributed to by public transport access trips, and for males, this share is 10%. The travel physical activity difference between the two groups widened more when expressed in volumes—6.3 MET-h for females and 10.9 MET-h for males per capita per week. We used

weekly non-travel physical activity of 25.3 and 26.4 MET-h for males and females, respectively (Anjana et al., 2014).

Traffic injuries

We used case-level traffic fatality data reported by Delhi traffic police for 2010 through 2012 (Goel et al., 2018). We did not use police-reported traffic injury data due to high levels of underreporting of injury in Indian cities (Mohan, Tiwari and Bhalla, 2017). Instead, we used GBD-reported data (see below) to estimate DALYs corresponding to road deaths. During the 3-year period, there were 5,972 fatalities, equivalent to 11.9 deaths per 100,000 persons. Pedestrians, cyclists and PTWs contributed to 87% of all fatalities. In total, 38% of the fatalities occurred with freight vehicles (trucks) as the other vehicle involved, 37% with PTW and cars, and 17% with buses and other public transport modes. For 2014, the total number of deaths was estimated at 2,154, using the 2010–2012 death rate and projected population. Among the victims, 81% were males and 94% were 15 years or older. See SI for more details on traffic deaths and the road users involved.

Traffic emissions and population exposure

We estimated transport emissions using a bottom-up approach. We developed a dynamic time-trend annual emissions model that accounts for changes in vehicle technology, fuel use and emission standards (Goel and Guttikunda, 2015). To parameterise this model, we used data reported in literature, analysed secondary datasets and conducted primary surveys (Goel et al., 2015). In 2014, PTWs, cars, three-wheeled auto rickshaws and buses contributed 12%, 18%, 1% and 5% of transport PM_{2.5} emissions, respectively, and light- and heavy-duty freight vehicles contributed 64% of emissions. We updated the atmospheric transport modelling system (ATMoS) dispersion model for the Greater Delhi region (Guttikunda and Calori, 2013) with spatially and temporally resolved transport emissions. Using the model, we obtained modelled annual-average PM_{2.5} concentrations and source contributions at 1 km × 1 km resolution. To account for elevated exposure levels during on-road travel, we conducted a study to measure PM_{2.5} exposure in 11 transport microenvironments in Delhi that included all modes of transport and surface and underground public transportation stops (Goel et al., 2015). We used a portable, optical-sensor based, real-time PM_{2.5} monitor to measure exposure in different modes of transport. To estimate population-weighted PM_{2.5} exposure, we integrated spatio-temporal movement of population (using the travel survey) with spatio-temporal variation in modelled PM_{2.5} concentrations and accounted for on-road elevated exposure in corresponding transport microenvironments. The annual-average population-weighted concentrations was 118 ug/m³, accounting for 30% contribution from regional pollution observed in Indo-Gangetic plains (Guttikunda, Nishadh and Jawahar, 2019), and the population-weighted contribution of transport to PM_{2.5} concentration was 21%.

Health impact model

We developed a health impact model that used sex- and age-stratified aggregate population exposure of PM_{2.5} concentrations and sex-stratified exposure of travel physical activity. For traffic injuries, we developed a model to predict injury outcomes resulting from changes in travel patterns. The model uses road death counts classified into pairs of victim road user type and the other road user involved (e.g., for a pedestrian killed in a crash with car, pedestrian is victim and car is other road user). This data can be expressed as a two-way matrix (see SI). The model uses a non-linear relationship between travel exposure and injury risk within the ITHIM modelling framework (Woodcock, Givoni and Morgan, 2013; Sá et al., 2017;

Garcia et al., 2021). We used the latest meta-analysis for parameterising non-linearity of the model (Elvik and Goel, 2020). To model health effects of $PM_{2.5}$, we used integrated-exposure response functions (Burnett et al., 2018) for the six GBD-reported causes of deaths attributed to ambient $PM_{2.5}$: ischemic heart disease (IHD), ischemic stroke, lower respiratory infections (LRI), lung cancer, chronic obstructive pulmonary disease (COPD) and diabetes (Stanaway et al., 2018). Out of these six, dose-response functions are age specific (5-year band) for IHD and stroke and common across ages for the other four. We modelled all-cause deaths (i.e., non-communicable diseases (NCD) and lower respiratory infections (LRI)) using the global exposure mortality model (GEMM) (Burnett et al., 2018) for sensitivity analysis. For physical activity, following the approach by Götschi et al. (2015), we modelled eight disease end-points that include breast and colon cancers in addition to the six diseases for $PM_{2.5}$. We used the GBD India Compare online portal (Indian Council of Medical Research, Public Health Foundation of India and Evaluation, 2017) to access Delhi's baseline year cause-specific deaths and DALYs stratified by sex and 5-year age groups (see SI).

