Model development for quantifying the multiple environmental-health-economic benefits from low-emission urban transport development strategies in Delhi, India

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Model development for quantifying the multiple environmental-health-economic benefits from low-emission urban transport development strategies in Delhi, India

Doctor of Philosophy (Ph.D.) Thesis

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ABSTRACT

Urban outdoor air pollution in the developing world, which is mainly brought on by particulate matter ($PM_{2.5}$), is a significant public health problem. Climate change mitigation and air pollution reduction actions provide several advantages, including increased energy efficiency, improved air quality, and public health. These advantages are generally known as "co-benefits". In this thesis, first, a comprehensive analysis of the widely used Air Pollution Health Risk Assessment (AP-HRA) tools was carried out to understand how the health hazards of air emissions and their origins are measured and how air pollution-related impacts are quantified. Second, climate co-benefits from utilizing the battery-electric bus (BEB) fleet in the Delhi public transportation system as a part of the Delhi electric vehicles policy 2020 and also adopting nonmotorized transportation (Walking and cycling) in Delhi, India, are quantified in detail. To this aim, two different integrated quantitative modeling frameworks are developed. The first model is used to estimate the expected environmental, health, and economic co-benefits from replacing the currently existing public bus fleet with the new BEBs in Delhi, using a detailed battery energy simulation model, considering the impact of the battery capacity loss on the annual operational time (hours of service) of the BEB. The results reveal a significant reduction of 315 kt/y in CO_2 emission and 44 t/y of avoided $PM_{2.5}$ emission from the utilization of the BEB fleet in the Delhi urban transportation system. The expected reduction in mortality and respiratory diseases related hospital admission cases from the avoided near roadway $PM_{2.5}$ exposure ranges from 67 (low) to 1370 (high) and 137 (low) to 2808 (high), respectively, which will be associated with the considerable annual economic benefits of UDS 18.7 (low) to 383.2(high) million for the local government in Delhi.

The second model is used to evaluate the multiple benefits of switching from personal motorized transportation to NMT (nonmotorized transportation) in Delhi, taking into account the inhabitant's willingness to use NMT (walking and cycling) mode. To determine the willingness to accept NMT, a cross-sectional survey is carried out in Delhi. The results are then used to estimate the anticipated health benefits of both increased physical activity and avoiding exposure to $PM_{2.5}$ near roadways in specific traffic areas throughout Delhi's 11 major districts. The economic advantages of reduced deaths and diseases due to NMT in Delhi are determined, using the value of statistical life (VSL) and cost of disease methodologies. The results reveal that, increased physical activity and avoiding exposure to $PM_{2.5}$ near roadways are expected to reduce the mortality rate by 17529 cases in addition to reducing other morbidities, as indicated in this study, while physical activity plays a significant role in lowering mortalities and morbidities. The associated cost savings from mortalities are approximately USD 4,869.8 million annually, which will positively impact Delhi's local government's finances.

According to this study, switching to battery electric public bus transportation from currently fossil fuel-run buses and developing a walking and cycling-friendly infrastructure in Delhi is not only supposed to improve public health but also make solid financial sense due to the significant health cost savings from reduced air pollution and increased physical activity. While the transport low-emission development strategies are cost intensive, failing to quantify and monetize the co-benefits, particularly co-benefits that outweigh the costs, such as public health, can lead to flawed policy recommendations of the Delhi local government.

Keywords: Co-benefits, Air Pollution Health Risk Assessment (AP-HRA), Relative risk (RR), Concentration-response functions (CRFs), Battery-electric bus (BEB), Health Impact Assessment (HIA), metabolic equivalents (METs), Value of statistical life (VSL), NMT (non-motorized transport).

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RESEARCH ACHIEVEMENTS

This dissertation resulted in the following journal papers and conference proceedings, which were all part of the thesis, in which I am leading the first author.

Journal papers:

1. Hassan Bhat,T., Farzaneh, H., Toosty, N.T. (2022). Co-Benefit Assessment of Active Transportation in Delhi, Estimating the Willingness to Use Nonmotorized Mode and Near-Roadway-Avoided $PM_{2.5}$ Exposure, *International Journal of Environmental Research and Public Health*: 19 (22), 14974

2. Hassan Bhat,T., Farzaneh, H.(2022). Quantifying the multiple environmental, health and economic benefits from the electrification of the Delhi public transport bus fleet, estimating a district-wise near roadway avoided $PM_{2.5}$ exposure, *Journal of Environmental Management*: 321 (1),116027

3. Hassan Bhat, T., Jiawen, G., Farzaneh, H. (2021). Air Pollution Health Risk Assessment (AP-HRA), Principles and Applications *International Journal of Environmental Research and Public Health*, 18 (4), 1935.

Conference Proceedings:

1. Hassan Bhat, T., Farzaneh, H. Environmental, health, and economic co-benefits assessment of the electrification of public transport in Delhi., *Ecodesign conference*, December 1-3, 2021, Tokyo, Japan

2. Hassan Bhat, T., Farzaneh, H. Co-Benefits of replacing personal motorized transport with active transportation under different scenarios in Delhi. *International Exchange and Innovation Conference on Engineering & Sciences*, Oct. 20-21, 2022, Fukuoka, Japan

CHAPTER 1

1.1. Introduction:

By 2050 air pollution-related premature mortality could be doubled, and air pollution is perceived to be the most severe environmental health-related threat the world faces [1]. Urban outdoor air pollution in the developing world, which is mostly brought on by particulate matter ($PM_{2.5}$), is a major public health problem [2]. At least 140 million people in India breathe air 10 times or more above the World Health Organization (WHO) acceptable limit, making the country home to 13 of the world's 20 cities with the highest yearly levels of air pollution [3][4]. After China and the United States, India is the third biggest emitter of greenhouse gases. According to forecasts by the United Nations (UN), India's population will continue to grow. However, GDP is expected to grow more quickly simultaneously, which means that as more people use more energy, consumption and emissions may rise significantly [5]**.** The leading causes of air pollution emissions and poor air quality in India are growing urbanization, rising industrialization, and related anthropogenic activities [6]. Currently, the main sources of air pollution in India come from Industrial pollution (51%), vehicles (27%), and crop burning, which accounts for 17% [7]. In India, air pollution contributed to over 1.67 million annual deaths, accounting for 17.8% of the total deaths in the country [8]. The health burden of ambient air pollution ranked fifth in India among significant health risk factors [9].

Epidemiological studies have indicated both short and long-term exposure to adverse health effects of air pollution [10]. Long-term exposure to pollutants is measured in months or years, and short-term exposure is measured in hours, days, or weeks [11]. The longer time and intensity of exposure, the more serious the health consequences, which can vary from minor eye irritation to even premature mortality. It is estimated that globally 8.9 million deaths happen due to air pollution exposure, resulting in 7.6% of the total yearly mortality and leading to 103.1 million healthy life years lost [12]. According to the WHO, 4.2 Million lose their lives every year due to ambient outdoor air pollution and 3.8 Million from indoor air pollution, mainly due to exposure to smoke from cookstoves and fuels [13]. Outdoor air pollution accounts for 2% of all cardiopulmonary diseases, 1.4 % of all deaths, and 0.4 % of disability-adjusted life years (DALYs) worldwide [14]. In the long and short term, exposure to particulate material (PM) has increased mortality and reduced life expectancy [15]. Increases in mortality, morbidity, premature death, cardiovascular and respiratory diseases are some of the adverse effects due to air pollution exposure [16], Lung cancer [17], and adverse impact on the activity of the central nervous system resulting in cognitive impairment [18], and harmful effects on fetal development and pregnancy [19]. Air pollution, primarily PM, may have carcinogenic effects on humans[20]. Increased PM_{10} concentration by 10 $\mu g/m^3$ has resulted in non-accidental mortality [21].

Several studies have repeatedly identified a correlation between air pollution exposure and mortality and morbidity [17], [22], [23] and increasing hospitalizations and emergency department visits [24]–[28]. The most frequent causes of early death in adults due to outdoor air pollution are ischemic heart disease and stroke, although there is evidence of other impacts, such as diabetes and neurodegenerative diseases. In children, this might include decreased lung development and function, respiratory infections, and exacerbation of asthma [29]. Particulate materials' health impacts are dominated by cardiovascular diseases [30]. Lung cancer, pregnancy, early childhood health impacts, and cognitive impairment are other health outcomes linked to air pollution [18], [19], [31], [32]. Secondary pollutants such as ozone are also associated with respiratory and circulatory diseases and mortalities [33], chronic respiratory diseases, and asthma [34]. Other studies have associated higher ozone concentrations with reproductive health [35], preterm birth [36], and cognitive disorders [37].

Chronic obstructive pulmonary disease (COPD) is expected to be responsible for 54.5 % of all premature deaths due to air pollution in India, followed by ischemic heart disease (IHD) for 24.0 %, stroke for 18.5 %, and lung cancer (LC) for 3.0 %, respectively [38]. Many health impact studies in the past on $PM_{2.5}$ effects have been conducted in India, indicating exposure to ambient fine particulate matter ($PM_{2.5}$) is a major cause of health impacts [38]–[42]. Some of these studies have ranked India as the highest-exposed country to $PM_{2.5}$ as more than half of the country's population lives exposed to annual mean ambient $PM_{2.5}$ concentrations of up to 150 g/m^3 [43]. According to the Global Burden of Disease (GBD) report, ambient air pollution causes 2 million premature deaths each year in India, placing air pollution-related health risks close or at the top and among all known risk factors for diseases [44]. Most Indian megacities, including Delhi, have air pollution levels exceeding the government's guidelines [45], [46]. A large portion of Delhi's population is exposed to high levels of hazardous pollutants. Delhi's $PM_{2.5}$ emission is expected to be responsible for 54,000 premature deaths in 2020 [47]. $PM_{2.5}$-related deaths in current policies will increase on average by 39.32% in 2025 and 100% by 2040 [25]. Studies have indicated that per capita mortality in India related to $PM_{2.5}$ would likely rise by 21% by 2030 if $PM_{2.5}$ levels stayed steady at their present levels, and over the next 15 years, average $PM_{2.5}$ levels would need to drop by 20–30% only to maintain $PM_{2.5}$ attributable mortality rates (deaths per 100,000 people per year). Thus, substantial reductions in $PM_{2.5}$-related mortality in India will require massive improvements in air quality.

In addition, air pollution has been found to have an adverse economic impact worldwide, leading to the loss of GDP due to mortality and morbidity. With the increase in the GDP of developing countries, air pollution costs have also been increasing. Air pollution costs India $119 billion in economic losses (or 0.44 % of India's GDP), accounting for 115% of the disease burden [8].

1.1.1. Air pollution problem in the transport sector in Indian urban areas:

India's energy consumption, travel demand, and transportation-related emissions have all increased substantially as the country's urbanization rate has risen, also leading to a significant increase in personal automobile ownership. The growing travel demand and rapid expansion in motor vehicle use in India are contributing to high levels of urban air pollution. Emissions from motor vehicles have been identified as a major source of air pollution in India, affecting public health [48]. Most Indian cities struggle to maintain air breathable for their citizens due to increasing ambient air pollution levels in densely populated megacities, like Delhi. The total number of motorized vehicles in Delhi is 11.4 Million [52], and Delhi's transportation sector contributes 40-72% of the whole pollution load. The average share of the transport sector in

$PM_{2.5}$ concentrations ranges from 17 % to 28 % in Delhi, making it the city's largest source of poor air quality [51], which accounts for 39% of $PM_{2.5}$ emissions [52]. Studies, which were primarily conducted in urban areas of India (Delhi), discovered that areas with high levels of air pollution had a higher prevalence of asthma, reduced lung function, and acute and chronic respiratory symptoms like coughing and wheezing [53]. Vehicle emissions are the most quickly increasing cause of air pollution in cities like Delhi. Nearly 55% of Delhi's population (7.8 million people) lives within 500 meters of a road, putting them in more danger of traffic pollution [54]. Since a large number of people are exposed to transport-related exhaust gases and particles, transportation emissions have received a lot of attention in recent years.

Various national sustainable policies, as well as pollution control measures particular to the city of Delhi, have been enacted in the past to minimize emissions from the transportation sector [55]; however, Delhi's air quality has worsened. Failure of different air pollution management measures to reduce urban air pollution has become a severe public health concern, particularly in Delhi. Implementation of sustainable urban transportation regulations in New Delhi, as well as a transition to public transportation such as electric buses, metro rail, battery-powered rickshaws, and NMT (Non-motorized transport), can help to reduce ambient air pollution in Delhi [56].

1.2. Physical inactivity and motorized transportation:

The urban transportation system endangers human health through accidents, air pollution, and physical inactivity. Such health issues have demanded significant health impact analyses in order to facilitate the creation of walking and bicycling-friendly infrastructure to improve public health. Non-motorized transport (NMT) especially walking and cycling, can reduce air pollution and physical inactivity, save lives, and lessen the effects of climate change. Physical inactivity is responsible for about 5 million annual deaths, while motorized transportation-related emissions were responsible for 74 thousand of premature deaths, and Delhi had the highest transportation-related death rates among India's major cities [57]. Sedentary lifestyles are one of the main factors increasing the risk of mortality from noncommunicable diseases (NCD), as 71% of all deaths worldwide, 41 million per year, are caused by NCDs. Cardiovascular diseases (17.9 million), Cancers (9.3 million), respiratory diseases (4.1 million), and diabetes (1.2 million) are major NCDs-related mortalities each year [58]. Studies have shown that being physically inactive raises the risk of psychological disorders, colon cancer, breast cancer, type 2 diabetes, coronary heart disease, and musculoskeletal conditions by about 15% to 20% [59].

Physical activity (PA) has been shown in numerous studies to significantly reduce mortality. Being overweight, obesity, type II diabetes, coronary heart disease, depression, and fracture risk can all be decreased by PA. According to Devi et al., sedentary lifestyles correspond to higher all-cause mortality [59]. As per WHO, about 1.6 million deaths have explicitly been linked to insufficient physical activity [58]. On a global scale, an increase in physical activity can prevent 3.9 million premature deaths, which equals 15% of all premature deaths, as indicated by Strain et al. [60]. It has been established that regular exercise can aid in preventing and treating NCDs, such as breast and colon cancer, diabetes, heart disease, and stroke. PA can also enhance mental health, quality of life, and well-being while preventing hypertension, obesity, and overweight [61]. Regardless of sex or age, PA is considered to have a preventative effect against depression and a beneficial impact on treating depression in non-clinical and clinical populations [62]. Walking for 30 minutes or bicycling for 20 minutes on most days lowers mortality risk by at least 10%, also 10% reduction in the risk of cardiovascular disease and a 30% reduction in the risk of type 2 diabetes, as well as a 30% reduction in the mortality rate from cancer [65].

In India, 20% of the population is not active, and 37% is just moderately active, respectively, failing to meet the WHO physical activity guidelines, leading to the risk of developing various NCDs in a large portion of the Indian population [66]. The prevalence of NCDs in India, including breast and colon cancer, diabetes, coronary artery disease, and hypertension, are mainly related to physical inactivity [59]. Regular PA can help prevent and treat many NCDs [66]. The commuters in Delhi are forced to use individualized modes of transportation due to the lack of a satisfactory alternative public transportation system [67]. As a result, the vast majority of adults were physically sedentary. Total physical activity in Delhi is estimated to be about 400.3 minutes per week for men and 265.3 minutes per week for women [59].

Being a low-emission and space-efficient mode of transportation, active transportation (mostly walking and bicycling) has grown in popularity in the transportation and environmental sectors in India. NMT or active transportation can provide both transportation (access to goods and activities) and recreation, while users may view a specific journey to serve both aims.

1.3. Co-benefits of low-emission urban transport system:

Climate change mitigation and air pollution reduction actions provide several advantages, including increased energy efficiency, improved air quality, and public health. These advantages are generally known as " climate co-benefits" [68]. Co-benefits which are known as supplementary benefits, refer to a number of equally significant justifications that might be satisfied by a single policy or practice [69]. Co-benefits are becoming a major topic in discussions about the environment and energy. In order to garner support for and ensure the optimization of policies, projects, and programs, particularly in developing countries, there is a greater need to identify policy interventions that have multiple benefits for climate and other developmental objectives. This is especially true in light of the global focus on achieving Sustainable Development Goals (SDGs) [70].

Due to the desired win-win outcomes of such policies towards both local and global aims, co-benefits from policies addressing climate change mitigations have been widely promoted. Co-benefits have been widely advocated in tandem with mitigation measures for greenhouse gas (GHG) reduction. Especially in emerging nations such as India, where urbanization and climate change adaptations are all significant challenges and economic co-benefits of non-motorized transportation [71]. Transition to new transportation patterns based on sustainable ideas like reduction in the number of motorized vehicles share mode trips, NMT, low-carbon vehicular technology, and fuel shift can safeguard natural resources, public health, ecosystems, and global climate. It also supports the economic (job creation, balanced regional growth, trade activities), social, and environmental pillars of sustainable development (inclusive development, poverty reduction, equity) [72].

Detailed Co-benefits in the transportation industry while including initiatives that reduce climate change are shown in figure 1.1 [73].

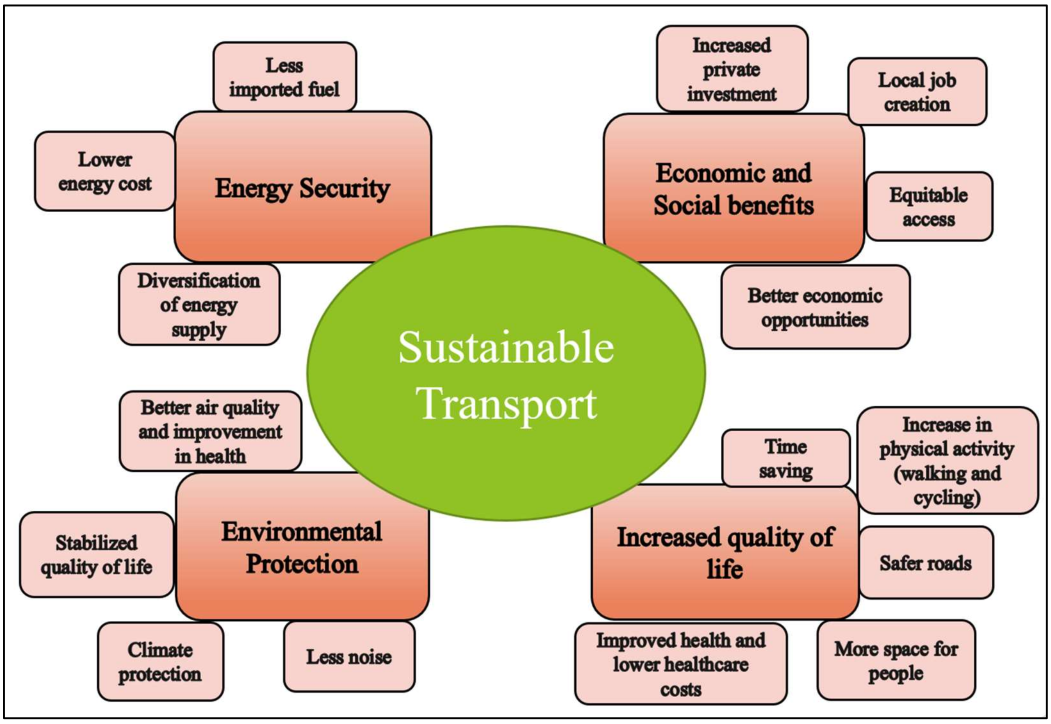

Figure 1. 1. Co-Benefits of Sustainable Transport

1.3.1. Co-benefits of the Battery-Electric-Bus (BEB) Fleet:

When it comes to future transport modes, BEBs offer a lot of potential because of their ability to reduce carbon emissions while also improving energy security, public health, and air quality in Delhi. BEBs have substantial energy security benefits when renewable energy sources are used to power them [74]. Life cycle assessment (LCA) studies that evaluated carbon emissions between electric and fossil fuel-based vehicles suggested electric vehicles such as BEBs can deliver significant emission savings in the long run [81].

Several studies have been conducted to estimate and quantify the expected environmental and economic co-benefits from the electrification of public transport and address their operational challenges. Lankao et al. highlighted that the cost of achieving the 2°C climate stabilization goal can be reduced by expanding the penetration of electric vehicles [79] . Previous studies have concluded that the electric bus operating system has the advantage over the fossil fuel-operated buses, not only in creating a larger profit margin for the bus operators, but also in terms of improved passenger satisfaction (by carrying more passengers per unit of the bus with lower energy consumption) [80]. Regarding the economic and environmental health impacts, another study has estimated that an electric bus fleet in Los Angeles would save USD 65 million in environmental expenses per year [81]. Liou et al. also estimated total emissions reduction benefits from converting all internal combustion vehicles to electric vehicles in Taiwan, including USD 760 million savings in GHG emissions reduction and USD 2091 million in health co-benefits from reduced air pollution per year [82]. Zhou et al.

concluded that in China's transportation system, BEBs could lower WTW (well-to-wheels) of petroleum by more than 85 % and overall CO2 emissions by 19–35 % over the life cycle of the vehicle[83].

In light of the long-term benefits, BEBs offer a viable alternative to traditional fossil-fuel-based modes of public transit, providing moderate benefits in terms of air pollution, public health, and energy security indicators in Indian urban areas [90].

1.3.2. Co-benefits of Nonmotorized transport (NMT):

Walking and bicycling for transportation provide significant health benefits to users by increasing physical activity [87]. Benefits include improved accessibility, more affordable travel, less congestion, cheaper infrastructure costs for parking lots and roads, energy conservation, decreased air and noise pollution, and decreased accidents for other drivers [88]. Additionally, it is an affordable form of transportation for millions of people with low incomes, particularly in Delhi. Given the long-term benefits, NMT is a feasible option for traditional fossil-fuel-based public transportation modes in Indian cities. A review of thirty health impact assessment studies from Europe, the United States, Australia, and New Zealand concluded that health benefits from increased PA outweighed the adverse effects of traffic accidents and exposure to air pollution by a large margin .It is estimated that, an increase in the median daily walking and bicycling time from 4 to 22 minutes can reduce 14% of GHG emissions in California, which results in decreasing the corresponding burden of cardiovascular disease and diabetes and could avoid 32,466 disability-adjusted life years (DALYs) [89]. Increased physical activity and reduced local air pollution from vehicle emissions can save 122 lives and net savings of about USD 200 million annually in New Zealand [90]. A study in Adelaide, Australia [91], showed that, increased cycling, public, and active transportation could reduce road traffic-related CO_2 emissions annually, ranging from 191,313 to 954,503 million tons and 160 to 542 deaths. Therefore, 2,113 to 7,674 DALYs could be avoided due to improved air quality, increased physical activity, and avoided traffic injury. Another study conducted in 6 European cities has shown that increases in cycling and walking trips to 35% and 50% of total city trips, respectively, will cut GHG emissions in the six cities by 1,139 to 26,423 metric tons per year, including varying degrees of health benefits [92]. A recent study has indicated cost savings of 15 billion euros per year in Europe for a 10% shift to active mobility modes [93].

As transportation-related emissions rise in Delhi, NMT is becoming increasingly popular among policymakers and environmentalists as a practical substitute for motorized transportation. Studies have addressed the significant impacts of improving bicycle and bus infrastructure on lowering CO_2 emissions [94] and increasing PA in 5% of the population [95], in India. Using the travel demand and health impact modeling approach, a study showed that active transportation could reduce the health burden (90,000 DALYs) annually in India [96]. Another study in India assessed alternative scenarios, including increased active travel, lower-carbon-emission motor vehicles, and a combination of the two, utilizing comparative risk assessment techniques [97]. The results of other studies indicated that, the most significant advantages would come from combining active transportation with low-emission motor vehicles, which can reduce 12995 DALYs in Delhi [98].

1.4. What will be elucidated in this research:

Following the previous studies, this study aims to quantify the expected climate co-benefits from the implementation of both clean transport technology and active transport scenarios in the urban transportation system in Delhi, India. The co-benefits include all environmental, health, and economic benefits from the two plausible scenarios of the future electrified urban bus fleet and the development of the NMT mode in this city. The reasons for considering the aforementioned scenarios in this study are as follows:

- Electrification of public transport is regarded as one of the key climate change mitigation strategies for the local government of Delhi to achieve sustainable development goals 13 (climate action), 8 (economic growth), 7(affordable and clean energy), and 3 (Good health and wellbeing). This underscores a key point that sits at the core of work on co-benefits. However, few studies have quantified the potential environmental, health, and economic co-benefits from the electrification of the urban bus fleet in Delhi.
- Due to their lower carbon footprint and significant economic advantages in terms of preventing health effects, NMT can be a crucial part of a strategy in Delhi to lower individual healthcare and transportation costs while enhancing public health and the environment. In addition to reducing greenhouse gas emissions and air pollution, cycling and walking can significantly improve physical inactivity, helping decarbonize transportation and directly contributing to many of the Sustainable Development Goals (SDGs).

1.5. Research Methodology:

An integrated co-benefits assessment modeling framework is developed in this study to assess the health, environmental, and economic co-benefits of the above two scenarios, which includes four main parts:

1.6.1. Estimation of the avoided emissions from introducing the new scenario:

A) Avoided emissions from replacing the CNG bus fleet with the new BEBs in Delhi:

To determine the avoided emissions from replacing the CNG bus fleet with the new BEBs,

the annual operational time of the BEB is estimated by developing a detailed simulation model of battery electricity management, taking into account time lost in charging as well as state-of-charge (SOC) and capacity loss of the BEB's lithium battery and emission factors. The annual avoided emissions are then estimated based on the period a BEB can deliver the transport service, considering the same transport demand of CNG buses.

