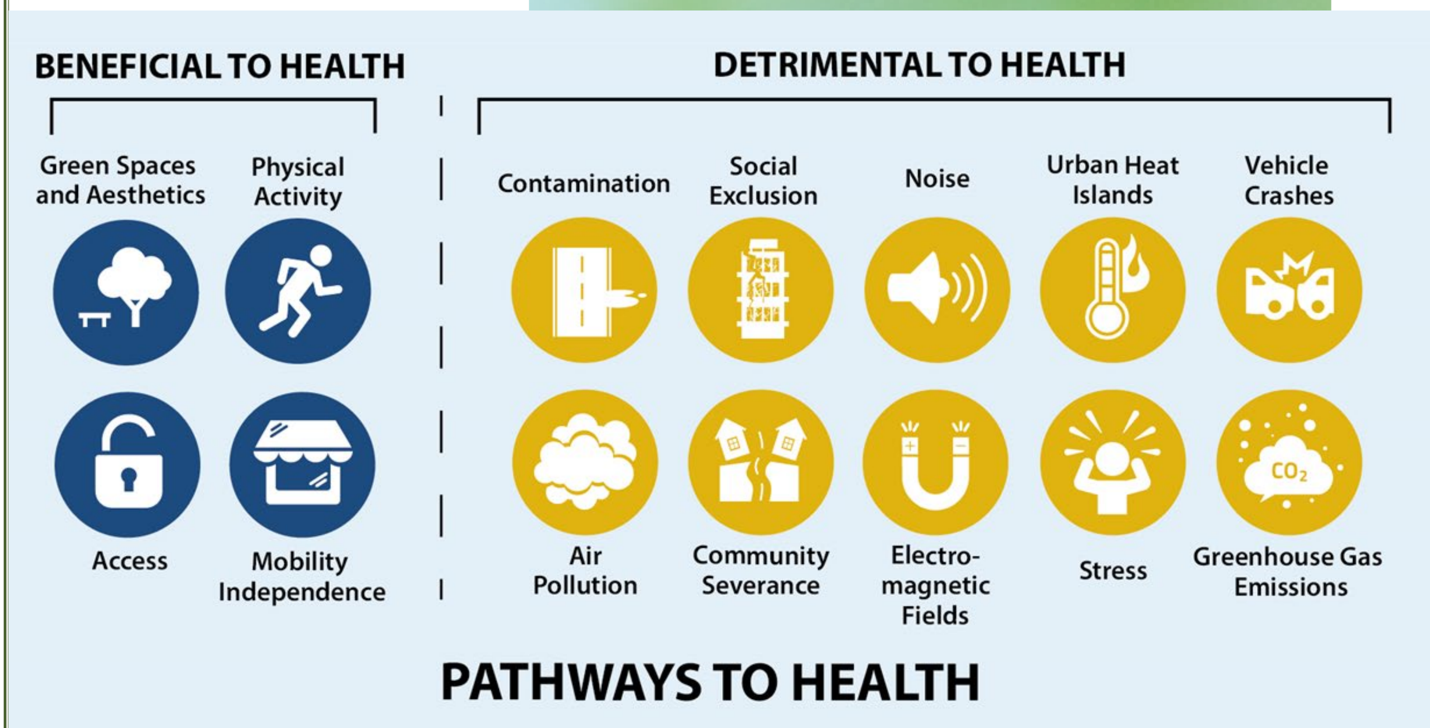
# FOURTEEN PATHWAYS BETWEEN URBAN TRANSPORTATION AND HEALTH: A CONCEPTUAL MODEL, LITERATURE REVIEW, AND BURDEN OF DISEASE ASSESSMENT IN HOUSTON

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16. Abstract

Transportation has been linked to several adverse health impacts, with a large, but modifiable, burden of disease. In this work, researchers conceptualized and documented the linkages between transportation and health. Following that, the researchers quantified the impacts of transportation on health in a case study in Houston, Texas, that focused on premature mortality attributable to three pathways: air pollution, noise, and motor vehicle crashes. Researchers found that the pathways linking transportation to health include some that are beneficial, such as when transportation serves as means for social connectivity, independence, physical activity, and access. Some pathways link transportation to detrimental health outcomes from air pollution, road travel injuries, noise, stress, urban heat islands, contamination, climate change, community severance, and restricted green space, blue space, and aesthetics. Researchers defined each pathway and summarized its health outcomes as they occur in the literature and showed that transportation-related exposures and associated health outcomes, and their severity, can be influenced by inequity and intrinsic and extrinsic effect modifiers. In Houston, the researchers estimated 302 (95 percent confidence interval [CI]: 185–427) premature deaths were attributable to transportation-related noise, compared to 330 fatalities from motor vehicles, 631 (95 percent CI: 366–809) from $PM_{2.5}$, and 159 (95 percent CI: 0–609) from $NO_2$. Transportation-related noise and motor vehicle crashes were responsible for 1.7 percent and 1.9 percent of all-cause premature deaths in Houston, respectively. The estimated premature death rate attributable to transportation-related noise was comparable to the death rate caused by suicide, influenza, or pneumonia in the United States. $PM_{2.5}$ was responsible for 7.3 percent of all-cause premature deaths, which is higher than the death rate associated with diabetes mellitus, Alzheimer's disease, or motor vehicle crashes in the United States. Households with lower median income had a higher risk of adverse exposure and premature deaths. Researchers also showed a positive relationship between health impacts attributable to air pollution and road traffic passing through census tracts, which was more prominent for $NO_2$. Although some of the pathways linking transportation and health are widely discussed in the literature, others are new or under-researched. This conceptual model can form the basis for future studies looking to explore the transportation-health nexus.

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## Executive Summary

Transportation is an integral part of daily lives, providing access to people, education, jobs, services, and goods. Transportation choices and patterns are influenced by four interrelated factors: the land use and built environment, infrastructure, available modes, and emerging technologies/disruptors. These factors influence how people can or choose to move themselves and goods. In turn, these factors impact various exposures and health outcomes. Indeed, transportation has been linked to several adverse health impacts, with a large, but modifiable, burden of disease.

In this study, researchers conceptualized and documented the linkages between transportation and health. In addition, researchers quantified the impacts of transportation on health in a case study in Houston, Texas, in the form of premature mortality. Researchers focused on quantifying the burden of mortality attributable to three pathways that are supported by a relatively robust evidence base: air pollution, noise, and motor vehicle crashes. Transportation-related noise is an emerging exposure whose burden of disease remains only partially recognized. Researchers compared premature deaths potentially attributable to transportation-related noise with deaths from motor vehicle crashes and ambient air pollution, two well-researched and widely recognized transportation-related risk factors. They also explored how these estimates vary according to socioeconomic status and exposure to road traffic.

The researchers started by developing a conceptual model to clarify the connections between transportation and health. To do so, they conducted a literature review focusing on publications from the past seven years. They complemented this with expert knowledge and synthesized information to summarize the health outcomes of transportation along 14 identified pathways. For the Houston case study, researchers employed a standard burden of disease assessment framework to quantify premature cardiovascular disease mortality attributable to transportation-related (road and aviation) noise and to quantify premature all-cause mortality attributable to air pollution exposures: $PM_{2.5}$ and $NO_2$ at the census tract level (n = 592). The results were compared to motor vehicle crash fatalities, which are routinely observed and collected in the study area. In addition to exploring the role of traffic in the air pollution attributable burden, researchers also investigated the distribution of premature deaths across the city and the relationship between household median income and premature deaths attributable to transportation-related noise and air pollution.

The researchers found that the pathways linking transportation to health include some that are beneficial, such as when transportation serves as means for social connectivity, independence, physical activity, and access. However, some pathways link transportation to detrimental health outcomes from air pollution, road travel injuries, noise, stress, urban heat islands, contamination, climate change, community severance, restricted green space, blue space, and aesthetics. Other possible effects may come from electromagnetic fields, but those effects are not definitive. Researchers defined each pathway and summarized its health outcomes as they occur in the literature. Results show that transportation-related exposures, associated health outcomes, and their severity can be influenced by inequity and intrinsic and extrinsic effect modifiers. In Houston, researchers estimated 302 (95 percent confidence interval [CI]: 185–427) premature deaths were attributable to transportation-related noise, compared to 330 fatalities from motor vehicles. Researchers also found that 631 (95 percent CI: 366–809) premature deaths were attributable to $PM_{2.5}$, and 159 (95 percent CI: 0–609) were attributable to $NO_2$. Complying with the World Health Organization air quality guidelines (annual mean: 10 μg/m$^3$ for $PM_{2.5}$) and the U.S. National Ambient Air Quality standard (annual mean: 12 μg/m$^3$ for $PM_{2.5}$) could save 82 (95 percent CI: 42–95) and 8 (95 percent CI: 6–10) lives, respectively. Transportation-related noise and motor vehicle crashes were responsible for 1.7 percent and 1.9 percent of all-cause premature deaths in Houston, respectively. The estimated premature death rate attributable to transportation-related noise was also comparable to the death rate caused by suicide, influenza, or pneumonia in the United States. $PM_{2.5}$ was responsible for 7.3 percent of all-cause premature deaths, which is higher than the death rate associated with diabetes mellitus, Alzheimer's disease, or motor vehicle

crashes in the United States. Households with lower median income had a higher risk of adverse exposure and premature deaths potentially attributable to transportation-related noise. A larger number of premature deaths was associated with living in the central business district and in the vicinity of highways and airports. Households with lower income also had a higher risk of air pollution exposure and attributable premature deaths. Findings also showed a positive relationship between health impacts attributable to air pollution and road traffic passing through census tracts, which was more prominent for $NO_2$.

Although some of the pathways linking transportation and health are widely discussed in the literature, others are new or under-researched. This study's conceptual model can form the basis for future studies looking to explore the transportation-health nexus. The researchers also propose the model as a tool to holistically assess the impact of transportation decisions on public health. This work further highlighted the significant contribution of transportation-related noise, ambient air pollution, and motor vehicle crashes to premature deaths in the city of Houston. The analogy between the estimated premature deaths attributable to transportation-related noise and motor vehicle crashes showed that the health impacts of transportation-related noise were as significant as motor vehicle crashes. An urgent need exists for imposing policies to reduce transportation-related noise emissions, air pollution, and human exposure and to equip health impact assessment tools with a noise burden of disease analysis function, an aspect which has been overlooked in many health impact and burden of disease assessments.

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## List of Abbreviations

| | |
|---|---|
| ADT | Annual Daily Traffic |
| AEDT | Aviation Environmental Design Tool |
| AV | Autonomous Vehicle |
| BMI | Body Mass Index |
| CARTEEH | Center for Advancing Research in Transportation Emissions, Energy and Health |
| CBD | Central Business District |
| CDC | Centers for Disease Control and Prevention |
| CI | Confidence Interval |
| $CO_2$ | Carbon Dioxide |
| COPD | Chronic Obstructive Pulmonary Disease |
| CVD | Cardiovascular Disease |
| DALY | Disability-Adjusted Life Year |
| dB | Decibel |
| EMF | Electromagnetic Field |
| EPA | Environmental Protection Agency |
| ERF | Exposure-Response Function |
| EV | Electric Vehicle |
| FAA | Federal Aviation Administration |
| FARS | Fatality Analysis Reporting System |
| FHWA | Federal Highway Administration |
| FIA | Federation Internationale de l'Automobile |
| GHG | Greenhouse Gas |
| GT | Gigatons |
| HEAT | Health Economic Assessment Tool |
| HF | Heart Failure |
| HIA | Health Impact Assessment |
| HR | Hazard Ratio |
| ICD | International Classification of Disease |

| | |
|---|---|
| ICEV | Internal Combustion Engine Vehicle |
| INM | Integrated Noise Map |
| ITHIM | Integrated Transport and Health Impact Model |
| LUR | Land Use Regression |
| MI | Myocardial Infarction |
| $NO_2$ | Nitrogen Dioxide |
| NTNMT | National Transportation-Related Noise Mapping Tool |
| $O_3$ | Ozone |
| PAF | Population Attributable Fraction |
| PAH | Polycyclic Aromatic Hydrocarbon |
| PM | Particulate Matter |
| $PM_{2.5}$ | Particulate Matter with a Diameter Equal or Less than 2.5 Micrometers |
| QOL | Quality of Life |
| RR | Relative Risk |
| TNM | Traffic Noise Model |
| TRAP | Traffic-Related Air Pollution |
| UHI | Urban Heat Island |
| UK | United Kingdom |
| VIA | Visual Impact Assessment |
| VMT | Vehicle Mile Traveled |
| VMTA | Vehicle Mile Traveled per Area |
| WHO | World Health Organization |
| WPT | Wireless Power Transfer |

## Background and Introduction

Transportation allows people to move around, partake in activities that compose daily routines, and access people, education, jobs, services, and goods. The choices that determine how transportation will facilitate the movement of people and goods are partly a reflection of transportation demand—the derived need for transportation based on the economies, societies, and technologies of a city or region. Transportation also promotes the growth of cities (Marshall, 2000) and the expansion of urbanization and catalyzes the transfer of knowledge and the exchange of cultures and ideas (Marshall, 2000; Dvir and Pasher, 2004). Throughout history, transportation has been essential in shaping and giving rise to civilizations.

Despite the convenience and connectivity transportation can provide and its critical role in urban and modern-day societies, there are many byproducts of transportation systems that pose significant health risks and have resulted in the degradation of public health, especially in urban communities. For instance, road crashes are the eighth leading cause of deaths worldwide (World Health Organization [WHO], 2018a), traffic-related air pollution (TRAP) is conservatively estimated to result in nearly 200,000 premature deaths annually (Bhalla et al., 2014), and transportation-related noise produces a burden of disease similar to that of secondhand smoke (Hänninen et al., 2014). Additional health risks occur as a result of other transportation-related factors, such as stress, increased urban heat, contamination, restricted green space, blue space, urban aesthetics, climate change, community severance, and the inequitable distribution of benefits and harms, which further contribute to existing and gross inequities in health, often at the expense of lower socioeconomic groups and ethnic minorities.

## Problem

In this report, researchers built on existing work in a growing field by focusing on how transportation is linked to public health and health inequities. The researchers also detected a gap in the literature because a comprehensive conceptual model linking transportation and public health does not exist.

In addition, the health burden attributable to some transportation-related risk factors, such as air pollution and motor vehicle crashes, is well established and studied, while the burden attributable to other risk factors, such as transportation-related noise, is not—partly because some risk factors are only emerging. In this work, researchers developed a comprehensive conceptual model linking transportation and public health and, by conducting an urban case study in Houston, Texas, quantified the health burden, in the form of premature mortality, attributable to transportation-related noise, crashes, and ambient air pollution.

## Approach

Researchers conducted this work in three workstreams, as follows:

1. Work Package 1—A literature review, expert assessment, and conceptualization exercise to develop the conceptual model. This work is reported in detail in Glazener et al. (2021).
2. Work Package 2—An analysis of data from Houston, Texas, to estimate the burden of premature mortality attributable to transportation-related noise and motor vehicle crashes and explore the role of socioeconomic status in the distribution of this burden. This work is reported in detail in Sohrabi and Khreis (2020).
3. Work Package 3—An analysis of data from Houston, Texas, to estimate the burden of premature mortality attributable to ambient air pollution and explore the role of socioeconomic status in the distribution of this burden. This work is reported in detail in Sohrabi et al. (2020).

The remainder of this report documents the methods and results separately by work package and refers to them as Work Package 1, 2, or 3 based on the definitions above.

# Methodology

## Work Package 1: Development of Conceptual Model and Literature Review

### Purpose of the Conceptual Model

In this work package, researchers framed the development of the conceptual model and the discussion around the ability of the transportation system to enable the movement of people and goods. Transportation—and the systems, technologies, activities, land use and infrastructure behind it—impacts health in numerous ways, particularly in urban areas (Khreis et al., 2016). The researchers decided to focus on urban areas because estimations project that the global urban population will account for nearly 68 percent of the worldwide population by 2050 (United Nations Department of Economic and Social Affairs, 2017), thereby exposing more people to the adverse health impacts associated with urban transportation. The nature of transportation is also dynamic and evolving, partly due to emerging technologies, often referred to as disruptors, that, when paired with growing public health concerns, require a thorough analysis to holistically frame specific health outcomes that result from transportation decisions and consider strategies to mitigate the adverse ones. Understanding and formulating the numerous ways by which transportation decisions affect public health will help in studying the transportation and health nexus in a holistic manner and support policy and decision-making that prioritize health in cities. Moreover, by providing a conceptual model, the researchers aim to aid practitioners in their evaluation of transportation impacts on health, highlight research gaps, and make recommendations for both future research and practice.

Before researchers embarked on developing the conceptual model, a literature review on the intersection of transportation and public health was conducted. The development of the model required multidisciplinary knowledge, drawing information from multiple fields to contextualize the relationship in an assessment framework. The first report to link a wide range of health outcomes to transportation was Health on the Move, a 1991 report from the United Kingdom (Hannah et al., 1991). It was updated in 2011 to include an even broader range of pathways relating transportation to public health outcomes: access, physical activity, injury, pollution, stress, climate change, loss of land and planning blight, community severance, and danger (Mindell et al., 2011). Each of these pathways are included in this paper and integrate the impacts of loss of land and planning blight and danger into pathways labeled *green space and aesthetics* and *social exclusion*. In 2015, Dannenberg and Sener examined the relationship between transportation and health through five pathways, namely safety (motor vehicle crashes), air quality, physical activity, equitable access, and noise. Similarly, Lyons et al. (2014) developed a conceptual model based on four pathways—(physical) activity, safety, air quality, and access—to holistically integrate public health benefits within existing state transportation systems in the United States (U.S.). Widener and Hatzopoulou (2016) identified seven pathways—noise, air pollution, motor vehicle crashes, stress, physical activity, access, and interpersonal contact, while van Wee and Ettema (2016) conceptualized the relationship between transportation and health through four pathways: physical activity, exposure to air pollution, casualties, and subjective well-being. In addition, Götschi et al. (2017) developed a conceptual model identifying the behavioral considerations that determine the utility of active travel modes, citing health benefits as a key determinant in mode choice considerations, although references to specific health outcomes as a result of active travel is missing. The recurrence of several pathways (motor vehicle crashes, access, air pollution, noise, stress, and physical activity) justified their inclusion in this discussion. More recently, Frank et al. (2019) developed a model linking built environment and transportation decisions to health through six pathways that fall under the two categories of *behavior* and *exposure*. Behavior refers to encouraging or discouraging certain behaviors in ways that affect human health, and this category includes the pathways of dietary intake, physical activity, and social interaction. Exposure refers to human exposure to harmful substances and stressors, and this category includes the pathways of air pollution, traffic safety and crime, and noise (Frank et al., 2019). Frank et al. (2019) outlined that these pathways lead to biological responses, including increased body mass index (BMI), systemic inflammation, and stress, which in turn lead to chronic physical and mental diseases that increase healthcare utilization and cost. Nieuwenhuijsen (2020) published a conceptual model exploring transportation's role in creating carbon-neutral, livable, and healthy cities and suggested that urban design elements such as density, diversity, distance, and design lead to specific mode choices, such as using the car, cycling, and walking, which in turn have significant impacts on morbidity and mortality. The public health impacts occur through a number of possible pathways, including air pollution, noise, temperature, UV, stress, social contacts, and physical activity (Nieuwenhuijsen, 2020).

The work that resulted in the final conceptual model largely expands on the conceptual model developed by Khreis et al. (2017a), which is a development of a previous effort reported in Khreis et al. (2016). Khreis et al. (2017a) identified nine pathways linking transportation to public health: motor vehicle crashes; air pollution; noise; heat islands; lack of green space and biodiversity loss; physical inactivity; social exclusion; community severance; and climate change. In this paper, researchers ultimately included 14 interlinked pathways that connect transportation to various public health outcomes: green space and aesthetics, physical activity, access, mobility independence, contamination, social exclusion, noise, heat, road travel injuries, air pollution, community severance, electromagnetic fields, stress, and greenhouse gases. In a nonsystematic literature review, researchers also researched and listed the health outcomes related to each of these pathways as they occur in the literature.

Although many of the pathways in the final conceptual model have been included in previous conceptual models, the researchers added three pathways that have not been identified in previous works: contamination, electromagnetic fields, and mobility independence. The researchers defined and described these linkages, and for each pathway, listed its associated health outcomes, which is another addition to the literature. The influence of intrinsic and extrinsic factors that can modify associated health outcomes were noted, as was the severity of these outcomes within a community. Issues of inequity also influence the relationship between transportation and health. An equity component has been added to the model to communicate the relevance of equity and its influence on urban transportation, such as the unequal distribution of transportation infrastructure, transportation-related exposures, and associated health outcomes. Finally, researchers concluded by making recommendations for future research and practice.

Methods for developing the transportation-public health conceptual model started with examining existing conceptual models that detailed transportation's impact on health, as referenced above, to frame the concept of transportation and identify potential pathways between transportation and health for this model. Pathways included from preexisting models were road travel injuries, air pollution, noise, heat, green space, physical inactivity, stress, social exclusion, community severance, greenhouse gases, and access. Next, a literature review was conducted that provided a bottom-up perspective on pathways as they occur in the literature, using pathways from existing models as keywords to expand on existing work. Last, the researchers solicited input from experts who provided a top-down perspective on framing the issues to assess the linkages between transportation and health. Consultation with experts led researchers to include other pathways, such as contamination and mobility independence. The electromagnetic fields pathway was included after reviewing literature related to emergent and disruptive transportation technologies. The literature review and expert consultation were conducted in parallel, with multiple iterations. This approach ensured that the most relevant and recent sources contributed to the evaluation of these pathways and their health impacts. The following describes the researchers' methodology in detail.