Health impact assessments

We present the health burden estimates for the baseline year and health impacts resulting from future scenarios for people 15 years or older. For the baseline year (2014), we estimated the health burden attributed to $PM_{2.5}$ pollution from transport and traffic injuries, and the health burden prevented due to baseline levels of travel physical activity. For $PM_{2.5}$ we used counterfactual $PM_{2.5}$ levels (2.4–5.8 $\mu\text{g}/\text{m}^3$) as used in GBD (Burnett and Cohen, 2020). We used the attribution method to estimate transport's share in health burden, which is calculated as the product of health burden attributed to total $PM_{2.5}$ and the proportion of total $PM_{2.5}$ pollution contributed by transport. For health benefits due to active travel, we calculated the difference between the prevented health burden from total physical activity and from physical activity excluding active travel. Total physical activity includes activity from both travel and non-travel domains. We used population aggregate exposure for modelling all three pathways.

For future scenarios, we adopted mode shares from three international settings: London (LDN), New York City (NYC), and Amsterdam (AMD). For the three scenarios, we estimated changes in health burden for the two pathways of injuries and physical activity. We did not conduct scenario modelling of air pollution as there are multiple anthropogenic sources of pollution in Delhi besides transport contributing significantly to overall $PM_{2.5}$ concentrations, and there remains large uncertainties in terms of their future trajectories (Guttikunda and Calori, 2013). Because the scenario cities have negligible use of PTWs, the mode share of scenario car trips was distributed among cars and PTWs in the same ratio as in the baseline Delhi (see **Table 2**). Delhi has multiple national highways passing through the city that are often used by long-distance freight vehicles, which has been a major concern due to their contribution to worsening air pollution in the city (Goel and Guttikunda, 2015a). For each scenario, we assumed that vehicle kilometres travelled by freight vehicles will be reduced by half based on recommendations by the Environment Pollution Prevention and Control Authority (EPCA, 2015). The reduction will be achieved by restricting the entry of freight vehicles into the city that do not have Delhi as their destination. These changes in freight movement have been assumed to have no direct impact on physical activity. The injury model uses the ratio of vehicle kilometres travelled in the scenario to the baseline, which is 0.5 in the case of freight vehicles. The mode shares presented for Delhi in **Table 2** are the mean values of the Monte Carlo simulations accounting for uncertainty in travel survey estimates. We assumed the total distance travelled across all modes remained constant between the baseline and the scenario. In the LDN and NYC scenarios, the reduction in travel time of walk and cycle was added to

Table 2: Mode share and travel physical activity of baseline Delhi and scenario settings.

Mode	Delhi	LDN	NYC	AMD
Walk	44%	30%	39%	23%
Cycle	6%	2%	0.01%	27%
Powered two-wheelers#	12%	22%	17%	16%
Car	8%	15%	12%	11%
Public transport and others	31%	31%	31%	23%
Total	100%	100%	100%	100%
Weekly travel physical activity from walking (MET-h)				
Male	8.9	7.2	8.6	4.9
Female	6.9	5.9	6.5	5.9
Weekly travel physical activity from cycling (MET-h)				
Male	3.5	1.2	0.06	4.5
Female	0.2	0.09	0	2.6
Total weekly travel physical activity (MET-h)				
Male	12.4	8.4	8.7	9.4
Female	7.1	6.0	6.5	5.9

#For the scenarios cities, mode share of powered two-wheelers is obtained by apportioning car trips to cars and powered two-wheelers using the same relative distribution as baseline Delhi.

PTW and car. In the AMD scenario, the reduction in travel time of walk and public transport was added to PTW, car, and cycle. For each scenario, we used the same gender split of total travel time within a mode as the baseline.