B) Avoided emissions from replacing motorized transportation with NMT:

Avoided emissions are calculated based on the total per capita extra distance traveled and the total VKT (vehicle kilometers) replaced by walking and cycling based on developing a detailed daily trip model, taking into account the willingness of people in Delhi to use walking and cycling travel modes. The willingness to use NMT in Delhi is estimated, using a logistic regression model based on the collected data from a cross-sectional interview with 250 inhabitants in Delhi.

1.6.2. Estimation of the near-roadway $PM_{2.5}$ exposure:

In order to assess the impact of avoided emissions (particularly $PM_{2.5}$) on improving public health in Delhi, a near-roadway $PM_{2.5}$ dispersion model is developed and applied to the selected traffic zones in 11 major districts of Delhi. In the BEB scenario, a steady state gaussian dispersion model is developed to estimate the hourly concentration at 200 meters downwind distance from the center of the street. Additionally, a ground-level concentration model is developed to assess the short-term area concentration of $PM_{2.5}$ over the area in the upwind and crosswind directions, taking into account the relationship between wind coordination. In the case of the NMT scenario, an air dispersion modeling tool called CALRoads View (Lakes Environmental Software) is used to predict pollutant concentrations for receptors located within 150 meters on either side of the roadways.

1.6.3. Health impact assessment (HIA):

To establish a link between the avoided concentration of $PM_{2.5}$ and health benefits, a health risk assessment model is developed in the third part, which estimates the relationship between changes in $PM_{2.5}$ concentrations and the occurrence of specific health outcomes in the selected traffic areas, using the concentration-response function (CRF) for several diseases. The CRF coefficient values used in this study are derived from the relative risk (RR) level, which measures the likelihood of an adverse health outcome among the population exposed to a higher level of ambient air pollution than a lower level of ambient air pollution. The values of the RR utilized in the study are extracted from a detailed meta-analysis of previous studies. To this aim, a systematic review of epidemiological studies, meta-analyses, and review articles is conducted to assess the relationship between changes in $PM_{2.5}$ concentrations and changes in the incidence of each health endpoint.

1.6.4. Economic impact assessment:

The Value of Statistical Life (VSL) approach is used in this study to calculate the mortality cost of $PM_{2.5}$ exposure cost of illness (COI), and the cost of an emergency room visit (ERV) approach is used to determine the cost of treatment.

1.7. Thesis organization

Chapter 2: In this chapter, the concept of Air Pollution Health Risk Assessment (AP-HRA) will be discussed, offering an outline for the proper conducting of AP-HRA for different scenarios, explaining in broad terms how the health hazards of air emissions and their origins are measured and how air pollution-related impacts are quantified. Seven widely used AP-HRA tools will be deeply explored in this part, taking into account their spatial resolution, technological factors, pollutants addressed, geographical scale, quantified health effects, classification method, and operational characteristics. Finally, a comparative analysis of the proposed tools will be conducted using the SWOT (strengths, weaknesses, opportunities, and threats) method.

Chapter 3: This chapter investigates the co-benefits from the utilization of the battery-electric bus (BEB) fleet in the Delhi public transportation system as a part of the Delhi electric vehicles policy 2020. To this aim, an integrated quantitative assessment framework is developed to estimate the expected environmental, health, and economic co-benefits from replacing the currently existing public bus fleet with the new BEBs in Delhi. First, the model estimates the avoided emissions from deploying the BEB fleet, using a detailed battery energy simulation model, considering the impact of the battery capacity loss on the annual operational time (hours of service) of the BEB. Second, considering fine particles ($PM_{2.5}$) as the most health-harming pollutant, the model calculates the near roadway avoided $PM_{2.5}$ exposure in the selected traffic zones of 11 major districts of Delhi, using a Gaussian dispersion model. Third, the near roadway avoided $PM_{2.5}$ exposure is further used in a health impact assessment model, which considers concentration-response functions for several diseases to evaluate the public health benefits from introducing the BEB fleet in Delhi.

Chapter 4: This chapter aims to estimate avoided mortalities and morbidities and related economic impacts due to adopting the nonmotorized transportation (NMT) policy in Delhi, India. To this aim, an integrated quantitative assessment framework is developed to estimate the expected environmental, health, and economic co-benefits from replacing personal motorized transport with NMT in Delhi, taking into account the inhabitants' willingness to use NMT (walking and cycling) mode. The willingness to accept NMT is estimated by conducting a cross-sectional survey in Delhi, which is further used to estimate the expected health benefits from both increased physical activity and near roadway avoided $PM_{2.5}$ exposure in selected traffic areas in 11 major districts in Delhi. The value of statistical life (VSL) and cost of illness methods are used to calculate the economic benefits of avoided mortalities and morbidities from NMT in Delhi.

Chapter 5: The last chapter summarizes the major findings of the research, and the study limitations and future work will be further elaborated in this chapter.

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CHAPTER 2

Air Pollution Health Risk Assessment Models

Abstract: Air pollution is a major public health problem. A significant number of epidemiological studies have found a correlation between air quality and a wide variety of adverse health impacts emphasizing a considerable role of air pollution in the disease burden in the general population ranging from subclinical effects to premature death. Health risk assessment of air quality can play a key role at individual and global health promotion and disease prevention levels. The Air Pollution Health Risk Assessment (AP-HRA) forecasts the expected health effect of policies impacting air quality under various policy, environmental and socio-economic circumstances, making it a key tool for guiding public policy decisions. This chapter presents the concept of AP-HRA and offers an outline for the proper conducting of AP-HRA for different scenarios, explaining in broad terms how the health hazards of air emissions and their origins are measured and how air pollution-related impacts are quantified. In this chapter, seven widely used AP-HRA tools will be deeply explored, taking into account their spatial resolution, technological factors, pollutants addressed, geographical scale, quantified health effects, method of classification, and operational characteristics. Finally, a comparative analysis of the proposed tools will be conducted, using the SWOT (strengths, weaknesses, opportunities, and threats) method.

2.1. Introduction:

Since air pollution is one of the most significant health hazards, there is a sufficient scientific basis to justify developing approaches to incorporate epidemiological assessment into health-related risk. Although the idea of AP-HRA has been around since the 1950s, the health-care system worldwide has not adopted them as quickly. AP-HRAs can play a critical role at both individual, community, and global health promotion and disease prevention levels. According to the (WHO), "AP-HRAs estimate the health impact to be expected from measures that affect air quality, in different socioeconomic, environmental and policy circumstances. It is, therefore, an important tool for informing public policy decisions" [1]. It synthesizes information on exposures to air emissions, health impacts, and community risk used for regulatory decision-making and public participation [2].

AP-HRAs help to understand health benefits, which will be an outcome due to improved air quality and have been used in many studies like the global burden of disease by WHO. Over the last decade, they have evolved from more qualitative approaches to quantitative tools. These tools help in assessing, planning, and supporting climate change and health measures, as well as assessing the full range of health and economic consequences of industry restrictions and air quality improvements. Policymakers can use these tools to track health indicators, consider health-related issues when making choices, and forecast potential economic, health, and environmental repercussions from certain sectors [3]. HRA tools assess the health risks of the major pollutants such as oxides of sulfur (SOx) and oxides of nitrogen (NOx), ground-level ozone (O_3), and particles ($PM_{2.5}$) on the population which is exposed to these pollutants [4]. They relate the change in the level of air pollutant concentration to the expected mortality rates due to ischemic heart diseases, stroke, lung cancer, and respiratory infections, using Concentration Response Functions (CRFs) [5]. Three main steps involved in developing the HRA tools include 1) population exposure assessment, 2) Health effect estimation related to air pollution, and 3) calculation of the uncertainty of the analysis [1]. The HRA tools can facilitate policy decision-making by evaluating the associated costs and health benefits of climate change mitigation actions. These tools can also help raise public awareness regarding the adverse health impact of low air quality and finally connect governing authorities with scientific research throughout the regulatory process.

The HRA tools have been widely used in evaluating air quality policies in the United States [6] and the European Union [7]. In addition, many countries have developed their own Nationally Appreciate Mitigation Action (NAMA) based on using the HRA tools, considering the different air pollution reduction scenarios. These studies range from local, national, regional, and global scales, which are reported in Table 2-1.

Table 2- 1. Recent studies in the air pollution health risk assessment.

Purpose of the Study	**Region**	**Health Impacts**	**Ref**
Evaluating the mortality impact of fine particles reduction policies and Air quality modeling in Spain.	Spain	All-cause deaths	[8]
Assessing the geographical spread and economic benefit of the ozone health consequences associated with climate change in the United States in 2030	USA	Mortality and morbidity impacts related to ozone	[9]
Reductions of $PM_{2.5}$ Air Concentrations and Premature Mortality in Japan	Japan	Mortality	[10]
Assessing the health-related benefits of attaining the ozone level standard	USA	Mortalities, emergency department admissions, hospitalization, restricted activity day, and school absences	[11]

Purpose of the Study	Region	Health Impacts	Ref
Estimation of the national public health burden associated with exposure to atmospheric $PM_{2.5}$ and ozone	USA	Reduced life years and life expectancy; and mortalities	[12]
Evaluation of air quality in six Indian cities to create a knowledge base for multi-pollutant pollution, dispersion modeling of ambient particulate concentrations	India	Premature mortality	[13]
Evaluation of the health-related economic externalities of air emissions from particular emission sources or industries that can be used to help emission reduction policymaking.	Europe	Mortality and morbidity	[14]
Using multi-sectoral emissions inventory to estimate health impacts in terms of premature mortality and morbidity in Delhi	Delhi, India	Premature mortality and morbidity effects	[15]
Health benefits from the adaptation of cleaner brick processing technologies	Dhaka, Bangladesh,	Mortality and morbidity, health cost savings	[16]
Study the linkages between indoor and outdoor PM in Ulaanbaatar, Mongolia	Ulaanbaatar, Mongolia	Premature deaths	[17]
Estimation of the citywide morbidity and mortality attributable to ambient fine particulate matter ($PM_{2.5}$) and ozone in New York City	New York City, USA	Health impacts and disparities	[2]
Assessment of the intercontinental impact of ozone emissions on human mortality	Northern Hemisphere, North America, East Asia, South Asia, and Europe	Premature mortality	[18]
Estimation of the mortality impacts of 20% of anthropogenic primary $PM_{2.5}$ and $PM_{2.5}$ precursor emission decreases in each of the four major industrial regions (North America, Europe, East Asia, and South Asia)	Europe, East Asia, and South Asia, North America,	Premature mortality	[19]
Evaluation of the external health costs of air emissions in Europe and the contribution of international shipping activities	Europe	Health-related cost of Air pollution	[14]

Purpose of the Study	Region	Health Impacts	Ref
Calculation of premature deaths from cardiopulmonary and lung cancer due to $PM_{2.5}$ levels and the effect of reductions in black carbon emissions on surface air quality and human mortality	Global	Mortality	[20]
Estimation of premature air pollution-related mortalities prevented, ozone-related yield reductions of large food crops avoided, and health damage avoided	Global	Mortalities, Morbidities and avoided Ozone-related reduction of yield of major food crops.	[21]
Estimating the global and national health burden of atmospheric $PM_{2.5}$ pollution due to surface transport emissions.	Global	Mortality	[22]

2.2. Methodological approaches used in the AP-HRAs:

The health risk assessment for air pollution contains the mathematical estimation and modeling of several processes, including population estimates, population exposure to pollutants, and adverse health impacts assessment through specific concentration-response functions [23]. In general, precise data are required, such as: population data, air quality data, baseline mortality or disease rates, and risk estimation (change of the health effect related to the concentration change of air pollutants, which is referred to as coefficient, β) from epidemiological studies that quantify the association between health effects and exposure to air pollution. The flow diagram (see Figure 2.1) represents the methods, typical models, and data inputs of AP-HRA.

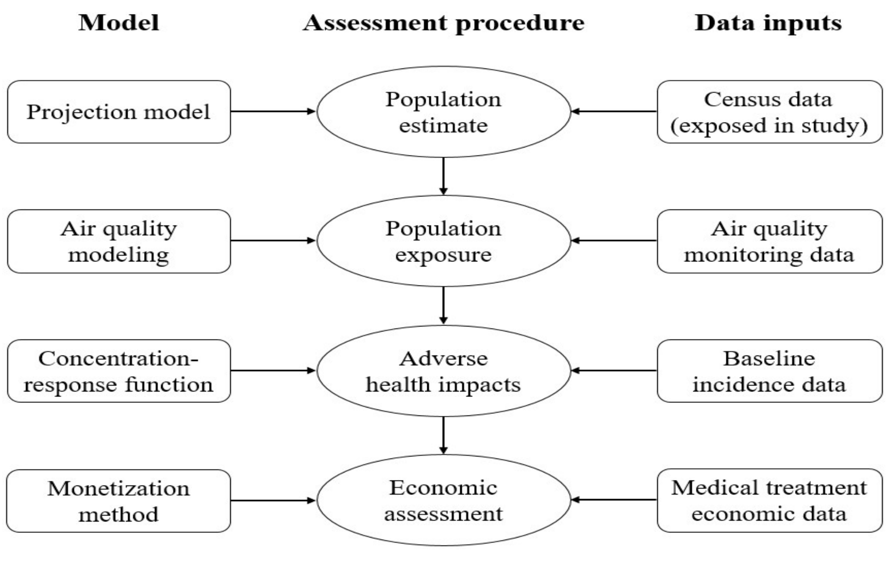

Figure 2. 1. The flow diagram of AP-HRA methods, typical models, and data inputs.

2.2.1. Population Estimates:

The first stage of AP-HRA is to estimate the population exposed to air pollution once the temporal and spatial resolution in the study has been determined. Past and current data is accessible from some national census databases or the latest World Population Prospects published by the UN Department of Economic and Social Affairs [24]. In most cases, the health risk assessment is conducted for a particular socio-economic and environmental scope with some potential mitigation policies to be implemented. Therefore, the population data for the incoming few years achieved from population forecast models is usually required for the scenario setting.

2.2.2. Population Exposure to Air Pollution:

The adverse health impacts are mainly derived from population exposure to contaminated air. Therefore, one core component of AP-HRA is the assessment of exposure to specific air pollutants for the target population, which is a comprehensive integral part of pollution concentration, the time-activity pattern of the population of interest (e.g., exposure period and level), the proportion of susceptible population and characteristics of pollutants (e.g., solubility and pattern of physiological contact). Most studies take the ambient concentration of air pollutants as a surrogate indicator for pollution exposure, as the measurement is conducted much more simply and conveniently [25]. Environmental agencies worldwide have set air quality criteria to identify the concentration of those health-related pollutants [26]. Typically, the WHO air quality guidelines (2005) determined specified indicators of four primary air pollutants, including PM_{10}/$PM_{2.5}$ (particles with a diameter less than 10 μm or 2.5 μm), NO_2, SO_2, and O_3, and proposed the interim targets and air quality guidelines (AQG) [27]. The interim targets are intended for countries as incremental steps to move towards AQG. The guidelines are selected based on concentration-response functions to suggest the concentration level that, if achieved, would contribute to significant benefits for the protection of public health.

Table 2- 2. Air quality indicators of typical air pollutants.

Pollutant	Indicator		Interim target-1	Interim target-2	Interim target-3	Air Quality Guideline (AQG)
$PM_{2.5}$	annual mean	10 μg/m³	35	25	15	10
	24-hour mean	25 μg/m³	75	50	37.5	25
PM_{10}	annual mean	20 μg/m³	70	50	30	20
	24-hour mean	50 μg/m³	150	100	75	50
O_3	8-hour mean	100 μg/m³	160	-	-	100
NO_2	annual mean	40 μg/m³	-	-	-	-
	1-hour mean	200 μg/m³	-	-	-	-
SO_2	24-hour mean	20 μg/m³	125	50	-	20
	10-minute mean	500 μg/m³	-	-	-	500

Generally, modeling and monitoring are two major methods to estimate population exposure. Monitoring data can be directly used by collecting past and current air quality data near the monitoring sites. At the same time, modeling measurements can be combined with advanced monitoring technologies to facilitate: i) simulation of air quality in different geographical areas, using specific socioeconomic or environmental conditions; and ii) prediction of changes in exposure, taking into account the future policy implementations [28]–[30].

Recent analytical methodologies that have been commonly adopted in estimating the population exposure to air pollution can be classified as follows:

- The Global Model of Ambient Particulates model (GMAPS) which was developed by the World Bank to estimate the ambient concentration of PM_{10} on the city-level and used in the previous Global Burden of Disease (GBD) studies [31];
- The global-regional chemistry transport model TM5, as well as the source receptor (SR) relationship, developed from TM5 which have been widely applied to evaluate the response of ambient air quality indicators to changes in emissions of various pollutants from the certain source in different control strategy scenarios [72–74];
- Global atmospheric models such as GEOS-Chem [35] and MOZART [36], which use a similar approach, are also available to provide the ambient concentration estimates of ozone and/or $PM_{2.5}$;
- Land-use regression models which can estimate outdoor pollutant concentrations through specific geographic information of the source, landscape characteristics, and roadway [77,78];

Hierarchical Bayesian models are applicable for multiple-pollutants estimation by using tiered Bayesian statistical procedures [79,80].

2.2.3. Health Impact:

The most important part of an AP-HRA is to quantify the health risk related to air pollution exposure. Various adverse health effects (also called health endpoints) attributed to short-term and long-term exposures can be categorized as follows:

1. For short-term exposure:

    Mortality

    - Hospital admissions or emergency department visits caused by respiratory diseases
    - Hospital admissions or emergency department visits caused by cardiovascular diseases
    - Days of restricted activity
    - Absence from work or school
    - Other acute symptoms

2. For long-term exposure:

    - Mortality caused by cardiovascular and respiratory disease
    - Lung cancer
    - Chronic incidence caused by respiratory or cardiovascular disease

- Decline in physiologic functions
- Intrauterine growth restriction

Different subgroups of the population suffer the various risks of health effects caused by air pollution exposure. These vulnerable populations include ailing individuals, children and the aged, and sex differences would, in some cases, influence the burden of health effects. Statistical data such as the mortality or morbidity rate among the population exposed to a particular air pollutant concentration is necessary. Numerous methodologies have been developed on short and long-term exposure (see Table 2-3), while most of them were conducted separately within different areas, resulting in generalizability limitation [27].

Table 2- 3. Epidemiological studies of short and long-term exposure and their features.

Category	Methodology	Advantage	Disadvantages
Short-term exposure	Time-series studies: using the statistical model to estimate the influence of temporal (usually daily) changes in air pollutant concentrations on daily health incidence in the population exposed.	• Avoid disturbance caused by long-term variations such as individual occupations and socioeconomic conditions. • lower costs associated with data collection.	• Uncertainty caused by the quality of health data. • Unable to quantify the chronic effects of air pollutants.
	Case-crossover studies: studying the risk of an acute health case after momentary exposure.	• Get rid of confounders from time-independent factors. • Improve causal inferences on the individual level.	• Unsuitable to estimate the risk from exposures with a time trend.
	Panel studies: assessing the respiratory diseases associated with air pollution among susceptible subgroups.	• Availability of detailed health- and exposure-related information of individuals.	• Uncertainty caused by the relatively small sample size.
Long-term exposure	Cohort studies: examining the risk of health endpoints attributed to long-term pollution exposure.	• Consider the total impact of all types of health cases.	• High cost and complication of implementation. • High demand for spatial, temporal and average concentration data.

2.2.3.1. Concentration-Response Functions (CRFs):

The health risk is represented by concentration-response functions (CRFs), which link the health endpoints attributed to exposure to air pollutant concentration changes. The relationship estimation between concentration change of air pollutants, ΔC, and change in health effects (usually an incidence or mortality rate), Δy usually contains three steps: i) determining a functional form of the CRF; ii) estimating the coefficient values of the CRF; and iii) deriving the relationship between ΔC and Δy from the CRF. There are two forms of the CRF, linear and nonlinear. Linear and log-linear models are often used for simplification based on biological evidence [31][41] but nonlinear models (e.g., logistic model) may also be applied for comprehensive computation, depending on the baseline data, as well as specific air pollutants and endpoints [42]. For best regression fitness, the Akaike Information Criterion (AIC) approach may be used, and the model with a lower value of AIC is preferred [43]. Table 2-4 shows the different forms of CRFs which are widely used in health impact risk assessment studies.

2.2.3.2. Relative Risk (RR):

The coefficient values of the CRF are typically derived based on Equation (2-1) from the level of Relative risk (RR), which describes the risk of an adverse health effect among the population exposed to a higher ambient air pollution level relative to a lower ambient level.

$$\mathbf{RR=exp(\beta\times\Delta C)} \tag{2-1}$$

Table 2- 4. CFRs in health impact risk assessment*

Functional Form	Formula of CRFs	Relationship between ΔC and Δy
Linear function	$y=\alpha+\beta\times C$	$\Delta y=y_0-y_c=\beta\times(C_0-C)=\beta\times\Delta C$
Log-linear function	$\ln(y)=\alpha+\beta\times C$	$\Delta y=y_0-y_c=y_0(1-\frac{1}{\exp(\beta\times\Delta C)})$
Logistic function	$y=prob(occurrence\ \vert C\times\beta)=(\frac{\exp(C\cdot\beta)}{1-\exp(C\cdot\beta)})$	

*In the above table, α represents a combination of all the independent variables, and β is the excess incidence rate of health outcome per 1 μg/m^3 increase of pollutants.

Previous epidemiological studies [44][45][46] postulated that RR associated with ambient air pollution is in a linear relationship with the concentration level, with several alternative linear function models established as below, where c represents the concentration of air pollutants and c_t represents the minimum level below which there is no obvious adverse health impact (also called threshold value):

$$\begin{aligned}&\textbf{For } c < c_t\textbf{, } RR_{Lin50}(c)=1,\\&\textbf{For } c_t < c < 50\textbf{, } RR_{Lin50}(c)=1+\gamma(c-c_t),\\&\textbf{For } c > 50\textbf{, } RR_{Lin50}(c)=1+\gamma(50-c_t).\end{aligned} \tag{2-2}$$

However, the studies focused on estimating the RR functions are mainly carried out in Europe and North America, where the pollutant concentration is low. Therefore, the models mentioned above may not be suitable for other regions, especially for developing countries where the concentration of the pollutant is relatively higher. Instead, the gradual diminution of the marginal increase in RR is extracted from the logarithm model [47] or power model [48][47] of RR and concentration. The WHO has subsequently recommended the logarithmic model for GBD to measure the health impact attributable to air pollution at the national level [49].

- Logarithm model:

$$\begin{aligned}&\textbf{For } c < c_t\textbf{, } RR_{Log}(c)=1,\\&\textbf{For } c \geq c_t\textbf{, } RR_{Log}(c)=[(c+1)/(c_t+1)]^{\rho}.\end{aligned} \tag{2-3}$$

- Power model:

$$\begin{aligned}&\textbf{For } c < c_t\textbf{, } RR_{Power}(c)=1,\\&\textbf{For } c \geq c_t\textbf{, } RR_{Power}(c)=1+\theta(c-c_t)^{\eta}.\end{aligned} \tag{2-4}$$

Based on the above mathematical forms used for burden assessment, recent studies have also conducted the meta-analysis of observed data and proposed an integrated exposure-response function (IERs) that flattens out at high exposures:

$$\begin{aligned}&\textbf{For } c < c_t\textbf{, } RR_{IER}(c)=1,\\&\textbf{For } c \geq c_t\textbf{, } RR_{IER}(c)=1+\alpha[1-\exp(-\gamma(c-c_t)^{\delta})].\end{aligned} \tag{2-5}$$

where α, γ, and δ jointly characterize the CRF which is derived from a fitting process.

2.2.3.3. Result Integration:

- **Mortality and morbidity:**

Results of AP-HRAs are often summarized into several metrics, including numbers of deaths or diseases, years of life lost (YLL), disability-adjusted life years (DALY), or changes in life expectancy [23]. The excess deaths or diseases (ED) derived from an increase in concentration can be calculated as follow:

$$\mathbf{ED=\Delta y\times Population} \tag{2-6}$$

It can also be expressed in terms of the population attributable fraction [50]–[52]:

$$\mathbf{ED=PAF\times I\times P} \tag{2-7}$$

Where PAF (population attributable fraction) is the fraction of disease burden attributable to pollution; I is the mortality incidence per year, and P is the all-age population. PAF can be then computed as below:

$$\mathbf{PAF}=\frac{\mathbf{p(RR\text{-}1)}}{\mathbf{p(RR\text{-}1)+1}} \tag{2-8}$$

Where RR represents the relative risk of premature mortality obtained from the IER model, and p represents the fraction of the population exposed. When all people in the region of interest are exposed to the air pollutant, that is p=1.

Disability -Adjusted Life Year (DALY) :

One DALY can be considered as one lost year of "healthy" life, while the total number of DALYs in the entire population can be regarded as the gap between an ideal health status where all people have no disease and disability and the current health status [53]. DALYs can be considered as the sum of YLL and YLD:

$$\mathbf{DALY = YLL + YLD} \tag{2-9}$$

YLL is a measure of the years of life lost due to premature death. The basic formula for a given cause, age, and sex is shown below:

$$\mathbf{YLL=N\times L} \tag{2-10}$$

Where N represents the number of deaths, and L represents standard life expectancy at the age of death in years. YLD measures years lost due to disability. The basic formula considering the certain disease, age, and gender is shown below:

$$\mathbf{YLD=I\times DW\times L} \tag{2-11}$$

Where I represent the number of cases, L represents the average years of disease, and DW represents the disability weight, reflecting the severity ranging from 0 (healthy) to 1 (dead).