## Framing Key Concepts of Transportation and the Relationship with Public Health

Four key factors that are not mutually exclusive affect transportation. The existing conceptual models that were reviewed often discuss transportation as a result of mode choice and urban design. Researchers expanded upon these concepts by further distinguishing land use and the built environment from transportation infrastructure and mode choice, as well as by including the impact of emergent and disruptive transportation technologies—an issue of increasing relevance with potentially large impacts on the future transportation landscape. A description of these factors follows:

1. ***Land Use and Built Environment***: Patterns of land use and the built environment, including but not limited to density, land use diversity and mix, distance to public transportation, and destination accessibility, affect the viability and desirability of different transportation modal options. Land use policies that encourage density and accessibility can contribute to the production of certain transportation infrastructures when coupled with investment (McFadden et al., 2014). Land use and the built environment can incentivize the development and adaptation of emergent and disruptive technologies. For example, car-oriented cities with low-density and urban sprawl may have more interest in technologies meant to improve automobile travel, such as connected and autonomous vehicles (Bansal et al., 2016) or ride-hailing services (Clewlow and Mishra, 2017). In urban areas where alternative modes of transportation are supported by land use and the built environment—for example, heterogenous land use mix and dense and compact development—electric bikes or scooters and bike and scooter sharing may be sought after.
2. ***Transportation Infrastructure***: This category accounts for the design, construction, and maintenance of various transportation infrastructure, including roads, parking spaces, cycling lanes and parking, pedestrian sidewalks, public transportation and freight hubs, railways, and electric grids, among others. The presence and quality of transportation infrastructure impact modal choice and the viability of modal options. Further, in the long term, it can alter land use and built environment characteristics, such as increasing urban sprawl. Transportation infrastructure decisions can also make emergent and disruptive transportation technologies more or less desirable and viable.
3. ***Transportation Mode Choice***: Transportation mode refers to the way humans and goods move around, including by walking, cycling, using public transportation, private vehicles, and taxis (both cars and powered two-wheelers), freight vehicles, or a combination thereof. New transportation modes include scooters and electric scooters. Transportation mode also includes the choice of vehicle type and last-mile connections to and from public transport. Although motor vehicles are the prominent mode of transportation in many high-income regions, mode choice is determined by the safety, convenience, availability, affordability, feasibility, and accessibility of modal options (for example, distance and travel time) (Simons et al., 2013), as well as by perceptions and attitudes toward different modes (Handy et al., 2005). Transportation mode choice further impacts the adaptation of and investment in transportation technologies and infrastructure. In the long term, transportation mode choice can result in altered land use and built environment—for example, urban sprawl.
4. ***Transportation Technologies and Disruptors***: This category includes emergent and disruptive transportation technologies, such as autonomous, connected, electric, and shared vehicles. These technologies, in addition to innovations in other fields, such as 3D printing and drones, are influencing transportation and the factors that affect it. These technologies can encourage or discourage the use of a certain transportation mode; increase or decrease the necessity for specific types of transportation infrastructure; create the need for a new kind of transportation infrastructure; and in the long term, dictate land use and built environment characteristics.

Public health broadly pertains to the protection and improvement of people's health and the communities they live in (Centers for Disease Control and Prevention [CDC], 2020). The relationships between the social, cultural, and physical environments an individual lives in and that individual's characteristics and choices influence health outcomes (WHO, 2017). Each of the transportation factors detailed previously is influenced by the environments people live in and their preferences. Transportation has, therefore, become an inherent factor in shaping health outcomes.

## Literature Review

The foundation for developing the conceptual model and identifying the health outcomes associated with each of its pathways is a literature review covering 294 published articles and papers related to transportation and public health, as identified by the Transportation Research Board and Google Scholar databases. These articles were screened and shortlisted from searches using the following keywords: *transportation*, *transport*, *mobility*, *public health*, and *active transportation* in conjunction with *motor vehicle crashes*, *road travel injury*, *air pollution*, *noise*, *green space*, *aesthetics*, *physical activity*, *community severance*, *social exclusion*, *electromagnetic field*, *greenhouse gases*, *urban heat island* (UHI), *accessibility*, *contamination*, *independence*, and/or *stress* and subsequent references found within those papers; essentially, the conceptual model guided the literature review of each pathway. The findings from the reviewed literature and references within those papers included health outcomes that allowed researchers to populate a table containing the known health outcomes associated with each pathway. The results were not systematically reported but focus on systematic reviews, meta-analyses, and articles published between January 1, 2013, and October 19, 2020, to provide up-to-date information and add value to previously published conceptual models. Older articles were used if they represented seminal or unique research; were necessary to understand recent findings; or if a lack of recent research existed.

## Expert Knowledge and Assessment

Discussion and consultation with experts in the fields of public health, urban planning, and transportation further informed findings and validated the nature of the linkages between transportation and public health. These interviews were informal since persons consulted are colleagues of the authors. Interviews were not conducted in a systematic manner but occurred as needed when the authors sought additional input about a specific pathway or the overall conceptual model. The researchers also referred to existing conceptual models that defined transportation and public health linkages to inform the new conceptual model and pathways. Discussions and multiple iterations among experts informed the final conceptual model. The model and results of the literature review are reviewed in the Results section.

# Work Package 2: Quantifying Premature Mortality Attributable to Transportation-Related Noise and Motor Vehicle Crashes and the Role of Socioeconomic Status

## Motivation and Contribution to the Literature

In this work package, the researchers focused on quantifying and analyzing the burden of disease, in the form of premature mortality (death), attributable to transportation-related noise and motor vehicle crashes. The researchers selected noise as an emerging exposure that receives less attention in the burden of disease assessments and transportation planning and policy, and whose burden of disease remains partially recognized. WHO recently reviewed its noise guidelines for Europe after a series of systematic reviews that established that noise contributes to serious health outcomes, such as cardiovascular disease, adverse birth outcomes, cognitive impairment, metabolic outcomes, mental health, annoyance, effects on sleep, hearing impairment and tinnitus (WHO, 2018d). However, in the context of burden of disease assessments, studies mainly quantified cardiovascular diseases and deaths from cardiovascular causes attributable to noise (Tobías et al., 2015; Briggs et al., 2015; Mueller et al., 2018a). On the other hand, motor vehicle crashes were recognized as a key transportation-related health issue decades ago and have received substantial policy attention and investments (Khreis et al., 2016).

From a methodological standpoint, previous studies share similar methods for quantifying the burden of disease attributable to noise. Typically, the baseline exposure level is compared with either level of exposures recommended by health authorities or a no-exposure scenario (zero noise levels), and the burden of disease for the health outcome of interest is quantified by employing exposure-response functions (ERFs) extracted from the literature (Tobías et al., 2015; Mueller et al., 2017a). Previous studies on the burden of disease attributable to noise vary based on the source of noise exposure considered as the input to the analysis. In the literature, the burden of disease from both ambient environmental noise (Tobías et al., 2015) and transportation-related noise

(Tainio, 2015; Briggs et al., 2015) was estimated. Health impacts from crashes, however, are directly extracted from motor vehicle crash datasets (Briggs et al., 2015; Götschi et al., 2015). In previous studies, the transportation-related noise and motor vehicle crashes burden of disease was measured using the number of deaths (Tobías et al., 2015), premature deaths (Mueller et al., 2017a), disability-adjusted life years (DALYs) (Mueller et al., 2018a), and health care costs (Ling-Yun and Lu-Yi, 2016). The spatial resolution of previous burden of disease assessments and analysis varied from census tract level (Mueller et al., 2017a; Mueller et al., 2017b), to city (Stassen et al., 2008; Tainio et al., 2016), to national (Bhalla et al., 2014; Briggs et al., 2015; Hänninen et al., 2014), and to continental levels (WHO, 2018b).

The input data needed for assessing transportation-related risk factors and their impact on health is a key component of the burden of disease analysis and the health impact assessment process. In addition to the quality and reliability of data, exposure data with explicit transportation sources should be used for quantifying impacts of the transportation sector on public health instead of ambient exposures originating from multiple sources. The spatial level of the analysis is usually dependent on the availability of data. A finer spatial resolution can help decision-makers gain better insight into health equity issues within cities and identify high-risk spots more precisely. However, downscaling data inappropriately can result in increased uncertainty and/or error in the burden of disease estimations.

This work contributes to the literature by specifying the transportation component of the exposure (i.e., using two sources of transportation-related noise as opposed to ambient environmental noise exposure), estimating the burden of disease attributable to transportation-related noise at the census tract level with further analyses by socioeconomic status and its spatial variation across the city, and comparing the estimated burden of disease from noise to motor vehicle crashes fatalities. For the case study, the premature deaths attributable to transportation-related noise (from road traffic and aviation) and motor vehicle crashes were quantified and analyzed for the city of Houston, Texas, the fourth largest city in the U.S. For the third work package, data from Houston was used to quantify the burden of premature mortality due to ambient air pollution exposure.

## Study Setting and Definitions

The burden of disease attributable to transportation-related noise and motor vehicle crashes were assessed in Houston. Houston had 2,303,482 residents in 2016 (U.S. Census Bureau, 2016). Houston is the largest city in Texas, encompassing 636.5 square miles (1,646 square km) of land area (World Population Review, 2019) located in three counties: Harris, Fort Bend, and Montgomery. The burden of disease analysis was conducted at the finest reasonable spatial resolution: the census tract level. The rationale behind analyzing the burden of disease at the census tract level is that mortality data were only available at the county level, so researchers had to downscale the mortality data to assign them to a finer spatial level. To minimize the error of this approximation yet still investigate the spatial distribution of health outcomes, researchers chose to limit the spatial resolution of this study to the census tracts level. Consequently, 592 census tracts were included in this study which were fully or partially located within the city's boundaries.

The researchers quantified the health impacts in the form of attributable premature deaths. Premature deaths are defined as a measure of unfulfilled life expectancy, which is considered the number of deaths before reaching the expected age. The life expectancy in the U.S. was 78.6 years old in 2016 (Xu et al., 2018). Given that and according to the availability of the baseline mortality data (in 5-year intervals), deaths of adults less than 75 years old were considered premature deaths in this study. The researchers estimated the premature deaths attributable to aviation and road traffic noise for the cardiovascular diseases. Since the risk of mortality from cardiovascular diseases (CVDs) is associated with transportation-related noise for individuals older than 30 years old (details are provided in subsequent sections), hereafter, the term *premature death* refers to deaths of individuals aged 30 to 75 years old. For motor vehicle crashes, deaths of individuals younger than 75 years old were considered premature deaths.

## Input Data

The data used in this study were collected from multiple sources, namely, the U.S. Census Bureau, CDC, Texas Department of Transportation (TxDOT), and U.S. Department of Transportation, as described in the following sections.

### *Population, Socioeconomic, and Geographic Data*

Population and economic data were collected from the U.S. Census Bureau for 2016 at the census tract level. The distribution of the burden of disease by median household income at the census tract level was analyzed, as sourced from the U.S. Census Bureau, to indicate socioeconomic status. The average of the median household income in Houston in 2016 was 60,784 dollars, while the lowest and highest median household income at the census tract level were 10,128 and 246,058 dollars, respectively. Figure 1 shows the spatial distribution of the median household income across the city.

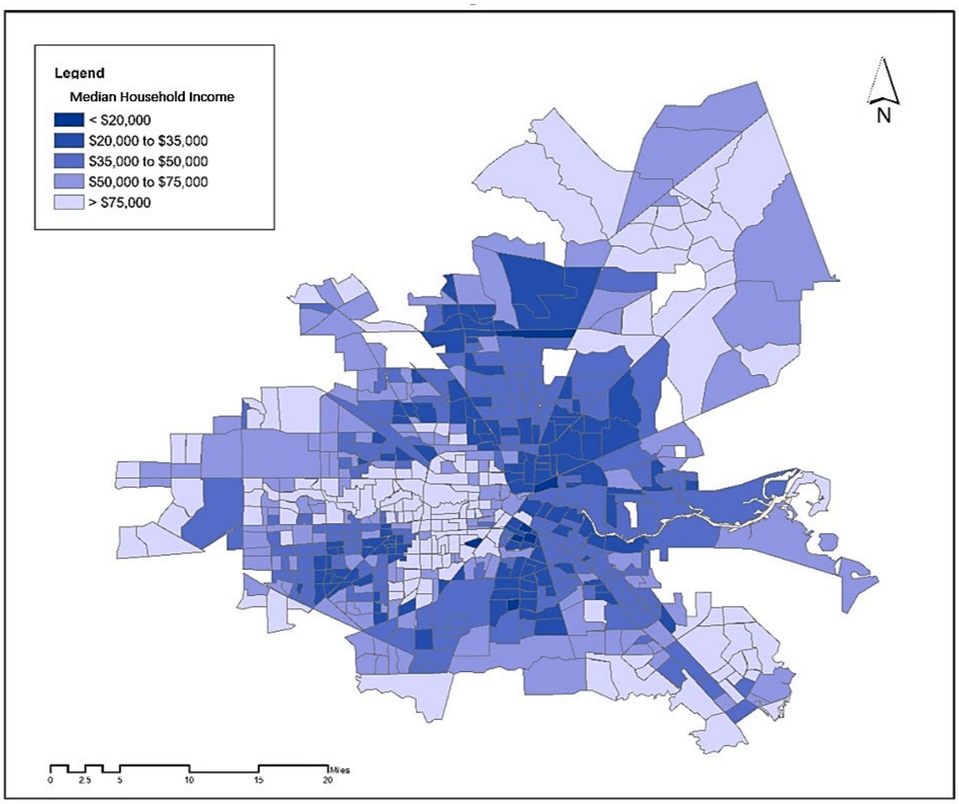



**Figure 1. Spatial Distribution of Median Household Income at the Census Tract Level.**

The geographical limits of Houston were sourced from the city's open data portal, which was used to identify census tracts within the city's boundaries (retrieved from https://cohgis-mycity.opendata.arcgis.com/datasets/houston-city-limit).

### *Motor Vehicle Crashes Data*

Premature deaths from motor vehicle crashes were defined as the fatalities of individuals younger than 75 years old. Fatalities from motor vehicle crashes were collected from the Fatality Analysis Reporting System (FARS) and provided by the National Highway Traffic Safety Administration for the year 2016. The location of motor vehicle crash occurrences, along with the number of fatalities, was publicly available from https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars. However, information on the physical address of the individual(s) involved in the crash was not available.

A supplementary analysis of the crash data was conducted to explore the spatial distribution of premature deaths from motor vehicle crashes. To this end, researchers categorized the crashes into two categories: (1) local crashes and (2) highway crashes. Highway crashes refer to crashes that occurred on highways. The remainder of crashes were assigned to the census tract where they occurred. For the supplementary comparison between premature deaths attributable to transportation-related noise and motor vehicle crashes, it was assumed that local crashes occurring within a census tract can be attributable to residents of that census tract. The highways' map, sourced from the Texas roadway inventory data by TxDOT from 2016 (retrieved from https://www.txdot.gov/inside-txdot/division/transportation-planning/roadway-inventory.html), was used to identify crashes that occurred on highways.

### *Mortality Data*

The baseline mortality data for Texas were sourced from the CDC (retrieved from https://wonder.cdc.gov/mcd.html). The mortality data were available both in the form of the number of deaths and crude mortality rates[1] at the county level, with 95 percent confidence interval (CI). For quantifying the premature deaths attributable to noise, the number of deaths from CVD for people aged 30 to 75 years old was used in this study. Given that Houston is located in three counties—Harris, Fort Bend, and Montgomery—the mortality data for these three counties were collected. As of the time of inquiry (January 2019), the mortality data were available for the year 2016. Researchers distributed the number of mortality cases (available at the county level) across census tracts proportionally based on their population size, assuming constant mortality rate for census tracts located within a county. To remain consistent with premature death data, the population aged 30 to 75 years old was used for assigning mortalities to census tracts. In 2016, a total number of 17,704 all-cause premature deaths were reported in Houston (30 to 75 years old), of which 5,384 deaths were caused by CVD, 465 deaths were caused by heart failure (HF), and 569 were caused by myocardial infarction (MI) (representing 30.5 percent, 2.5 percent, and 3.2 percent of all-cause premature deaths, respectively). The summary statistics of the mortality data at the census tract level are reported in Table 1.

**Table 1. Summary Statistics of the Data and Estimated Results at the Census Tract Level.**

| Variable | Sample Size (# of Census Tracts) | Min. | Median | Mean | Max. |
|---|---|---|---|---|---|
| All-cause Premature Deaths (persons) | 592 | 0.198 | 27.109 | 29.390 | 134.650 |
| CVD Premature Deaths (persons) | 592 | 0.062 | 9.095 | 10.689 | 78.001 |
| MI Premature Deaths (persons) | 592 | 0.006 | 0.978 | 1.194 | 15.039 |
| HF Premature Deaths (persons) | 592 | 0.005 | 0.799 | 0.986 | 8.701 |
| Aviation Noise Premature Deaths Ratio | 398 | 0.0% | 0.6% | 0.5% | 1.4% |
| Road Traffic Noise Premature Deaths Ratio | 592 | 0.0% | 1.2% | 1.3% | 3.9% |
| Transportation-Related Noise Premature Deaths Ratio | 592 | 0.1% | 1.7% | 1.8% | 4.7% |
| Crash Fatality Ratio | 119 | 0.0% | 0.0% | 0.9% | 59.9% |
| Median Income (dollar) | 592 | 10,128 | 48,587 | 60,784 | 246,058 |

Note: CVD: Cardiovascular Disease; MI: Myocardial Infarction; HF: Heart Failure.

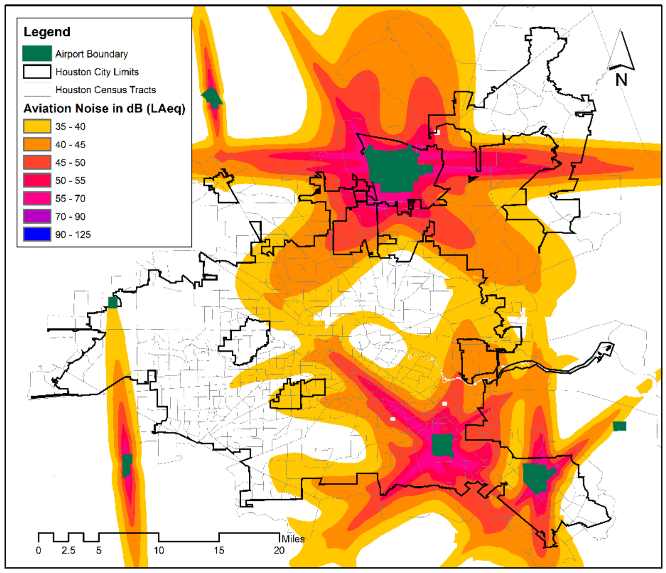
### *Noise Data*

Road traffic and aviation noise data were collected from the National Transportation-Related Noise Mapping Tool (NTNMT) generated by the U.S. Department of Transportation's Bureau of Transportation Statistics (retrieved from https://data-usdot.opendata.arcgis.com/documents/usdot::2018-noise-data/about). The noise map was generated by implementing the Aviation Environmental Design Tool version 2b (AEDT 2b) developed by the

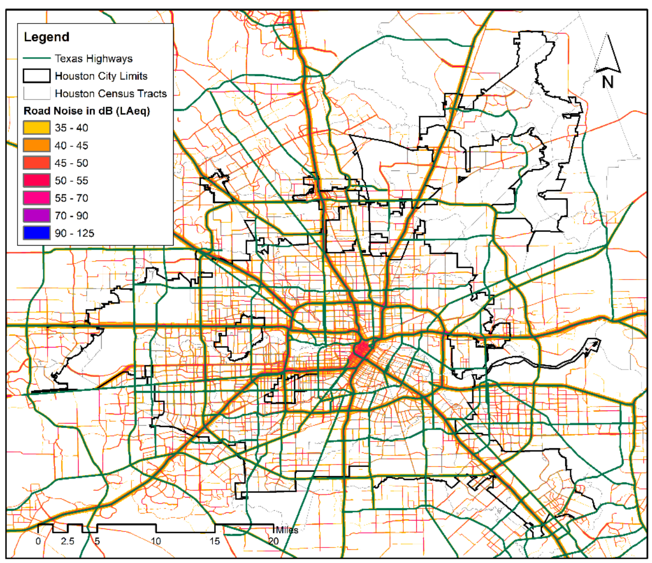
[1] Crude mortality rate is the total number of deaths of residents in a county divided by the total population for the county (for a calendar year) and multiplied by 100,000.

Federal Aviation Administration (FAA) and the acoustic algorithms from the Traffic Noise Model 2.5 (TNM) proposed by the Federal Highway Administration (FHWA). The transportation-related noise map was generated utilizing traffic data, roadway inventory, and aircraft flight operation data and by simplifying assumptions—namely, atmospheric absorption for aviation noise, nonhomogeneous atmospheric effects in road traffic noise modeling and TNM's default temperature and humidity levels (68 degrees F, 50 percent relative humidity), acoustically soft ground, average pavement material and texture of the road, and even distribution of average annual daily traffic (ADT) data across 24 hours (U.S. Department of Transportation, 2017). The modeling engines of the NTNMT, AEDT 2b, and FHWA's TNM models have been previously validated. The validation of FHWA's TNM models for 100 hours of traffic noise at 17 sites across the U.S. verifies the accuracy of TNM, in which the average difference between predicted and measured sound levels was as low as 1.0 dB for all wind conditions and 0.5 dB after removing strong winds (Rochat and Fleming, 2002). The AEDT 2b is introduced as a replacement of the Integrated Noise Map (INM) previously developed by FAA. The comparison of AEDT 2b and INM in terms of the predicted noise contour area shows consistency between the two models (FAA, 2017). The INM model was validated by FAA comparing the model results to observed noise data and showing that average sound exposure level during take-off, cutback, climb, and approach can be estimated as up to 2.0 dB difference for three-engine narrow-body aircraft; 6.2 dB difference for two-engine narrow-body aircraft; 3.3 dB difference for two and three-engine wide-body aircraft; and 3.4 dB difference for four-engine wide-body aircraft (Flathers, 1982). In addition, the national transportation-related noise map (including both road and aviation noise) has been evaluated by subject matter experts who confirmed that levels were within a reasonable order of magnitude (U.S. Department of Transportation, 2017).

The transportation-related noise inventory was developed using an A-weighted, 24-hour equivalent sound level noise metric (denoted by $L_{Aeq}$) that represents the approximate average noise energy due to transportation-related noise sources over 24 hours at defined receptors. The aviation noise was captured at a grid of receptors with distances that varied between 0.005 and 0.250 nautical miles (9.26 and 463.00 meters), depending on the size of the airport and the distance to the airport. The road traffic noise receptors were located on a uniform grid with a resolution of 98.4 feet (30 meters). Each receptor was modeled at a height of 4.92 feet (1.5 meters) above ground level. Noise levels were adjusted to account for ground effects and free-field divergence differences between the source reference location and the receptor location. Figure 2 shows the distribution of the average daily aviation and road traffic noise across Houston. The noise map was developed for noise level higher than 35 dB $L_{Aeq}$ only.