Results

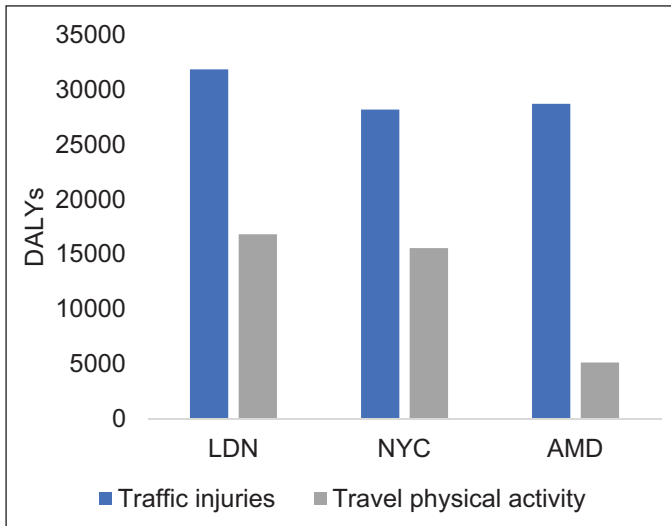
Baseline and scenario health burden

Table 3 presents both the health burden of transport expressed in DALYs through the pathways of transport-related $PM_{2.5}$ concentrations and traffic injuries and the prevented health burden due to travel physical activity. Traffic injuries result in a health burden about three times higher than $PM_{2.5}$. The combined health burden due to two risk factors is equivalent to 6.9% of total NCDs plus injury burden in Delhi. Baseline levels of active travel prevent the equivalent of 40% of the combined health burden due to $PM_{2.5}$ and injuries. Note that traffic-related $PM_{2.5}$ health burden is 21% of the total $PM_{2.5}$ burden. We can further classify traffic-related $PM_{2.5}$ health burden into different vehicle types. Within transport, PTWs and cars contribute 30% of traffic-related $PM_{2.5}$ emissions, buses and other road-based public transport contribute 6% and freight vehicles contribute 64%. This implies that 30% of 21% (i.e., 6%) of total $PM_{2.5}$ can be attributed to personal motorised transport (PTWs and cars).

Figure 2 presents the increase in health burden from traffic injuries and changes in travel physical activity. Use of motorised transport increased and travel physical activity reduced in all scenarios (see **Table 2**), resulting in additional health burden due to the two risk factors. Injuries of pedestrians and motorcyclists contribute the most to injuries in the LDN and NYC scenarios, while in the AMD scenario, cycle injuries are also prominent. Within each scenario,

Table 3: Cause-specific health burden of transport in DALYs for the baseline year (negative numbers indicate health burden prevented).

Cause	Transport PM _{2.5}	Road traffic injuries	Travel physical activity
Ischemic heart disease	29,216		−35,624
Stroke	2285		−3458
Lung cancer	2943		
Lower respiratory infections	4631		
COPD	15,336		−18,700
Diabetes	9193		−24,022
Breast cancer			−1809
Colon cancer			−784
Alzheimer's disease and other dementias			−916
Major depressive disorder			−4311
Traffic injuries		170,860	
Total	63,600	170,860	−89,620

**Figure 2:** Increase in health burden from injuries and travel physical activity for scenarios of Delhi's travel patterns based on London, New York City and Amsterdam.

additional burden from injuries is much greater than the additional burden from reduced physical activity. Because the burden of traffic injuries is almost the same across the three scenarios, the difference across scenarios is dominated by changes in physical activity. The increase in injury burden is almost doubled in each scenario if the baseline levels of freight use continue.

Discussion

We estimated the health burden of transport in Delhi from the three pathways of PM_{2.5} (pollution, traffic injuries and physical activity). For future scenarios of travel patterns, we estimated health impacts due to changes in injuries and physical activity. We found that despite extremely high levels of pollution in Delhi, the health burden due to traffic-related PM_{2.5} is about one third of the burden due to traffic injuries. This is partly because transport is only a part of the overall air pollution problem, contributing to one fifth of all PM_{2.5} pollution in Delhi. The other prominent sources include industry, construction activities, waste burning and residential biomass burning (Guttikunda and Calori, 2013). And partly because traffic injuries are more common among the younger population while diseases caused by PM_{2.5} have greater prevalence among the older population. Death and disability of young people due to injuries result in greater number of life years lost and years lived in disability. Besides the age patterns, the per capita traffic death rate in Delhi is about five times as high as the median death rate in European cities, which are among the safest in the world (ITF, 2019).