- **Economic Assessment:**

The economic costs of the health effects can be monetized using two approaches: the value of a statistical life (VSL) method[54] and the cost of illness (COI) method [55]. VSL can be calculated through the willingness to pay (WTP) approach, which measures people's willingness to pay for reducing a marginal death risk, following the equation shown as below [56]:

$$\mathbf{VSL}=\frac{\mathbf{dWTP}}{\mathbf{dP}} \tag{2-12}$$

WTP represents the willingness to pay to avoid premature death and morbidity, and P represents the probability of death. The values of WTP are directly obtained through a survey-based conjoint analysis. The cost of Illness (COI) method indicates the economic cost of some morbidity endpoints based on the mean estimation of unit values. Generally, the total COI comprises hospital admission and medical costs due to missed workdays or restricted activity days. For this purpose, relevant data is obtained through the survey and interviews with medical practitioners. Since detailed information on treatment costs is not accessible in all regions, the following transfer approach can be used to calculate the illness treatment cost in region i, in comparison with the European Union (EU) [57]:

$$\mathbf{C_{morb(i)}=C_{morb(EU)}\times(\frac{PCI_i}{PCI_{EU}})^{e}} \tag{2-13}$$

Where $C_{morb(i)}$ and $C_{morb(EU)}$ represent the illness treatment cost in the region i and EU country, PCI_i and PCI_{EU} are the per capita income in the region and EU, respectively. The value of $C_{morb(EU)}$ can be obtained from the European valuation table [58], and e is the elasticity coefficient of WTP [59].

2.3. AP-HRA Tools:

There are currently various quantitative HRA tools developed by governmental and non-governmental entities to provide timely information regarding air pollutant exposure and its health impacts. Among them, COBRA (Co-Benefits Risk Assessment), Simair, Air Q+, BenMAP-CE (Environmental Benefits Mapping and Analysis Program—Community Edition), Ecosense, Household Air Pollution Intervention Tool (HAPIT), GAINS (Greenhouse gas—Air pollution Interactions and Synergies model) were developed to quantify the number of air pollution-related premature mortalities, disability-adjusted life years, and cases of disease [60]. These tools use common data for population, sources for baseline mortality rates, and concentration-response associations, but they vary in degree of technical complexity, exposure information source, and format [61]. They use a different methodological approach, spatial resolution, and geographical scope. However, most of these tools are preset to estimate the effects of NOx, Sulfur Oxides (SOx), $PM_{2.5}$ and PM_{10}. The input data can also vary depending upon the source of air pollution and its impact on a specific population or sub-population, like children or air pollution by a particular sector [53][62]. Some of the tools allow user-specified inputs. However, most of these tools use default values for demographic, concentration-response functions, and health data to estimate the population's exposure level. Table 2-5 represents some of the widely used quantitative HRA tools.

BenMap-CE estimates health impacts and monetary benefits from reductions in $PM_{2.5}$ and ozone. The possible economic consequences of air pollution-related health impacts can be quantified by BenMap-CE, enabling users to measure the potential health and economic benefits of improving air quality in any country or region of the world, using the air quality, population, baseline health and concentration-response criteria of the GBD. [63]. The health impacts include heart attacks, Premature mortality, and other air pollution-related health effects due to air quality changes. After determining ambient air quality changes using user-specific air quality data, BenMAP-CE relates health effects or health endpoints with changes in the air pollution concentration, using CFRs.

HAPIT is a web-based tool that was developed to estimate the expected health benefits from low indoor $PM_{2.5}$ emission development strategies in middle and low-income countries. It can be used to estimate averted premature deaths and DALYs and health-associated costs of the different intervention scenarios by using the best available background disease and data available for the exposure-response [64]. HAPIT can be used to evaluate the implication of the intervention scenarios for improving indoor air quality in countries where a significant portion of the population uses solid fuel, allowing policymakers to compare the relative merits of interventions within and between different countries. HAPIT depends on up-to-date national health background information and the tools and databases built for the Comparative Risk Assessment (CRA) which were used for the 2010 Global Burden of Disease (GBD 2010). Exposure-response details are used in 57 countries where solid fuels account for 50% of primary cooking fuel [65].

COBRA evaluates the human health and economic impacts of the state-level low emissions development strategies in the US by translating the reduced PM and other concentrations of air pollutants into preventable causes of death. It helps identify the best option with the highest health benefits or reduce health risks in a cost-efficient manner [66]. COBRA uses county-level predicted $PM_{2.5}$ concentrations as a proxy of $PM_{2.5}$ exposures for individuals living in those counties and estimates the health effects by comparing them with exposure-response relationships based on the available data from the EPA. A Gaussian dispersion model is being used in the COBRA tool that accounts for dry and wet deposition as well as first-order chemical atmospheric transition. The S-R matrix includes transfer coefficients in the U.S. between emissions and county-level $PM_{2.5}$ concentrations and integrates meteorological inputs determined in the 1990 EPA guideline impact analysis based on weather observation[67].

The Simple Interactive Model for better Air quality (SIM-air) is used to assess the implications of integrated air quality management policies in developing countries' urban areas. It combines the Geographical Information System (GIS) with the local emission data inventories in cities in evaluating various air quality scenarios. SIM-air uses the source-receptor transfer matrix (SRTM) to convert emissions of the concentrations, which is an output from a chemical transport model. It provides the necessary information for the policymakers to prioritize their air quality management policies, optimizing options for both public health and costs impacts in order to better adapt to local ambient standards in urban areas [68].

AirQ+ software tool for health risk assessment of air pollution is one of the most widely used tools for calculating the possible health impacts of improving air quality. It assesses the short-term and long-term exposure to both outdoor and indoor emissions of PM_{10}, $PM_{2.5}$, O_3, NO_2, and black carbon. AirQ+ helps measure the health impacts of atmospheric and household air pollution and aims to measure cancer risks and contain unit risk values for nickel, benzene, vinyl chloride, and chromium (VI) arsenic, and benzopyrene calculates the number of preventable premature deaths and diseases due to improvement in the air quality using the Health Impact Function (HIF) equations. The HIF estimates the count of premature deaths and diseases by using baseline rates of mortality or morbidity, population data, air pollutant concentrations, and concentration-response parameters[63].

EcoSense is an atmospheric dispersion and air pollution exposure assessment model that helps estimate the health and environmental impacts and related economic impacts in Europe.

It calculates long-term effects on human health, ecosystem, and crops by airborne pollutants, taking into account the chemical transformation and dispersion of pollutants. The CRFs are used to quantify the DALYs and morbidity rates caused by long-term exposure to NO_2, PM, and Ozone[27]. EcoSense integrates local and regional dispersion models with complex exposure-response network functions to quantify the impacts of elevated concentrations of air pollutants and also the economic value for the different impact categories like human health, building materials, forests and ecosystems, and crops.

GAINS model identifies the cost-effective portfolios of pollution reduction policies that achieve air quality improvements at a minimum cost. GAINS helps address the risks of fine particulate matter and ground-level ozone to human health and the danger of acidification disruption to habitats, excess nitrogen accumulation (eutrophication), and exposure to high ozone levels. The environmental and health impacts of primary pollutants ($PM_{2.5}$-PM_{10}) particles, sulfur dioxide (SO_2), non-methane volatile organic compounds (VOC), ammonia (NH_3), and nitrogen oxides (NOx) are quantified in a multi-pollutant context. For the change in the emissions, source-receptor relationships have been established, and compressive transport models together with atmospheric chemistry, are used to simulate complex physical and chemical reactions [91]. The GAINS uses the Eulerian Unified EMEP model to assess the fate of atmospheric pollutants [92]. The health impact estimation of GAINS is based on epidemiological studies quantifying mortalities due to long-term exposure to $PM_{2.5}$ or SOMO35.

Table 2- 5. Widely used quantitative HRA tools.

Tool	Developer	Study Area	Reference
Environmental Benefits Mapping and Analysis Program—Community Edition (BenMap-CE)	The United States Environmental Protection Agency (EPA)	USA, Turkey, Spain	[69][70][8]
Greenhouse gas—Air pollution Interactions and Synergies (GAINS) model	International Institute for Applied Systems Analysis (IIASA)	Europe, China	[7][71][72]
CO-Benefits Risk Assessment (COBRA) Health Impacts Screening and Mapping Tool	The United States Environmental Protection Agency (EPA)	USA	[66] [73][74][75][76]

Tool	Developer	Study Area	Reference
Air Quality (Air Q+)	World Health Organization (WHO)	Iran, Italy	[68][77][45]
Air Q+ and BenMAP-CE	EPA and WHO	USA	[78]
The Simple Interactive Model for better Air quality (SIM-air)	Urban Emissions	India, Europe	[79] [80][13]
Household Air Pollution Intervention Tool (HAPIT)	Household Energy, Climate, and Health Research Group at the University of California, Berkeley	India, Mozambique	[81][82][83]
Ecosense	Institute of Energy Economics and Rational Energy Use (IER), University of Stuttgart	Greece France, Brazil	[84][85][86]
TM5- FASST	JRC Ispra (Italy)	China, Multinational study	[87][88]
Aphekom	French Institute of Public Health Surveillance	25 European cities, 10 European cities	[89][90]

Table 2-6 represents the comparison between the above-mentioned AP-HRA tools, concerning their methodologies, scopes, input parameters, and predicted health impacts.

Table 2- 6. Comparison between the AP-HRA tools.

Characteristic	AIRQ2.2	BenMAP-CE	COBRA	HAPIT	SIM-Air	GAINS	EcoSense
Health Impacts							
Mortality (cases)	√	√	√	√	√	√	√
Disability-adjusted life years (DALY)	√	√	√	√		√	√
Morbidity (cases)	√	√	√	√	√		√
Economic Impacts	√	√	√		√		√
Pollutants:							
$PM_{2.5}$	√	√	√	√	√	√	√
PM_{10}	√	√			√	√	√
Ozone	√	√				√	√
NO_2	√	√	√			√	√
SO_2	√	√	√			√	√
CO	√	√				√	√
Other	Black smoke		VOC			CO_2, VOC, CH_4, N_2O	Hydrocarbons, dioxins and heavy metals
Spatial Resolution							
Regional	√	√			√	√	√
National	√	√	√			√	
City-level	√	√			√	√	
Household/Indoor	√			√		√	√

A comparative SWOT (strengths, weaknesses, opportunities, and threats) analysis of the afore mentioned tools has been carried out in this research, which is summarized in Table 2-7.

2.4. Discussions and conclusion:

Air pollution health risk assessment tools have different advantages regarding simplicity, consistency, comparability, and quality assurance. These tools also help policymakers by providing necessary information to make action plans to reduce air pollutants by reducing the combustion of fossil fuels. Substantial progress has been made in evaluating the health and other environmental effects of the HIA tools. These tools have advanced over the past decade because of growing epidemiological data that offers quantitative parameters of air emissions and health impact on the concentration-response relationship, which has helped decision-makers educate the public about the potential estimated benefits of improved air quality [62]. Simultaneously, low-quality baseline morbidity rates, especially in low-income countries, make it challenging to measure air-pollution-related morbidity effects worldwide [61] accurately. Each of these tools has its limitations and strengths. Nevertheless, knowing them is crucial while assessing air pollution's health and economic impact.

To estimate air pollution, most tools rely on air quality modeling, but some may also collect these data from air quality monitor observations or derive information from both monitors and models. Using the models for health impact assessment offers an advantage and covers a broader spatial area. On the other hand, monitoring data represents real atmospheric concentrations over a discrete amount of time in a given area [61].

There are several complexities in the use of air quality models for health impact assessment. In epidemiological studies from which concentration-response comparisons are extracted, modeled concentrations do not correlate to the method or spatial resolution of the characterization of exposure and may contribute to the inaccuracy of the analysis. In addition, the inherent uncertainty of simulated concentrations may not have enough resolution to represent the actual exposure patterns. So, it sometimes becomes a challenge to deliver reasonable outcomes for policymakers and other people who don't have specialized skills in the field while keeping harmony between the tools utilized and the multifaceted nature of the data.

It's essential to use the most precise and highly accurate data in the health impact assessment tools [93]. In addition to that, some unknown uncertainties and their interaction with each other are also usually not known. For example, the air we breathe could blend different pollutants with various sources and pass through different chemical reactions in the atmosphere. Furthermore, considering air pollution as the only factor responsible for many health outcomes and mortalities may not be the only solution. Multiple factors, such as social and cultural behaviors, should be considered in AP-HRA tools. While developing a tool for HIA studies, the main features like spatial resolution, emissions, health impacts, population exposure characterization methods, accessibility, sophistication, and application in policy contexts should be considered.

Table 2- 7. SWOT (strengths, weaknesses, opportunities, and threats) analysis of the selected AP-AHP tools.

Tool	Strength	Weakness	Opportunities	Threats
AirQ+	- Health impacts Quantification of indoor/outdoor air pollution. - Quantification of the cancer risks and includes unit risk values for chromium (VI), arsenic, nickel, benzene, vinyl chloride, and benzopyrene is an additional feature in the tool. - Multilanguage versions of the tool are available.	Evidence-based health outcome relationships are not strong, especially with the air pollutants like NO_2, BC (Black Carbon), and long-term ozone exposure.	There is an opportunity to refine further the spatial resolution in the analysis carried out with AirQ+ and integrate new user-friendly features like additional explanations for input data and components to calculate economic impacts and DALYs.	Often unrefined spatial resolution in the analysis is carried out with AirQ+, which may cover a whole country or city's spatial domain [63].

Tool	Strength	Weakness	Opportunities	Threats
COBRA	- It helps researchers create a new scenario that suggests improvements in pollution from baseline emissions smoothly and efficiently. - Detailed and comprehensive estimation of the health and economic gains that are related to decreasing the atmospheric $PM_{2.5}$ concentrations over a given year of study.	- Entirely concentrated on state-wise health impacts assessment in the US, making it difficult to be used in other regions. - The SR Matrix doesn't reflect the interaction which takes place in the atmosphere between the air pollutants.	Currently, COBRA has baseline data, which is only appropriate for the USA. There is an opportunity to add baseline data to make it suitable for regional or global HIA studies. The tool needs to continue to evolve and integrate the functionality and improve the sophistication of analysis.	- Some health endpoints like, upper respiratory symptoms, lower respiratory symptoms, and acute bronchitis are using a comparatively small sampling group and estimated from a single local survey, which increases the estimation's uncertainty. -For consistent distribution of air pollutants, an initial probabilistic method adjusted by the developers has been only used in the COBRA, which reduces the accuracy of the results.

Tool	Strength	Weakness	Opportunities	Threats
BenMAP—CE	Merging the CFRs with basic pooling strategies (e.g., random effects and fixed effects) to construct a new function that can adequately consider the diverse demographics data.	- The degree to which different mixtures of air pollutants pose a greater or lesser risk and the extent to which concentration-response associations observed in one group is limited to the particular case studies and cannot easily be extended to other cases. - Estimating health impacts due to air quality is limited to a single year period and cannot be carried out on a multiple-year horizon[61].	Incorporating new features into the tool, such as the estimate of the health impacts due to the exposure to multiple pollutants [63].	Spatial shifts in city-wide environmental concentrations, diverse sets of individual activity patterns, and indoor ambient air pollution differences[62].

Tool	Strength	Weakness	Opportunities	Threats
HAPIT	- HAPIT is an easy-to-use tool that helps estimate averted DALYs, averted premature deaths, and choosing Cost-Effective interventions. - Information on total households studied in the intervention, $PM_{2.5}$ exposure to pre and post-intervention population, and the average proportion of the population using intervention helps estimate the cost per intervention of the initiative the annual operating costs per household.	- The estimation period is short can’t be indicative of long-term trends. - Equal exposures among household members is assumed in the HAPIT. However, the exposure levels vary among the household members.	To decrease the uncertainty in the results, information about the baseline and intervention $PM_{2.5}$ exposure levels should be included for the developing countries where solid fuel is mostly used.	Background diseases and economic characteristics of a population are assumed to remain relatively unchanged in HAPIT. This presumption will hold for a short lifespan. Therefore, for long-term interventions, such as shifting from fossil fuel to renewable energy or electricity, the forecasts will have to be periodically updated.

Tool	Strength	Weakness	Opportunities	Threats
GAINS	Compressive Transport models and atmospheric chemistry to simulate complex physical and chemical reactions [91].	- The atmospheric dispersion model in GAINS is simplified into the basic linear function form based on the regression of results from TM5 and the relevant response-source model, resulting in uncertainty. - The health impact is assessed according to general RR value obtained from European and American epidemiological studies, which is unsuitable and inaccurate for other areas [91].	- Future projections of activity data such as macroeconomic drivers, energy, and fuel consumption are exogenous to the GAINS model, derived from other model calculations or national experts provided to ensure timeliness and authority. - Alternative pathways can also be specified in the GAINS Expert mode, improving the applicability for more scenarios.	Other models that focus on emission estimation or health impact assessment separately can provide more precise results and, if combined, would be a better alternative option than GAINS.

Tool	Strength	Weakness	Opportunities	Threats
ECOSENSE	- Comprehensive estimation of air pollution impacts on human health and Ecosystems. - Robust database including details of major air pollutants, hydrocarbons, and heavy metals [94].	Considering a simple linear source-receptor model for assessing the atmospheric chemistry interactions that perform a nonlinear behavior in nature.	Validation of the meteorological models used in the EcoSense tool to make it more appropriate for the developing countries by reviewing the meteorological databases and concentration-response functions.	- Inability to capture complicated atmospheric chemistry processes [61]. - The exact estimation of the form and severity of the related environmental impacts is hindered by limited knowledge of receptor size [84]. - Present projections of the external cost of climate change vary considerably, reflecting the high uncertainty of the forecasts since much of them would take place over the long term.
SIM-AIR	Multiple benefits (Environmental—health—economic) assessment of the climate change action plans, considering interactions between emissions, dispersion of pollution, impacts, and options for management [79][95].	Uncertainty in spatial analysis resolution matching the project (mainly urban areas).	For the study of pollution inventories and health effects, the database of concentration-response functions and emission sources is included in the tools that can be modified with relevant data from cities.	Recognizing the uncertainty of inventories is important and needs to be adjusted carefully as per the local data.

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CHAPTER 3

Quantifying the multiple environmental, health, and economic benefits from the electrification of the Delhi public transport bus fleet

Abstract: This chapter investigates the co-benefits from the utilization of the battery-electric bus (BEB) fleet in the Delhi public transportation system as a part of the Delhi electric vehicles policy 2020. To this aim, an integrated quantitative assessment framework is developed to estimate the expected environmental, health, and economic co-benefits from replacing the currently existing public bus fleet with the new BEBs in Delhi. First, the model estimates the avoided emissions from deploying the BEB fleet, using a detailed battery energy simulation model, considering the impact of the battery capacity loss on the annual operational time (hours of service) of the BEB. The annual operational time of the BEB is greatly affected by its battery degradation, which results in time lost due to charging the battery. This indicates that the annual passenger-kilometres (PKM) delivered by the BEB is less than the regular bus, under the same traveling condition. Second, considering fine particles ($PM_{2.5}$) as the most health-harming pollutant, the model calculates the near roadway avoided $PM_{2.5}$ exposure in the selected traffic zones of 11 major districts of Delhi, using a Gaussian dispersion model. Third, the near roadway avoided $PM_{2.5}$ exposure is further used in a health impact assessment model, which considers concentration-response functions for several diseases to evaluate the public health benefits from introducing the BEB fleet in Delhi. The research findings indicate that, the utilization of the new BEB fleet leads to a 74.67% reduction in the total pollutant emissions from the existing bus fleet in Delhi. The results of the integrated co-benefits assessment reveal a significant reduction in $PM_{2.5}$ emissions (44 t/y), leading to avoidance of mortality (1370 cases) and respiratory diseases related hospital admissions (2808 cases), respectively, and an annual savings of about USD 383 million from the avoided mortality and morbidity cases in Delhi.

3.1. Introduction

As one of the low emission development strategies, the Delhi Electric Vehicles Policy, 2020 seeks to meet the main goal of improving Delhi's air quality by speeding up the deployment of battery electric vehicles (BEVs), so that by 2024 they comprise 25% of all new vehicle registrations and significantly enhance Delhi's environment by reducing emissions from the transportation sector. BEVs are regarded as one of the most environmentally friendly alternatives to traditional fuel vehicles. Such policy intervention will have many co-benefits. Studies have indicated several co-benefits of electric vehicles, such as energy savings, carbon emission reduction, and local air quality management in the long run [1], [2].

As a part of the policy implementation, the Delhi government would offer financial incentives, waive road taxes and registration costs, and build a vast network of charging stations and battery-swapping stations. Between 2019 and 2022, the policy's initial goal is for electric buses to account for at least half of all new stage-carriage buses (i.e., for all public transport vehicles with 15 seats or more) [3]. From the viewpoint of urban air pollution, the justification for electric buses, and more generally, zero-emission buses, has been evident. Their health advantages in decreasing mortality and morbidity have been demonstrated economically.

With respect to the Delhi Electric Vehicle Policy, the projected climate co-benefits of using the BEB fleet in the urban transportation system of India's megacity of Delhi are analyzed in this chapter by developing a quantitative assessment methodology for environmental, health, and economic benefits. Figure 3.1 depicts the research approach followed in this study.

The main contribution of this chapter can be summarized as follows:

1- Few studies have quantified the potential environmental, health, and economic co-benefits from the electrification of the urban bus fleet in Delhi. The developed model is used to assess the expected co-benefits in 11 major districts and, subsequently, the whole urban transportation system in Delhi.
2- In addition to fuel efficiency and carbon intensity as the two main factors which are used in estimating the avoided emissions from replacing conventional buses with the BEB fleet, this study further emphasizes the impact of degraded battery capacity on the annual PKM delivered by the BEB, providing a more accurate estimation of the environmental co-benefits.
3- To more precisely estimate the avoided mortality and morbidity cases from the electrification of the bus fleet in Delhi, this study drives a pooled estimate of the RR values for six health outcomes, including total mortality, COPD, cardiovascular mortality, respiratory mortality, and morbidity, and related hospital admissions.

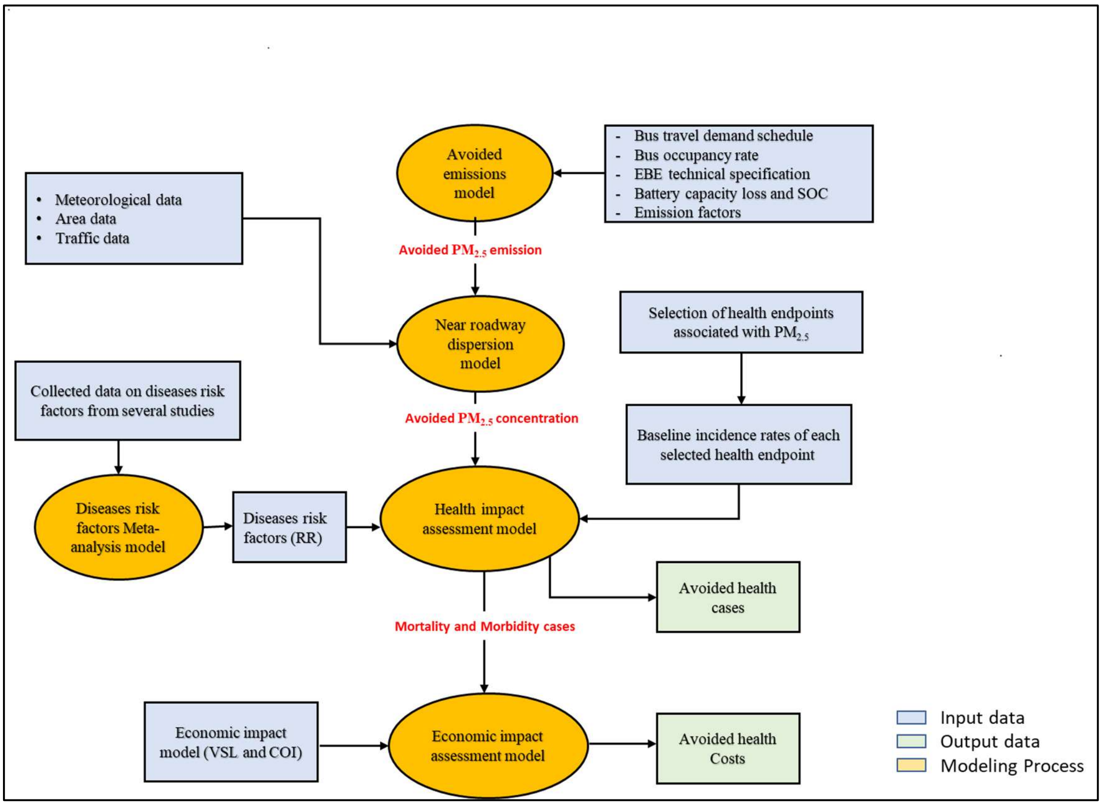


Figure 3. 1 Methodological approach used in this study

3.2. Integrated co-benefits assessment modeling framework:

3.2.1. Estimation of the avoided emissions by replacing the CNG bus fleet with BEBs:

In order to estimate the exact avoided emissions from replacing the CNG bus fleet with the new BEBs, it is necessary to realize the difference between their operational times (hours of service). The operational time is defined as the period that a bus can deliver the transport service throughout the year. Compared with a CNG bus, for a BEB, there is a need to spend a considerable time for charging the vehicle's battery (almost 4 hours per charging). The electric bus is out of service during the charging periods and cannot deliver the transport service. The annual operational time of the BEB can be calculated as follows:

$$\boldsymbol{\tau_{BEB} = \tau_{CB} - nT_{charging}} \tag{3-1}$$

Where, $\boldsymbol{\tau_{BEB}}$ is the operational time of the BEB; $\boldsymbol{\tau_{CB}}$ is the operational time of a CNG bus, considering the same traveling condition; n is the number of times to charge the battery per year and $\boldsymbol{T_{charging} = 4\ hrs}$. Therefore, the avoided emissions from replacing current CNG buses with the BEBs may be estimated, as follows:

$$\boldsymbol{AE_{BEB} = \alpha E_{CB}} \tag{3-2}$$

$$\boldsymbol{\alpha} = \frac{\tau_{BEB}}{\tau_{CB}} \tag{3-3}$$

Where, $\boldsymbol{AE_{BEB}}$ is the avoided emissions from replacing a CNG bus with a BEB [t/h]; and $\boldsymbol{E_{CB}}$ is the annual emissions from a CNG bus [t/h], and $\boldsymbol{\alpha}$ is the ratio of the operational time of the BEB to the CNG bus. It is noted that, the BEBs are considered as zero-emission vehicles, and the lifecycle emission of electricity is not considered in this calculation.