**(a)**




**(b)**

**Figure 2. (a) Aviation, and (b) Road Traffic Noise Maps in Houston.**

### *Burden of Disease Assessment Model*

The researchers used a standard burden of disease assessment framework (Mueller et al., 2017a). This framework is employed to estimate the premature deaths attributable to transportation-related noise. In brief, the inputs to the burden of disease assessment model include the noise exposure levels as well as the baseline mortality rate from CVD in the studied region. Next, the relative risk (RR) of CVD deaths in association with the difference between current transportation-related noise exposure levels and the counterfactual transportation-related noise exposure level was estimated using ERFs sourced from the best available and most relevant epidemiological study (next section). Then, the population attributable fraction (PAF) can be calculated using Equation 1. The PAF represents the ratio of CVD deaths attributable to transportation-related noise from all CVD deaths for the difference between current noise exposure level and the counterfactual exposure level.

$$PAF = \frac{RR_{diff} - 1}{RR_{diff}} \qquad \text{Equation 1}$$

where $RR_{diff}$ is the RR of CVD deaths in association with the difference between current transportation-related noise exposure levels and the counterfactual transportation-related noise exposure level.

Finally, the attributable deaths are estimated using the mortality rate and population counts for people aged 30 to 75 years old, and the estimated PAF (Equation 2). The motor vehicle crash data, however, translated directly into mortality since these were observations of deaths from crashes. The employed burden of disease assessment framework is shown in Figure 3. This procedure was used for each disease category across each of the 592 included census tracts.

$$Attributabl\ Mortality = PAF \times Mortality\ rate\ \times Population\ counts \qquad \text{Equation 2}$$

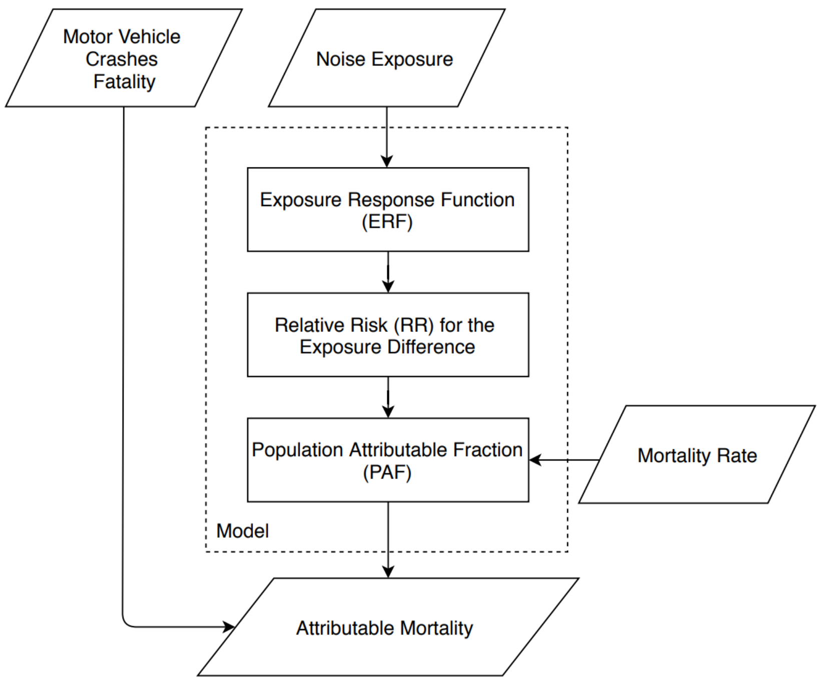



**Figure 3. Burden of Disease Assessment Framework: Work Package 2.**

### *Exposure-Response Functions*

The researchers sourced the ERFs from the study by Héritier et al. (2017) after considering several epidemiological and meta-analysis studies that have been used (or discussed) in previous noise burden of disease assessments (Beelen et al., 2009a; Huss et al., 2010; Sørensen et al., 2011; Gan et al., 2012; Babisch, 2014; Halonen et al., 2015; Héritier et al., 2017; van Kempen et al., 2018).

The selection of the ERF in this study was based on three criteria. First, the selected ERF needed to associate noise with mortality and not morbidity, as in Sørensen et al. (2011). Second, since the researchers were investigating the detrimental health impacts of two transportation-related noise sources—road traffic and aviation—studies reporting ERFs for both sources were prioritized (Héritier et al., 2017; van Kempen et al., 2018). Considering the first and second criteria, the researchers excluded the studies that have not associated transportation-related noise to mortality and have not estimated ERFs for both aviation and road traffic noise (Beelen et al., 2009a; Huss et al., 2010; Sørensen et al., 2011; Gan et al., 2012; Babisch, 2014; Halonen et al., 2015). Among the studies that met the first and second criteria, Héritier et al. (2017) estimated ERFs for both aviation and road traffic noise using a mutual database. Moreover, van Kempen et al. (2018) synthesized ERFs from previous studies and estimated ERFs for different sources of noise. Third, the selected ERF needed to be compatible with the classification for the causes of death data as sourced from the CDC. To avoid underestimating the health outcomes of transportation-related noise, researchers selected the study that associated noise to mortality from a wider range of CVDs. Héritier et al. (2017) associated road traffic and aviation noise with mortality from a wide range of CVDs, with international classification of disease (ICD 10) codes ranging from I00 to I99 for road traffic noise, I21, I22, and I50 for aviation noise, and in line with the CDC definitions (CDC, 2017). Conversely, the study by van Kempen et al. (2018) only established the ERFs for some CVDs, offering a smaller range of health outcomes that included ischemic heart disease (I120–I125) and stroke (did not code by ICD 10). Thus, researchers selected the ERFs from the Héritier et al. (2017) study, which meets all three selection criteria: investigating noise and the risk of mortality, estimating ERFs for road traffic *and* aviation noise, and covering the widest range of CVD mortality.

Héritier et al. (2017) found statistically significant associations between exposure to road traffic and aviation noise and CVD mortality. Multipollutant models were used for estimating the ERFs, including linear terms for each noise source that controls for effect of the other source of noise. This study was a population-based cohort study conducted in 4.4 million adults, older than 30, in Switzerland, and for road traffic noise and aviation noise levels higher than 35 dB and 30 dB, penalized for the evening and nighttime ($L_{den}$[2]). The estimated ERFs were adjusted for a comprehensive set of potential confounders: sex, neighborhood index of socioeconomic position (low, medium, high), civil status (single, married, widowed, divorced), education level (compulsory education or less, upper secondary level education, tertiary level education, not known), annual average nitrogen dioxide ($NO_2$) concentration, mother tongue, and nationality. Based on the estimated ERFs for road traffic noise and CVD mortality, the RR was 1.025 (95 percent CI = 1.018–1.032) for each 10 dB increase in $L_{den}$. Respectively, the RR of MI and HF mortality for aviation noise was 1.027 (95 percent CI = 1.006–1.049) and 1.056 (95 percent CI = 1.028–1.085) for 10 dB increase in $L_{den}$. Researchers did not find statistically significant associations between aviation noise and CVD mortality and, as such, only investigated the burden of HF and MI attributable to aviation noise.

### *Overlap of Attributable Health Impacts*

Road traffic and aviation noise were both associated with MI and HF. Therefore, the estimated premature deaths from HF and MI attributable to road traffic and aviation noise may overlap. This overlap may result in double-counting premature deaths attributable to transportation-related noise in the studied area. In this work package, the researchers ran a supplementary analysis and examined the overlap between the MI and HF outcomes based on probability theory. Given that the researchers did not have information about the target population of the diseases, the double-counted premature deaths were approximated using addition rules in probability. For instance, the total risk of HF premature deaths from aviation and road traffic noise can be expressed as follows:

$$\mathrm{P}(M_A^{HF} \cup M_R^{HF}) = \mathrm{P}(M_A^{HF}) + \mathrm{P}(M_R^{HF}) - \mathrm{P}(M_A^{HF} \cap M_R^{HF}) \qquad \text{Equation 3}$$

where $\mathrm{P}(M_A^{HF})$ is the risk of HF premature death from aviation noise, which equals to the ratio of HF premature deaths from aviation noise and all-cause HF premature deaths in a census tract; $\mathrm{P}(M_R^{HF})$ is the risk of HF premature deaths from road traffic noise, which equals to the ratio of HF premature deaths from road traffic noise and all-cause HF premature deaths in a census tract; and $\mathrm{P}(M_A^{HF} \cap M_R^{HF}) = \mathrm{P}(M_A^{HF}) \times \mathrm{P}(M_R^{HF} | M_A^{HF})$, according to addition rules in probability (DeGroot and Schervish, 2012).

[2] The average sound level over a 24-hour period, with a penalty of 5 dB added for the evening hours (19:00 to 22:00) and a penalty of 10 dB added for the nighttime hours (22:00 to 7:00).

When multiple events occur, if the outcome of one event does not affect the outcome of the other events, they are called independent events (Milton and Arnold, 2002). Researchers used the RR for premature deaths associated with road traffic and aviation noise, which are estimated by controlling for the effect of the other source of transportation-related noise. Therefore, researchers assumed that the estimated risk of HF premature deaths from road traffic and aviation noise are independent. Given that the conditional probability of HF premature deaths from road traffic noise would be equal to the probability of HF premature deaths from road traffic noise ($\mathrm{P}(M_R^{HF}|M_A^{HF}) = \mathrm{P}(M_R^{HF})$), Equation 3 can be written as:

$$\mathrm{P}(\mathrm{M_A^{HF}} \cup \mathrm{M_R^{HF}}) = \mathrm{P}(\mathrm{M_A^{HF}}) + \mathrm{P}(\mathrm{M_R^{HF}}) - \mathrm{P}(\mathrm{M_A^{HF}}) \times \mathrm{P}(\mathrm{M_R^{HF}}) \qquad \text{Equation 4}$$

The term $\mathrm{P}(M_R^{HF}) \times \mathrm{P}(M_A^{HF})$ represents the overlap between the estimated risk of HF premature deaths from aviation and road traffic noise.

Based on the above theorem, the overlap between estimated premature deaths from aviation and road traffic noise can be calculated similarly for MI. Calculations showed that 2 (95 percent CI: 0–3) premature deaths attributable to HF and MI can be double-counted when the summation of premature deaths attributable to transportation-related noise in Houston is reported. The double-counted mortalities are relatively small compared to the existing uncertainties in the burden of disease analyses.

### *Noise Exposure Calculation and Conversion*

To assign noise exposures to the population living in each census tract, it was assumed that:

- The population was distributed evenly within each census tract since no information was available on the specific residential locations of the population within each census tract; nor did researchers have a detailed population grid.
- The mortality rate was constant within each census tract since the mortality rate, which was only available at the county level, was assigned to tracts proportionally based on their population size.

Given these assumptions, the population exposed to a given level of noise could be calculated by finding the area within a census tract that corresponds to each exposure level. For example, in Figure 4, the population living in areas $A_{N35}^1$ and $A_{N35}^2$ are exposed to aviation noise levels equal to 35 dB $L_{Aeq}$. The population living in the area $A_{N30}^1$, $A_{N40}^1$ and $A_{N45}^1$ are exposed to 30, 40, and 45 dB $L_{Aeq}$, respectively. The population exposed to the 35 dB $L_{Aeq}$ aviation noise can be estimated by:

$$P_{N35}^{Ci} = \frac{\sum_{n=1}^{N} A_{N35}^{n}}{A_{Ci}} \,.\, P^{Ci} \qquad \text{Equation 5}$$

where $P_{N35}^{Ci}$ represents the population at census tract $i$ ($C_i$) exposed to the noise level 35 dB $L_{Aeq}$. $A_{N35}^n$ is the *n^th^* area exposed to 35 dB $L_{Aeq}$, while *n* can vary from 1 to *N*. $A_{Ci}$ and $P^{Ci}$ represent the area and the population of the census tract $i$. The population exposed to other levels of noise can be estimated similarly using Equation 5. Since the noise data were only available for levels higher than 30 dB $L_{Aeq}$, noise exposures could not be estimated for the noise levels less than 30 dB $L_{Aeq}$, which are represented by the white areas in Figure 4.

Based on the constant mortality rate within a census tract assumption, the number of deaths can be estimated for each area. Note that because of the differences in the exposure levels, the $RR_{diff}$ is not consistent across the exposed areas within each census tract; therefore, the attributable mortality needs to be estimated separately for the areas with the different noise exposures, even within a census tract. ArcMap spatial analysis tools were used to determine the exposure levels and areas.

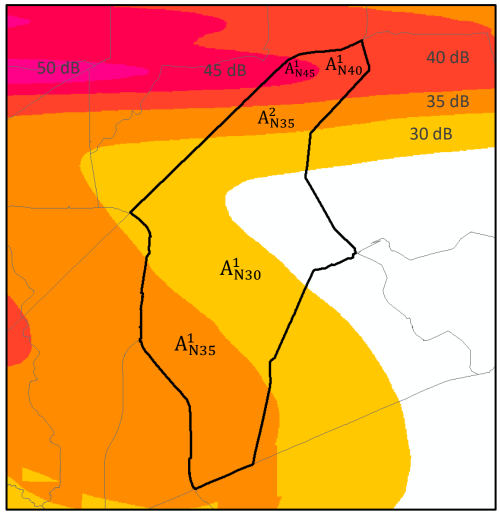



**Figure 4. Aviation Noise Exposure Levels in a Given Census Tract ($C_i$).**

The NTNMT reports noise exposure with $L_{Aeq}$. However, the ERFs selected for the burden of disease assessment associated CVD mortality with $L_{den}$. To convert $L_{Aeq}$ to $L_{den}$ *before* calculating the noise exposure, a suggested conversion guideline between noise indicators proposed by Brink et al. (2018) was used. In this context, the aviation and road traffic noise in $L_{Aeq}$ were converted to $L_{den}$ as follows:

$$L_{den}^{aviation} = L_{Aeq}^{aviation} + 3.5 \text{ (95\% CI} = 0.1\text{–}6.9) \qquad \text{Equation 6}$$

$$L_{den}^{road} = L_{Aeq}^{road} + 3.6 \text{ (95\% CI} = 2.2\text{–}5.0) \qquad \text{Equation 7}$$

### *Contrafactual Scenarios*

Given that the ERFs were originally estimated for exposures greater than 35 dB $L_{den}$ for road traffic noise and 30 dB $L_{den}$ for aviation noise, the counterfactual noise levels were selected accordingly. Therefore, the contrafactual scenarios were defined as:

- The daily average of road traffic noise level that did not exceed 35 dB $L_{den}$.
- The daily average of aviation noise level that did not exceed 30 dB $L_{den}$.

In this context, the attributable premature deaths were estimated for the difference between the current and counterfactual noise level of 35 dB $L_{den}$ for road traffic noise and 30 dB $L_{den}$ for aviation noise. In other words, it was assumed that the population exposed to noise levels less than 35 dB and 30 dB $L_{den}$ (road traffic and aviation noise, respectively) had no increased risk of CVD death.

### *Sensitivity Analyses*

Uncertainties are inherited in variables incorporated in the burden of disease assessment studies, mainly arising from uncertainty in the baseline health data, the exposure model predictions, and the selected ERFs, among others. To explore the range of uncertainties from the variables included in the analysis, including (1) the baseline mortality rates, (2) the ERFs, and (3) the conversion of the noise metrics, researchers ran two uncertainty analyses. First, the most conservative and most extreme burden of disease scenarios were estimated using the combinations of the lower and upper95 percent CI for each of the three variables named above. Second, the researchers reran the analysis for each variable *individually*. In this context, the burden of disease for the upper and lower 95 percent CI of each variable was estimated.

In addition to the abovementioned uncertainty analyses, a sensitivity analysis was run to better understand the relation between inputs and outputs of the burden of disease assessment. To this end, researchers examined the changes in the estimated attributable premature deaths using a 10 percent marginal change in exposure values of noise, baseline mortality rate, noise conversion, and the ERFs.

## Work Package 3: Quantifying Premature Mortality Attributable to Ambient Air Pollution and the Role of Socioeconomic Status

### Motivation and Contribution to the Literature

In this third work package, researchers quantified and analyzed the burden of disease attributable to air pollution in the form of premature deaths and also analyzed the spatial variation of estimated premature deaths across Houston to investigate the possible role of exposure to road traffic. The unequal distribution in health impacts of air pollution were examined in terms of population socioeconomics.

Mortality attributable to air pollution in urban areas has been quantified in a number of studies. One study in Bradford, United Kingdom, showed that the exposure to air pollution and its attributable burden of mortality inversely correlated with population socioeconomic status proxied by household income and with ethnic minorities (Mueller et al., 2018a). However, no study has formally investigated whether living in areas with a higher level of road traffic correlates with the spatial variation of air pollution health outcomes. Such an analysis can be used to demonstrate the significance of road traffic in the burden of disease estimates when running full-chain burden of disease assessment models is time consuming and cost intensive (Khreis et al., 2018).

From a methodological standpoint, previous burden of disease assessment studies share a similar methodology for quantifying the health burden that can be attributable to air pollution, much like the methodology reviewed in Work Package 2. Generally, the baseline exposure level is obtained and compared with either the level of exposure recommended by health authorities or a no-exposure scenario. Next, the RR of the detrimental health outcome is calculated for each exposure difference using ERFs extracted from the literature. Finally, the attributable health outcome for the population is estimated for each exposure difference using the baseline mortality rates and population data. The air pollution burden of disease analyses have been conducted at different spatial levels, including census tract level (Mueller et al., 2017a; Mueller et al., 2017b), neighborhoods (Kheirbek et al., 2016), lower super output area (Mueller et al., 2018a), and citywide estimations (Tainio et al., 2016). The spatial level of the analysis is often dependent on the availability of data. For example, Lelieveld et al. (2015) captured the contribution of air pollution to mortality for a 100 × 100 km spatial resolution. Air pollution data are often estimated using air quality models. Different studies used different pollutants, including particulate matter with a diameter of 2.5 micrometers ($PM_{2.5}$) (Mueller et al., 2018a; Mueller et al., 2015; Kheirbek et al., 2016), $NO_2$ (Mueller et al., 2018a; Brønnum-Hansen et al., 2018), and ozone ($O_3$) (Lelieveld et al., 2015), in which a higher burden of disease was attributed to $PM_{2.5}$ and $NO_2$ than to $O_3$. Air pollution burden of disease assessment studies in cities are mainly conducted in Europe. In the U.S., an analysis of the health impacts of air pollution by Goodkind et al. (2019) showed that $PM_{2.5}$ was responsible for 107,000 deaths in 2011. Kheirbek et al. (2016) estimated the burden of disease of traffic-related $PM_{2.5}$ in New York City and examined the relation between the estimated burden of disease and poverty at the neighborhood level.

For this work, a burden of disease assessment was run for two criteria air pollutants: $NO_2$ and $PM_{2.5}$. $NO_2$ and $PM_{2.5}$ are traffic-related pollutants that have been associated with stronger adverse health effects, including premature mortality. $NO_2$ is, however, considered more specific to TRAP. Air pollution concentrations were estimated by a land use regression (LUR) model and a universal kriging framework. Researchers quantified premature deaths that could be attributable to these exposures using a standard burden of disease assessment methodology separately for each pollutant.

As mentioned in the second work package, the finer the spatial resolution of the analysis, the better the insight into health inequality issues, contributors, and high-risk spots that can be effectively targeted by policies. Therefore, the analysis was run at the census tract level to capture spatial variations at a fine scale. To examine health inequalities, researchers compared the distribution of air-pollution-attributable health impacts by household median income across the city. Researchers also compared the burden of disease attributable to air pollution when complying with the WHO air pollutant guidelines versus the U.S. National Ambient Air Quality Standard (NAAQS) from the U.S. Environmental Protection Agency (U.S. EPA).

## Study Setting and Definitions

The burden of disease attributable to air pollution was quantified in Houston for the year 2010, the year for which air pollution models existed. Houston had 2,099,451 residents in 2010. Five hundred ninety-two census tracts that were fully or partially located within Houston city's boundaries were included in this study.

The life expectancy in the U.S. was 78.7 years old in 2010 (Murphy et al., 2013). The risks of mortality in association with $NO_2$ and $PM_{2.5}$ were sourced from meta-analysis studies for individuals older than 30 years old (details are provided in subsequent sections). Hereafter, the term premature death refers to the death of individuals aged 30 to 78 years old who died in a non-accidental or suicidal manner.

## Input Data

The data used in this study were collected from multiple sources—namely, the U.S. Census Bureau, CDC, and TxDOT, as described in the following sections.

### *Population, Socioeconomic, and Geographic Data*

Population and socioeconomic data were collected from the U.S. Census Bureau for 2010 at the census tract level, along with the census tracts' geographic characteristics. Researchers stratified the estimated burden of disease by the median household income at the census tract level, as sourced from the U.S. Census Bureau. The average households' median income in Houston in 2010 was 52,857 dollars. Houston geographical limits were sourced from the city's open data portal, which was used to identify the census tracts within the city's boundaries (retrieved from https://cohgis-mycity.opendata.arcgis.com/datasets/houston-city-limit).