We found that prevented health burden due to baseline levels of active travel is greater than the health loss due to traffic-related PM_{2.5} and about half as large as health loss due to traffic injuries. The preventive effect of physical activity underscores the potential loss in health that may result from a future mode shift away from active travel and public transport. In scenarios based on mode shares of London and New York City, an increase in health burden due to reduced physical activity (16,800 and 15,500 DALYs, respectively) is close to the contribution of all cars plus PTWs to the PM_{2.5} health burden in the baseline (30% of 63,600 = 19,080 DALYs). In other words, even if a part of active travel is replaced by motorised modes in the future, it can easily negate benefits achieved from cleaner transport, for example, electric vehicles. Our results indicate that a mode shift from walking and cycling to motorised transportation should be recognised for its unobserved, and potentially far greater, effect on population health through reduced physical activity.

We found that walking to public transport is a significant contributor to overall physical activity, more so among females who have greater dependence on public transport than males. Thus, use of public transport can improve health by providing an opportunity to engage in active travel for trips that are too long for walking or cycling. This finding has also been reported in multiple international settings (Goel et al., 2022; Rissel et al., 2012). Thus, public transport is an important intervention that should be included within the broad framework of active travel policies in cities.

Our study adds to the growing literature on health impact modelling in LMICs. Our findings are in line with similar work done in other LMIC cities. For example, for Accra, Ghana, Garcia et al. (2021) reported that traffic injuries may negate benefits from greater physical activity in scenarios with greater use of active travel. This is similar to the dominance of injury burden that we found in future scenarios for Delhi. The health impact modelling study by Woodcock et al. (2009) for London and Delhi reported greater health benefits from a shift to active travel than from cleaner motor vehicles, which is again similar to our findings above.

From 2014, the baseline year of our study, to 2019, there have been 650,000 cars plus PTWs registered every year. For a population of 19 million and an average household size of five (Delhi Police, 2020), this implies 17 new vehicles for every 100 households every year (assuming each new vehicle is for a unique household). The policy responses to this rapid growth in vehicles have often been short-sighted in their approach and even detrimental to sustainable and active transport (Goel and Pant, 2016). For example, to reduce vehicular pollution, there

is large focus on technological measures, such as improvement of emission standards (Goel and Guttikunda, 2015b) and subsidising electric vehicles (Transport Department, 2020), while there are no policies in place to discourage ownership or use of vehicles. To reduce congestion, grade-separated junctions are constructed and roads are widened, and these have been found to substantially increase the risk of pedestrians and other vulnerable road users (Goel et al., 2018; Goel and Pant, 2016; Khatoon et al., 2013). With the stated aim of “improving safety” for pedestrians (Delhi Police, 2020), foot-over-bridges are installed to replace at-grade signalised crossing (Rankavat and Tiwari, 2015), ignoring access for the disabled and elderly and increasing barriers for walking in general.

Because pollution levels can be measured and injuries can be observed, they get disproportionate attention in transport decision making. With no processes in place to measure travel patterns (as household surveys or volume counts) on a regular basis, the impact of these policies on reducing active travel remains underappreciated and is only inferred from rising levels of vehicle ownership. Our study underscores that air pollution, traffic injuries and physical activity are interrelated. As recommended by Salvo et al. (2021), there is a need to adopt a “health in all policies” approach to transportation engineering and planning. Such an approach will result in “transportation systems that prioritize active travel through wide-spread and safe walking, cycling, and public transit infrastructure” (Salvo et al. 2021).

In India, as in many LMICs, growth in private motorised vehicles is often treated as an inevitable outcome of rising income levels. However, this is an incomplete diagnosis and underplays the contribution of policies, such as those discussed above, that are complicit in encouraging greater use of vehicles and moving people away from active travel or public transport. In the latest climate change conference (COP26), India has pledged net-zero emissions by 2070 (Vaughan, 2021). To attain this ambitious goal, reduction of in-use emissions will not be enough, and there is also a need to phase out production of vehicles while minimising their use. For policy makers, it is important to envision an alternative trajectory of development that does not include continued usage and growth in the number of personal motor vehicles.

Additional File

The additional file for this article can be found as follows:

- **Supplementary Information.** Detailed methodology. DOI: <https://doi.org/10.16997/ats.1231s1>

Competing Interests

The authors have no competing interests to declare.

Authors Contributions

All authors conceptualised the study. RG led the data collection, analysis, and writing with inputs from SG and GT.

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