The operational time of a BEB is affected by battery degradation and capacity loss. Capacity loss, also known as capacity fading, is a phenomenon that occurs for rechargeable batteries over time, in which the amount of charge a battery can provide at the rated voltage decreases. Many degradation mechanisms occur in Li-ion batteries and are exacerbated by various internal and external stressors [4]. Capacity loss occurs not only during the usage period "cyclical loss", but also during the storage period "calendar loss". The ambient temperature substantially influences capacity loss; Aging rates rise with decreasing temperature below 25 °C, but increase with increasing temperature over 25 °C [5]. The number of charging in a year, *n*, is calculated from an accurate hourly estimation of the state of charge (SOC) of the battery:

$$\boldsymbol{SOC_t = SOC_{t-1} - \frac{T_{Load,t}}{R_{Load,t}}} \tag{3-4}$$

$$\boldsymbol{SOC_{min} < SOC_t < SOC_{max}} \tag{3-5}$$

Where, $\boldsymbol{TLoad_t}$ and $\boldsymbol{RLoad_t}$ refer to the utilized electrical load based on the PKM delivered by the electric bus, and the actual remaining load of the battery in time step *t* [kWh], respectively. $\boldsymbol{SOC_t}$ and $\boldsymbol{SOC_{t-1}}$ are the battery SOCs in time step *t* and *t-1*. The battery SOC varies between a lower limit ($\boldsymbol{SOC_{min} = 20\%}$) and an upper limit ($\boldsymbol{SOC_{max} = 80\%}$). If the battery *SOC* reaches its lower limit, the electric bus is sent to the charging station for recharging up to its upper limits. The actual remaining load of the battery, $\boldsymbol{RLoad_t}$, is affected by the battery capacity degradation ($\boldsymbol{Q_{loss,t}}$):

$$\boldsymbol{RLoad_t = \left(1 - Q_{loss,t}\right)C_0} \tag{3-6}$$

$$\boldsymbol{Q_{loss,t} = Q_{Cal,t} + Q_{Cyc,t}} \tag{3-7}$$

Where, $\boldsymbol{C_0}$ is the nominal capacity of the battery [kWh] and $\boldsymbol{Q_{loss,t}}$, the battery capacity loss in time step *t,* which includes the battery calendar and cyclical aging losses:

$$\boldsymbol{Q_{Cal,t} = \gamma e^{(-E_a/RT)t^{0.5}}} \tag{3-8}$$

$$\boldsymbol{Q_{Cyc,t} = \beta_1 \mathrm{Ah}_t\, e^{\beta_2 C_{rate}}} \tag{3-9}$$

In the above equations, γ, $\beta_1$and β_2 are constant coefficients, which their values are given in [6]; E_a is the activation energy of the battery [J/mol]; R is the gas constant [J/molC], T is the ambient temperature [C]; C_{rate} is the electric current in which a battery is charged and discharged and rated at 3C for the electric bus. Ah_t is the storage throughput, which is the amount of energy that cycles through the battery. The amount of Ah_t is degraded with respect to the battery capacity loss, as follows:

$$\boldsymbol{Ah_t = Ah_{t-1} + Ah_o\left(1 - Q_{loss,t-1}\right)} \tag{3-10}$$

Ah_o is the initial storage throughput of the battery. The above calculations indicate that, both utilized electrical load ($T_{Load,}$) and degraded capacity (Q_{loss}) of the battery affect the annual time lost in charging ($nT_{charging}$).

3.2.2. Prediction of near roadway avoided $PM_{2.5}$ exposure:

Concentrations of air pollutants at specific sites are assumed to be indicative of population exposures. However, emission levels may be higher in locations near specific sources of air pollution, such as major roads, power plants, and big stationary sources, necessitating additional measures to minimize pollution levels for residents [7]. Most epidemiological and risk evaluations currently rely on simple exposure measures, such as the distance between highways and residential areas, to represent traffic-related air quality implications. To be able to relate the avoided emissions from replacing the CNG buses with the EBEs to the health endpoints, a near-roadway dispersion model is developed in this research, taking into account the concentration of $PM_{2.5}$ as the major air pollutants. The model estimates the hourly concentration at downwind distance *x* (km) and crosswind distance *y* (km), using a steady-state gaussian depression model [8] as follows:

$$\boldsymbol{C = \frac{EH}{2\pi v_s \delta_y \delta_z} exp\left[-0.5\left(\frac{y}{\delta_y}\right)^2\right]} \tag{3-11}$$

And:

$$\boldsymbol{H = \left[exp\left(-0.5\left(\frac{z-h}{\delta_z}\right)^2\right)\right] + \left[exp\left(-0.5\left(\frac{z+h}{\delta_z}\right)^2\right)\right]} \tag{3-12}$$

$$\boldsymbol{\delta_y = 465.12 x tan(0.0174(\theta - \mu \ln(x))}) \tag{3-13}$$

$$\boldsymbol{\delta_z = \partial x^{\rho}} \tag{3-14}$$

Here, C is the concentration $(\mathrm{g/m^3})$; E is the pollutant emission rate from the buses (mass per unit time). Since there are no emissions from the BEBs, therefore, $E = AE_{BEB}$. v_s is the mean wind speed $(\mathrm{m/s})$ at release height; z is the receptor height which is considered the same as the average human height; δ_y *and* δ_z are the "standard deviation of lateral and vertical concentration distribution (m); *h* is the effective source height, which is considered as the vertical distance between the bus exhaust pipe and ground. θ, μ, ∂ and ρ are constant coefficients that can be defined based on the given values for the stability category at the local area. x is the distance from the source (bus located in the roadway) to the receptor (people located near-roadway), which is shown in Figure 3.2. It is noted that, in the polar coordinate system, the relationship between wind coordination with x and y should be taken into consideration in the above calculation. The wind speed at release height, v_s, can be calculated, using the following formula:

$$\boldsymbol{v_s = v_0 \left(\frac{h}{z_0}\right)^p} \tag{3-15}$$

Where, v_0 and z_0 are the observed wind speed and reference measurement height, respectively. p is the wind profile exponent, and its value can be estimated based on the stability category in the local area. In order to estimate the short-term area concentration of the $PM_{2.5}$ over the area in the upwind and crosswind directions, the ground level concentration model is used in this study, which can be represented as follows [8]:

$$\boldsymbol{C = \frac{E}{2\pi v_s} \int_x \frac{H}{\delta_y \delta_z} (\mathbf{erfc}\left(\frac{y}{\delta_y}\right)) dx} \tag{3-16}$$

Where, **erfc** refers to the complementary error function. In the above equation, the integral part can be calculated by using a trapezoidal approximation with m intervals [9] .

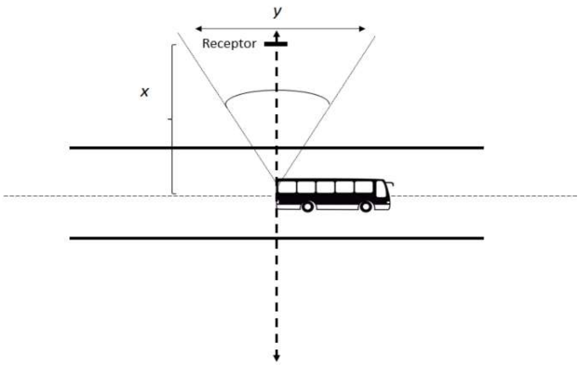


Figure 3. 2. Road and receptor coordinate system used in the desperation model

3.3.Health Impact Assessment (HIA) assessment model:

In order to quantify the health benefits of avoided $PM_{2.5}$ levels in a specific area, the air quality health risk assessment (AP-HRA) is used, with specific concentration-response functions and relative [10], [11]. Total mortality, COPD, cardiovascular mortality, respiratory mortality and morbidity, and related hospital admissions are the six health outcomes which are considered for health impact analysis in this study. $PM_{2.5}$ particles that penetrate deep into the lungs are the most health-harming pollutants as they are linked to an increased risk of premature deaths [12]. Concentration-response functions (CRFs) are used to estimate the relationship between a change in air pollutant concentration ($PM_{2.5}$ in this study) and a change in health effects (usually an incidence or mortality rate). The CRF coefficient values are generally obtained from relative risk

(RR), representing the probability of an unfavorable health consequence among the population exposed to a greater ambient air pollution level than a lower ambient level. Tables 3-1 and 3-2 show the methods used to assess the relative risk (RR) of long-term $PM_{2.5}$ exposure and the baseline mortalities used to calculate averted mortality and morbidity in this study. India has baseline mortality rates of 142.1, 165.8, 116.4, and 6.5 per 100,000 people for COPD, IHD, stroke, and LC, respectively [13]. Excess deaths or illnesses (EDI) resulting from the rise in $PM_{2.5}$ concentration can be estimated as follows:

$$EDI = PAF \times I \times P \tag{3-17}$$

Where, *PAF* (population attributable fraction) denotes the proportion of illness burden owing to pollution, *I*, is the annual baseline mortality rate, and *P* denotes the total population. The *PAF* may then be calculated as follows [14].

$$PAF = \frac{p(RR-1)}{p(RR-1)+1} \tag{3-18}$$

p is the proportion of the population exposed.

Table 3- 1. Methods for assessing the relative risk of long-term $PM_{2.5}$ exposure

Outcome	Relative risk function*
Total mortality, Cardiopulmonary mortality, and Respiratory mortality	$RR = exp\ [\beta(C - C_0)]$
Lung cancer mortality	$RR = [(C+1)/(C_0+1)]^{\beta}$

*β is a coefficient that assesses a health outcome's reaction to a change in pollutant concentration. and $\mathbf{C}$ and $\mathbf{C_0}$ represent the pollutant concentrations in the baseline and intervention scenarios [10].

Table 3- 2. Baseline incident rates

Mortality/Morbidity[1]	Baseline Incidence per 100,000
Total Mortality[1]	1013
Cardiovascular Mortality[1]	497
Respiratory Mortality[1]	66
COPD Morbidity (Hospital Admissions)[1]	101
Respiratory Disease (Hospital Admissions)[1]	1260
Lung Cancer (LC)[2]	9.06

[1]From [15], [16].
[2]From [17].

Estimation of the correct values of RR is a critical issue in the health impact assessment that needs highly aggregated epidemiological data. As one of the main originalities of this research, a comprehensive $PM_{2.5}$ related RR meta-analysis was performed for selected diseases from the previous studies undertaken in Asian countries. The meta-analysis was based on a systematic quantitative review in which all relevant empirical evidence that meets the pre-specified eligibility standard and criteria is collected and combined, using a statistical method to generate a pooled estimate that is closest to Delhi-specified RR values. Based on the inclusion criteria, 64 studies were included. Figure 3.3 shows the geographical distribution of the studies selected for meta-analysis in this study. Most of the research came from China (n = 47) and India (n = 7) for total Mortality, COPD, Cardiovascular Mortality, respiratory mortality, LC, and respiratory morbidities related to hospital admissions. The detailed data used in the analysis is given in Figure (3.11-3.16).

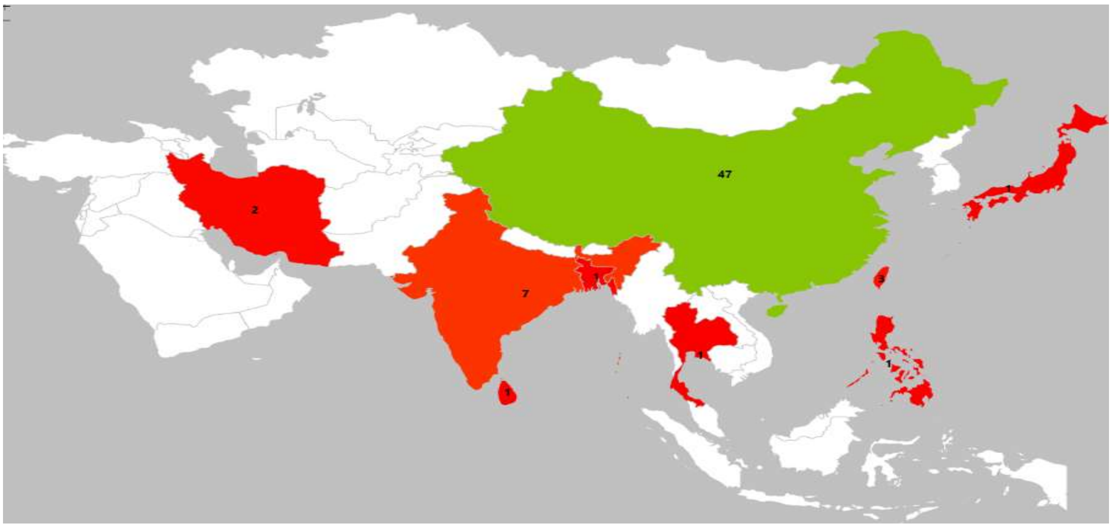


Figure 3. 3. The geographical distribution of the selected studies for meta-analysis

The pooled value extracted from the meta-analysis ($\boldsymbol{RR^p}$)is estimated as follows [18]:

$$\boldsymbol{RR^p} = \frac{\sum y_i RR_i}{\sum y_i} \tag{3-19}$$

$$y_i = \frac{1}{SE\{\log RR_i\}^2} \tag{3-20}$$

Where, SE is the standard error. The overall calculation flow in the health impact assessment model is shown in Figure 3.4.

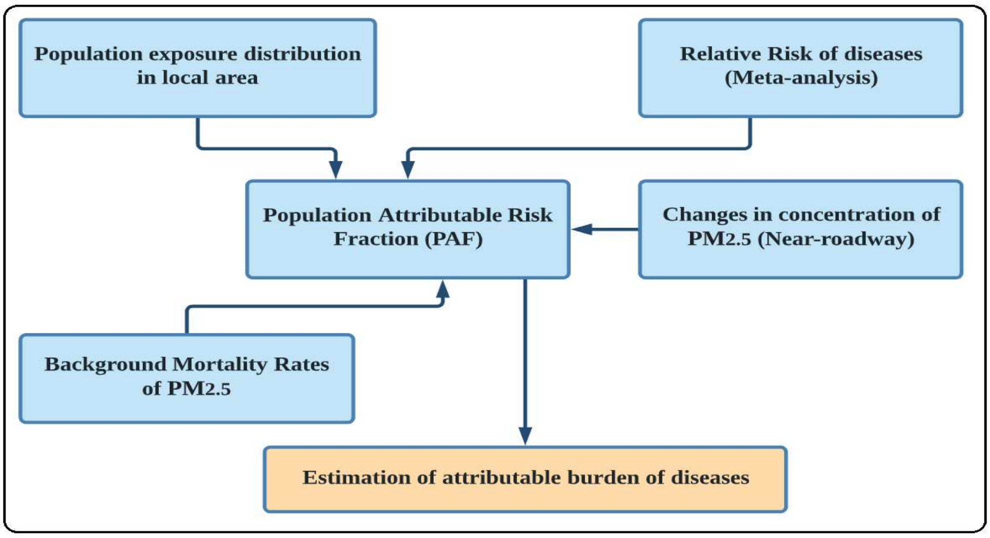


Figure 3. 4. Calculation flow in the HIA model

3.4.Economic impacts assessment model:

In this study, the Value of Statistical Life (VSL) approach was used to calculate the mortality cost from $PM_{2.M}$ exposure. Due to the lack of data availability on VSL in India, the value of the VSL for India in 2020 was estimated based on the available data of VSL in the US, using the following formula:

$$\mathbf{VSL_{IND}} = \mathbf{VSL_{US}} \times \left(\frac{\mathbf{Y_{IND}}}{\mathbf{Y_{US}}}\right)^{\mathbf{e}} \tag{3-21}$$

Where, $\mathbf{Y_{IND}}$ and $\mathbf{Y_{US}}$ are the per capita GDP of India and the US which are estimated at USD 1927 thousand and USD 63,413 thousand in 2021[19], [20]. $\mathbf{VSL_{US}}$ and $\mathbf{VSL_{IND}}$ are the values of the VSL of the US and India in 2020 [USD], respectively. VSL of the US is assumed to be $10 million [21], [22]. e refers to the VSL's income elasticity. In this study, a given value of 1 for e is considered for low- and middle-income nations.

The cost of an emergency room visit (ERV) is estimated as follows:

$$\text{ERV} = \text{One workday loss} + \text{hospital charge} + \text{medication charge} + \text{transport charge} \tag{3-22}$$

With an annual increase in medical costs in India between 5 to 12% [16], [23]. The monetary burden of health impacts grows in tandem with the rising cost of treatment. As a result, a low (5%) and high (10%) increase in the price of medicines and hospital admission charges is considered when estimating monetary burden trends

Following the above approach, the value of VSL in India is estimated at USD 0.279 million, which lies within the range of USD 0.15 to 0.36 million addressed in previous studies [24]–[26], considering the Indian annual average GDP per capita growth [27]. The Cost of illness (COI) approach was used to determine the cost of hospital admissions, COPD, respiratory diseases, and

LC [28], [29]. Table 3-3 shows the values for the different health endpoints considered in this study.

Table 3- 3. Values of the health endpoints used in this study

Health endpoint	Valuation (USD) with a yearly 10% increase in the cost of treatment		Method of cost calculation
Total mortality	279,411		VSL approach (This study)
Increase in the cost of treatment	5%	10%	
COPD hospital admissions	205	345	CoI approach [28]
Respiratory diseases hospital admissions	48	80	CoI approach [28]
LC hospital admissions	1708	1,886	CoI approach [30]

3.5.Results and Discussion:

3.5.1. Avoided emissions from the utilization of BEB fleet:

The average speed of a Delhi public transportation bus fleet is estimated to be 15 km/h [31], [32], with a 39.6 % occupancy rate [33]. CNG Bus fuel efficiency is estimated at 3.08 km/kg$_{CNG}$ [34], and the operating period for DTC (Delhi Transport Corporation) buses is between 5:00 a.m. and 11:00 p.m. (DTC, 2020). There are currently 5327 operating public transportation buses in Delhi DTC and DIMTS (Delhi Integrated Multi-Modal Transit System), with an average daily mileage of 200 kilometers per bus [35]. The details of the average occupants and delivered passenger kilometers (PKM) for one CNG bus are given in Table 3-4. The contribution of the CNG buses to overall air pollution in Delhi is shown in Table 3-5.

Table 3- 4. Daily transport service delivered by a CNG bus in Delhi

Operational Time	Average occupants	PKM
5:00 to 6:00	25	375.0
6:00-7:00	26	390.0
7:00-8:00	33	495.0
8:00-9:00	51.67	775.1
9:00-10:00	56.88	853.2

Operational Time	Average occupants	PKM
10:00-11:00	55.29	829.4
11:00-12:00	51	765.0
12:00-13:00	29.94	449.1
13:00-14:00	29.94	449.1
14:00-15:00	35.21	528.2
15:00-16:00	26.47	397.1
16:00-17:00	26.47	397.1
17:00-18:00	26.79	401.9
18:00-19:00	26.79	401.9
19:00-20:00	33.91	508.7
20:00-21:00	25.37	380.5
21:00-22:00	25	375.0
22:00-23:00	25	375.0

Table 3- 5. Contribution of the CNG bus fleet to overall air pollution in Delhi

Emissions	$PM_{2.5}$[a]	NOx[a]	CO[a]	VOC[a]	CO_2[b]
CNG bus emission factors (gm/km)	0.184	25.66	11.92	3.311	1308
CNG bus fleet contribution to overall air pollution in Delhi (t/y) [c]	59.5	8296	3854	1070	422,925

[a]- From [34]
[b]- From [36]
[c]- From [37]

The BEBs are supposed to deliver the same amount of PKM that CNG buses will deliver. As previously discussed, the total operational time of a BEB is less than one CNG bus due to the battery's annual capacity loss and required charging time. This can be further discussed in Figure 3.5, which shows the variation of the battery SOC during the first (Jan 1st to 4th) and last (Dec 26th to 29th) weeks of the operation period. As can be seen in this figure, the BEB starts to operate at 5:00 am, using a fully charged battery. The battery SOC declines to 20%, and the BEB is sent to the charging station to charge the battery, which takes about 4 hours. After charging, BEB is re-operated until 11 pm. There are two key points in this figure: 3.5) the battery charging process takes place during the operating period (5:00 am to 10:00 pm), indicating the BEB is out of service during this period. When it approaches the last week of the year, the SOC declines more rapidly and the number of changings per day increases due to the gradual degradation of the battery capacity, which indicates that the battery capacity loss greatly influences the operational time of the BEB. Using the detailed methodology explained in section 3.2, the annual operational time for a BEB is estimated at 4907 hrs, compared with a standard CNG bus (6570 hrs), which suggests that $\boldsymbol{\alpha = 0.7467}$ (Eq (2)). Therefore, about 74.67% of the total pollutant emissions from the current CNG buses can be avoided by using the same number (5327) of the BEBs in Delhi, taking into account the same traveling condition. Table 3-6 shows the detailed specification of the BEB used in this study.

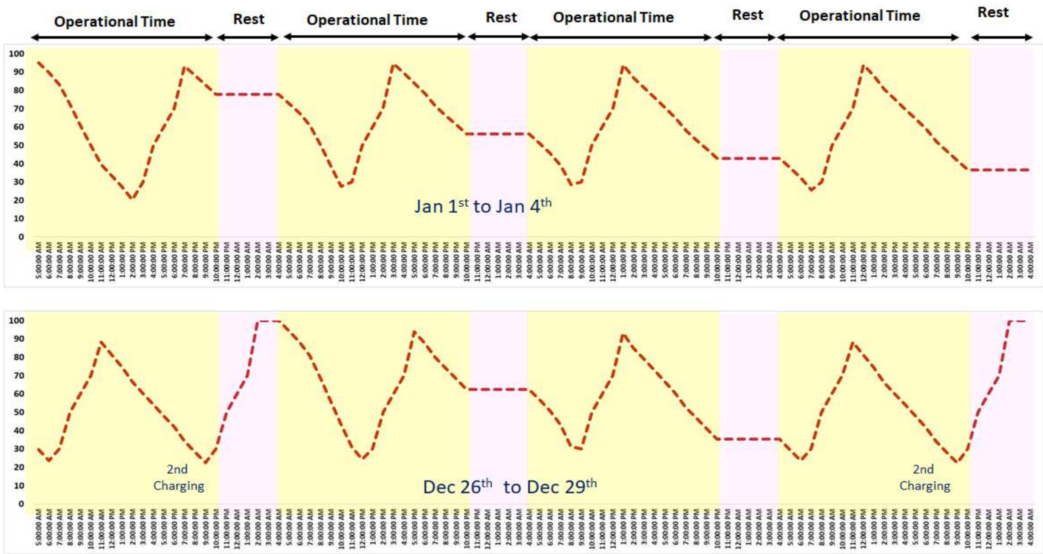


Figure 3. 5. Estimation of the battery SOC (%) in the first and last weeks of the operation

Table 3- 6. Technical specification of the BEB used in this study

Motor [38].	Integrated Motor Generator Max Power: 245 kW Continuous Power: 145 kW
HV Battery Specification [38].	Li-Ion Battery Pack- ~186 KWH (Expandable)

Figure 3.6 represents the estimation of the actual remaining capacity and capacity loss of the battery throughout one operational year for a BEB in Delhi, taking into account the travel demand given in Table 3-4. The annual charging time estimated from the hourly SOC of the battery is reported in Table 3-7.

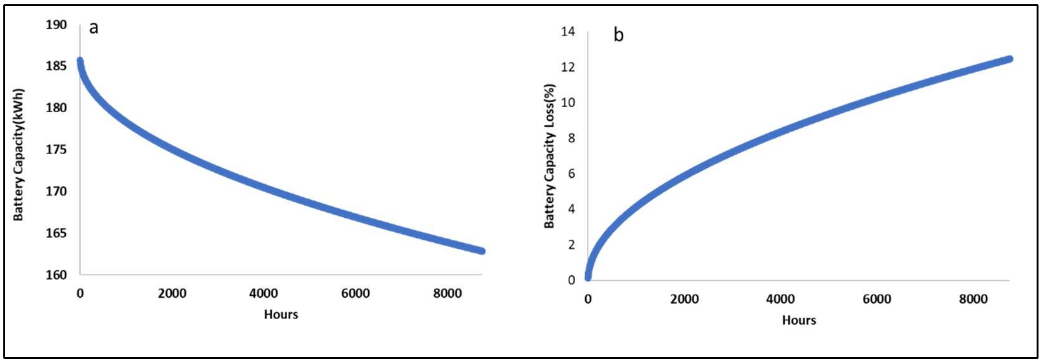


Figure 3. 6. a) Annual battery actual remaining capacity b) Annual battery capacity loss.