### *Mortality Data*

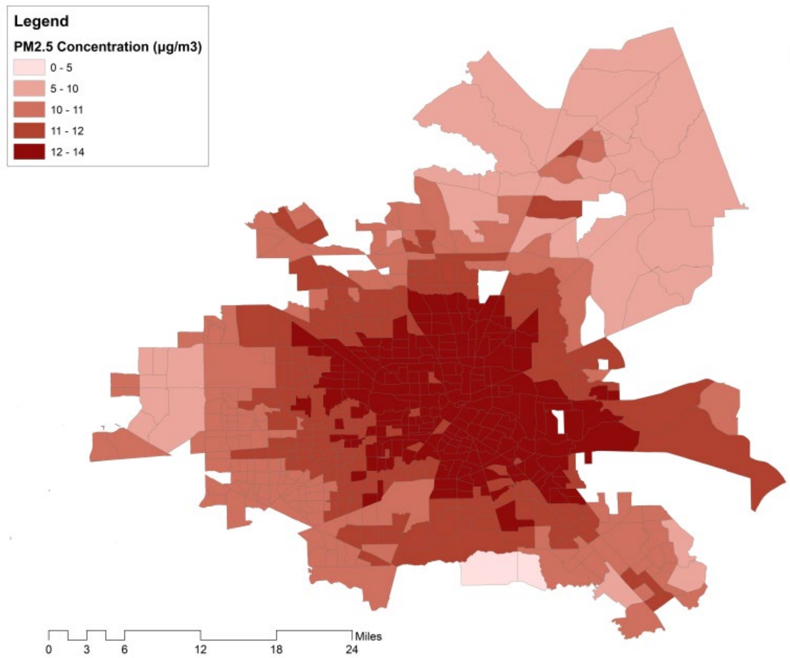
The baseline mortality data for Texas in the year 2010 were sourced from the CDC (retrieved from https://wonder.cdc.gov/mcd.html). The mortality data were available both in the form of the number of deaths and crude mortality rates at the county level, with 95 percent CI. To quantify premature deaths attributable to air pollution, the number of all-cause natural deaths for people aged 30–78 years old was used in this study. Given that Houston is located in three counties—Harris, Fort Bend, and Montgomery—the mortality data for these three counties were collected. The number of mortality cases (available at the county level) were distributed across census tracts proportionally based on their population size. In 2010, a total number of 8,667 all-cause premature deaths (natural deaths excluding accidental mortalities) were reported in Houston (30–78 years old).

### *Pollution Data*

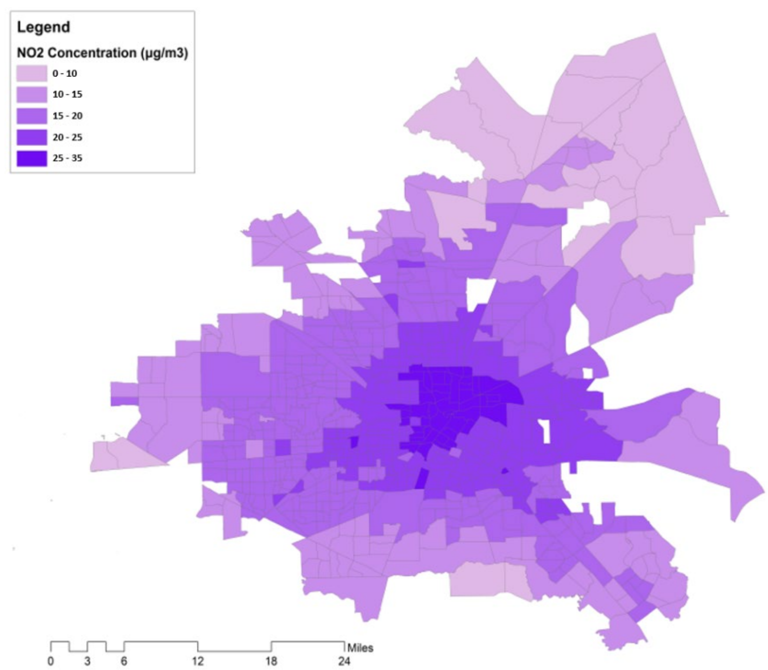
$NO_2$ and $PM_{2.5}$ concentrations were sourced from a previously published and validated LUR model and a universal kriging framework, also employed in a previous CARTEEH study (Alotaibi et al., 2019). Researchers used the annual average concentrations in $\mu g/m^3$ for the year 2010 at the centroid of each census tract. The data were originally estimated at the centroid of the census blocks that are one level smaller than census tracts. The area-weighted average of concentrations at census blocks (that are contained within each census tract) were assigned to census tracts. $NO_2$ concentrations were converted from ppb to $\mu g/m^3$ through multiplying by 1.88 (WHO, 2006). The spatial distribution of the two pollutants is shown in Figure 5. The following paragraphs briefly discuss the models used for estimating $NO_2$ and $PM_{2.5}$ concentrations.

The $NO_2$ estimates were obtained from a LUR model developed by Bechle et al. (2015). In brief, the model uses satellite data and U.S. EPA air quality monitor readings of $NO_2$ concentrations alongside several covariates (e.g., impervious surfaces, elevation, major roads, residential roads, and distance to the coast) to estimate $NO_2$ concentrations. The final model used has a relatively high predictive power at unmeasured locations that was tested using a holdout cross-validation with good model performance ($R^2$ = 0.82) comparable with other continental-scale $NO_2$ LUR models (Beelen et al., 2009b; Hystad et al., 2011; Vienneau et al., 2013).

On the other hand, annual average concentrations of $PM_{2.5}$ were estimated using data from 17 years (1999–2015). The data were derived from regulatory monitors, and estimates were constructed in a universal kriging framework (Kim et al., 2020). Partial least squares were estimated for model performance from hundreds of geographic variables, including land use, population, and satellite-derived estimates of land use and air pollution. Holdout cross-validation indicated good model performance (10-fold CV−$R^2$ = 0.85). Annual $PM_{2.5}$ concentrations were estimated at the census tract centroids (with similar procedures as were described above).




**(a)**




**(b)**

**Figure 5. (a) PM2.5 and (b) NO2 Annual Average Concentrations across Houston at the Census Tract Level in 2010.**

### *Road Traffic*

In this study, the annual average daily vehicle mile traveled per area (VMTA) was used to investigate the relation between road traffic and the air pollution health burden at the census tract level. VMTA represents the density of vehicle mile traveled (VMT) at a census tract level. The VMT was calculated by aggregating the multiplication of the road segment length and ADT passing through all road segments located within a census tract. Then, the VMT was divided by the census tract's area. Equation 8 shows the VMTA calculation for each census tract:

$$VMTA = \frac{ADT.Road\ Length}{Census\ Tract\ Area}\left(\frac{veh.mi}{mi^2}\right) \qquad \text{Equation 8}$$

In addition to roads located within the census tract, the possible impacts of roads near the census tract's boundary were considered. According to WHO, $PM_{2.5}$ and $NO_2$ concentrations decrease to background concentrations within 100–150 m (328–492 feet) of a roadway (Goldstone, 2015). Consequently, researchers included the VMT passing through all roads within 492 feet of the census tract's boundary to estimate the VMTA of that census tract.

The researchers identified the roads located within 492 feet of the census tract boundary using ArcGIS and included those in VMTA calculations. Road network and ADT data were sourced from the Texas roadway inventory data by TxDOT (https://www.txdot.gov/inside-txdot/division/transportation-planning/roadway-inventory.html). The data were not available for 2010; therefore, the ADT data from 2011 were used. Researchers assumed that the spatial distribution of road traffic across census tracts was consistent between 2010 and 2011. A summary of road traffic statistics is presented in Table 2.

**Table 2. Summary Statistics of Input Data.**

| Variable | Sample Size (Census Tracts) | Min. | Median | Mean | Max. |
|---|---|---|---|---|---|
| All-cause premature deaths (persons) | 592 | 1 | 14 | 15 | 61 |
| $NO_2$ concentration (μg/m$^3$) | 592 | 7.47 | 19.38 | 19.52 | 34.09 |
| $PM_{2.5}$ concentration (μg/m$^3$) | 592 | 6.80 | 11.61 | 11.41 | 13.30 |
| VMTA (veh.mi/mi$^2$) | 592 | 0.72 | 99.27 | 163.04 | 1077.54 |
| Median household income (dollar) | 592 | 9926 | 43,352 | 52,857 | 214,861 |

### *Burden of Disease Assessment Model*

A standard burden of disease assessment framework was used, as previously described in Work Package 2. In brief, the inputs to the burden of disease assessment model included the $NO_2$ and $PM_{2.5}$ concentrations, as well as the baseline all-cause death rate in the studied region. Next, the $\mathrm{RR}_{\mathrm{diff}}$ of all-cause mortality in association with the difference between current concentrations and the counterfactual concentrations were estimated, as shown in Equation 9.

$$\mathrm{RR}_{\mathrm{diff}} = \mathrm{RR} \times \frac{(\mathrm{E}_{\mathrm{current}} - \mathrm{E}_{\mathrm{counterfactual\ exposure}})}{\mathrm{RR}_{\mathrm{unit}}} \qquad \text{Equation 9}$$

where $RR$ is the RR as extracted from the literature, $E_{current}$ represents the current concentration level, $E_{\mathrm{counterfactual\ exposure}}$ represents the counterfactual exposure level, and $RR_{unit}$ is the exposure unit of RR obtained from the original ERFs. Then, the PAF was calculated similarly to Work Package 2. Finally, the attributable deaths were estimated using the mortality rate and population counts for people aged 30–78 years old and using the estimated PAF, similar to Work Package 2. The employed burden of disease assessment framework is depicted in Figure 6. This procedure was used for estimating the attributable premature deaths across the 592 census tracts separately for each pollutant.

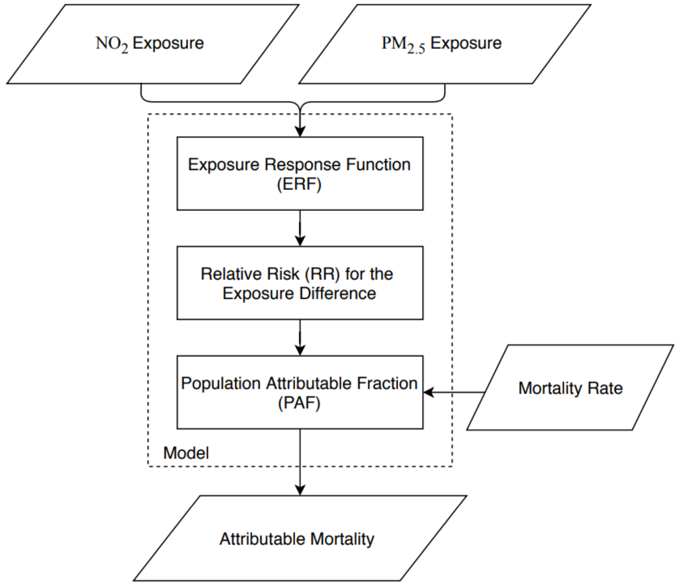



**Figure 6. Burden of Disease Assessment Framework: Work Package 3.**

### *Exposure-Response Functions*

The researchers extracted the ERF for $NO_2$ and $PM_{2.5}$ from two meta-analyses. The first meta-analysis included data from 22 cohort studies with a total of 367,251 participants and was used for the ERF of $NO_2$ and mortality (Beelen et al., 2014). Based on the documented ERF, which associated natural deaths with $NO_2$, the RR of deaths per 10 μg/m$^3$ $NO_2$ was estimated as 1.02 (95 percent CI: 0.99–1.04) for individuals older than 30 years. This RR was adjusted for sex, calendar time, smoking status, smoking intensity, smoking duration, environmental tobacco smoke, fruit intake, vegetable intake, alcohol consumption, BMI, educational level, occupational class, employment status, marital status, and area-level socioeconomic status (Beelen et al., 2014). Note that the lower limit of the RR, 0.99, implies that no adverse health effect is associated with 10 μg/m$^3$ increase in $NO_2$ exposure.

The ERF for $PM_{2.5}$ was extracted from a meta-analysis by WHO (2014). This meta-analysis was performed on 14 studies and resulted in RR for different regions. For the U.S., using a linear ERF, the overall RR of natural deaths associated with $PM_{2.5}$ was estimated as 1.07 (95 percent CI: 1.02–1.12) per 10 μg/m$^3$ for individuals 20 years and older. The RR was not adjusted for the impact of $NO_2$, and as such, researchers estimated the burden from both pollutants separately and emphasize that these numbers should not be added up.

### *Counterfactual Scenarios*

Premature deaths attributable to air pollution were estimated for three counterfactual scenarios:

- Zero exposure of the population to air pollution.
- Air pollution concentrations complying with the WHO air quality guideline values, where in exceedance.
- Air pollution concentrations complying with the U.S. NAAQS, where in exceedance.

In the first scenario, the current concentrations, as estimated from the air pollution models, were compared to zero concentrations to demonstrate the overall burden of disease of ambient air pollution in the city. Note that the zero-exposure scenario is not a realistic scenario and is only defined for comparison purposes. In the second scenario, the current concentrations were compared to the WHO air quality guideline values. WHO recommends that $NO_2$ does not exceed 40 μg/m$^3$ annual mean and $PM_{2.5}$ does not exceed 10 μg/m$^3$ annual mean (WHO, 2006). In the third scenario, researchers compared the current concentrations with the U.S. NAAQS established by U.S. EPA. The NAAQS annual average limits for $NO_2$ and $PM_{2.5}$ are 99, and 12 μg/m$^3$, respectively (U.S. EPA, 2016a). The

RR of mortality in association with $NO_2$ and $PM_{2.5}$ was rescaled for the difference between the current concentration levels and the counterfactual concentration levels.

### *Sensitivity Analyses*

Uncertainties are inherent in variables incorporated into burden of disease assessment studies, mainly arising from the uncertainty in the baseline health data and the selected ERFs, among others. To explore the range of uncertainty from the variables included in the analysis, including the baseline mortality and ERFs, two uncertainty analyses were run. First, the most conservative and most extreme burden of disease scenarios were estimated using the combinations of the lower and upper 95 percent CI for each of the variables above (baseline mortality and ERFs). These two scenarios are reported in parentheses after the central estimated values of premature deaths attributable to air pollution. Second, the researchers examined the impacts of uncertainty in input data for each variable on premature death estimations, individually reran the analysis for the lower and upper 95 percent CI of each variable and reported the estimated premature deaths.

# Results

## Work Package 1: The Conceptual Model and Literature Review Results

### Overview

The conceptual model developed in this work package is meant to detail how transportation factors influence health through numerous beneficial and detrimental interlinked pathways that are recognized in the literature to varying extents. By highlighting the complex intersectionality of transportation and health and the wide range of pathways and health outcomes associated with transportation, this model is intended to:

- Guide future research to further explain and understand the health outcomes of transportation.
- Evaluate the impact of transportation on public health.
- Guide future practice and policy to consider and address these issues holistically.
- Promote awareness and increase the focus on pathways and health issues associated with transportation.
- Promote cross-disciplinary education, training, and workforce development across transportation and health.
- Highlight the importance of cross-disciplinary approaches to prepare researchers, practitioners, and policy makers to resolve transportation-related health issues.
- Highlight the necessity of systemic reforms to transportation and health rather than a *one exposure–one outcome–one intervention* approach, which often fails to account for the entirety of public health issues or introduces narrow focuses and negative consequences.
- Foster research in the area of cumulative risk assessment, which seeks to elucidate the health impacts of complex exposures to chemical or physical hazards and nonchemical or social stressors.

Figure 7 shows the conceptual model proposed to define the relationship between transportation and public health. Land use and the built environment, transportation infrastructure, transportation mode choice, and emergent and disruptive technologies all influence the transportation systems and patterns in an urban area. As such, the purple diamond labeled *transportation* is an umbrella term that encompasses the four interrelated factors displayed in the four boxes above it. The distinct framing of transportation is not to suggest that it is a separate entity from those four factors but rather to communicate that transportation is the cumulative result of interactions between these four factors.

This conceptual model identifies 14 pathways that link transportation to health outcomes of morbidity and premature mortality. The pathways beneficial to health are colored blue on the left side of the dotted line while those detrimental to health are colored yellow on the right side. The model acknowledges the impact of inequity and intrinsic and extrinsic characteristics that influence the exposure to, and severity of transportation-related health outcomes within a community.

Table 3 is a consolidated list of all the health outcomes associated with each pathway that were identified in the nonsystematic literature review. The next section defines and discusses each of the pathways independently and lists their associated health outcomes as shown in Table 3.

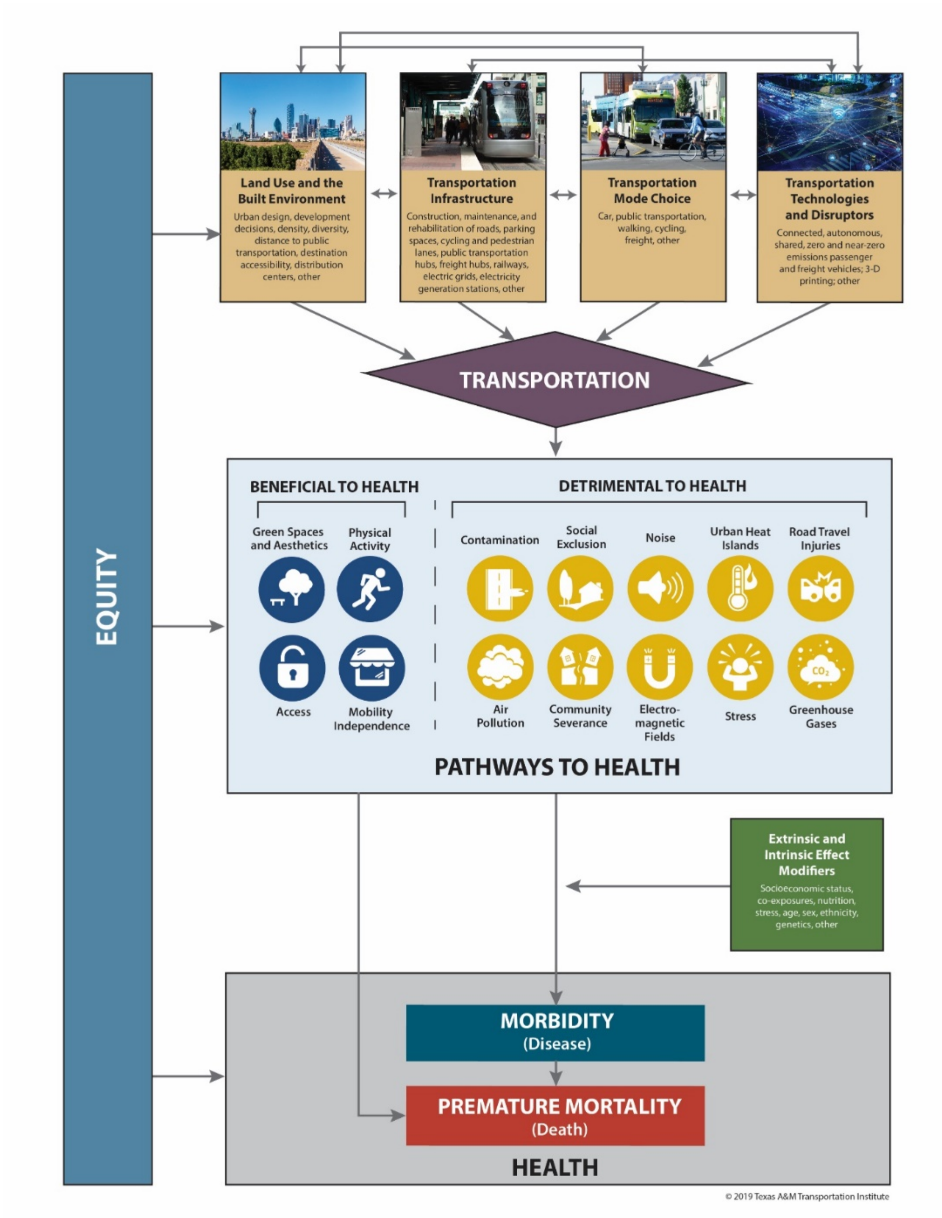



**Figure 7. Conceptual Model of the Linkages between Transportation and Health.**

**Table 3. Public Health Outcomes Associated with Transportation-Related Pathways.**

| 1. Green Spaces, Blue Space, and Aesthetics | Pathway Definition |
|---|---|
| Decreased risk of all-cause and premature mortality | Green space is land that is partially or completely covered with grass, trees, shrubs, or other vegetation that is accessible to the public. Blue space refers to space covered by water, including ponds, streams, rivers, lakes, seas, and oceans. Urbanization trends prioritize land use for transportation and related infrastructure over green spaces, which have measured health benefits for urban populations. Within the context of transportation, aesthetics refers to the visual integration of transportation facilities into the surrounding landscape, which can elicit positive and negative health effects depending on the scale of visual integration. Health benefits from green spaces can also arise due to improved physical activity (see health benefits from physical activity). |
| Decreased risk of respiratory disease | |
| Decreased risk of cardiovascular disease (including stroke) | |
| Decreased risk of high blood pressure | |
| Decreased risk of type-2 diabetes | |
| Decreased risk of stress | |
| Decreased risk of anxiety | |
| Improved immune function | |
| Improved cognitive function | |
| Improved mental health | |
| Improved sleep patterns | |
| Improved pregnancy outcomes | |
| Improved self-reported health | |
| **2. Physical Activity** | **Pathway Definition** |
| Decreased risk of premature mortality | Physical activity is the movement of the body that requires energy expenditure. Physical activity can be inhibited due to motorized transportation dependence and can be increased by walking, cycling, or using public transportation. |
| Decreased risk of cardiovascular disease (including stroke and ischemic heart disease) | |
| Decreased risk of hypertension | |
| Decreased risk of cancer | |
| Decreased risk of diabetes | |
| Decreased risk of obesity | |
| Decreased risk of cognitive decline and dementia (including Alzheimer's disease) | |
| Decreased stress | |
| Decreased risk of mental health problems (including anxiety and depression) | |
| Improved mental well-being | |
| **3. Access** | **Pathway Definition** |
| Decreased risk of all-cause mortality | Access refers to the ability of individuals to reach essential goods and services, such as health facilities and services, healthy food, green space, physical activity facilities, jobs, and education, utilizing various transportation modes. |
| Decreased risk of cardiovascular disease | |
| Decreased risk of cancer | |
| Decreased risk of inadequate nutrition | |
| Decreased risk of obesity | |
| Decreased risk of mental health decline | |
| **4. Transportation Independence** | **Pathway Definition** |
| Improved mental well-being | Transportation independence is the ability to utilize various transportation modes to access commodities and neighborhood facilities and participate in social, cultural, and physical activities without assistance or supervision. |
| Improved motor skills development | |
| Improved self-esteem | |
| Improved QOL | |
| Sustained cognitive ability | |
| **5. Contamination** | **Pathway Definition** |
| Hypertension | Contamination refers to oils, gasoline, heavy metals, PM, lead, and PAHs that are chemicals and pollutants found on roadway surfaces due to motor vehicle traffic. They can contaminate water sources, soils, and the air, potentially ending up in what humans eat, drink, and come into contact with. |
| Low blood pressure | |
| Renal dysfunction (including kidney failure) | |
| Liver failure | |
| Premature birth | |
| Low birthweight | |
| Abdominal pain | |
| Nausea | |
| Ulcers | |
| Fatigue | |
| Headache | |

| | |
|---|---|
| Memory loss | |
| Sleeplessness | |
| Depression | |
| Arthritis | |
| Rashes | |
| **6. Social Exclusion** | **Pathway Definition** |
| Premature mortality<br>Cardiovascular disease<br>Mental health problems<br>Stress | Social exclusion refers to the culmination of transportation-related inhibitions and/or deprivations—affordability, accessibility, availability, geographical location, time, and fear—that limit the opportunity to participate in normal activities. Adverse health effects from social exclusion can also arise due to reduced physical activity (see health benefits from physical activity) and from inadequate income, where social exclusion prevents employment. |
| **7. Noise** | **Pathway Definition** |
| Cardiovascular disease (including stroke, heart attack, and other ischemic heart diseases)<br>Hypertension<br>Diabetes<br>Obesity<br>Exacerbation of asthma<br>Reproductive complications (including premature birth and low birth weight)<br>Cognitive impairment<br>Disruption to concentration and educational attainment<br>Mental health problems<br>Stress<br>Annoyance<br>Sleep disturbance | Noise refers to motorized vehicle sounds at levels that are detrimental to health. |
| **8. Urban Heat** | **Pathway Definition** |
| Premature mortality<br>Cardiovascular disease (including stroke and arrhythmia)<br>Hypertension<br>Respiratory disease (including COPD and asthma)<br>Diabetes<br>Premature birth<br>Heat stress<br>Hospitalizations | UHIs are urban areas with increased heat in comparison with rural areas. In these urban areas, heat is produced by heat-absorbing asphalts and concretes used for transportation infrastructure. Urban heat can also lead to adverse health effects from increased motor vehicle crashes (see health effects from motor vehicle crashes). |
| **9. Road Travel Injuries** | **Pathway Definition** |
| Premature mortality<br>Injury<br>Hospitalizations | A motor vehicle crash is any incident involving a motor vehicle that may result in death, injury, or disability. Road travel injuries can also occur when no motor vehicle is involved—for example, when falling during walking or cycling or when these transportation users crash. |
| **10. Air Pollution** | **Pathway Definition** |
| Premature mortality<br>Cardiovascular disease (including stroke, arrhythmia, congestive HF, and heart attack)<br>Deep venous thrombosis<br>Cancers (especially lung cancer)<br>Respiratory diseases and infections (including COPD, childhood asthma, and pneumonia)<br>Respiratory inflammation<br>Allergies<br>Diabetes<br>Obesity | Air pollution refers to the emission and dispersion of toxic substances into the air. Air pollution results from motor vehicle exhaust and non-exhaust emissions, in addition to the formation of secondary pollutants in ambient air. |

| | |
|---|---|
| Reduced sperm quality | |
| Premature birth | |
| Low birthweight | |
| Congenital anomalies | |
| Autism and child behavior problems | |
| Dementia | |
| Neurodegenerative disease | |
| Mental health problems | |
| Bone conditions | |
| Fungal infection | |
| **11. Community Severance** | **Pathway Definition** |
| Premature mortality | Community severance refers to transportation infrastructure and/or motorized traffic that divides space and people and interferes with the ability of individuals to access goods, services, and personal networks. It can also limit social interaction and reduce transportation independence. |
| Cardiovascular disease | |
| Mental health problems | |
| Stress | |
| **12. Electromagnetic Fields** | **Pathway Definition** |
| Adverse and beneficial impacts regarding:<br>Cell growth<br>Genes<br>Neural system<br>Immune system<br>Circulatory system<br>Endocrine system | An electromagnetic field is comprised of moving electrically charged particles. The differences in voltage from transportation-related technology and infrastructure can create electromagnetic fields. |
| Behavioral development issues in children | |
| Cognitive development issues in children | |
| Nerve tissue stimulation | |
| Reproductive complications | |
| Retinal phosphene occurrence | |
| **13. Stress** | **Pathway Definition** |
| Stroke | Stress is the body's response to any demand. It may result from increased travel times, congestion, searching for parking, interaction with other drivers, and safety. |
| Heart disease | |
| Hypertension | |
| High cholesterol | |
| Obesity | |
| Mental health problems | |
| Depression | |
| Anxiety | |
| Insomnia | |
| Substance abuse | |
| Unhealthy diet | |
| **14. Greenhouse Gases** | **Pathway Definition** |
| Premature mortality | Greenhouse gases are select gases—carbon dioxide, methane, nitrous oxide, and fluorinated gases—that trap heat in the atmosphere and contribute to climate change and associated extreme weather events, more intense heat waves, and drought. Greenhouse gases can also lead to adverse health effects from increased urban heat and worsened air pollution (see health effects from urban heat and air pollution). |
| Physical injury | |
| Adverse mental and physical health outcomes | |
| Change in vector-pathogen relations and vector-borne disease | |
| Poor nutrition | |

## Pathways to Health

### *Green and Blue Spaces and Aesthetics*

Green space is land that is partially or completely covered with grass, trees, shrubs, or other vegetation accessible to the public (U.S. EPA, 2017a), and blue space refers to space covered by water, including ponds, streams, rivers, lakes, seas, and oceans (Gascon et al., 2015). Aesthetics refers to the visual integration of transportation facilities into the surrounding landscape (TxDOT, 2009). Green and blue space views can be blocked by urban transportation facilities, infrastructure, and construction, which can degrade the aesthetics of an area (TxDOT, 2009).

Green spaces mitigate the adverse effects of harmful, transportation-related environmental exposures like UHIs, air pollution, and noise (Hartig et al., 2014; de Vries et al., 2013). As some cities begin to encourage nonmotorized travel, some transportation infrastructures such as highways and parking lots may no longer be necessary and an opportunity to increase green space may exist. Such is the case in Hamburg, Germany, where car-free policies are being gradually implemented (Nieuwenhuijsen and Khreis, 2016). The more typical occurrence, however, is that urban growth, which includes the expansion of transportation infrastructure, results in the loss of green space (WHO, 2016).

In addition, green space and aesthetics may contribute to physical activity through active commuting (Wahlgren and Schantz, 2014), although it is important to acknowledge that some evidence suggests that the presence of green space alone might not significantly affect physical activity (Hogendorf et al., 2019). Safety and the quality of green space are the most influential factors in determining activity levels (Hartig et al., 2014; de Vries et al., 2013). One systematic review of literature examining the connection between nature and health found inconsistent associations between childhood active transportation and green spaces, often due to parental perceptions of safety and park accessibility (Ding et al., 2011). Inconsistent relationships between active transportation and green spaces were shown for older individuals as well (Hartig et al., 2014). Notably, pleasant aesthetics contribute to feelings of safety and comfort (Lovasi et al., 2009).

Views of natural aesthetics have long been associated with improved health, beginning with the seminal report that documented the difference in hospital patients' recovery due to the view of natural aesthetics or brick walls outside their hospital windows (Ulrich, 1984). FHWA has produced guidelines for visual impact assessments (VIAs) that measure the impact of highway construction on aesthetics (FHWA, 2015). By utilizing a VIA, the adverse visual effects of highway construction, which may include a reduction in green space or increased community severance, are expected to be mitigated or otherwise minimized to avoid negative health outcomes caused by transportation-related construction.

Studies have associated green space with many health benefits, including decreased risk of all-cause mortality (Rojas-Rueda et al., 2019), stroke and other cardiovascular diseases, respiratory diseases, premature mortality (Gascon et al., 2016), stress, anxiety (Gascon et al., 2015; Zijlema et al., 2018), type-2 diabetes, and high blood pressure (Twohig-Bennett and Jones, 2018). Green space has also been associated with improved mental health (Zijlema et al., 2018), physical activity (Gascon et al., 2016), improved cognitive function, (Kondo et al., 2018), immune function (Egorov et al., 2017), sleep patterns (Astell-Burt et al., 2013), pregnancy outcomes, and self-reported health (Twohig-Bennett and Jones, 2018). Associations between blue space access, physical activity, and mental health have also been determined to be positive (Gascon et al., 2017; Völker and Kistemann, 2015; Völker et al., 2018). However, urban sprawl is reducing the per capita share of green space in many cities (Fuller and Gaston, 2009). Overall, investment in green spaces is lagging; for example, the 100 largest cities in the U.S. spent a combined $7 billion in 2019 (The Trust for Public Land, 2019) to maintain and enhance park land, a small fraction of the $44.7 billion budget of FHWA in the same year (FHWA, 2019).

### *Physical Activity*

Physical activity refers to body movement requiring energy expenditure. In contrast, physical inactivity refers to a lack of body movement and is considered a public health crisis due to its role in the obesity epidemic and contribution to numerous other diseases (Khreis et al., 2016). Land use policies that promote high density, connectivity, and active transportation infrastructure can boost physical activity (Panter et al., 2016; Rafiemanzelat et al., 2017). For example, the *complete street* is a design concept that aims to integrate active transportation in urban spaces that were previously incompatible (Litman, 2015). Modal diversity for transportation can increase physical activity due to the incorporation of active transportation in the daily commute (Costa et al., 2015; Frederick et al., 2018). In a review of 148 U.S. cities, Frederick et al. (2018) found that modal diversity is inversely associated with obesity and physical inactivity. Populations living in counties with high transportation modal diversity expressed lower obesity rates (25.2 percent versus 30.8 percent in automobile-dependent counties), a smaller share of physically inactive residents (19.4 percent versus 25.9 percent in automobile-dependent counties), and 1,400 fewer years of life lost per 100,000 inhabitants compared to populations in automobile-dependent counties (Frederick et al., 2018). Although driving increases the likelihood of a sedentary lifestyle and more disease (Frederick et al., 2018), active transportation contributes to a more physically active lifestyle and lower BMI (Flint and Cummins, 2016; Martin et al., 2015), with minor risks posed by air pollution exposure or motor vehicle crashes (Mueller et al., 2015). Investing in quality active travel infrastructure has been estimated to significantly improve active travel rates. A health impact assessment study of 167 European cities suggested the modal share of cycling could rise precipitously—as high as 25 percent of all trips—if cycling networks were expanded (Mueller et al., 2018b). Furthermore, electric bikes, or *e-bikes*, have been found to promote active travel and increase cardiovascular health benefits (Hoj et al., 2018). However, trips that are shifted from conventional bicycles to electric bikes typically require less physical activity (Bourne et al., 2018). Still, individuals who shift to electric bikes tend to ride further distances than those who use conventional bicycles (Sundfør et al., 2020). This form of emerging technology is beneficial for decreasing transportation time, increasing convenience (and potentially ridership), and limiting physical fatigue compared to traditional bikes (Hoj et al., 2018).

Support for autonomous vehicles (AVs) has increased after examining car-sharing efficiency (Fagnant and Kockelman, 2015). The ability to perform tasks other than driving while in an AV reduces the cost of using motor vehicles and incentivizes vehicle usage. The potential safety issues presented by AVs, specifically for active transportation users (Sandt and Owens, 2017), are discussed further in the Road Travel Injuries section of this report, but one major concern is that AVs may discourage physical activity. Moreover, since AV-sensing technology is still being developed, all road users will need to adjust to the operation of AVs in shared street spaces.

Additional barriers to physical activity include violence (fear of assault, for example), high-density traffic, poor air quality, and a lack of parks, sidewalks, and recreational facilities (WHO, 2018b). Physical inactivity has been associated with various mental health problems, including dementia and Alzheimer's disease (Hamer and Chida, 2009); cardiovascular disease, including ischemic heart disease and stroke (Kyu et al., 2016); premature mortality; obesity (Mueller et al., 2015); cancer; diabetes (Kyu et al., 2016); stress (Cohen et al., 2014); and hypertension (Diaz and Shimbo, 2013). Physical inactivity is a leading contributor to global mortality, resulting in 3.2 million global deaths annually (WHO, 2018b). On the other hand, physical activity can sustain cognitive capabilities and improve mental well-being by lowering the risk of depression and anxiety (Smith et al., 2017; Anderson and Shivakumar, 2013). Health experts recommend 150 minutes of moderate exercise per week (or 75 minutes of vigorous activity weekly), a recommendation that was not met by 28 percent of adults worldwide in 2016, with higher levels of noncompliance displayed in higher-income countries (WHO, 2018c).

### *Access*

In this report's context, *access* is defined as the ability for individuals to reach jobs, education, goods, and services—including health facilities and services, public transportation, healthy food, green and/or blue space, social networks (including family), and leisure facilities (Litman, 2018). The ability to access these elements is a key factor for mitigating social exclusion (Allen, 2008). Several strategies to increase accessibility include built environment and land use interventions, such as complete streets (Litman, 2015), densification, and transit-oriented development (Renne et al., 2016). These strategies may decrease the distance to public transportation and increase active transportation rates, thus reducing morbidity and mortality (Nieuwenhuijsen, 2018). On the other hand, accessibility poverty refers to increased transit time and costs that limit access and may lead to the exacerbation of issues like social exclusion and community severance (Lucas et al., 2016), which in turn lead to adverse health outcomes of their own, including adverse mental health outcomes (Cohen et al., 2014).

In Britain, people with disabilities took 30 percent fewer trips (one-way course of travel with a single main purpose) than people without disabilities in 2014 (UK Department of Transportation, 2014). Over 80 percent of people with disabilities noted the most common issue with using buses was getting to the bus stop (UK Department of Transportation, 2014). Further, about 18 percent and 12 percent of disabled commuters commented that the most difficult destinations to reach when traveling were the hospital and the doctor, respectively (UK Department of Transportation, 2014). In addition, 77 percent of job seekers in Britain do not have regular access to a motor vehicle (Johnson et al., 2014), and 34 percent of British households indicated poor accessibility to bus and rail services (Heinen and Chatterjee, 2015). Moreover, the cost of public transportation is cited as a barrier for 25 percent of people ages 18 to 24 and 21 percent of people over 50 (Johnson et al., 2014). For people 65 and older, participating in activities outside the home can result in higher levels of well-being (Ravulaparthy et al., 2013), so it is beneficial to them when they have the ability to travel to these activities.

The association between travel time and travel distance to healthcare services and patients' health outcomes was investigated in a systematic review of 108 studies (Kelly et al., 2016). The authors concluded that an association exists between living further away from health care and worse health outcomes, including survival rates, length of stay in the hospital, and not attending a follow-up appointment (Kelly et al., 2016). Similar transportation barriers were found to impede access to pharmacies for medicine (Syed et al., 2013).

Another concern relates to access to healthy food. *Food deserts* are defined as neighborhoods with low spatial and economic access to healthy and affordable food options (U.S. Department of Agriculture, 2014). Two studies measured accessibility to healthy food by public transit in Cincinnati, Ohio (Widener et al., 2015; Farber et al., 2014). They found that accessibility to healthy food could be unpredictable for people dependent on public transportation due to the variability of public transportation services, which leaves individuals who do not live within walking or cycling distance of a grocery store or have access to a private vehicle vulnerable to inadequate nutrition. Food deserts have been linked to adverse health outcomes, including obesity (Ghosh-Dastidar et al., 2014). Furthermore, consumption of fruits and vegetables decreases the risk of several types of cancer (Higdon et al., 2007), cardiovascular disease (Bazzano et al., 2002), and protects against adverse health effects of air pollution (Barthelemy et al., 2020), but access to these foods are limited in food deserts. However, several studies suggest that relationships between food deserts and health outcomes are inconsistent (An and Sturm, 2012; Dubowitz et al., 2015; Holsten, 2009; Lee, 2012); therefore, more research in this area is warranted.

### *Mobility Independence*

Mobility independence is the ability to utilize various transportation modes to access commodities and neighborhood facilities and participate in meaningful social, cultural, and physical activities without assistance or supervision (Rantanen, 2013). Quality of life (QOL) is impacted by six factors, one of which is the level of independence (WHO, 1997). Therefore, poor mobility independence may influence poor QOL.

The elderly and children are population groups that may be dependent on capable individuals for transportation assistance due to declining/developing motor skills and awareness. A systematic review of qualitative studies in the United Kingdom highlighted the importance of mobility independence for populations over 60 years old in rural areas (Graham et al., 2018). Graham et al. (2018) highlighted that the ability to travel independently enabled elderly people to be self-reliant and socially connected. Furthermore, mobility independence promotes healthy aging through physical activity and engagement in community activities, which sustain cognitive ability (Rantanen, 2013). Mobility independence may also positively influence mental well-being and self-esteem (Mindell and Karlsen, 2012). To maintain adequate levels of mobility independence for the elderly, accessible, safe, reliable, and affordable alternative and independent modes of transportation need to be provided in place of driving, if and when those populations need to rely on other modes (Shrestha et al., 2017). Children's rates of independent active transportation were reported to be higher in areas where parents perceived more land use diversity, higher residential density, shorter distances to school, road safety, and available walking/cycling infrastructure (De Meester et al., 2014). The built environment, transportation infrastructure, and mode choice all influence mobility independence (Marzi et al., 2018).

### *Contamination*

Oils, gasoline, heavy metals, PM (Asian Development Bank, 2015), lead, and polycyclic aromatic hydrocarbons (PAHs) are chemicals and pollutants that can be found on roadway surfaces due to motor vehicle traffic (Schwarz et al., 2016; Burant et al., 2018; Gaffield et al., 2003; Khan and Strand, 2018). They result from road surface, brake, and tire wear (Adamiec et al., 2016). Chemicals and pollutants can contaminate water sources, soils, and air, which pose significant threats to humans and the environment (Adamiec et al., 2016). These contaminating substances can cause liver failure, renal dysfunction and kidney failure (Mohod and Dhote, 2013), arthritis, abdominal pain, depression, fatigue, headache, memory loss, hypertension, low blood pressure, nausea, premature birth, low birth weight, rashes, sleeplessness, and ulcers (CDC, 2018; Jaishankar et al., 2014).

In urban areas, roads and parking lots that do not allow rainfall absorption are sprawling and increase the volume and velocity of polluted runoff (U.S. EPA, 2017b). Pollution from runoff threatens water quality and may cause illness due to water and food source contamination (Kibblewhite, 2018).

For example, high concentrations of PAHs (carcinogens produced by incomplete combustion in motor vehicle engines) have been found in agricultural fields near highways where road traffic is heavy (Kibblewhite, 2018). Motor vehicle traffic can increase lead concentrations in soils that are hundreds of meters from the roadway; however, this is dependent on the history and frequency of motor vehicle traffic in the area (Schwarz et al., 2016, Pouyat et al., 2008). In China, for example, traffic emissions were one of the main sources of lead pollution in soil between 1990 and 2017 (Zhang et al., 2019). Humans may be exposed to the contaminated soil by inhalation, ingestion, skin contact, and lead-enriched crop ingestion, which poses a risk to human health and food security (Zhang et al., 2019). Minimizing vehicle trips, and the associated infrastructure, by supporting alternative modes of transportation can reduce the overall presence of these harmful substances. Similarly, the provision of green spaces and the development of biodegradable and environmentally conservative vehicle and road surface materials can mitigate the effects of roadway contamination (Asphalt Pavement Association of Oregon, 2013; FHWA, 2016). Leaded fuels are no longer permitted in many countries, but the phasing out of leaded fuels played out over different periods, and the risk of exposure may still be present where leaded fuels were permitted more recently. In fact, lead is nonbiodegradable and does not decay; it therefore presents a long-term health risk despite widespread bans of leaded fuels in the 1990s (Xintaras, 1992). As of 2017, Algeria was the only country still allowing the use of leaded fuel in motor vehicles (Johnston, 2017).

### *Social Exclusion*

Social exclusion refers to the culmination of transportation-related inhibitions and/or deprivations—affordability, accessibility, availability, appropriateness, geographical location, time, and fear—that limit the opportunity to participate in community activities and be socially engaged. Social exclusion is a consequence of accessibility inadequacies and contributes to social isolation and loneliness, which are each associated with negative health outcomes (Julien et al., 2015); a systematic review found these situations result in a 29 and 26 percent increased likelihood in mortality, respectively, which is almost as high as the 32 percent increased mortality in adults who live alone (Holt-Lunstad et al., 2015). Transportation-related social exclusion affects certain groups more than others—most notably, low-income groups, the disabled, elderly, adolescents, women, and minorities (Mackett and Thoreau, 2015).

One deterrent to public transportation use and a contributing factor to social exclusion is fear of crime. Crime poses a threat to the physical safety of passengers and leads to decreased ridership, thereby impacting access to jobs, education, health services, and leisure activities, especially for low-income individuals (Pablo Madriaza et al., 2016). The Federation Internationale de l'Automobile (FIA) report on women's safety using public transportation noted that perceived fear of crime on public transit has been a barrier for some women to job participation (Allen and Vanderschuren, 2016). Furthermore, crime on marshrutkas (public minibuses) has negatively affected women's transportation experiences in Bishkek, the capital of Kyrgyzstan, which has led to greater mobility restriction and risk for social exclusion (Turdalieva and Edling, 2018). Fear of sexual harassment is an additional limitation on women's utility of public transportation (Asian Development Bank, 2015). Fear pervades women's participation in active transportation, and fear of crime and harassment while walking is a strong deterrent in cities around the world (Crabtree and Nsubuga, 2012). Obviously, people who are prevented from accessing public transportation or participating in active transportation due to fear of crime suffer the consequences of social exclusion.

A study found that elderly Japanese individuals, especially women, were at higher risk (9–34 percent) of premature mortality when socially excluded (Saito et al., 2012). Negative health outcomes resulting from these inhibitions and/or deprivations include poor mental health, cardiovascular disease (Leigh-Hunt et al., 2017), and stress (Cohen et al., 2014), each of which diminishes QOL, life chances, and choices (Church et al., 2000; Kenyon et al., 2002).

### *Noise*

For this study, *noise* is defined as motorized vehicle sounds at levels that are detrimental to health. WHO recently updated its noise level guidelines through a series of systematic reviews that recommend noise levels from road traffic stay below 53 decibels (dBs) in the European region (WHO, 2018d). FHWA has standards for traffic noise that range from 67 to 72 dB, depending on surrounding land uses (FHWA, 2010). Noise level is dependent on transportation-related factors like road networks, junctions, traffic flow and speed, acoustics, and meteorological conditions. Similar to motor vehicle crashes, noise pollution is more pervasive and extreme in developing countries (Schmidt, 2005).