Table 3- 7. Charging time (excluding rest period) estimated from the hourly SOC.

Time spans within the operational period	Charging hours in a year
5:00-12:00	1032
12:00-18:00	423
18:00-23:00	208
Total	1663

Considering the annual operational time, the amount of avoided emissions from replacing all CNG buses with the new BEB fleet in Delhi is given in Table 3-8.

Table 3- 8. Avoided emissions from replacing all CNG buses with the new BEB fleet (t/y).

$PM_{2.5}$	NOx	CO	VOC	CO_2
44.4	6,196.7	2,878.6	799.6	315,874.4

3.5.2. Near roadway avoided $PM_{2.5}$ exposure:

In order to assess the impact of the avoided $PM_{2.5}$ emissions from replacing the CNG public transport bus fleet with BEBs, the near roadway concentration model explained in section 3.2.2 was applied to a selected traffic zone, entitled "Chaudhary Charan Singh Marg (Latitude: 28.65578, Longitude: 77.31986)" located in Anand Vihar (AV), which covers 4 km of the bus route, shown in Figure 3.7. The AV area is part of the Shahdara district in Delhi's NCT, with a population density of 19518 persons per km², which is considered as one of the most congested urban areas in Delhi [39]. The near roadway model estimates $PM_{2.5}$ concentration in a downwind distance of 0.2 km from the buses to the near roadway passengers.

Figure 3. 7. Selected traffic zone in this study

The average bus traffic flow is reported at 95 buses per hour in this traffic zone [40] with an average of 508 PKM per hour, where the avoided $PM_{2.5}$ emission from replacing them with the new BEBs can be estimated at 346 kg per year. The results of the near-roadway hourly concentration of avoided $PM_{2.5}$ exposure in the selected traffic zone are shown in Figure 3.8 (a,b), taking into account the local wind speed and solar elevation angle in the AV urban area. The average ground level area concentration of $PM_{2.5}$ in a receptor grid (4× $\mathbf{0.2}\boldsymbol{km^2}$), covering the selected traffic zone, is estimated at 2.13 μg/m^3.

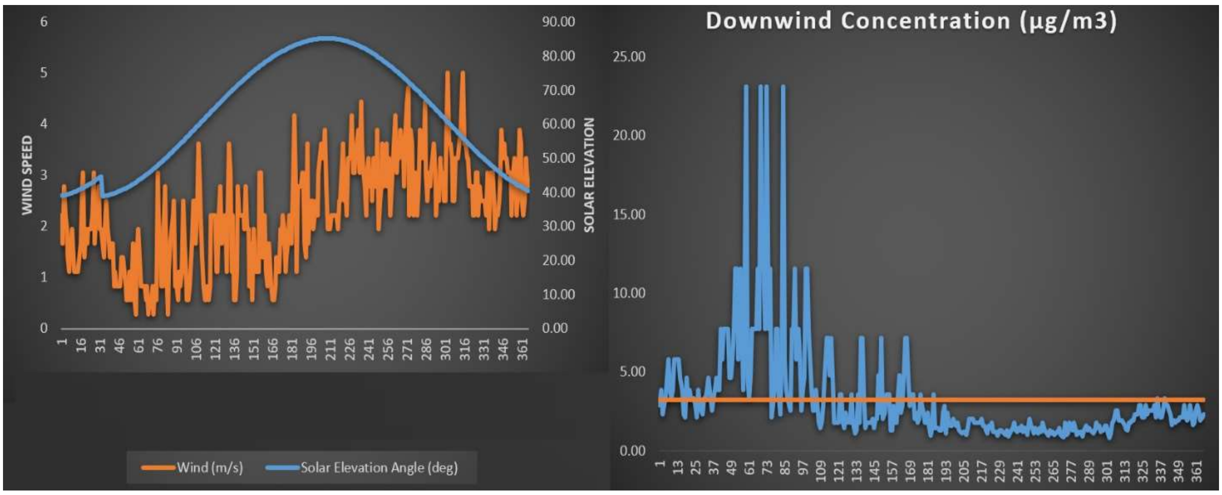


Figure 3. 8. (a) Variation of the wind speed and solar elevation angle and (b) Estimated near roadway avoided $PM_{2.5}$ exposure in the selected traffic zone at receptor point (0.2 km from the roadway)

The same calculation method was used to estimate the average reduced level of $PM_{2.5}$ exposure in all 11 districts in Delhi, considering the average bus traffic flow [40] in a selected traffic zone, which is shown in Figure 3.9 . Table 3-9 shows the detailed data used in this estimation. From Figure 3.9, it can be observed that, New Delhi and Southeast districts have the lowest (0.73 μg/m^3)

and the highest (2.73 μg/m³) near roadway avoided $PM_{2.5}$ exposure among all districts in Delhi, respectively.

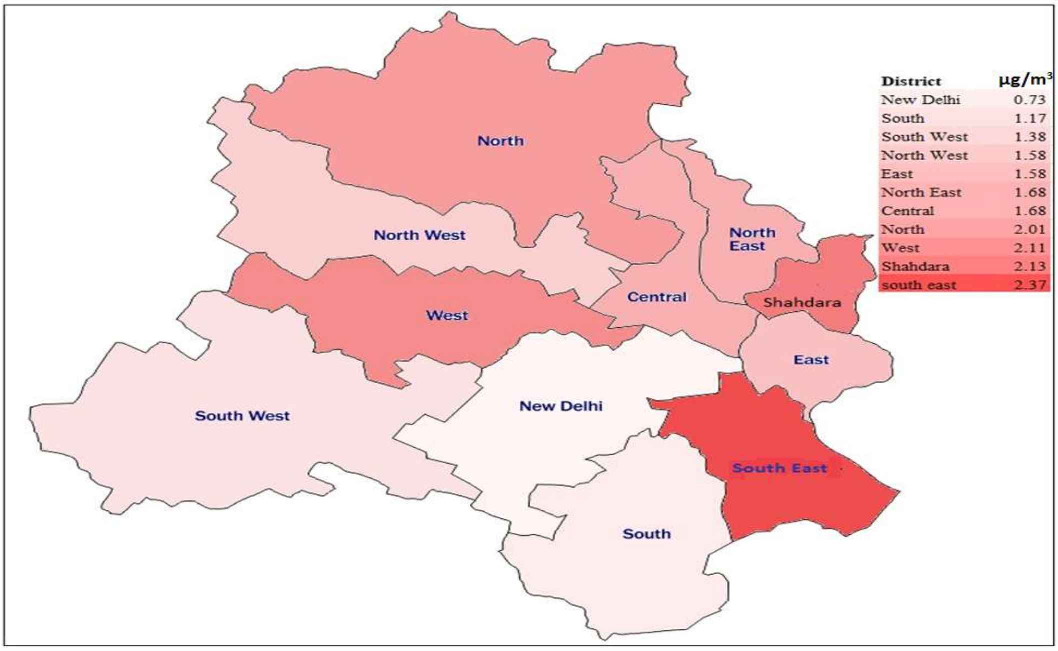


Figure 3. 9. Estimated near roadway avoided $PM_{2.5}$ exposure from the utilization of the new BEB fleet in the different districts of Delhi

3.5.3. Public health and economic co-benefits:

The avoided mortalities, morbidities, and respiratory diseases related-hospital admission resulting from the near roadway avoided $PM_{2.5}$ exposure in the different districts is depicted in Figure 3.10. The RR values used for the health burden estimation were extracted from the meta-analysis of 64 studies explained in section 3.3 (see Table 3-10). The detailed results of the meta-analysis (meta-analysis results are based on the inclusion criteria, 64 studies were included in the metanalysis. RAVMAN (Version 5.4.1) was used to construct forest plots and pooled Risk Ratio (RR) for Total Mortality, COPD, Cardiovascular Mortality, Respiratory mortality, LC, and Respiratory morbidities related Hospital Admissions) are given in figures (See Figures 3-11 to 3-16). As explained earlier, the avoided health burden is a function of both bus traffic and near roadway population density in each district. Thus, although the southeast, Shahdara, and north districts have the highest avoided $PM_{2.5}$ emission and exposure through their intensive bus traffic conditions, the reduction of expected health cases is particularly prominent in the northeast and central districts due to higher near roadway population density in these districts. More precisely, the utilization of the BEB fleet in the densely populated districts, such as the northeast (36155 persons per kilometer), results in greater prevention of mortality and hospital admission cases per kilometer of the roadway.

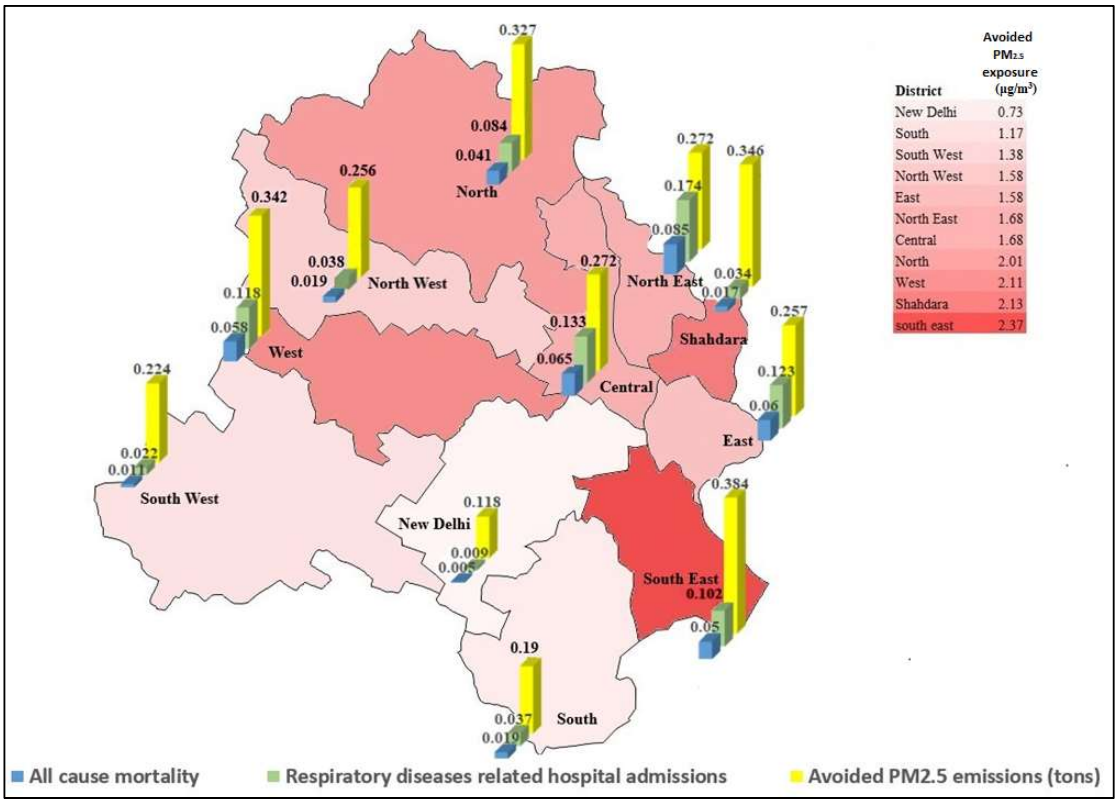


Figure 3. 10. Avoided health burden per 1 kilometer of near roadway.

Table 3- 9. Data used for the estimation of the near roadway avoided $PM_{2.5}$ exposure.

District	Traffic Zone	Average number of buses per hour	Annual bus kilometer
Northwest Delhi	Rohtak Road	71	1,861,412
South Delhi	Aurbindo Marg	53	1,382,328
West Delhi	Mahatma Gandhi Marg	95	2,486,088
Southwest Delhi	Azad Hind Fauz Marg	62	1,624,104
Northeast Delhi	Wazirabad Road	75	1,978,884
East Delhi	Vikas Marg	71	1,870,085
North Delhi	GT Karnal Road	90	2,373,084
Central Delhi	Bahadur Shah Zafar Marg	75	1,978,884
New Delhi	Vandemataram Marg	33	856,728
Southeast Delhi	Mathura Road	106	2,793,564
Shahdara	Chaudhary Charan Singh Marg	96	2,518,500

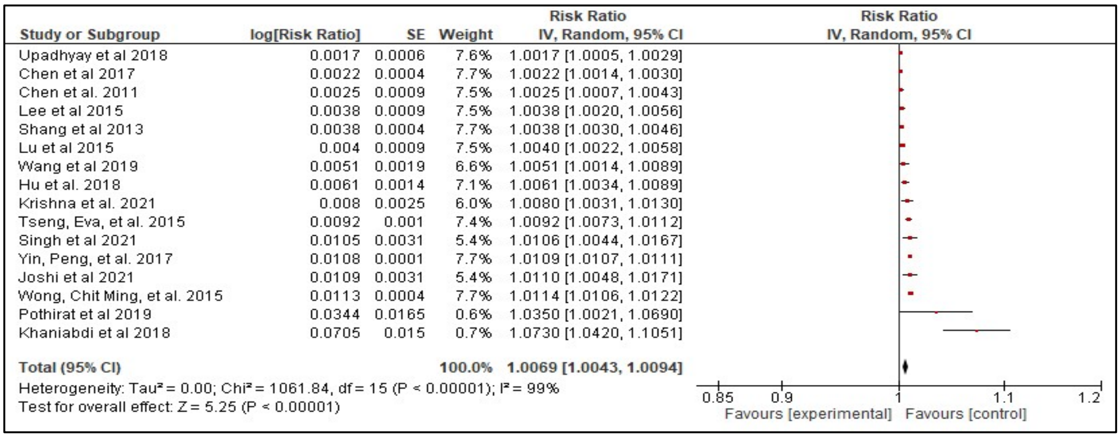


Figure 3. 11. Meta-analysis results All-Cause mortality

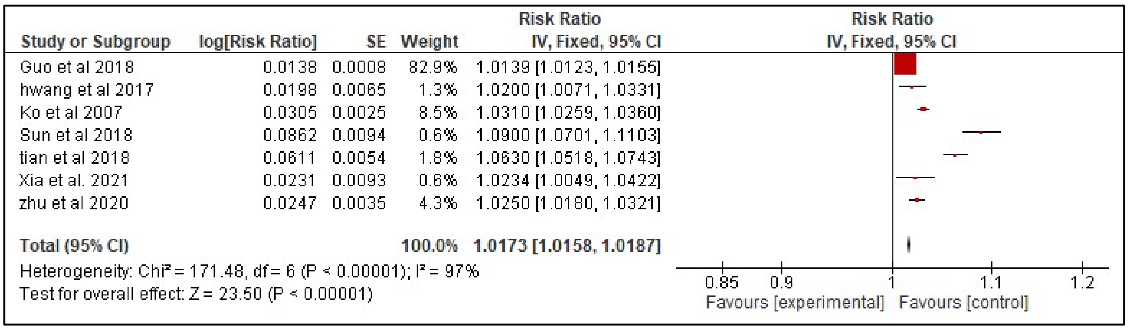


Figure 3. 12. Meta-analysis results COPD

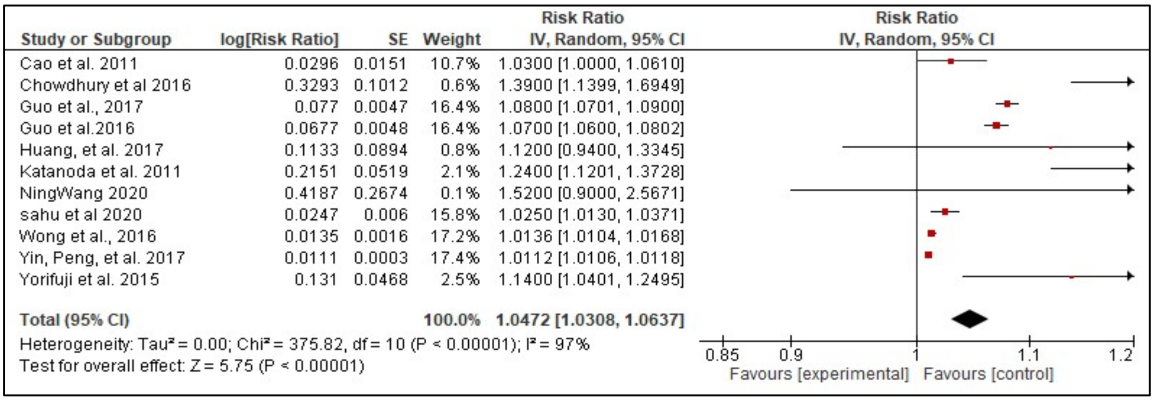
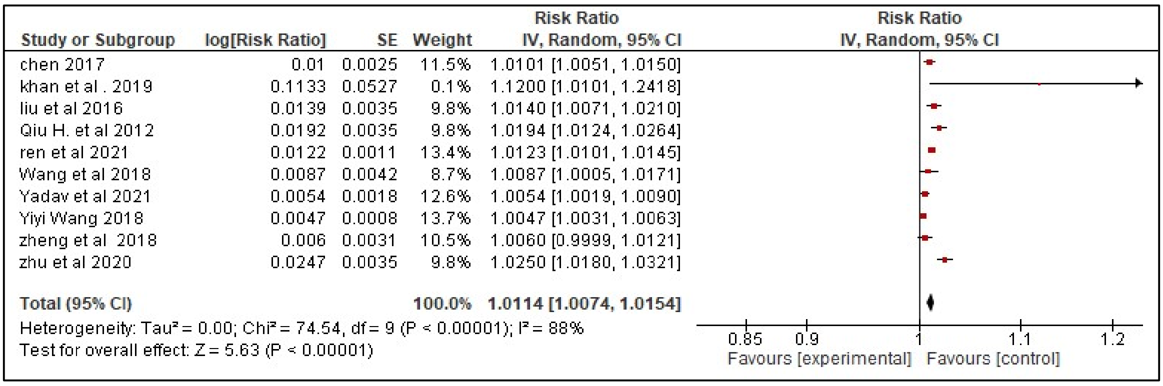


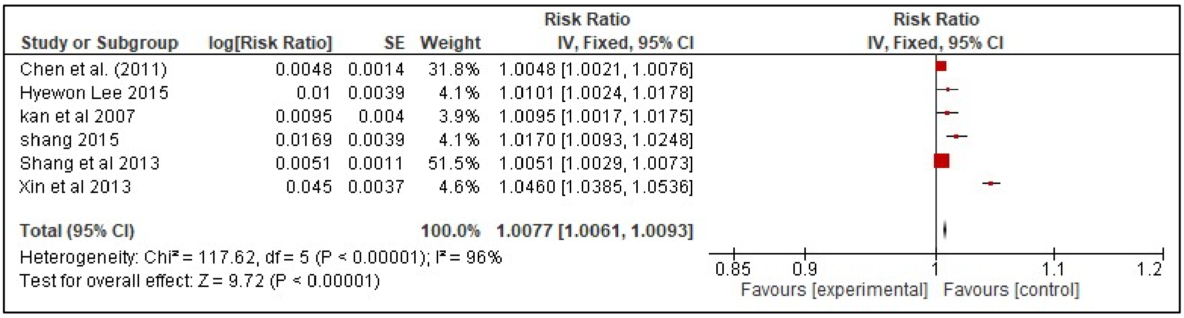
Figure 3. 13. Meta-analysis results Lung Cancer



Study or Subgroup	log[Risk Ratio]	SE	Weight	Risk Ratio IV, Random, 95% CI
chen 2017	0.01	0.0025	11.5%	1.0101 [1.0051, 1.0150]
khan et al . 2019	0.1133	0.0527	0.1%	1.1200 [1.0101, 1.2418]
liu et al 2016	0.0139	0.0035	9.8%	1.0140 [1.0071, 1.0210]
Qiu H. et al 2012	0.0192	0.0035	9.8%	1.0194 [1.0124, 1.0264]
ren et al 2021	0.0122	0.0011	13.4%	1.0123 [1.0101, 1.0145]
Wang et al 2018	0.0087	0.0042	8.7%	1.0087 [1.0005, 1.0171]
Yadav et al 2021	0.0054	0.0018	12.6%	1.0054 [1.0019, 1.0090]
Yiyi Wang 2018	0.0047	0.0008	13.7%	1.0047 [1.0031, 1.0063]
zheng et al 2018	0.006	0.0031	10.5%	1.0060 [0.9999, 1.0121]
zhu et al 2020	0.0247	0.0035	9.8%	1.0250 [1.0180, 1.0321]
Total (95% CI)			**100.0%**	**1.0114 [1.0074, 1.0154]**

Heterogeneity: Tau² = 0.00; Chi² = 74.54, df = 9 (P < 0.00001); I² = 88%
Test for overall effect: Z = 5.63 (P < 0.00001)

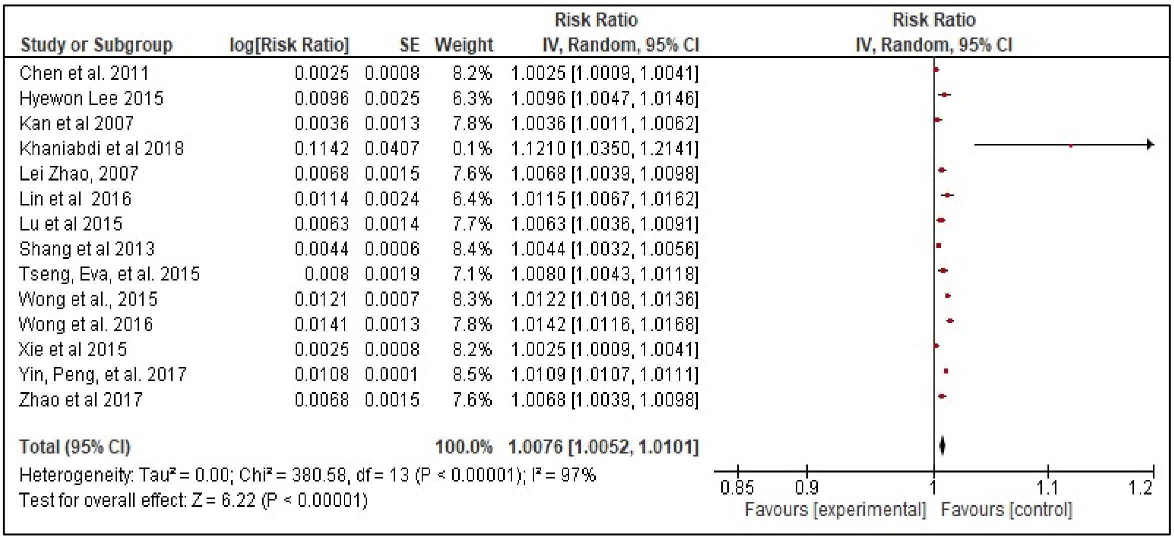
Figure 3. 14. Meta-analysis results respiratory diseases related hospital admissions



Study or Subgroup	log[Risk Ratio]	SE	Weight	Risk Ratio IV, Fixed, 95% CI
Chen et al. (2011)	0.0048	0.0014	31.8%	1.0048 [1.0021, 1.0076]
Hyewon Lee 2015	0.01	0.0039	4.1%	1.0101 [1.0024, 1.0178]
kan et al 2007	0.0095	0.004	3.9%	1.0095 [1.0017, 1.0175]
shang 2015	0.0169	0.0039	4.1%	1.0170 [1.0093, 1.0248]
Shang et al 2013	0.0051	0.0011	51.5%	1.0051 [1.0029, 1.0073]
Xin et al 2013	0.045	0.0037	4.6%	1.0460 [1.0385, 1.0536]
Total (95% CI)			**100.0%**	**1.0077 [1.0061, 1.0093]**

Heterogeneity: Chi² = 117.62, df = 5 (P < 0.00001); I² = 96%
Test for overall effect: Z = 9.72 (P < 0.00001)

Figure 3. 15. Meta-analysis results Respiratory mortality



Study or Subgroup	log[Risk Ratio]	SE	Weight	Risk Ratio IV, Random, 95% CI
Chen et al. 2011	0.0025	0.0008	8.2%	1.0025 [1.0009, 1.0041]
Hyewon Lee 2015	0.0096	0.0025	6.3%	1.0096 [1.0047, 1.0146]
Kan et al 2007	0.0036	0.0013	7.8%	1.0036 [1.0011, 1.0062]
Khaniabdi et al 2018	0.1142	0.0407	0.1%	1.1210 [1.0350, 1.2141]
Lei Zhao, 2007	0.0068	0.0015	7.6%	1.0068 [1.0039, 1.0098]
Lin et al 2016	0.0114	0.0024	6.4%	1.0115 [1.0067, 1.0162]
Lu et al 2015	0.0063	0.0014	7.7%	1.0063 [1.0036, 1.0091]
Shang et al 2013	0.0044	0.0006	8.4%	1.0044 [1.0032, 1.0056]
Tseng, Eva, et al. 2015	0.008	0.0019	7.1%	1.0080 [1.0043, 1.0118]
Wong et al., 2015	0.0121	0.0007	8.3%	1.0122 [1.0108, 1.0136]
Wong et al. 2016	0.0141	0.0013	7.8%	1.0142 [1.0116, 1.0168]
Xie et al 2015	0.0025	0.0008	8.2%	1.0025 [1.0009, 1.0041]
Yin, Peng, et al. 2017	0.0108	0.0001	8.5%	1.0109 [1.0107, 1.0111]
Zhao et al 2017	0.0068	0.0015	7.6%	1.0068 [1.0039, 1.0098]
Total (95% CI)			**100.0%**	**1.0076 [1.0052, 1.0101]**

Heterogeneity: Tau² = 0.00; Chi² = 380.58, df = 13 (P < 0.00001); I² = 97%
Test for overall effect: Z = 6.22 (P < 0.00001)

Figure 3. 16. Meta-analysis results Cardiovascular Mortality

Table 3- 10. RR values per 10 µg reduction in $PM_{2.5}$ concentration (meta-analysis).