Noise level is often a byproduct of the prominent transportation mode in an area, but transportation mode choice is usually influenced by the built environment and existing transportation infrastructure (Zhao, 2014; Hong et al., 2014). Encouraging mixed-use, dense, and connected developments are all factors that can lead to increased active transportation, which can reduce noise pollution from transportation (Nieuwenhuijsen, 2016; U.S. Department of Transportation, 2015). It is worth noting that increasing population density may possibly be accompanied by the risk of exposing more individuals to noise and air pollution and possibly other environmental stressors if no mitigation policies are put in place (Marshall et al., 2005; Vardoulakis et al., 2003; Yuan et al., 2019). Other feasible traffic noise reduction strategies include physical barriers (FHWA, 2017), low-noise tires and road surfaces (European Commission, 2017), and vegetation near roadways (Jang et al., 2015; Peng et al., 2014).

Another option to reduce road traffic noise is the deployment of electric vehicles (EVs) (Maffei and Masullo, 2014). Compared to an internal combustion engine vehicle (ICEV), an EV has less overall noise due to the absence of engine noise. However, as speed increases, the noise levels of the two vehicle types become increasingly similar due to tire-on-road sounds. A 15 dB difference between EVs and ICEVs was measured while idling, but no noise level difference was measured at speeds over 50 km/h (Maffei and Masullo, 2014). While EVs may not be the cure for busy highway traffic noise, the implementation of EVs may potentially provide relief for busy residential roads in neighborhoods with lower traffic speeds. Still, redesigning roads and urban cores to promote alternative modes of transportation may be a more sustainable approach to reduce noise and bring along various other health benefits through, for example, the increase in physical activity. There are also concerns about the safety of blind or visually impaired pedestrians with EV deployment (Parizet et al., 2014). Further, EVs still require extensive road infrastructure, thereby limiting land for green spaces while increasing heat (Maria et al., 2013); play a role in motor vehicle crashes; contribute to air pollution (Timmers and Achten, 2016; Soret et al., 2014); and do not address the many adverse health effects of physical inactivity.

Noise contributes to many health issues, such as mortality from cardiovascular diseases (including stroke, heart attack, and ischemic heart disease) (Héritier et al., 2018; Héritier et al., 2017; van Kempen et al., 2018); diabetes; hypertension; obesity (van Kempen et al., 2018); sleep disturbance (Basner and McGuire, 2018); annoyance (Guski et al., 2017); cognitive impairment (Clark and Paunovic, 2018a); reproductive complications (including low birth weight and preterm birth) (Ristovska et al., 2014; Nieuwenhuijsen et al., 2017); stress (Basner et al., 2014); and mental health problems (Clark and Paunovic, 2018b). Furthermore, transportation-related noise level and annoyance have been found to exacerbate asthma symptoms in adults, indicating that the respiratory system may be affected by noise (Eze et al., 2018). The burden of disease attributable to noise is comparable to that from secondhand smoke (Hänninen et al., 2014). Traffic noise in Barcelona, for example, is responsible for 18,000 DALYs, the largest of all transportation-related burden of diseases (Mueller et al., 2017d). In Western Europe, over 1 million DALYs are lost annually due to road traffic noise (WHO, 2011). In Houston, Texas, an estimated 302 premature deaths (adults 30–75 years) were attributable to transportation-related (road and aviation) noise, compared to 330 premature fatalities from motor vehicle crashes (Sohrabi and Khreis, 2020).

### *Heat*

UHIs are urban spaces with greater surface and air temperatures than surrounding areas (Coseo and Larsen, 2014). UHIs are becoming more common in cities as the built environment and transportation infrastructure, composed of heat-absorbing concretes and asphalts, continue to expand and replace trees, vegetation, and open and green spaces (Nieuwenhuijsen, 2016; Khreis et al., 2017a) that can cool temperatures (Petralli et al., 2014; Doick et al., 2014). Differences between urban and rural temperatures can be observed in cities around the world: 8°C in Barcelona, Spain (Mueller et al., 2017e), 6°C in Adelaide, Australia (Soltani and Sharifi, 2017), and 4°C in Las Vegas, Nevada (Kenward et al., 2014). An observational study of temperature-related mortality in 13 countries concluded that moderate deviations from the average ambient temperature can explain the majority of temperature-related mortality (Gasparrini et al., 2015). The impact of moderate and extreme heat on temperature-related mortality was most pronounced in Thailand, where the share of temperature-related mortality attributable to warmer temperatures was 22.6 percent; it is also high elsewhere, such as 14.8 percent in Italy, 16.2 percent in Spain, 18.1 percent in Taiwan, and 19.8 percent in Brazil (Gasparrini et al., 2015).

There have been numerous occasions in which heat waves have proved fatal. Two examples are the 2003 Paris heat wave, which resulted in 15,000 premature deaths (Fouillet et al., 2006), and the 2006 California heat wave, which resulted in 600 premature deaths and caused 16,000 emergency room visits (Knowlton et al., 2009; Ostro et al., 2009). The frequency of heat waves will increase throughout the 21st century (Lemonsu et al., 2014); for every 1°C increase in heat wave intensity, there is a 4.5 percent increase in mortality risk (Anderson and Bell, 2011). Cities like New York, Los Angeles, and Tokyo have recently employed urban cooling programs, while several European cities have mapped UHI-prone areas to identify at-risk populations in extreme heat events and provide access to cool places during heat waves (Shickman, 2017).

Research gaps exist in explaining the extent of transportation's impact on UHIs. However, some existing research provides useful insight into transportation factors that can influence UHI intensity. A handful of built environment characteristics, such as impervious surfaces, building height, road orientation, and green spaces, can modify the effects of UHIs (Coseo and Larsen, 2014). Coseo and Larsen (2014) measured the difference in the daytime and nighttime UHI temperatures in neighborhoods in Chicago, Illinois. They found that the percentage of impervious surface and tree canopy in an urban block explains 68 percent of the variance in air temperature at night and up to 91 percent of the variance in air temperature at night during an extreme heat event.

A reduction in VMT, vehicles on the road, and heat-absorbing concretes and asphalts accompanied by green space provision may contribute to decreased UHI occurrence. In addition, car-sharing reduces the number of private vehicles on the road and the heat-absorbing materials required for parking (Paradatheth, 2015), while EVs emit 20 percent of the heat that ICEVs produce (Li et al., 2015).

Increasing ambient temperatures have been associated with higher rates of mortality (Gasparrini et al., 2015), hospital admissions (Hondula and Barnett, 2014), cardiovascular disease (including arrhythmia and stroke), diabetes, hypertension, respiratory disease (including chronic obstructive pulmonary disease [COPD] and asthma) (Bunker et al., 2016), motor vehicle crashes (Basagaña et al., 2015), heat stress (Lemonsu et al., 2015), and premature birth (Schifano et al., 2016).

### *Road Travel Injuries*

Most road travel injuries are caused by a collision involving a motor vehicle and are referred to as motor vehicle crashes, which may result in death, injury, or disability. People most affected by motor vehicle crashes are vulnerable road users, like pedestrians, cyclists, and motorcyclists, who account for over 50 percent of all traffic deaths worldwide (WHO, 2018a). The total number of motor vehicle crash fatalities in the U.S. has declined the last two years after reaching a decade-high 34,748 in 2016. While over 70 percent of fatalities were vehicle occupants, pedestrians and cyclists accounted for 20 percent of motor vehicle crash fatalities (National Highway Traffic Safety Agency, 2017). Motor vehicle crashes in low- and middle-income countries account for 93 percent of global roadway fatalities, despite accounting for only half of the world's registered vehicles (WHO, 2018a).

It is also important to note that pedestrians and cyclists may experience premature mortality or injury from falls where no motor vehicle was involved. In fact, four to nine times as many pedestrians are injured from a fall while walking for travel as from collision with a vehicle (Methorst et al., 2017). Mindell et al. (2012) investigated road safety by travel mode; more male cyclist deaths occurred from falls than from traffic crashes in older groups aged 50 to 59 and 70+ in England (Mindell et al., 2012). Further, for injuries resulting in hospital admission, the risk from falls was very similar for cycling and walking (Mindell et al., 2012).

Land use and the built environment, transportation infrastructure, mode choice, and vehicle technology all influence road travel injuries. Most notably, the more sprawled the development, the greater the dependence is on personal automobiles (Litman, 2013), which inherently increases the risk of road travel injuries since more cars occupy the road. Although the rate of crashes for vulnerable road users is high, evidence supports that increased volume of active transportation users can improve safety. It is not easily done, however, because the existing road infrastructure in many major cities is built to accommodate motor vehicles first, rendering pedestrian and cycling infrastructure insufficient to support increased active transportation (Nieuwenhuijsen et al., 2016). In car-dominated societies, developing active transportation infrastructure may encourage individuals to shift from motorized to active transportation and improve active transportation safety due to what is known as the safety in numbers effect (Elvik and Bjørnskau, 2017), which documents that a greater number of active transportation users is strongly associated with fewer road travel crashes. However, the extent to which this is causal or due to confounding factors that increase the safety of pedestrians and cyclists is unclear (Mindell, 2019). As such, motivating individuals to partake in active modes of transportation may not only improve their individual health (see physical activity pathway) but may also increase the safety of their peers who choose active transportation.

The risk exposure induced by motor vehicle use could be reduced in part by the continued innovation of connected vehicles and AVs since 90 percent of roadway crashes are due to human driver failure (Kockelman et al., 2016). In 2018, over 2,800 people were killed and 400,000 were injured by distracted drivers in the U.S. (National Highway

Traffic Safety Agency, 2020). In Europe, 10–30 percent of all motor vehicle crashes were due to distracted road users (European Commission et al., 2015). However, the integration of AVs is not an overall positive since AVs and human drivers must learn to share the road (Bhavsar et al., 2017). Google's AVs have been in several crashes, each occurring because human drivers were unprepared for the AV to stop for pedestrians and road obstructions or adhere to certain roadway rules (Millard-Ball, 2018). Tesla's AVs have also been involved in fatal crashes due to driver overconfidence in the vehicles' autopilot capabilities (The Guardian, 2018). Even though AVs are expected to reduce road dangers that result from human error, there are concerns about AV-sensing technologies that fail to identify active transportation users (Sandt and Owens, 2017). Spaces where AVs and nonvehicle users share the road present the risk that an AV may prioritize the safety of its passengers above all else, thereby endangering other road users and potentially discouraging physical activity through active transportation. This presents an often-cited ethical dilemma for AV developers known as the *trolley problem.* Although the trolley problem is not specific to AVs, how developers address the trolley problem has potential health ramifications for active transportation users, like reduced physical activity or increased motor vehicle crashes. In the context of AVs, the problem can show up in several variants. Instead of a running trolley, there is for example an AV being surprised by a situation where it either continues in its lane killing a school class running out in front of the car or takes evasive action off the road killing the driver. The choice is then in the hands of the autopilot (Johansson and Nilsson, 2016).

Road travel crashes were ranked as the eighth leading cause of death in the world and the leading cause of death among people aged 5–29 (WHO, 2018a). Annually, road travel crashes are responsible for 1.35 million deaths and up to 50 million injuries globally (WHO, 2018a). Europe has the lowest fatality rate, at 49 fatalities per 1 million inhabitants, which is half the U.S. fatality rate and less than a third of the global mean (European Commission, 2019).

### *Air Pollution*

Air pollution results from the emission and dispersion of toxic substances in the air. Ninety percent of the urban European population is exposed to air pollution levels that exceed WHO standards (European Environmental Agency, 2017). Conservative estimates from the World Bank in 2014 attributed 184,000 annual deaths worldwide to TRAP (Bhalla, 2014), although a different study attributed 137,000 deaths just in China in 2013 to traffic-related $PM_{2.5}$ (Global Burden of Disease Working Group, 2016). More recently, $O_3$ and $PM_{2.5}$ were estimated to be responsible for 385,000 global deaths in 2015 (Anenberg et al., 2019). Further, deaths attributable to transportation tailpipe emissions increased by 6.6 percent, and total $PM_{2.5}$ and $O_3$ mortality increased by 9.4 percent between 2010 and 2015 globally (Anenberg et al., 2019). Vehicle emissions are estimated to be responsible for almost 20 percent of all ambient $PM_{2.5}$ and $O_3$-related mortality in Germany, the U.S., and the United Kingdom (Lelieveld et al., 2015).

The total number of VMT and the number of vehicles on the road have increased in countries around the world (Kumar et al., 2018), negating the benefits of emission-reducing technologies. Air pollution can discourage people from going outside and being active and disproportionately harms communities of color and lower socioeconomic status within cities (Khreis et al., 2016) because they generally have both higher exposure and higher susceptibility.

The potential implementation of car-sharing networks, specifically once AV technology is widely available, may present adverse public health outcomes since shared cars can operate continuously, thereby resulting in greater vehicle emissions (Cohen and Shirazi, 2017). Car-sharing does decrease the number of vehicles on the road, but there is a gap in research investigating the emissions trade-off between the current pattern of vehicle use and continually operating shared AVs. Although support for EVs is growing due to the allure of low emissions, it is also worth noting that EVs cause more pollution during production (Eckart, 2017) and boast higher non-exhaust pollution rates (due to EV weight and its effect on tire, brake, and road friction) than ICEVs (Timmers and Achten, 2016). Further, nearly 63 percent of electricity in the U.S. in 2019 was generated by burning fossil fuels (U.S. Energy Information Administration, 2019). Clearly, solar-powered and other forms of clean energy require greater investment and research, in conjunction with mitigation of non-exhaust pollution, for EVs to reduce TRAP. Progress on electrification of road transportation comes from Norway, where 96 percent of electricity is produced through hydroelectric processes, and the market share of EVs is approaching 50 percent (Figenbaum et al., 2015; Norwegian Electric Car Association, 2020) and potentially reducing traffic-related exhaust emissions (Olstrup et al., 2018). Measurements of ambient air pollution in three cities (Stockholm, Gothenburg, and Malmö) in 2015 were compared to ambient air pollution concentrations from 1990. The concentration of NOx—an exhaust pollutant associated with ICEVs (Stockfelt et al., 2017)—has been decreasing in each of the three cities between 1990 and 2015 (Olstrup et al., 2018).

TRAP contributes to many adverse health outcomes, including premature mortality (Beelen et al., 2014); respiratory diseases, including lung cancer (Raaschou-Nielsen et al., 2013), COPD (Lindgren et al., 2009), pneumonia (Nhung et al., 2017), childhood asthma (Khreis et al., 2017b), and respiratory infections in children (MacIntyre et al., 2014); cardiovascular diseases (Lu et al., 2015), including heart attack (Hoek et al., 2013), congestive HF (Shah et al., 2013), stroke (Stafoggia et al., 2014), and arrhythmia (Lee et al., 2014); neurodegenerative diseases (Landrigan, 2017), including dementia (Power et al., 2016), mental health problems (Power et al., 2016), autism, and child behavior problems; congenital anomalies (Vrijheid et al., 2011); reproductive issues, including reduced sperm quality (Lafuente et al., 2016), preterm birth (Sapkota et al., 2012), and low birth weight (Fleischer et al., 2014); deep vein thrombosis (Brook et al., 2010); bone conditions (Prada et al., 2017); diabetes (Eze et al., 2015); and obesity (Jerrett et al., 2014). Emissions from exhausts as well as from brake and tire abrasions can also resuspend heavy metals and PM. Moving traffic can resuspend road dust (Jancsek-Turóczi et al., 2013). Health outcomes that have been associated with road dust include carcinoma (including lung cancer), respiratory inflammation, asthma, COPD, cardiovascular disease, allergies, fungal infection, low birth weight, and premature mortality (Khan and Strand, 2018). Lead, platinum group elements, aluminum, zinc, and vanadium road dust particles seem to be most commonly associated with adverse health effects (Khan and Strand, 2018).

### *Community Severance*

Community severance refers to transportation infrastructure and/or motorized traffic (speed or volume of traffic) that divides places and people, interfering with the ability of individuals to access goods, services, and personal networks (Mindell et al., 2017). It can also limit social interaction and reduce mobility independence. Limited research focuses on measuring the continued effects of community severance, partly because there was no way of measuring community severance until recently. Identifying a causal relationship between community severance and health risks is difficult when studies are not conducted in the same area because community severance is a context-dependent issue (Anciaes et al., 2016a).

Solutions to removing the burdens presented by obstructive infrastructure do exist. The most straightforward one is removing the infrastructure itself, which occurred in the case of the deconstruction of the Cheonggyecheon Expressway in Seoul, South Korea. The removal of this highway has resulted in faster travel times, reduced the local UHI effect, and returned urban land to green space, in addition to uprooting a divisive element of the built environment (Newman and Kenworthy, 2015). Other approaches may include burying or sinking transportation infrastructure, including pedestrian-friendly features such as cross walks, or redesigning roads so that traffic flow does not present an obstacle to active travelers (protected cycle lanes, reduced number of vehicle lanes, or inserting a median) (Mindell and Anciaes, 2020).

*Pedestrian delay* describes the time spent waiting to cross streets and roads due to traffic flow, crossing facilities, or road design that contributes to community severance (Anciaes et al., 2016b). To minimize liability for AV manufacturers in the event of a motor vehicle crash, developers are exploring the consequences of respecting pedestrian right of way, which could reduce pedestrian delay. However, this step could cause slower vehicle traffic and increase travel times due to frequent stopping, resulting in greater vehicle emissions (Millard-Ball, 2018). The relationship that is established between AVs and active transportation users will not only have a dramatic effect on the severity of community severance but also on issues such as social exclusion, access, and even air pollution exposure.

Community severance can increase as a result of road safety concerns and may restrict access to public transportation (James, 2005). Community severance is thus strongly associated with reduced social interactions (Boniface et al., 2015) and social exclusion (Cohen et al., 2014); reductions in physical activity; stress (Cohen et al., 2014); poor mental health; cardiovascular disease (Leigh-Hunt et al., 2017); increases in exposure to air pollution (Hart and Parkhurst, 2011); and overall reduced mobility independence and access. It therefore increases morbidity and premature mortality (Mindell et al., 2017).

### *Electromagnetic Fields*

An electromagnetic field (EMF) is composed of moving electrically charged particles. EMFs can be created by differences in voltage and can be present near electricity generation stations, electric grids, and other similar infrastructures used to accommodate transportation technologies and disrupters (autonomous, connected, electric, and shared vehicles) (WHO, 2018e).

EMFs are an issue of current concern in approaches for charging EVs. One limitation of EVs is the mileage per battery charge, which is substantially less than fuel-efficient ICEVs (Gao et al., 2015). Charging stations for battery-powered vehicles are becoming common in many cities, and more convenient modes of charging, like wireless power transfer (WPT), are being researched to address concerns regarding mileage (Bi et al., 2016). *Dynamic charging* is a method of WPT that is conducted when a charging station creates an EMF that transfers power to an EV battery during operation (Bi et al., 2016). Because the vehicle would be able to recharge during operation, the vehicle could travel farther. In addition, the size of the battery could be reduced, mitigating some of the weight-related, non-exhaust air pollution problems posed by EVs (Bi et al., 2016). However, concern exists about how the EMF from WPT will affect humans, electronic and implanted medical devices, and the environment (Gao et al., 2015). Several studies have suggested that charging stations built in accordance with the International Commission on Non-Ionizing Radiation Protection standards should ensure human safety (Watanabe and Ishida, 2016; Ding et al., 2014b; Wen and Huang, 2017; Bi et al., 2016). However, other studies have noted precautions about proximity to WPT stations that are in use (Christ et al., 2013; Gao et al., 2015), as well as the potential risks of EMFs produced by dynamic charging in open traffic environments (Bi et al., 2016). Further research is needed to understand the health implications of wireless charging stations and the resulting EMFs, even when the magnetic or electric fields do not exceed practiced standards.

Transportation-related EMF exposure may contribute to reproductive complications (Li et al., 2017); potential hindered cognitive and/or behavioral development in children (Calvente et al., 2016); stimulation of central and peripheral nervous tissues; and retinal phosphene occurrence (Bi et al., 2016), as suggested in several studies. Further, a systematic review of EMF health effects found both adverse and beneficial effects concerning genes, cell growth, and the performance of the neural, circulatory, immune, and endocrine systems depending on the intensity, frequency, and duration of EMF exposure (Kostoff and Lau, 2013). Conversely, one observational study of pacemaker surgery patients concluded that EMFs produced by EVs do not affect cardiac implantable electronic devices, indicating that driving and charging EVs is likely safe for people with these devices (Lennerz et al., 2020). Another observational study investigated the effect of static magnetic fields from EVs on neuropsychological cognitive functions and determined that the effects were not considerable (He et al., 2019). More research is warranted in this emerging area to address heterogeneity of findings to inform more concrete conclusions on the health effects of EMFs from the transportation sector.

### *Stress*

Stress, the body's response to any demand, has been labeled the health epidemic of the 21st century and estimated to cost Americans $300 billion annually (Fink, 2017). Stress is associated with travel. Travel duration is a frequent stressor for users of motorized modes. For car users, stress might result from congestion, searching for parking, interaction with other drivers, and safety (Ding et al., 2014a). Traffic noise (Das et al., 2015) and the lack of green space availability (Khreis et al., 2016) are also a result of transportation decisions that impact the stress levels of individuals (Zijlema et al., 2018). Public transportation users may be stressed by waiting times, overcrowding, costs, and uncertainty over routes and timetables. Of the five most congested cities in the world, three are in South America—Bogotá, Colombia; Rio de Janeiro, Brazil; and São Paulo, Brazil, in descending order—while Mexico City, Mexico; and Istanbul, Turkey, are the fourth and fifth (INRIX, 2020). Among these cities, the average motor vehicle commuter will spend 169 hours in traffic congestion annually (INRIX, 2020). In the U.S., the average commuter spends 99 hours in traffic congestion every year, at a national cost (time that could be spent more productively) of $1,400 per commuter (INRIX, 2020).

Mode choice plays an important role in determining levels of stress related to commuting, with driving being the most stressful mode (Legrain et al., 2015). Legrain et al. (2015) concluded that active and public transportation users have lower levels of stress, thereby increasing the health benefits of ensuring accessibility and modal diversity in cities. Avila-Palencia et al. (2017) found an inverse relationship between stress levels and commuting via bicycle, even after adjusting for individual and environmental confounders and using different thresholds of perceived stress. Cycling to work at least four days a week resulted in a lower risk of being stressed relative to people who cycled less or not at all (Avila-Palencia et al., 2017).