	Avoided all-cause mortality	**COPD**	**LC**	**Respiratory diseases hospital admissions**	**Cardiovascular Mortality**	**Respiratory Mortality**
Pooled value of RR with 95% CI	1.0069	1.0173	1.0472	1.0114	1.0076	1.0077
Statistical test	I^2=99%* (p<0.00001)	I^2=97% (p<0.00001)	I^2=97% (p<0.0001)	I^2=88% (p<0.00001)	I^2=97% (p<0.00001)	I^2=96% (p<0.00001)

* I^2 refers to the test of heterogeneity; p is the statistical p-value; CI is the confidence interval

The findings were further generalized to the whole Delhi public transportation system, considering the total bus route network length of 16200 km [41]. The approximated values of the avoided health burden and costs resulting from the electrification of the bus fleet in the whole city of Delhi are given in Table 3-11, considering the lowest and highest levels of the avoided $PM_{2.5}$ exposure.

Table 3- 11. Annual Avoided health burden and costs from the utilization of the BEB fleet in the Delhi public transportation system

	Mortality Cases			**Morbidity Cases**			**Total Avoided cost (1000 $)**	
	All causes	**Respiratory**	**Cardiovascular**	**COPD**	**Lung Cancer**	**Respiratory**	**5%***	**10%***
Upper Limit	1370	100	736	342	82	2,808	383,144	383,298
Lower Limit	67	5	40	17	4	137	18,737	18,745

*Increase in the cost of treatment reported in Table 3-3.

As reported in Table 3-11, the avoided mortality and morbidity cases and costs anticipated from reducing $PM_{2.5}$ exposure in near roadway areas in Delhi are very high. This finding emphasizes the importance of considering sources in terms of their impact (like what can be seen in the near roadway areas), not just the emissions. Impacts can vary by an order of magnitude, even within a single county or sector. This can be further clarified, as follows:

Assessment of the human health risk presented by emissions can be established by the combination of many factors like the source, quantity released, intake per unit release, risk of adverse effect per unit intake, size, density, and closeness of populations to sources [42]–[44]. The health and economic co-benefits of reducing $PM_{2.5}$ varies depending on where the emission reduction takes place and the type of source [42]. Sources that emit substantial amounts of $PM_{2.5}$ (like vehicular emissions), which are located close to important population centers, would be expected to have a higher damage cost as the most impacted region from the mobile emissions is between 150-200 meters from the roadway [45]. Since a large portion of Delhi's population lives or works within 500 meters of main arteries, 41% of Delhi's population is exposed to high traffic-related air pollution [46]. It is noted that, near road emissions pose a substantially higher health risk due to the higher intake fraction (the fraction of emissions that are inhaled), as intake fraction values from vehicle emissions are many times larger than those from other industry sources due to high-level pollutant concentrations in the traffic micro-environment. The intake fractions are more significant in regions with higher population densities like Delhi [47]–[49]. As previously explained in the modeling approach, the intake fraction is a function of both population attributable fraction and population density. Therefore, given higher values of the population density and $PM_{2.5}$ concentration in near roadway areas in Delhi, reducing near road emissions, mainly from public buses, could result in significant health advantages.

Previous studies have employed transfer coefficients to assess the monetized benefits of pollution, producing national non-source-specific damage cost ($/ton) estimates, that could be applied to the expected reductions in emissions for a variety of policy settings. Such studies have used transfer coefficients to quantify both health consequences and economic valuation. However, this approach has its own limitations because it is based on several strong assumptions, including the population, meteorology, and source attributes such as plant stack heights, emission exit velocity, topography, plant dimensions, and other factors at the policy site are identical (or at least similar) to those at the study site. If this assumption is broken, the per-ton transfer figures will either overestimate or underestimate the real damage cost at the policy site [50], [51]. The avoided cost estimated in this research is based on a detailed estimation of the near roadway $PM_{2.5}$ exposure in major traffic areas in Delhi, which might be comparable with other similar highly populated megacities in Asia. From Table 3-11, the per capita avoided cost of the near roadway $PM_{2.5}$ exposure can be estimated at $21.3 in Delhi, which is comparable with the megacities in China such as Beijing ($41.2), Shanghai ($38.8), and Tianjin ($35.9) [52]. However, the avoided damage cost ($426,000 to $8,700,000) per ton in Delhi (with a 10% increase in the cost of treatment) is much higher than the cities in developed countries. For example, the $PM_{2.5}$ exposure damage cost for Los Angeles County, CA, ranges from $52,000 to $2,900,000 per ton [44] and for the road transfer inner London, UK, from $410,000 to 1,273,000 $ per ton [53], implying the impact of high population density and near roadway $PM_{2.5}$ concentration in Delhi.

Based on the above discussion, a comparative analysis of the economic value of mortality risk reductions per ton of $PM_{2.5}$ emissions from mobile sources was conducted between the case of the Delhi's near roadway in this study and other megacities, considering the impact of the population density, VSL, and $PM_{2.5}$ concentration. The result is represented in Figure 3.17.

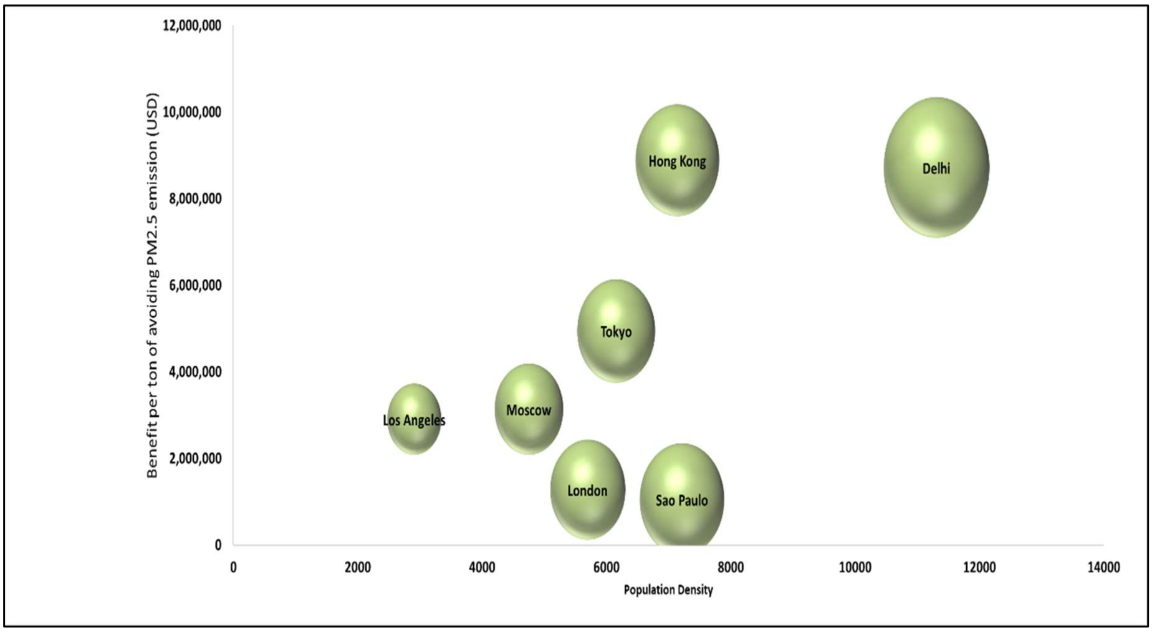


Figure 3. 17. A comparative analysis of avoided health burden per ton from mobile sources between the case of Delhi in this study and different cities of the world.

The data used in the calculation of the benefit per ton of avoiding $PM_{2.5}$ in the selected cities are: 1) Details of the avoided mortality cases collected from [44], [53], [54] ; 2) The required data for calculating the VSL collected from [55].

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CHAPTER 4

Co-Benefit Assessment of Active Transportation in Delhi, Estimating the Willingness to Use Nonmotorized Mode

Abstract: This chapter aims to estimate avoided mortalities and morbidities and related economic impacts due to adopting the nonmotorized transportation (NMT) policy in Delhi, India. To this aim, an integrated quantitative assessment framework is developed to estimate the expected environmental, health, and economic co-benefits from replacing personal motorized transport with NMT in Delhi, taking into account the inhabitants' willingness to use NMT (walking and cycling) mode. The willingness to accept NMT is estimated by conducting a cross-sectional survey in Delhi, which is further used to estimate the expected health benefits from both increased physical activity and near roadway avoided $PM_{2.5}$ exposure in selected traffic areas in 11 major districts in Delhi. The value of statistical life (VSL) and cost of illness methods are used to calculate the economic benefits of avoided mortalities and morbidities from NMT in Delhi. The willingness assessment indicates that, the average per capita time spent walking and cycling in Delhi is 11.054 and 2.255 minutes, respectively. The results from the application of the NMT in Delhi show the annual reduction of CO_2 and $PM_{2.5}$ by 121.5 kilotons and 138.9 tons, respectively. The model estimates the expected co-benefits from increased physical activities and reduced $PM_{2.5}$ exposure at 17529 avoided cases of mortality with an associated savings of about USD 4870 million in Delhi.

4.1. Introduction

While there are inadequate studies in India conducted to estimate the co-benefits of NMT transportation, most of these studies have mainly focused on traffic injuries and air pollution and associated health benefits rather than the benefits of extra physical activity (PA) [38]. By developing an integrated environmental-health-economic benefits quantitative assessment modeling framework (Figure 4.1), this chapter seeks to quantify the expected health and economic co-benefits of both increased PA and improved air quality resulting from implementing the NMT policy in Delhi, India. As shown in Figure 4.1, the willingness-based trip demand model is used to estimate the total kilometers and time the inhabitants are willing to spend on NMT due to choosing to walk and bike instead of driving cars and motorized two-wheelers. The impact of the potential factors such as age, gender, education, income, and travel distance on the probability of the willingness to use NMT is analyzed, utilizing a logistic regression model on the collected data from a cross-sectional interview with 250 inhabitants in Delhi. The results of the trip demand model are used in two sub-models: 1) The physical activity sub-model converts the extra daily minutes of walking and cycling to metabolic equivalents (METs), which is further used in a health risk assessment to estimate the relationship between physical activity and the beneficial impact of lowering the occurrence of specific health outcomes in the selected traffic areas. 2) The near-road air pollution sub-model is used to calculate the potential reduction in motorized vehicle kilometers due to travel distance covered by walking and cycling and also, its associated near roadway avoided $PM_{2.5}$ exposure in 11 major districts in Delhi. The relationship between changes in $PM_{2.5}$ concentrations and the occurrence of specific health outcomes in the chosen traffic areas is estimated, using the concentration-response function (CRF) for several diseases in order to establish a connection between the avoided exposure of $PM_{2.5}$ and health benefits. The relative risk (RR) level, which predicts the likelihood of an adverse health outcome among the population exposed to a higher level of ambient air pollution than a lower level of ambient air pollution, served as the basis for the CRF coefficient values used in this study. The values of the RR used in the study were taken from a thorough meta-analysis of earlier research. In order to achieve this, meta-analysis and review articles were carried out to determine the correlation between alterations in $PM_{2.5}$ concentrations and alterations in the incidence of each health endpoint. Avoided mortalities and morbidities data from both sub-models are finally used to calculate the economic value of the avoided health burden from both avoided emissions and increase in physical activity using the value of statistical life (VSL) and cost of illness methods. The findings are generalized to the whole city of Delhi.

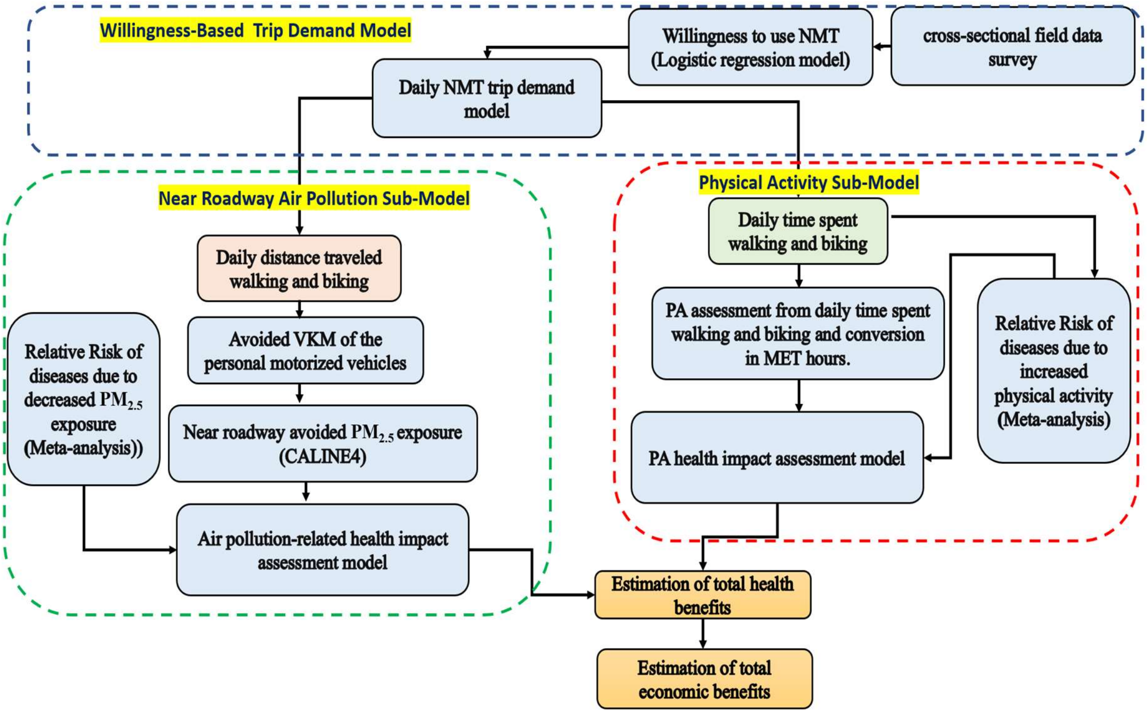


Figure 4. 1. Integrated quantitative approach used in this study

4.2. Model Development:

4.2.1. PA estimation model: Estimation of the weekly time spent for NMT:

The count model is first used to calculate the number of walks and bike trips an individual makes throughout an average day in order to estimate the weekly time spent walking and bicycling for transportation, as follows [39]:

$$\boldsymbol{M_{c,i}} = \boldsymbol{N_{c,i}} \times \boldsymbol{Pr_{c,i}} \times \boldsymbol{t_{c,i}} \qquad (4\text{-}1)$$

Where $M_{c,i}$ is the daily minutes spent traveling using mode c (walking or bicycle) for individual i ; $N_{c,i}$ is the expected daily number of trips taken using mode c for individual i ; $Pr_{c,i}$ is the probability that a trip taken by individual i using mode c and $t_{c,i}$ is the trip duration for a trip taken by individual i using mode c. $Pr_{c,i}$ expresses the willingness to adopt active transport (walking and bicycling), which can be further estimated by developing the following logistic regression model:

$$\boldsymbol{Pr.(Y_i = 1|X_i)} = \frac{e^{X_i^T\beta}}{1+e^{X_i^T\beta}}, \qquad \boldsymbol{i = 1, 2, \cdots, n} \qquad (4\text{-}2)$$

In the above equation, Y_i is the willingness to adopt active transport of the i^{th} $(i = 1,2, \cdots, n)$ individual. $X_i = (x_{i1}, x_{i2}, \cdots, x_{ij}, \cdots, x_{ip})^T$ is the $p \times 1$ vector of covariates corresponding to the i^{th} individual. X_i represents the vector of independent regressors, including age, gender, education, income, and travel distance which affect the individual's willingness to use a walking or bicycle mode for transport purposes. Furthermore, $\beta = (\beta_1, \beta_2, \cdots, \beta_j, \cdots, \beta_p)^T$ is the corresponding $p \times 1$ vector of regression coefficients, which can be estimated through the maximum likelihood estimation approach. The likelihood function of interest takes the following form.

$$\boldsymbol{L(\beta|Y, X)} = \prod_{i=1}^{n} (\boldsymbol{Pr.(Y_i = 1|X_i)})^{Y_i} (\boldsymbol{1 - Pr.(Y_i = 1|X_i)})^{1-Y_i}. \qquad (4\text{-}3)$$

The estimated coefficients of the above model are interpreted through odds ratios (ORs). The OR for the covariate x_{ij} can be estimated from the estimates of regression coefficients as given below.

$$\boldsymbol{OR(x_{ij})} = e^{\beta_j} \qquad (4\text{-}4)$$

The daily PA can be calculated, by combining the time spent cycling and walking multiplied by the intensity of each activity, as determined by metabolic equivalents (METs), which is explained as follows [39]:

$$\boldsymbol{DPA_i} = \frac{(\boldsymbol{MC_{walking,i}} \times 3.5) + (\boldsymbol{Mc_{biking,i}} \times 6.8)}{\boldsymbol{60min/h}} \qquad (4\text{-}5)$$

Where, DPA_i is the daily physical activity (from walking and cycling) for individual i in MET-hours. For transportation, the MET values for walking and cycling are 3.5 and 6.8, respectively [40].

4.2.2. Near roadway avoided PM2.5 exposure model:

The concentrations of air pollutants at particular locations are believed to represent population exposures. It is estimated that 55% of the population living within 500 meters of major roads in Delhi are exposed to hazardous emissions from transportation, where $PM_{2.5}$ is primarily produced by vehicle emissions [41]. It is crucial to use appropriate models with the vehicle and meteorological data to estimate near-road $PM_{2.5}$ exposure, since monitoring $PM_{2.5}$ concentrations cannot be done for all near-road regions. This research uses an air dispersion modeling tool called CALRoads View (Lakes Environmental Software) to forecast how mobile sources affect air quality near roads and intersections. The CALINE-4 model is a fourth-generation line source air quality dispersion model that uses a mixing zone concept to characterize pollutant dispersion near roadways. Using the Gaussian dispersion methodology, the model predicts pollutant concentrations for receptors located within 150 meters on either side of the roadways using input parameters such as site geometry and characteristics:

$$\boldsymbol{C(x,y) = \frac{q_\tau}{\pi\sigma_y\sigma_z u}\int_{y_1-y}^{y_2-y} \mathbf{exp}\left(\frac{-y^2}{2\sigma_y^2}\right)dy} \tag{4-6}$$

Where C is the concentration (g/m^3), y_1 and y_2 are the finite line source endpoint y coordinates (m), u is the wind speed (m/s), σ_y and σ_z are the horizontal and vertical Gaussian dispersion parameters which are a function of downwind distance x (m), q is the avoided $PM_{2.5}$ emissions from replacing the distance traveled of the vehicle category τ (g/s), which can be calculated, as follows:

$$\boldsymbol{q_\tau = (MC_{walking}K_{walking} + MC_{biking}K_{biking})EF_\tau} \tag{4-7}$$

Where, $MC_{walking}$, MC_{biking}, $K_{walking}$ and K_{biking} are the yearly time spent walking and cycling (s) and the average distance covered by walking and cycling in Delhi (km/s), respectively. EF_τ is the $PM_{2.5}$ emission factor of the vehicle category τ (g/km) $MC_{walking}$, MC_{biking} are calculated by Eq. (4-1) and $K_{walking}$ and K_{biking} are given values.

4.2.3. Health impact assessment model:

Excess deaths or illnesses (EDI) caused by an increase in $PM_{2.5}$ concentration can be estimated as follows [42]:

$$\boldsymbol{EDI = PAF \times I \times P} \tag{4-8}$$

Where I is the annual baseline mortality rate, P is the total population, and PAF (population attributable fraction) indicates the percentage of illness burden attributable to pollution. The PAF can then be calculated using the formula below [43]:

$$\boldsymbol{PAF = \frac{p(RR-1)}{p(RR-1)+1}} \tag{4-9}$$

P represents the population's exposure rate. The values of RR for physical activity and near-roadway $PM_{2.5}$ exposure are estimated in different ways. In order to accurately assess the correct values of RR, the health impact assessment requires highly aggregated epidemiological data. To this aim, in this study, a comprehensive meta-analysis was based on a systematic quantitative review, where all directly relevant empirical data that satisfies the eligibility standards and criteria were gathered, combined, and then statistically analyzed to produce a pooled estimate that was as close as possible to the RR values specified by Delhi. The following equation is used to estimate the final RR of willingness-based physical activity [39].

$$\boldsymbol{RR_{PA} = RR_m{}^{\left(\frac{DPA}{\alpha\, MET}\right)}} \tag{4-10}$$

Where, RR_{PA} is relative risk estimated from walking and bicycling physical activity; RR_m is the relative risk estimated from the meta-analysis of collected data from 61 studies on five physical activity-related health outcomes (all-cause mortalities, T2 Diabetes, Coronary heart diseases, Cancers, and Depressive disorders) to estimate the dose-response function and PA-related morbidities and mortalities as function of physical transportation activity (Figure 4.2- Figure 4.12).

The meta-analysis was based on collecting data from selected studies with reported values of RR of moderate-intensity PA (α ranges from 3 to 6 hours). Current global recommendations for adults' physical activity are 150 minutes (α =2.5 hours) of moderate-intensity aerobic physical activity per week [44]. The pooled values of RR collected from 64 studies related to total mortality, COPD, cardiovascular mortality, respiratory mortality, and morbidity, and related hospital admission (Figure 4.2-4.12) were used to calculate the relationship between a change in air pollutant concentration (in this study, $PM_{2.5}$) and a change in health effects, concentration-response functions (CRFs):

$$\boldsymbol{RR_{AP} = exp\ [\beta(C - C_0)]} \tag{4-11}$$

Where, RR_{AP} is relative risk estimated from the near roadway avoided $PM_{2.5}$ exposure, and β is a coefficient that evaluates the response of a health outcome to a change in pollutant concentration. C and C_o are the pollutant concentrations in the baseline and intervention scenarios. Table 4-1 represents baseline incident rates of diseases in Delhi used in this study. The geographical distribution of the studies used in the meta-analysis are shown in the figure 4.13.

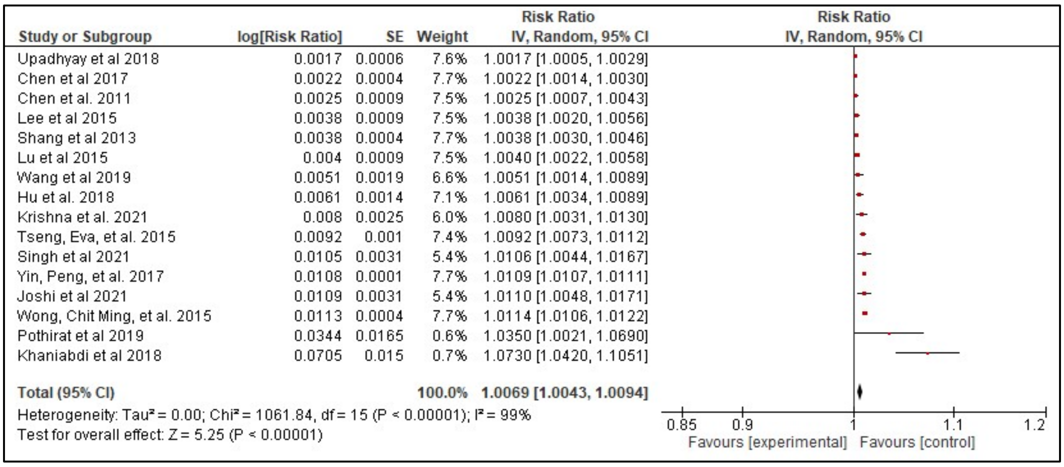


Figure 4. 2. $PM_{2.5}$ related All-Cause mortality (Metanalysis results)

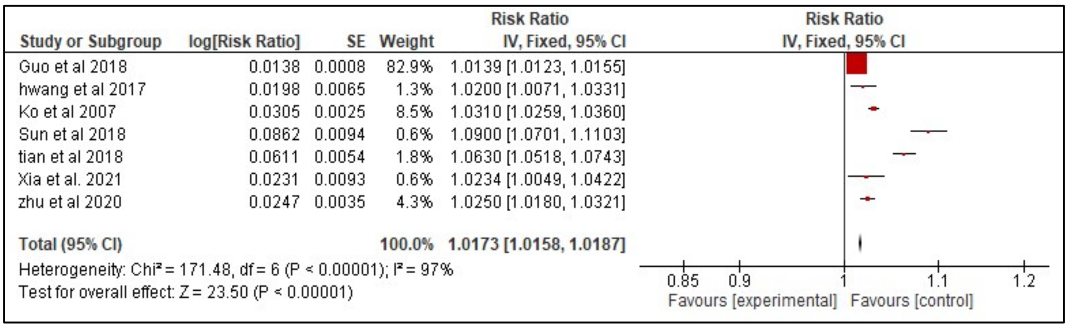


Figure 4. 3. $PM_{2.5}$ related COPD (Metanalysis results)

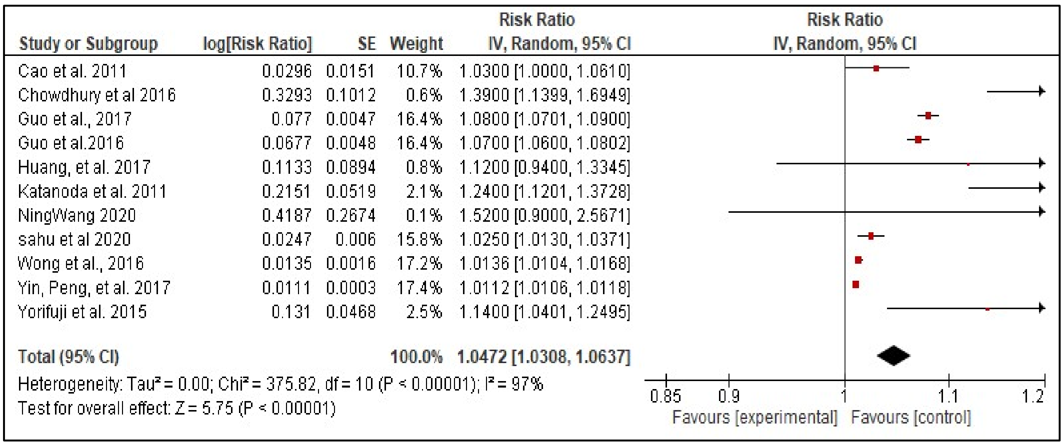


Figure 4. 4. $PM_{2.5}$ related Lung Cancer (Metanalysis results)

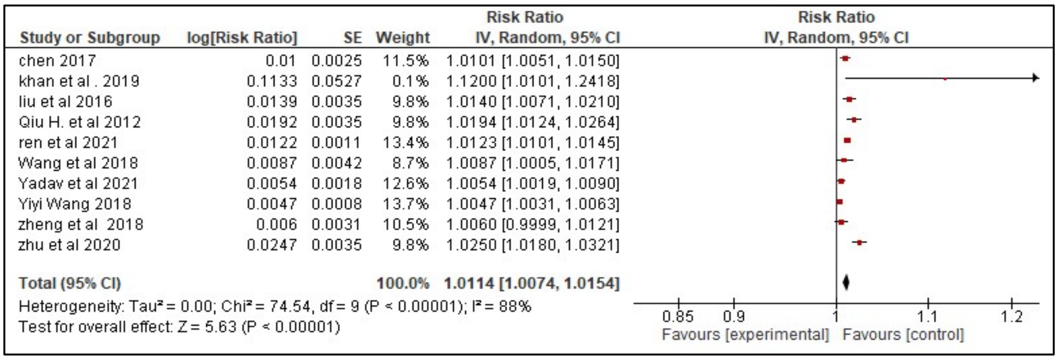


Figure 4. 5. $PM_{2.5}$ related hospital admissions (Metanalysis results)

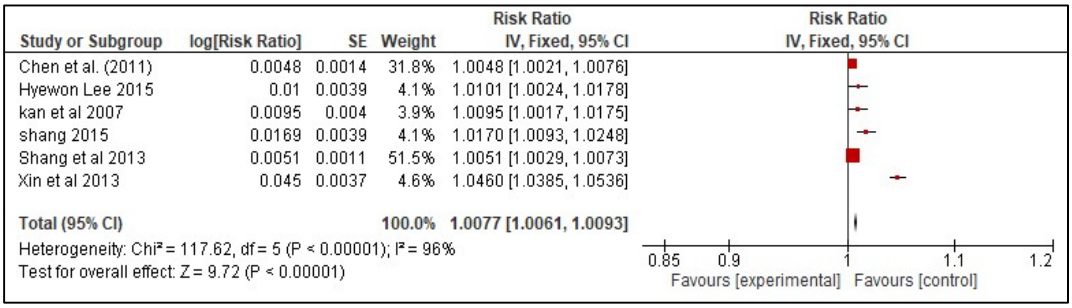


Figure 4. 6. $PM_{2.5}$ related Respiratory mortality (Metanalysis results)

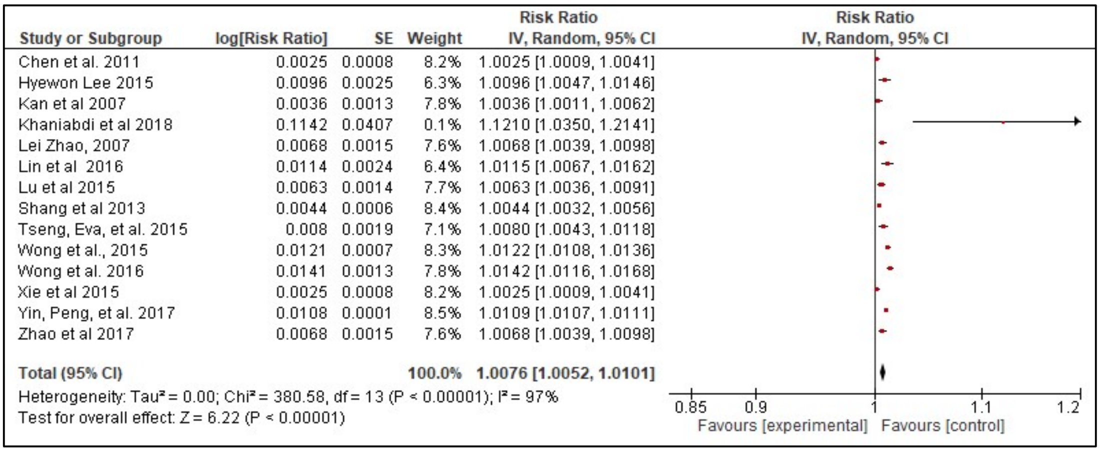


Figure 4. 7. $PM_{2.5}$ and Cardiovascular mortality (Metanalysis results)

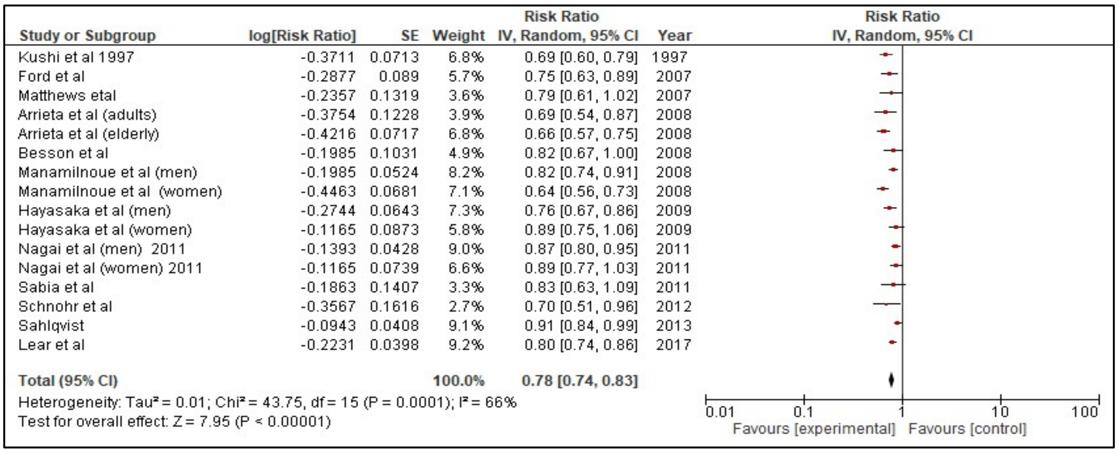


Figure 4. 8. PA related all-cause mortality (Metanalysis results)

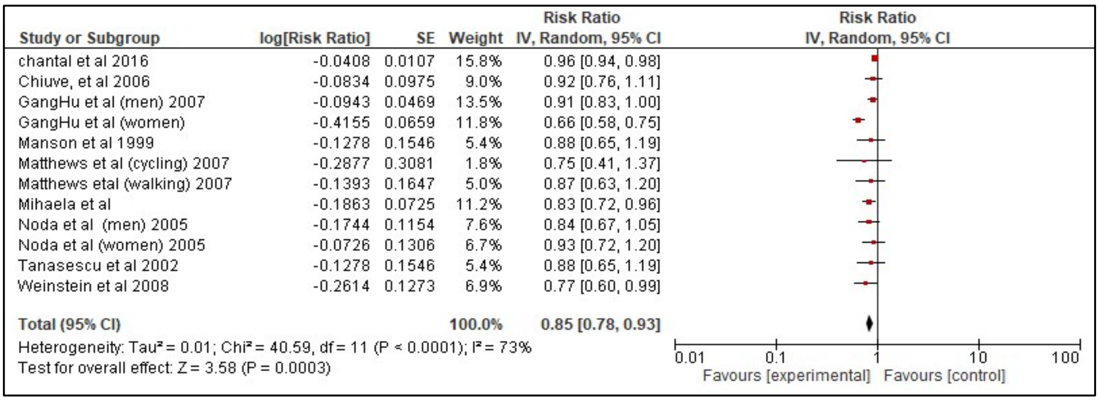


Figure 4. 9. PA related coronary heart diseases (Metanalysis results)

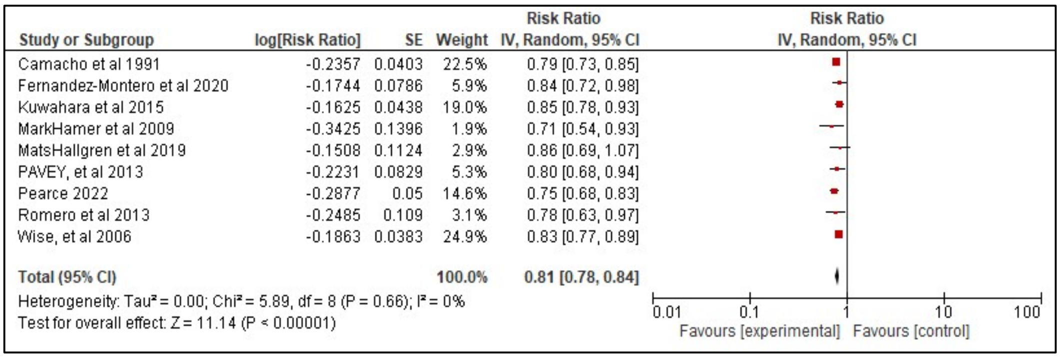


Figure 4. 10. PA related Depression (Metanalysis results)

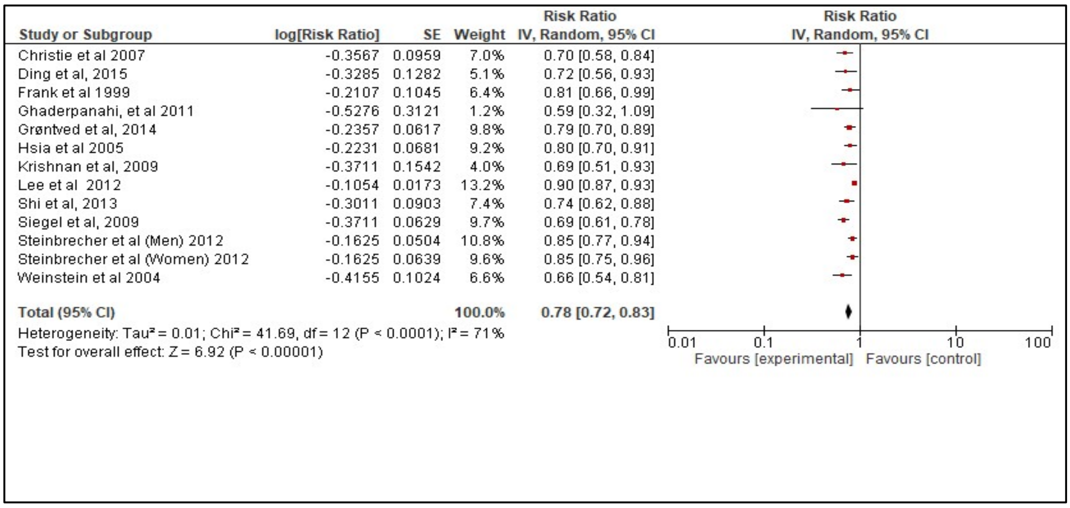


Figure 4. 11. PA related T2 Diabetes (Metanalysis results)

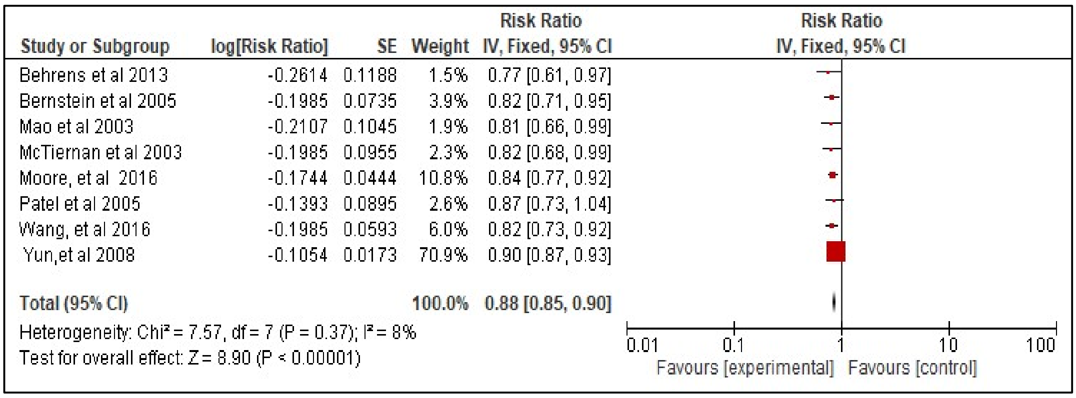
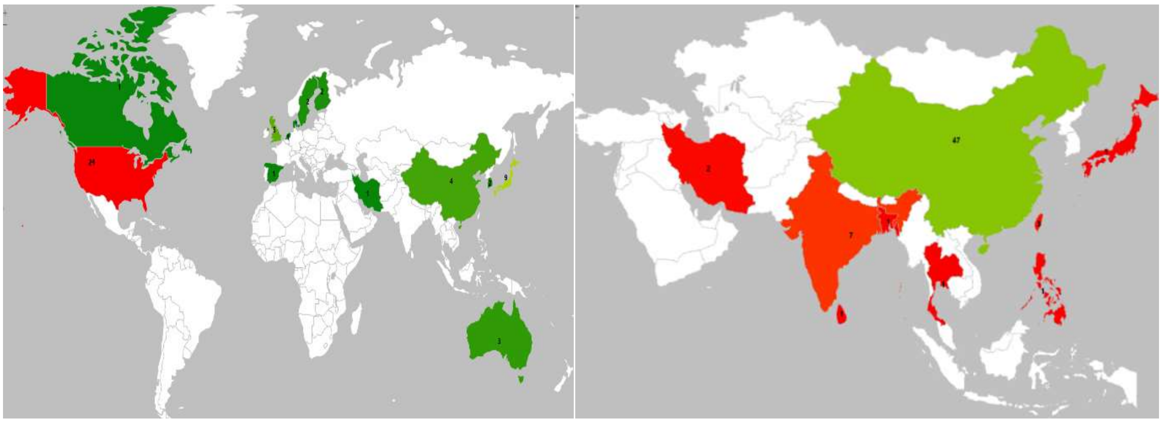


Figure 4. 12. PA related Cancer (Metanalysis results)



(a) **(b)**

Figure 4. 13. The geographical distribution of the studies that were chosen for the RR meta-analysis (a) Physical activity and health impacts (b) $PM_{2.5}$ and health impacts

Table 4- 1. Baseline incident rates of diseases in India (Delhi).

Mortality/Morbidity	**Baseline Incidence per 100,000**
Total Mortality[1]	1013
COPD Prevalence rate[2]	818
Diabetes T2 prevalence rate[2]	784
Respiratory Diseases rate[2]	608
Depressive disorders rate[2]	633
Diabetes mortality rate [2]	18
Ischemic/Coronary heart diseases prevalence rate[2]	2321
Cardiovascular mortality[1]	497
Respiratory mortality[1]	66
Cancer prevalence reate[4]	98.8
Lung Cancer prevalence rate (LC)[3]	9.06

[1]From [38-39]. [2]Form [47]. [3]From [48]. [4] From [49].

4.2.4. Economic impacts assessment model:

The Value of Statistical Life (VSL) approach and The cost of an emergency room visit (ERV) was used in this study to calculate the mortality cost of $PM_{2.M}$ exposure [42]. The cost of illness (COI) approach was used to determine the cost of treatment of coronary heart diseases, type 2 diabetes, Cancer and Depressive disorders, hospital admissions due to respiratory diseases, COPD, respiratory mortality, cardiovascular mortality, and LC. [47-48]. The values for the various health endpoints considered in this study are shown in Table 4-2.

Table 4- 2. Values of the health endpoints used in this study.

Health endpoint	Valuation (USD) with a yearly 10% increase in the cost of treatment	Method of cost calculation
Total mortality	279,411	VSL approach [42]
COPD hospital admissions	345	CoI approach [50]
Respiratory diseases hospital admissions	80	CoI approach [50]
LC	1,886	CoI approach [52]
Diabetes T2	23,862	[52-53]
Coronary heart diseases	3842	[55]
Depression	110	[55–57]
Cancer	1,065	[59]

4.3. Results and discussion:

4.3.1. Willing of people in Delhi to use NMT:

A cross-sectional survey was conducted from July 2 to July 8, 2022, in Delhi, India, to estimate peoples' willingness to accept active transportation as their usual travel mode. The survey encompassed different areas of Delhi, like Ashok Vihar, Nand Nagri, Dilshad Garden, Jhilmil, and Seema Puri. About 250 inhabitants were physically interviewed during the survey, while 50 responses were collected online. People were physically approached and were asked questions during morning hours while leaving for work and during evening hours while returning, especially near bus stops, public parks, and pedestrian crossings. For the online survey, questionnaires were shared with only those currently living in Delhi. The detailed questionnaire used in this research is described in Table 4-3.

Table 4- 3. Detailed questionnaire used in this survey

	Question	Response
1.	Willing to use NM modes (bicycle)	• Yes • No • Already using NM modes
2.	Willing to use NM modes (walking)	• Yes • No • Already using NM modes

Question	Response
3. Mandatory travel mode to work, school, business	• (Walk/Bicycle) • motorcycle • personal vehicle/car • Public transport
4. Non mandatory travel mode to shopping, personal, family, etc.	• (Walk/Bicycle) • motorcycle • personal vehicle/car • Public transport
5. Age-wise distribution	• Below 18years • 18 - 25 years • 25 - 45 years • 45 - 55 years • 55 - 65 yeas
6. Gender wise distribution	• Female • Male
7. Occupation level	• Student • Support • Middle • Higher
8. Monthly Income level	• below 15k • 15k to 30k • 30k to 50k • 50k to 75k • 75k to 100K • above 100K
9. Education level	• Nil • Only school • Graduation or Higher.
10. For which distance you prefer bicycles / walking as your transport mode?	• 1-2Km • 2-3 Km • 3-4 km • 4-5 Km • 5-6 Km
Personal vehicle ownership	• motorcycle • personal vehicle/car • Personal cycle • None

Question	Response
11. What are the main barriers towards walking and cycling in urban area?	• Few cycle lanes and bike parking areas • Safety: no separate road space for cycling and walking. • Inadequate bicycle rental and bike-sharing systems • No combination of cycling and rapid bus transit or rail systems) • No cycling/Walking Culture • Other

The questionnaire, consisting of 11 questions, initiated the most important survey inquiry, whether the respondent was willing to use active transport in Delhi. Then, separate questions were asked for walking and bicycling. The later part of the questionnaire asked about the mandatory and non-mandatory travel modes of the inhabitants of Delhi, India, along with their preferable distance to be covered by walking and bicycling. Finally, the survey enquired about the respondents' socio-economic condition (income and education) and demographic characteristics (age and gender). After discarding all missing and erroneous data, a total of 283 respondents' information was finally analyzed. All these variables are described in (Table 4-4) which depicts that 30.35% and 38.52% of the respondents were willing to use walking and bicycling, respectively, as their regular transportation modes. All the selected covariates were categorized to distinguish the probability of willingness for different categories of the corresponding predictors. Among the set of covariates, regular travel mode, monthly income, education level, and age were categorized into more than two categories. Such categorical variables require special attention, unlike continuous and binary predictors, which can be incorporated into the regression model without any modification. In the case of the covariates with more than two categories, one category needs to be considered as a reference category to which the remaining categories can be compared. This reference category is selected based on the purpose of comparison. Then, the remaining categories are transformed into binary variables and compared with the reference category of interest. The results of the model are presented in Table 4-5.

Table 4- 4. Characterization of selected variables along with descriptive statistics

Variables	Categories	Characteristics	Frequencies (%)
Willingness to walk	Yes No	Willed to use walking as a regular travel mode Unwilled to use walking as a regular travel mode	85 (30.35%) 198 (69.95%)
Willingness to bicycle	Yes No	Willed to use bicycling as a regular travel mode Unwilled to use bicycling as a regular travel mode	109 (38.52%) 174 (68.48%)
Regular travel mode	Public transport Private car Motorcycle	Used public transport as a mandatory travel mode Used private car as a mandatory travel mode Used motorcycle as a mandatory travel mode	99 (34.98%) 96 (33.92%) 88 (31.10%)
Distance to cover by walking	Short distance Long distance	Preferred to walk for 1-2 km of distance Preferred to walk for more than 2 km of distance	96 (33.92%) 187 (66.08%)
Distance to cover by bicycling	Short distance Long distance	Preferred to use the bicycle for 1-2 km of distance Preferred to use the bicycle for more than 2 km of distance	19 (6.71%) 264 (93.29%)
Monthly income	Low income Medium income High income	Monthly income of below 15,000 INR Monthly income of between 15,000−75,000 INR Monthly income of above 75,000 INR	90 (31.80%) 172 (60.78%) 21 (7.42%)
Education level	Illiterate Primary to secondary High	No education Studied up to school Graduated or higher studies	25 (8.83%) 91 (32.16%) 167 (59.01%)
Age group	Young Middle-aged Old	Aged between 10−18 years Aged between 18−45 years Aged above 45 years	18 (6.36%) 224 (79.15%) 41 (14.49%)
Gender	Male Female	Male respondents Female respondents	200 (70.67%) 83 (29.33%)

Table 4- 5. Estimated coefficients ($\widehat{\beta}$) obtained from LR models, OR and p-value [1]

Covariates	Willingness to Walk			Willingness to use Bicycle		
	$\widehat{\beta}$	OR	p-value	$\widehat{\beta}$	OR	p-value
Intercept	-0.328	0.720	0.637	0.342	1.408	0.696
Regular travel mode						
Public transport	(RC)	(RC)	(RC)	(RC)	(RC)	(RC)
Private car	-1.421	0.241	<0.001	-0.740	0.477	0.035
Motorcycle	-0.853	0.426	0.018	-0.692	0.501	0.042
Distance to cover						
Short distance	(RC[2])	(RC)	(RC)	(RC)	(RC)	(RC)
Long distance	0.102	1.107	0.741	1.172	3.228	0.066
Monthly Income						
Low	0.147	1.158	0.716	-0.017	0.983	0.963
Medium	(RC)	(RC)	(RC)	(RC)	(RC)	(RC)
High	1.482	4.402	0.005	0.603	1.828	0.242
Education level						
Illiterate	1.261	3.529	0.023	1.089	2.971	0.041
Primary to secondary	(RC)	(RC)	(RC)	(RC)	(RC)	(RC)
Higher education	0.779	2.179	0.051	0.321	1.379	0.351
Age group						
Young	(RC)	(RC)	(RC)	(RC)	(RC)	(RC)
Middle-aged	-1.011	0.364	0.102	-2.233	0.107	0.002
Old	-0.961	0.383	0.193	-2.925	0.054	<0.001
Gender						
Male	0.371	1.449	0.264	0.557	1.745	0.076
Female	(RC)	(RC)	(RC)	(RC)	(RC)	(RC)
McFadden's R^2	0.112			0.100		
Cox-Snell R^2	0.128			0.120		
Tjur's R^2	0.140			0.124		
p-value of the Hosmer-Lemeshow test	0.66 (>0.05)			0.19 >0.05)		

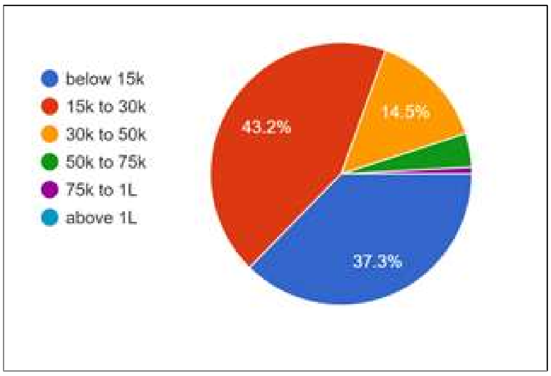
[1] Obtained from the Wald test; [2]Reference category

As indicated in the survey, 37 % of our responders fall in the low-income category, while 55 % percent are from the medium-income group and the rest are from the high-income category (Figure 14.14. a).