Time spent in traffic also reduces the opportunity for engaging in health-promoting activities. The consolidation of schools and the construction of new schools often results in a longer commute for most students (Voulgaris et al., 2017). Students who traveled to school using active transportation were physically active for over an hour more each day than their peers who traveled to school via motorized transportation. Furthermore, students who had to commute more than 30 minutes to school engaged in physical activity for 75 minutes per day less than their peers. Each minute spent commuting was also associated with 1.3 fewer minutes of sleep (Voulgaris et al., 2017). The health effects of physical inactivity have already been noted; moreover, sleep deprivation among teens can result in an increased risk of acute illness (Orzech et al., 2014), obesity, unhealthy diets (Chaput and Dutil, 2016), and motor vehicle crashes related to drowsy driving (Higgins et al., 2017). Generally, stress can result in anxiety, depression, mental health-related QOL, substance use, unhealthy diet, sleeplessness, weight gain (Goyal et al., 2014), obesity, high cholesterol, heart disease, hypertension, and stroke (Khoury et al., 2015).

### *Greenhouse Gas Emissions*

Greenhouse gases (GHGs) are gases such as carbon dioxide ($CO_2$), methane, nitrous oxide, and fluorinated gases that trap heat in the atmosphere (U.S. EPA, 2016b). In 2016, global GHG emissions totaled 49.3 gigatons (GT), 72 percent of which were from $CO_2$ (Olivier et al., 2017). In the U.S., 81 percent of GHG emissions are $CO_2$ (U.S. EPA, 2016b), 30 percent of which are produced by motor vehicles (U.S. Energy Information Administration, 2017). The transportation sector is the largest contributor to GHG in the U.S. (Kay et al., 2014), and the U.S. accounts for 23 percent of total energy-related $CO_2$ emissions globally (Intergovernmental Panel on Climate Change, 2015). The transportation sector is also one of the fastest-growing sources of global emissions, despite advances in vehicle efficiency (Intergovernmental Panel on Climate Change, 2015). In contrast with most other major sources of global emissions, fossil fuels remain the dominant final energy source in transport, with oil accounting for over 90 percent of the final energy demand (International Energy Agency, 2016)

Although $CO_2$ and other GHGs are not directly threatening to human health, the consequences of a 2°C increase in global mean temperature from levels recorded before global industrialization will result in harmful effects for human populations and the ecosystems that sustain them (Watts et al., 2018). Global warming can exacerbate the adverse health effects related to UHIs, air pollution, and physical activity. In addition, extreme flooding, storms, and drought cycles (which can each damage transportation infrastructure) and increased rates of infectious disease transmission induced by climate change (Patz et al., 2014) can result in displacement, adverse mental and physical health, altered vector-pathogen relations, worsened air pollution, physical injury, and premature mortality (Watts et al., 2015; Patz et al., 2014). The secondhand effects of these changes can harm crop yields, livestock, and fisheries, thereby preventing proper nutrition and causing degrading health. Mitigating GHG emissions will not only result in improved air quality, but it may also lead to co-benefits related to other pathways, including increased physical activity and social contact (Gao et al., 2018), which are associated with their own health benefits (Mindell et al., 2011).

The Intergovernmental Panel on Climate Change has determined that by 2050, GHG emissions should be 50–85 percent of what they were in 1990 to avoid irreparable environmental damage (Kay et al., 2014). Cities are the largest producers of GHGs globally (80 percent) due to energy consumption and increasing urbanization patterns (Dulal and Akbar, 2013). In urban transportation, the largest emissions reduction impact will come from limiting private vehicle usage, something that can be done by increasing employment and residential density, shortening the distances between trip origins and destinations, and encouraging alternative transportation modes to private vehicles. Gouldson et al. (2018) discussed the impacts of GHG reduction policies within cities. By taking a public health approach to land use planning, encouraging a modal shift away from private vehicles, and improving public transportation and passenger car efficiency and freight policies, an estimated 2.8 GT of GHG could be removed in cities worldwide by 2050 (Gouldson et al., 2018).

Efforts to reduce GHG emissions by supporting active transportation have been modeled by several studies. Maizlish et al. (2013) projected that increasing median active transportation levels across the San Francisco Bay Area population by 18 minutes per day would reduce GHG emissions regionally by 14 percent and reduce the burden of disease from cardiovascular disease and diabetes by 14 percent. If this change were implemented in conjunction with the widespread implementation of low-carbon emission vehicles, the result would be a 33.5 percent reduction in GHG (Maizlish et al., 2013). Similarly, Woodcock et al. (2009) modeled the effects of reduced motorization, the use of low-carbon emission vehicles, and increased active transportation on GHG emissions and health outcomes in London and Delhi. In Delhi, heart disease and cerebrovascular disease decreased by an estimated range of 11–25 percent each, diabetes by 6–17 percent, and road traffic injuries by 27 percent, resulting in a reduction of 1,000 motor vehicle-related deaths and 25,000 DALYs. In London, heart disease decreased by 10–19 percent, cerebrovascular disease by 10–18 percent, breast cancer by 12–13 percent, dementia by 7–8 percent, and depression by 4–6 percent, resulting in the reduction of 1,000 motor vehicle-related deaths and 15,000 DALYs (Woodcock et al., 2009). Both studies suggest that the bundling of policy measures—instead of implementing them in isolation—can be more effective in reducing GHGs and can produce significant public health co-benefits by reducing both the burden of disease and mortality.

## Equity and Modifiers

Two additional factors influence the abovementioned transportation-related exposures and their resulting health outcomes as well as health outcome severity. The first is inequity, which refers to the unfair and inappropriate distribution of exposures related to transportation planning (Litman, 2019). Inequity factors can modify the exposure to each of the 14 pathways at the population level due to the placement of, proximity to, and access to transportation facilities, services, infrastructure, and activities. The second factor is intrinsic and extrinsic individual characteristics, such as sex, age, race/ethnicity, genetics, and more, that influence the susceptibility of individuals to transportation-related exposures and subsequently the severity of health outcomes experienced by each individual. These factors include malnutrition (Walson and Berkley, 2018); the lack of antioxidant intakes (Barthelemy et al., 2020); exposure to stress (Salleh, 2008); and exposure to violence (Wright and Steinbach, 2001). These factors can modify and often amplify the adverse health effects of transportation-related exposures.

In the context of equity, one important factor to consider is where populations live in reference to major transportation infrastructure. Worldwide, rural healthcare access is becoming an issue for patients, partly due to transportation inequities as transportation infrastructure and services often do not extend to rural communities (Scheil-Adlung, 2015). Even when transportation services or infrastructure are available, the financial cost of utilizing them may pose another barrier to receiving healthcare (Scheil-Adlung, 2015). TRAP exposure and its associated adverse health effects tend to be higher and more concentrated in lower socioeconomic locales and ethnic minority communities. A wealth of studies, old and new, show that adverse exposure levels are often socially patterned, with more socioeconomically deprived or ethnically diverse communities being disproportionately exposed. Inequalities in air pollution exposure in the U.S. were related to income and race-ethnicity between 2000 and 2010 (Clark et al., 2017). Notably, these disparities were larger by race-ethnicity than income (Clark et al., 2017). In the U.S., exposure to $PM_{2.5}$ is disproportionate between ethnic groups when compared with their contribution to $PM_{2.5}$ concentrations. Specifically, African Americans and Hispanics are exposed to more $PM_{2.5}$ than they are responsible for producing, while non-Hispanic whites are exposed to less $PM_{2.5}$ than they produce (Tessum et al., 2019). This disparity occurs partly due to social, economic, and environmental factors that have resulted in minority neighborhoods living closer to high-traffic-volume roads, which increases their exposure to air pollution and other transportation-related exposures and adverse health effects (McAndrews and Marcus, 2014; Rowangould, 2013). Finally, a national-level study in the U.S. found that students attending high-risk (of exposure to ambient neurotoxicants) public schools were significantly more likely to be eligible for free/reduced price meals and to be Hispanic, Black, or Asian/Pacific Islander than White or another race (Grineski and Collins, 2018). This higher exposure is exacerbated by the greater susceptibility of poorer groups, including the very young and old, to the adverse impacts of a given exposure due to a higher likelihood of preexisting cardiorespiratory disease. Further, exposures are not limited to air pollution alone; they extend to other pathways, such as noise, heat, green space, and access to physical activity opportunities (Khreis et al., 2016; Mueller et al., 2018b).

The health impact of inequities and intrinsic and extrinsic factors has been spotlighted by the Coronavirus (COVID-19) pandemic (Millett et al., 2020). The CDC showed that a larger proportion of Native American/Black/Hispanic populations have contracted COVID compared to Whites (CDC, 2021). Hospitalization rates are between 2.8x-3.3x greater among these racial minority groups than White, non-Hispanic Americans, and the risk of mortality is between 1.9x-2.4x greater than that of White, non-Hispanic Americans (CDC, 2021). the numbers cited above are ratios of age-adjusted rates standardized to the 2019 U.S. intercensal population estimate. Adjusting by age is important because risk of infection, hospitalization, and death is different by age, and age distribution differs by racial and ethnic group.

The most common preexisting conditions among hospitalized COVID-19 patients are cardiovascular disease, diabetes, and chronic lung disease, morbidities that have been linked to transportation throughout this paper (Eze et al., 2015; Héritier et al., 2018; Raaschou-Nielsen et al., 2013). Hospitalization and mortality rates are 6x higher for individuals with these preexisting conditions (Stokes et al., 2020). Furthermore, lack of private vehicle ownership is a statistically significant indicator of increased likelihood of COVID-19 diagnosis and mortality in the U.S. (Khazanchi et al., 2020; Karaye and Horney, 2020). Public transportation ridership is higher among low-income and racial minority groups, which increases risk of exposure for already disadvantaged communities (Chen et al., 2020). Moreover, reductions in public transportation service due to COVID-19 has limited health care access for transit-dependent populations (Chen et al., 2020).

## Work Package 2: Premature Mortality Attributable to Transportation-Related Noise and Motor Vehicle Crashes and the Role of Socioeconomic Status

### Premature Mortality Attributable to Transportation-Related Noise

Table 4 summarizes the estimated premature deaths attributable to road traffic and aviation noise in Houston. Two hundred fifteen (95 percent CI: 153–279) premature deaths from CVD for the age group between 30 to 75 years old were attributable to road traffic noise. Respectively, 52 (95 percent CI: 20–96) and 35 (95 percent CI: 12–52) premature deaths from MI and HF were attributable to aviation noise. The total number of deaths attributable to transportation-related noise was therefore estimated as 302 (95 percent CI: 185–427) premature deaths in 2016. Analyzing the overlap of the estimated premature deaths attributable to MI and HF from road traffic and aviation noise showed that 2 (95 percent CI: 0–3) premature deaths may be double-counted. Given the uncertainties in calculating this overlap and the small number of potentially double-counted premature deaths as compared to the uncertainties inherited in the burden of disease analyses, the double-counted premature deaths were not considered in reporting the health outcomes attributable to transportation-related noise in this study.

**Table 4. Number of Premature Deaths Attributable to Transportation-Related Noise in Houston.**

| Exposure source | Age group | Contrafactual scenario | Cause of death (ICD-10[a]) | Adjusted RR[b] associated with 10 dB increase in $L_{den}$ (95% CI) | $L_{Aeq}$ to $L_{den}$ Conversion (95% CI) | Premature death cases (95% CI) | Attributable premature deaths (95% CI)[c] |
|---|---|---|---|---|---|---|---|
| **Road traffic noise** | >30 y | Reduction to 35 dB where in exceedance | CVD (I00–I99) | 1.025 (1.018–1.032) | +3.6 (2.2–5.0) | 5,384 (5,251–5,517) | 215 (153–279) |
| **Aviation noise** | >30 y | Reduction to 30 dB where in exceedance | MI (I21–I22) | 1.027 (1.006–1.049) | +3.5 (0.1–6.9) | 569 (525–611) | 52 (20–96) |
| | | | HF (I50) | 1.056 (1.028–1.085) | | 464 (427–504) | 35 (12–52) |
| | | | | | | **Total =** | 302 (185–427) |

[a] The 10th revision of the International Statistical Classification of Diseases and Related Health Problems (CDC, 2017).

[b] Adjusted for sex, neighborhood index of socioeconomic position (low, medium, high), civil status (single, married, widowed, divorced), education level (compulsory education or less, upper secondary level education, tertiary level education, not known), annual average $NO_2$ concentration, mother tongue and nationality and controlled for the other noise source exposure.

[c] Refers to the most conservative and extreme estimations using the combinations of the lower and upper 95% CI for variables.

The spatial distribution of premature deaths attributable to transportation-related noise is shown in Figure 8, in the form of percentage from all-cause premature deaths. The percentage of premature deaths attributable to transportation-related noise was higher in the census tracts located in the central business district (CBD) and in the vicinity of Houston's airports and highways. In more than 40 percent of census tracts, transportation-related noise was responsible for more than 2 percent of all-cause premature deaths in the city, with a more prominent role for road noise (Figure 9).

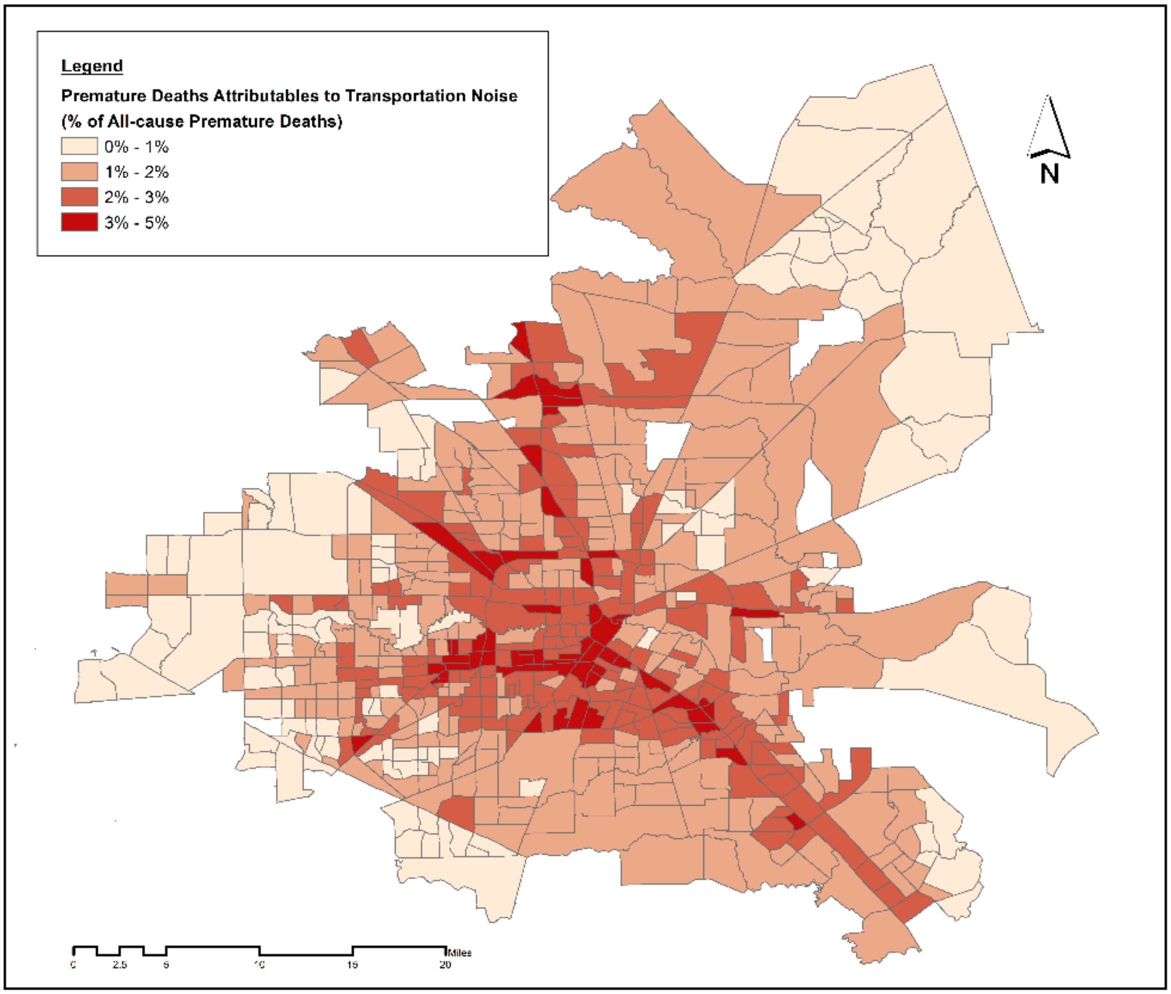



**Figure 8. Spatial Distribution of the Ratio of Premature Deaths Attributable to Transportation-Related Noise (Road Traffic and Aviation) to All-Cause Premature Deaths.**

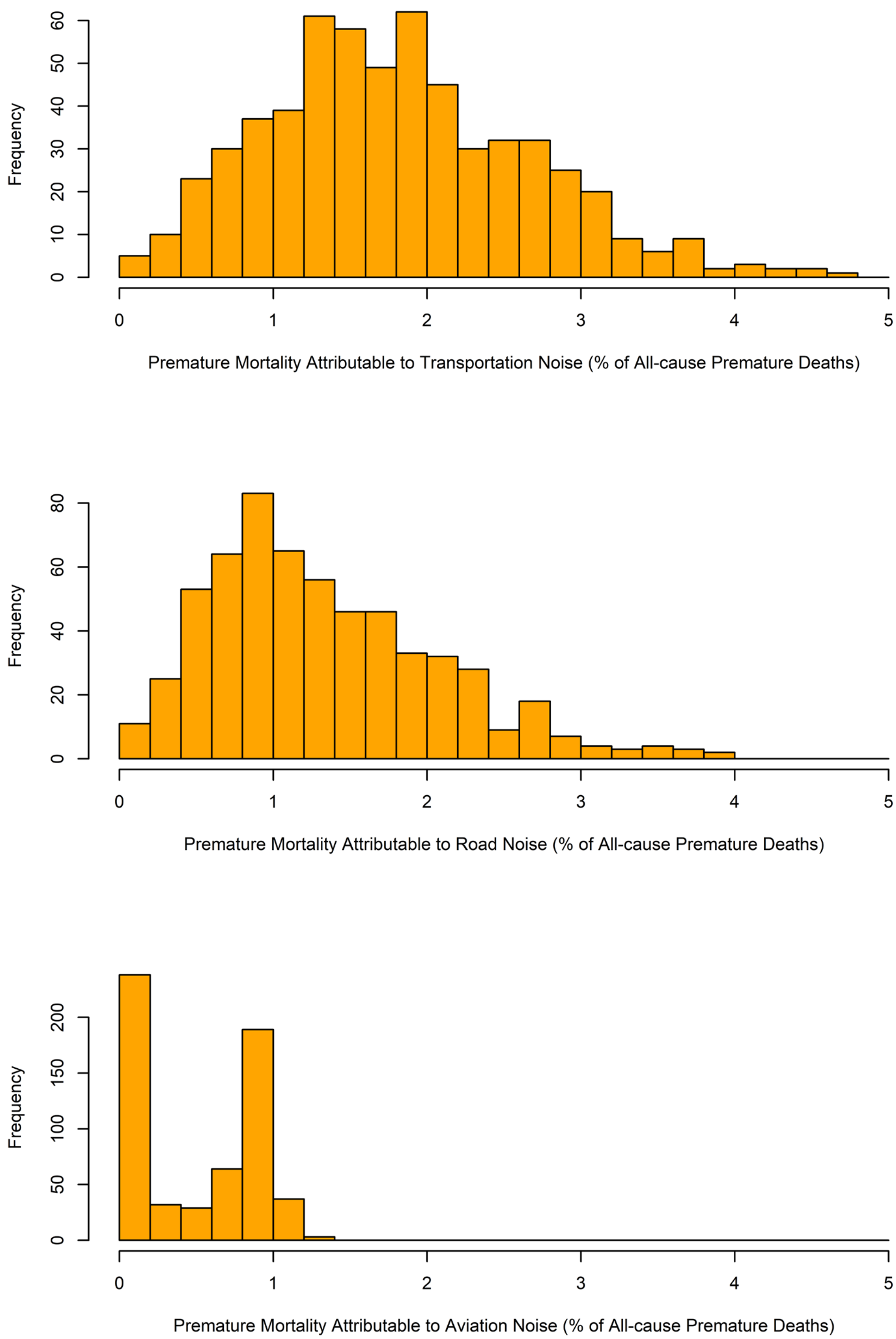



**Figure 9. Distribution of the Ratio of Premature Death Attributable to Noise from All-Cause Premature Deaths across the 592 Census Tracts.**

## Premature Mortality Attributable to Transportation-Related Noise by Household Income

The relation between median household income for each census tract and the premature deaths from transportation-related noise was explored to better understand the role of socioeconomic status in the distribution of the burden. Researchers showed an inverse correlation between the median household income at the census tract level and the ratio of premature deaths attributable to transportation-related noise from all-cause premature deaths (the average line shown in Figure 10). In other words, the ratio of deaths attributable to transportation-related noise reduces with the increase in the median household income until the $75,000 income level—from 2.3 percent to 1.7 percent (Table 5). For households with income higher than $75,000, an inverse relation is observed. A closer look at the health impacts of noise exposure sources shows that this relation is mainly from premature deaths attributable to aviation noise. The ratio of premature deaths from aviation noise to all-cause deaths mortality varies from 0.8 percent for households with a median income lower than $20,000 to 0.4 percent for households with a median income >$75,000 (Table 5).