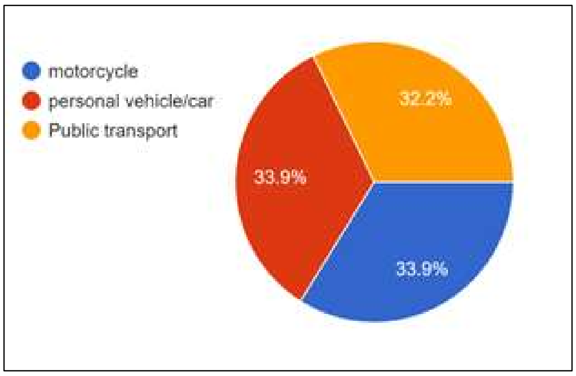
Based on the findings from the interview currently, public transportation, personal vehicles, and Motorcycles almost have an equal share in meeting regular travel mode demands to work, school, and business in Delhi (Figure 14.14. b).

Regarding current main barriers to NMT in Delhi, more than 75% of responders (Figure 14.14. a) are willing to switch over to NMT if their concerns about safety, inadequate infrastructure for NMT, and the nonexistent combination of NMT and rapid bus transit and rail systems are met. Survey results indicate that urban road design regarding NMT infrastructure and safety should be prioritized in transportation planning especially adding dedicated cycling/ walking lanes.

A combination of NMT and rapid bus transit and rail systems will help encourage people to use NMT as a regular mode of transportation. In addition, safe and convenient cycling and walking infrastructure and dedicated walking/cycling lanes can also encourage people in Delhi to switch over to NMT.



(a)



(b)

(c)

Figure 4. 14 : (a) Monthly income level of responders, (b) Mandatory regular travel mode, (c) Main barriers to choose NMT as regular mode of travel.

Since regular travel mode, monthly income, and education level are significant factors in the willingness to walk in Delhi, India. On the other hand, the LR model for the willingness to bicycle revealed the significant association of regular travel mode, distance to cover, education level, gender, and age group with such behavior are depicted in Table 4-5. The OR for private car users was 0.241, which is less than one. Hence, those who used private cars as their regular travel mode in Delhi have significantly $(1 - 0.241) \times 100\% = 75.9\%$ lower odds of preferring to walk than public transport users. Similarly, motorcycle users had 57.4% lower odds of willingness to walk regularly as a travel mode compared to those who used public transport. A lower likelihood of bicycling was observed for both the regular users of private cars and motorcycles than those of public transport. Distance to cover could significantly influence only the willingness to bicycle. For longer distances (more than 2 km), people preferred more ($OR=3.228>1$ and $p<0.10$) to use bicycling as a regular travel mode than shorter distances. Compared to the medium-income group, people with high incomes tended more to choose walking as their travel mode in daily life. Both illiterate and highly educated people preferred walking more than those who completed their primary or secondary education. On the other hand, only illiterate people were more likely to bicycle than primary to secondary educated ones. Both middle-aged and older people had a lower preference for bicycling than the younger group. On the other hand, compared to their female counterparts, males have a higher willingness to use bicycles in their daily lives. The p values of the Hosmer-Lemeshow test for both the LR models are greater than 0.05, which indicates that the corresponding models did not provide a poor fit to the data [60].

Based on the NMT willingness analysis findings, the average per capita time spent on walking and bicycling were estimated as 11.1 and 2.3 minutes, respectively, which is equal to cover an extra walking and cycling distance of 1.18 kilometers per day based on the average walking and cycling speed in Delhi. These results were further analyzed to evaluate the environmental and health impacts achieved by improving the infrastructure so that people in Delhi can adopt active transport as per their willingness.

4.3.2. Avoided $PM_{2.5}$ exposure from replacing distance traveled by private vehicles with NMT:

The near roadway concentration model described in section 4.2.2 was applied to selected traffic zones (0.2 x 1 km^2 area) in all 11 districts of Delhi while considering the population density in each district, in order to evaluate the impact of the avoided $PM_{2.5}$ exposure from replacing distance traveled by private vehicles with walking and cycling. The $PM_{2.5}$ concentration is estimated by the CalRoads software to be 0.2 km downwind from vehicles to the near roadway passengers. The heatmaps of avoided $PM_{2.5}$ exposure in the selected traffic zones in different districts in Delhi in shown in Figure 4.14. Per hour avoided vehicle kilometers (VKM) due to an increase in NMT and average near-road avoided $PM_{2.5}$ exposure in different districts in Delhi are shown in Table 4-6.

Table 4- 6. Per hour avoided VKM and average near road avoided $PM_{2.5}$ exposure in different districts in Delhi.

District	Traffic Zone	Per hour avoided VKM	Near road avoided concentration) μg/m^3
1. Northwest	Rohtak Road	261.3	0.62
2. South	Aurbindo Marg	235.3	0.62
3. West	Mahatma Gandhi Marg	232.9	0.62
4. Southwest	Azad Hind Fauz Marg	172.2	0.52
5. Northeast	Wazirabad Road	226.3	0.60
6. East	Vikas Marg	167.7	0.52
7. North	GT Karnal Road	200.9	0.56
8. Central	Bahadur Shah Zafar Marg	69.6	0.45
9. New Delhi	Vandemataram Marg	173.1	0.52
10. Southeast	Mathura Road	291.7	0.59
11. Shahdara	Chaudhary Charan Singh Marg (AV)	322.8	0.64

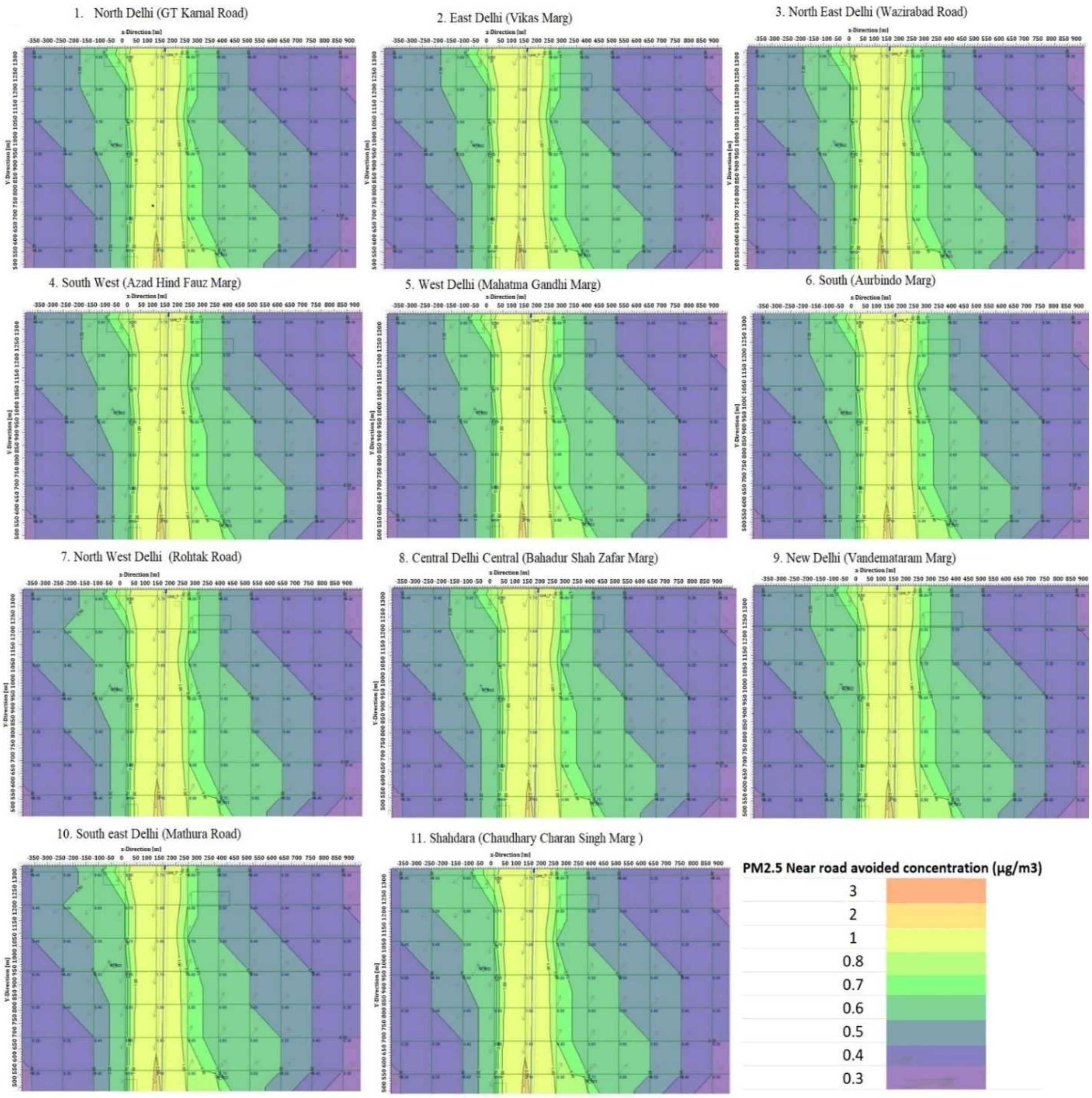
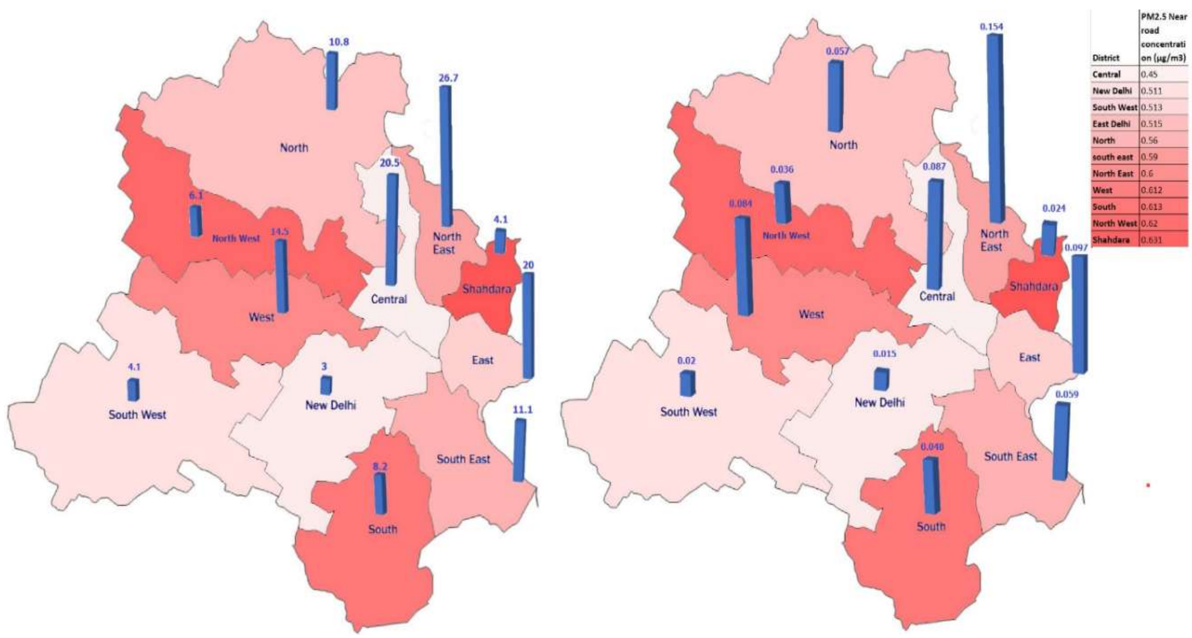


Figure 4. 15. Heatmaps of avoided $PM_{2.5}$ exposure in the selected traffic zones of Delhi.

4.3.3. Health and economic co-benefits:

Figure 4.15 (a) shows avoided mortalities and morbidities related to increased PA per km^2 in different districts of Delhi. Northeast Delhi has the highest health benefits due to high population density, while the New Delhi district has the lowest health benefits due to less population density. More specifically, the NMT (walking and bicycling) use in areas with high population density, like the northeast (36155 people per kilometer), leads to a more significant reduction in the number of morbidity and mortality cases. Figure 4.15 (b) shows the avoided mortalities related to avoiding $PM_{2.5}$ exposure near roadways in the various districts. The pooled values of RR used in health impact assessment for both PA and near-roadway avoided $PM_{2.5}$ exposure reported in Table 4-7 and Table 4-8. Table 4-9 includes detailed avoided morbidities per km^2 in different districts of Delhi. As previously stated, the avoided health burden in each district depends on both traffic and the population density along the nearest roadway. Therefore, despite the fact that the southeast, Shahdara, and north districts have the highest avoided $PM_{2.5}$ emission and exposure due to their heavy traffic conditions, the northeast and central districts have the highest expected avoided health cases due to higher near-roadway population densities.



(a) **(b)**

Figure 4. 16. Estimated annual mortalities per km^2 from (a) increased physical activity (b) near roadway avoided $PM_{2.5}$ exposure.

Table 4- 7. RR values per moderate PA extracted from the meta-analysis.

	Avoided mortality	**coronary heart diseases**	**Depression**	**Diabetes**	**Cancer**
Pooled value of RR with 95% CI	0.78	0.85	0.81	0.81	0.88

Table 4- 8. RR values per 10 µg reduction in $PM_{2.5}$ concentration (meta-analysis).

	Avoided mortality	Respiratory mortality	Respiratory diseases hospital admissions	COPD	Cardiovascular mortality	LC
Pooled value of RR with 95% CI	1.0069	1.0077	1.0114	1.0173	1.0076	1.0472

Table 4- 9. Avoided morbidities (1km²) with increased physical activity decreased near road $PM_{2.5}$ exposure.

District	CVD	Depression	T2 Diabetes	Cancer	COPD	LC	HA	RM	CVM
Northwest	13.93	4.98	6.16	0.46	0.004	0.001	0.045	0.003	0.018
South	18.67	6.67	8.26	0.62	0.005	0.001	0.059	0.004	0.024
West	33.03	11.8	14.62	1.09	0.009	0.001	0.104	0.006	0.041
Southwest	9.19	3.28	4.07	0.3	0.002	0.001	0.025	0.002	0.01
Northeast	61.05	21.82	27.02	2.02	0.016	0.002	0.192	0.011	0.076
East	45.81	16.37	20.28	1.52	0.01	0.001	0.121	0.007	0.048
North	24.58	8.78	10.88	0.81	0.006	0.001	0.071	0.004	0.028
Central	46.82	16.73	20.72	1.55	0.009	0.001	0.109	0.006	0.043
New Delhi	6.85	2.44	3.03	0.22	0.002	0.001	0.018	0.001	0.008
Southeast	25.33	9.05	11.21	0.84	0.006	0.001	0.073	0.004	0.029
Shahdara	9.19	3.28	4.07	0.3	0.003	0.001	0.03	0.002	0.012

The findings were then generalized to the entire Delhi, taking into account the total area of the route network length of 16200 km in Delhi [58-[62]. The total avoided CO_2 emissions and $PM_{2.5}$ exposure are estimated at 121.5 kilotons per year and 138.9 tons per year, respectively (The emission factors and avoided VKM are given in Table 4-10. Finally, the total avoided health and economic impacts of physical activity and associated reduction in near roadway $PM_{2.5}$ exposure are given in Table 4-11.

Table 4- 10. Total annual avoided $PM_{2.5}$ and CO_2 in Delhi based on reduced VKM.

Vehicle Type	Total VKM per year (Million)	Reduced VKM (Million)	Reduced $PM_{2.5}$ (Ton)	Reduced CO_2 (Kio Ton)
Car	6358.93	426.69	64.01	73.8
Motorcycle (2-wheeler)	11624.63	780.02	56.95	35.6
Three wheelers	2430.98	163.12	17.95	12.1
Total	20414.53	1369.82	138.9	121.5

From : [17], [62–65].

Table 4- 11. Avoided mortality, morbidity and economic impacts of improved PA and near roadway avoided $PM_{2.5}$ exposure resulting from implementing NMT in Delhi.

Mortality	**Morbidities**							**Economic impacts**
All causes Mortality (PA and AP)	**CHD**	**Depression**	**T2 Diabetes**	**Cancer**	**COPD**	**LC**	**HA**	**Avoided cost (million USD)**
17529	39,707	14,190	17,575	1,319	20	1.8	248	4,869.8

The results indicate that, compared to the near roadway avoided $PM_{2.5}$ exposure, the increased PA has a higher impact on preventing annual mortalities and morbidities in different districts of Delhi. This can be attributed to higher values of the relative risks of PA, leading to higher health impacts. In addition, the health benefits were seen as more prominent in the districts where the population density is higher, both in case of increased PA and decreased air pollution. The results emphasize that an increase of 11.2 minutes of physical activity or 1.18 km of extra distance walked per day can significantly reduce noncommunicable diseases related to mortalities and morbidities in Delhi. Comparing findings from this study with previous studies, which have predicted significant health and economic benefits of NMT policy implementation in India and other countries, emphasizes that the health benefits of active transport can outweigh the costs of NMT infrastructure requirements [63]. Similar studies in India have shown that active transportation can lower India's health burden by 90,000 DALYs annually [35] and integrating active transportation with low-emission vehicles can save 12995 DALYs in Delhi [36]. While considering economic impacts, a 10% shift to active mobility options has been indicated to save 15 billion euros annually in Europe [32].

Table 4.12 shows a comparative analysis of avoided mortality per metabolic equivalent (MET) in per million population between this study and previous studies from different regions of the world. For this comparative analysis, all cause baseline mortality rate per million due to physical inactivity [72]-[73] was used to calculate baseline mortalities due to physical inactivity and then compared with a decrease in mortality per million population with an increase in 1 MET per individual. The results of the analysis indicate a slightly higher rate of mortality due to physical inactivity, lifestyle, and other environmental factors in cities from lower-income (Delhi) and middle-income countries (Shanghai) than in higher-income countries in Japan (Miyagi), which is consistent with previous studies indicating the majority of people in low-income nations appear to fall short of the recommended levels of physical activity.

Table 4. 12. Comparative analysis of per minute avoided mortalities of physical activity between the case of Delhi in this study and different regions of the world

Region	**RR**	**Avoided mortality Per metabolic equivalent (MET) (per million population)** Based on moderate physical activity (150 minutes of physical activity per week or 10 METs per week)	**Ref**
China (Shanghai)	0.78	15.8	[66]
UK (Norfolk)	0.82	12.9	[67]
USA (Nationwide cohort study)	0.78	15.8	[68]
Finland (Nationwide Twin Cohort)	0.80	14.4	[69]
Canada (national population-based study)	0.82	12.9	[70]
Japan (Miyagi)	0.90	7.2	[71]
Delhi	0.78	15.8	(This study)

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CHAPTER 5

Findings and Conclusion

Sustainable transportation is important to climate change strategies, particularly in developing countries, including India, which can be integrated into development goals such as health and well-being, as well as clean energy and sustainable cities. Therefore, identifying tangible co-benefits to justify actions to fulfill climate change mitigation and other human development goals is critical. Public transportation, which runs on battery electricity and NMT, can be an essential component for such a strategy, as electric buses and NMT have a lower carbon footprint and provide substantial economic benefits in preventing health impacts.

In India, structural problems with transportation are manifested by pollution and congestion; thus, policymakers must choose the most effective solution for sustainable urban transportation, keeping in mind the physical environment, public health, and economic dimensions, including improving economic efficiency and social welfare. The ambition of using electric buses to reduce pollution and congestion is being hampered by a lack of charging infrastructure and the need for extensive training. In the case of NMT, the space on the road is shared by motorized and non-powered modes in Delhi, bicycle infrastructure has not been constructed, and pedestrian infrastructure has received little attention in most Indian cities, including Delhi. In most Indian cities, including Delhi, NMT means are important in meeting transportation needs. The reliance on NMT transit modes will increase in the foreseeable future if safety and infrastructure needs are met, notwithstanding the increased economic prosperity and interest in owning motor vehicles in urban areas. The provision of infrastructure for nonmotorized modes has not received enough attention required in transportation planning studies carried out to date in major cities; therefore, policymakers should pay special attention to this aspect.

Considering our findings and the current infrastructure regarding battery-electric public transport and NMT (Walking and cycling) in Delhi, the electrification of the bus fleet in the urban transportation system in Delhi is a challenging and cost-intensive scenario for the local government due to the cost of the battery and required investments in constructing charging stations. Although costs are substantial, failing to recognize the co-benefits, particularly benefits that outweigh the costs (e.g., public health), can lead to flawed policy implementation. Deploying battery swapping and charging stations across Delhi can help implement BEB transportation. While creating NMT facilities in Delhi may also be costly due to the need to build and improve bike lanes, paths, and crosswalks as well as design safer roads for NMT transportation. However, massive savings in annual health costs may outweigh investments in infrastructure in just a couple of years.

5.1. Major findings:

5.1.1. Public health, environmental and economic benefits of the utilization of BEB transportation:

- The utilization of the new BEB fleet leads to a 74.67% reduction in the total pollutant emissions from the existing bus fleet in Delhi.
- The results revealed a significant reduction of 315 kt/y in CO2 emission and 44 t/y of avoided $PM_{2.5}$ emission from the utilization of the BEB fleet in the Delhi urban transportation system.
- The expected reduction in mortality and respiratory diseases related hospital admission cases from the avoided near roadway $PM_{2.5\ exposure}$ ranges from 67 (low) to 1370 (high) and 137 (low) to 2808 (high), respectively, which will be associated with the considerable economic benefits for the local government in Delhi.

5.1.2. NMT (walking and cycling) as a part of the Sustainable transportation strategy in Delhi:

- Based on the NMT willingness analysis findings, the average per capita time spent on walking and bicycling were estimated as 11.1 and 2.3 min, respectively, which is equal to covering an extra walking and cycling distance of 1.18 km per day based on the average walking and cycling speed in Delhi.
- The increased physical activity and avoiding exposure to $PM_{2.5}$ near roadways are expected to reduce the mortality rate by 17529 cases in addition to reducing other morbidities, as indicated in this study, while physical activity plays a significant role in reducing mortalities and morbidities.
- The associated cost savings from mortalities were approximately 4,869.8 million USD annually, which will positively impact Delhi's local government's finances.

5.1.3. Valuing co-benefits to make low transport emission investments in Delhi:

- The monetization of health co-benefits significantly improves the financial viability of the transport low emissions strategies development in Delhi.
- As explained in chapter 3, the electric bus fleet could replace only 74.67% of the total existing CNG bus fleet under the same traveling condition. Thus, extra electric buses would be needed, if the local government intends to replace all CNG buses. Although, a 100% replacement scenario results in additional capital investment, the expected economic benefits from the avoided health outcome, would recover a major part of these initial costs. Based on the estimated economic benefits from the avoided health outcome, the BEB fleet can cover all initial capital cost, which is estimated at USD 1,784 million, within six years of implementation of the electrification of public transport in Delhi, taking into account its

lower operational and maintenance costs per kilometer compared to the conventional vehicles.

- The average investment in walking and bike lanes is around 1 million USD/km in Delhi. However, findings in chapter 4 indicated that the average saving from improving public health due to increased physical activity would be 0.3 million USD/ km per year which makes a strong case for the implementation of NMT infrastructure in Delhi.

5.2.Study limitations:

5.2.1. Uncertainty of near roadway assessment for $PM_{2.5}$ exposure:

Estimates of emissions, pollutant concentrations, population, and disease rates affect mortality due to air pollution caused by transportation. There are uncertainties at every analytical stage of the health effects of air pollution, including identifying emissions, pollutant concentrations, and associated health implications. The size and spatial distribution of transportation emissions also bring important uncertainties, so more details focus on near roadway stations for assessment for $PM_{2.5}$ should be done.

5.2.2 The detailed cost analysis of the studied low-emission scenarios:

In this study, the cost analysis of the proposed scenarios was not discussed. For example, the availability of charging infrastructure in Delhi is an important issue that will affect the future implementation of this policy. Charging systems is the most important part of electric mobility, but it is also one of the most significant perceived impediments to EV adoption in Delhi due to low availability and long charging periods. To carry out the Delhi Electric Vehicle Policy, this goal necessitates the simultaneous penetration of charging stations across Delhi, as there are currently only 72 public charging stations in Delhi. Therefore, setting up charging infrastructure at the public level needs to be analyzed in detail, before implementing a battery-electric public transport system in Delhi.

5.2.3. The lifecycle emissions of electricity generation:

The lifecycle emissions of electricity generation (from coal) were not addressed in this study. The results revealed that the additional electricity demand by the BEBs is considerable and is about 1.3 % of Delhi's current total electricity consumption, 34% of which should be supplied from the coal-fired power plants. Therefore, to maximize the environmental and health co-benefits from the electrification of the whole transport system in Delhi, the local government needs to decrease its reliance on fossil fuels for electricity generation and switch over to renewable sources for electricity generation.

5.2.4. The lack of data availability on RR and limits of the meta-analysis:

Data availability to calculate RR in the case of the Indian scenario remains a challenge due to limited access to the historical epidemiological statistics on different disease and mortality rates and also data for the hospital admission costs. Data availability to calculate RR related to physical activity and health impacts specific to the Indian scenario was also a challenge, as few studies are available. Moreover, most of the health impact studies on air pollution in India are currently based on the time-series analysis undertaken in large cities through primary research only. In order to tackle this challenge, this study mostly relied on available data from China, Europe, the USA, and other Asian countries that may not be 100% applicable in the case of the Indian scenario.

5.3. Future work

The current study has only quantified the health and economic co-benefits of Delhi's low-carbon transportation system (NMT and BEBs). However, other co-benefits of sustainable transport systems, which include a reduction in traffic congestion, road accident-related mortalities and injuries, noise reduction, increased energy efficiency, Local job creation, and other social benefits, could be considered as future work of this research.