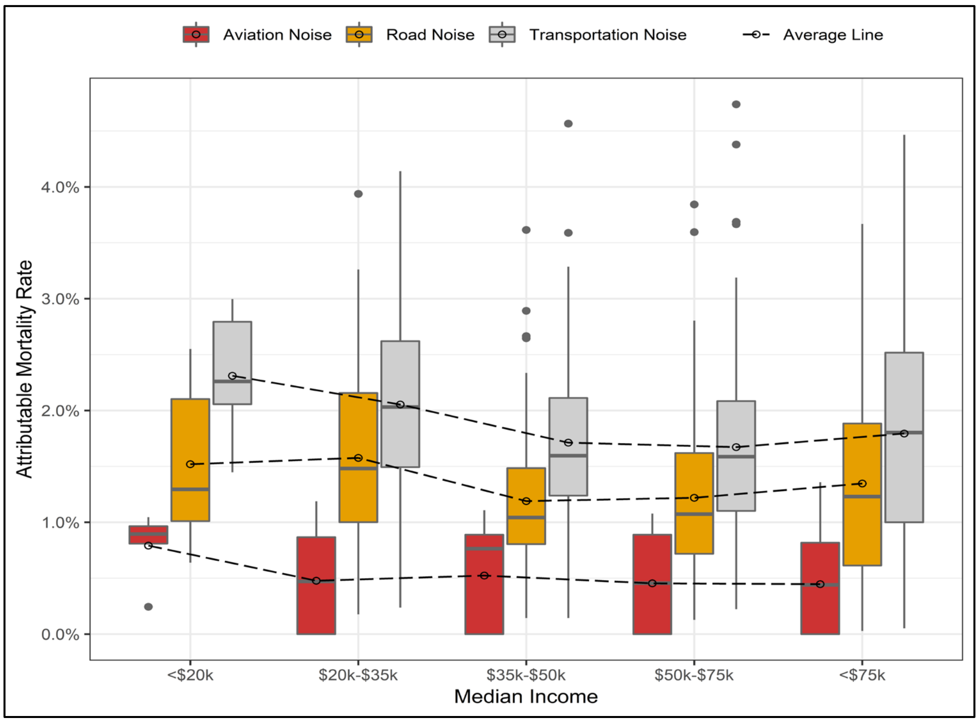



**Figure 10. Variation of the Ratio of Premature Deaths Attributable to Transportation-Related Noise (Road Traffic and Aviation Noise) by Household Median Income.**

**Table 5. Variation of Ratio of Premature Mortality Attributable to Transportation-Related Noise by Household Income.**

| Median Income Groups | Transportation-Related Noise | Road Noise | Aviation Noise |
|---|---|---|---|
| <$20k | 2.3% | 1.5% | 0.8% |
| $20k–$35k | 2.1% | 1.6% | 0.5% |
| $35k–$50k | 1.7% | 1.2% | 0.5% |
| $50k–$75k | 1.7% | 1.2% | 0.5% |
| $75k< | 1.8% | 1.3% | 0.4% |

## Sensitivity Analyses

The most conservative estimation of premature deaths attributable to road traffic noise resulted in 153 deaths, while the most extreme estimation resulted in 279 deaths (reported in parenthetical in Table 4). The most conservative and most extreme estimations for premature deaths attributable to aviation noise resulted in 32 (20 deaths from MI + 12 deaths from HF) and 148 deaths (96 deaths from MI + 52 from HF). Overall, the estimated premature deaths attributable to transportation-related noise in Houston varied between 185 to 427 (Table 4).

Results of the sensitivity analyses using the lower and upper 95th CI of each investigated variable are depicted in Figure 11. The uncertainty in the ERFs drove the largest uncertainty, in which the estimated attributable premature deaths to aviation and road traffic noise could be changed by up to 56.8 percent and 25.5 percent, respectively. The uncertainties in the MI and HF mortality rates resulted in up to an 8.0 percent deviation in the estimated attributable premature deaths due to aviation noise. The uncertainty resulting from the noise conversions was up to 6.2 percent for both road traffic and aviation noise. The results are shown in detail in Table 6. Overall, a higher level of uncertainty was associated with premature deaths attributable to aviation noise compared to road traffic noise.

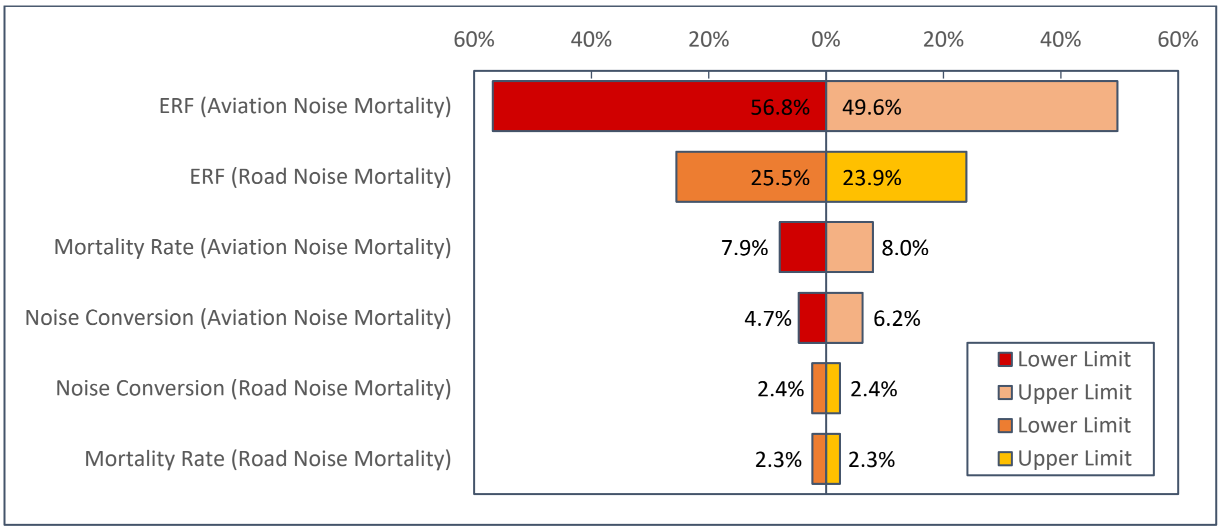



**Figure 11. Analysis of the Sensitivity of Estimated Premature Deaths to Variables Varying from Lower and Upper 95th CI.**

**Table 6. Sensitivity Analysis of Variables Varying from 5th to 95th CI.**

| Source | Variable | Estimated mortality | Lower limit | Difference from central estimate | Upper limit | Difference from central estimate |
|---|---|---|---|---|---|---|
| Road Noise | Mortality rate | 215 | 210 | 5 | 220 | 5 |
| | Noise Conversion | 215 | 210 | 5 | 220 | 5 |
| | ERF | 215 | 160 | 55 | 266 | 51 |
| Aviation Noise | Mortality rate | 87 | 80 | 7 | 93 | 7 |
| | Noise Conversion | 87 | 82 | 4 | 92 | 5 |
| | ERF | 87 | 37 | 49 | 129 | 43 |

The relation between inputs and outputs of the attributable premature death estimation was examined by running a sensitivity analysis to find the effect of different input margins. The results of this analysis are depicted in Figure 12. It is shown that 10 percent marginal changes in the mortality rate, ERF, and noise exposure will result in up to 10 percent, 8.8 percent, and 8.2 percent change in the estimated mortality, respectively, while controlling for the other variables. The noise conversion had the lowest marginal effect, with a 2.3 percent change in the estimated premature deaths associated with a 10 percent change in the noise conversion variable, as shown in detail in Table 7.

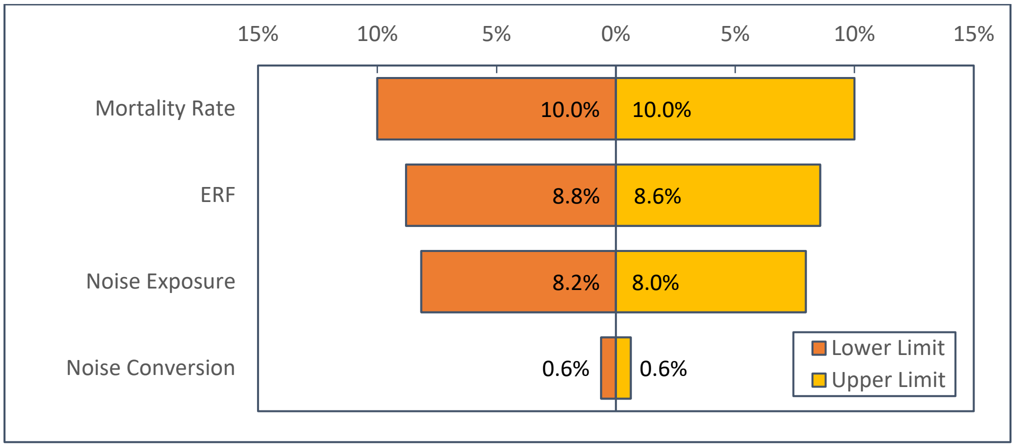



**Figure 12. Analysis of the Sensitivity of Estimated Premature Deaths to a 10 Percent Change in Variables.**

**Table 7. Sensitivity Analysis of 10 Percent Change in Variables.**

| Variable | Estimated mortality | Lower limit | Difference from central estimate | Upper limit | Difference from central estimate |
|---|---|---|---|---|---|
| Noise Exposure | 302 | 277 | 25 | 325 | 23 |
| Mortality Rate | 302 | 271 | 31 | 331 | 29 |
| Noise Conversion | 302 | 299 | 3 | 303 | 1 |
| ERF | 302 | 275 | 27 | 327 | 25 |

## Premature Deaths from Crashes

A total of 330 premature deaths from motor vehicle crashes were reported for individuals younger than 75 years old in Houston in 2016. The distribution of premature deaths from motor vehicle crashes across the city in 2016, as the percentage of crash fatalities from all-cause premature deaths, is shown in Figure 13. As the figure shows, the ratio of deaths attributable to crashes was higher in suburban areas than in the CBD.

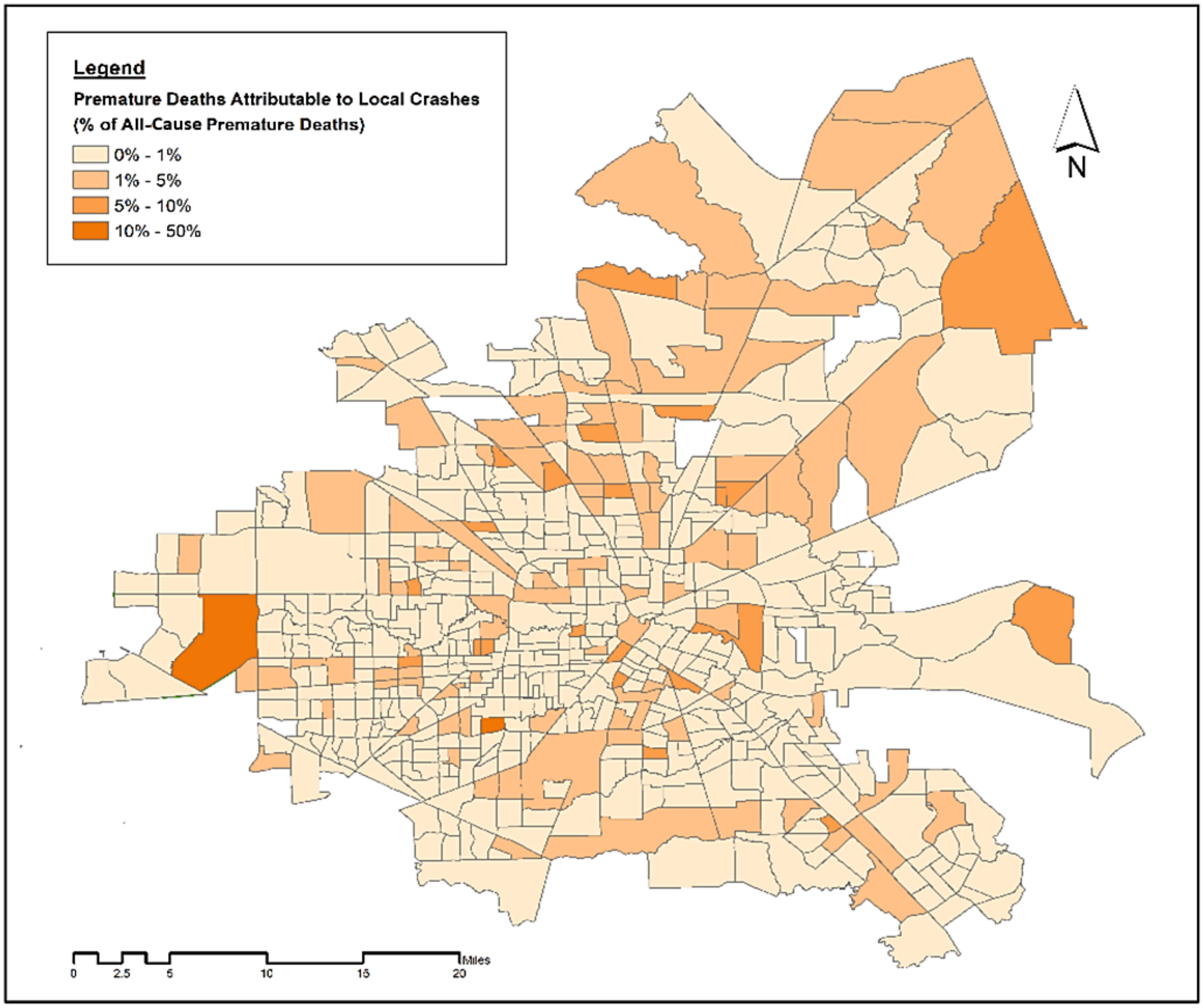



**Figure 13. Spatial Distribution of the Ratio of Premature Deaths Attributable to Local Roadway Crashes from All-Cause Premature Deaths.**

## Overall Impacts

Table 8 summarizes the estimated number of premature death cases attributable to transportation-related noise and motor vehicle crashes in Houston in 2016. Six hundred thirty-two premature deaths were attributable to transportation-related noise and crashes, which represents 3.6 percent of all-cause premature deaths in the city. Transportation-related noise and crashes were responsible for 1.7 percent and 1.9 percent of all-cause premature deaths, respectively.

**Table 8. Number of Premature Deaths Attributable to Noise and Motor Vehicle Crashes.**

| Exposure source | | Attributable premature deaths (95% CI) | % of all-cause premature deaths[a] |
|---|---|---|---|
| Noise | Aviation | 87 (32–148) | 0.5% |
| | Road traffic | 215 (153–279) | 1.2% |
| Motor Vehicle Crash | | 330[b] | 1.9% |
| Total | | 632 (528–759) | 3.6% |

[a] >30 and <75 years old.

[b] No uncertainty is associated with the crash fatalities since these are observed values.

## Work Package 3: Quantifying Premature Mortality Attributable to Ambient Air Pollution and the Role of Socioeconomic Status

### Premature Mortality Attributable to Air Pollution

Table 9 summarizes the estimated premature deaths attributable to the exposure to $NO_2$ and $PM_{2.5}$ in Houston in 2010. A total of 631 premature deaths for the age group between 30 and 78 years old were attributable to $PM_{2.5}$. Considering the most conservative and the most extreme burden of disease scenarios, the number of premature deaths attributable to $PM_{2.5}$ varied from 366 to 809 deaths, as shown between parentheticals in Table 9. Similarly, 159 (95 percent CI: 0–609) premature deaths were attributable to $NO_2$. Exceeding the WHO air quality guideline values resulted in 82 (95 percent CI: 42–95) preventable premature deaths attributable to $PM_{2.5}$. Moreover, 8 (95 percent CI: 6–10) premature deaths may be attributable to $PM_{2.5}$ exceeding the NAAQS.

**Table 9. Premature Deaths Attributable to Air Pollution in Houston.**

| Counterfactual Scenario | Premature Deaths Cases (95% CI) | Air Pollutant | Counterfactual Concentration (µg/m³) | Adjusted RR Associated with 10 µg/m³ Increase (95% CI) | Attributable Premature Deaths (95% CI) | % of Attributable Premature Deaths to All-Cause Deaths (95% CI) |
|---|---|---|---|---|---|---|
| Zero-exposure scenario | 8667 (8499–8834) | $PM_{2.5}$ | 0 | 1.07 (1.02–1.12) | 631 (366–809) | 7.3% (4.3%–9.2%) |
| | | $NO_2$ | 0 | 1.01 (0.99–1.04) | 159 (0–609) | 1.8% (0.0%–6.9%) |
| Complying with WHO guidelines | 8667 (8499–8834) | $PM_{2.5}$ | 10 | 1.07 (1.02–1.12) | 82 (42–95) | 0.9% (0.5%–1.1%) |
| | | $NO_2$ | 40 | 1.01 (0.99–1.04) | 0[a] (0–0) | 0.0% (0.0%–0.0%) |
| Complying with NAAQS | 8667 (8499–8834) | $PM_{2.5}$ | 12 | 1.07 (1.02–1.12) | 8 (6–10) | 0.1% (0.0%–0.1%) |
| | | $NO_2$ | 99 | 1.01 (0.99–1.04) | 0[a] (0–0) | 0.0% (0.0%–0.0%) |

[a] $NO_2$ concentration across the city was lower than the WHO air quality guideline values (and the NAAQS).

Figure 14 illustrates the range of the percentage of premature deaths attributable to air pollution (zero-exposure scenario) from all-cause deaths and its distribution across census tracts. The spatial distribution of premature deaths attributable to $PM_{2.5}$ and $NO_2$ (zero-exposure scenario) across census tracts is shown in Figure 15a and b, in the form of a percentage from all-cause premature deaths. The percentage of premature deaths attributable to $NO_2$ was higher in census tracts located in the CBD. In addition, a spatial similarity is observed between the distribution of air pollutants' health impacts and VMTA (Figure 15c).

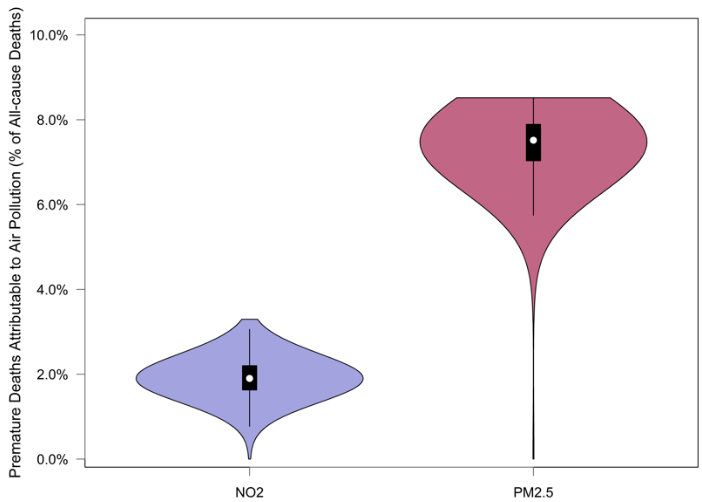
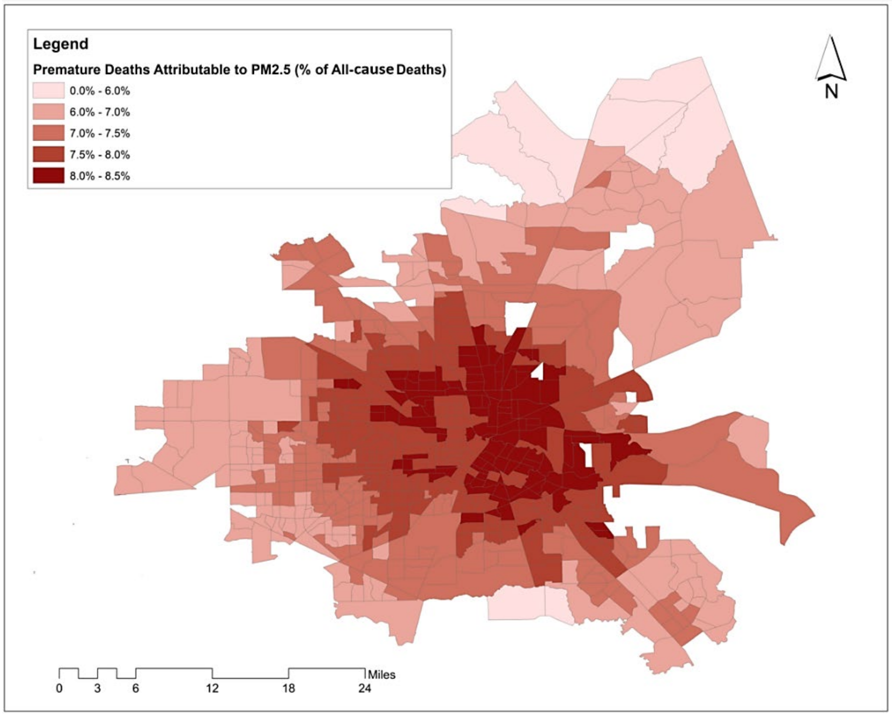
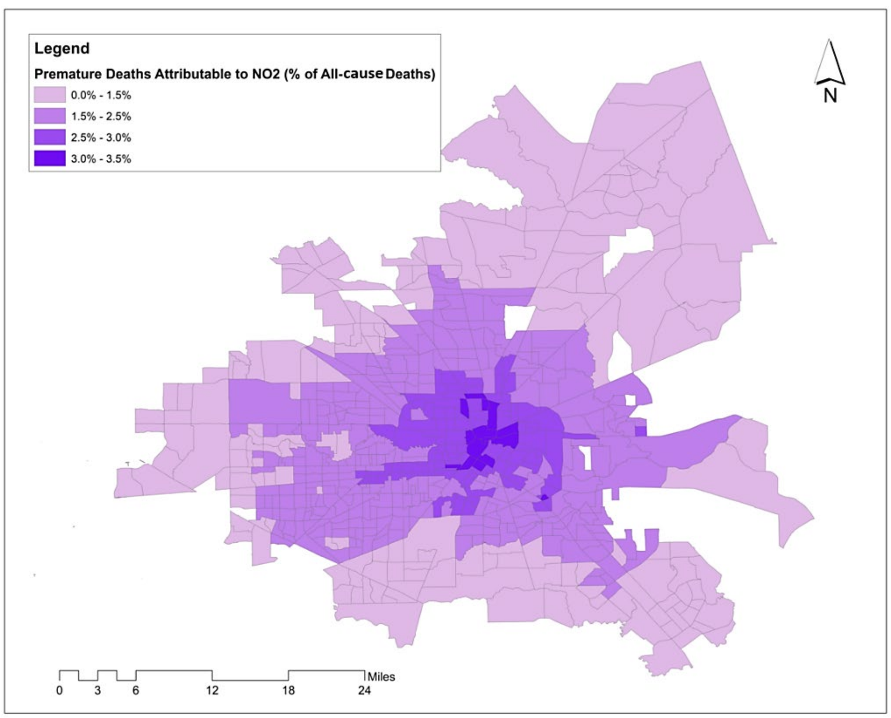


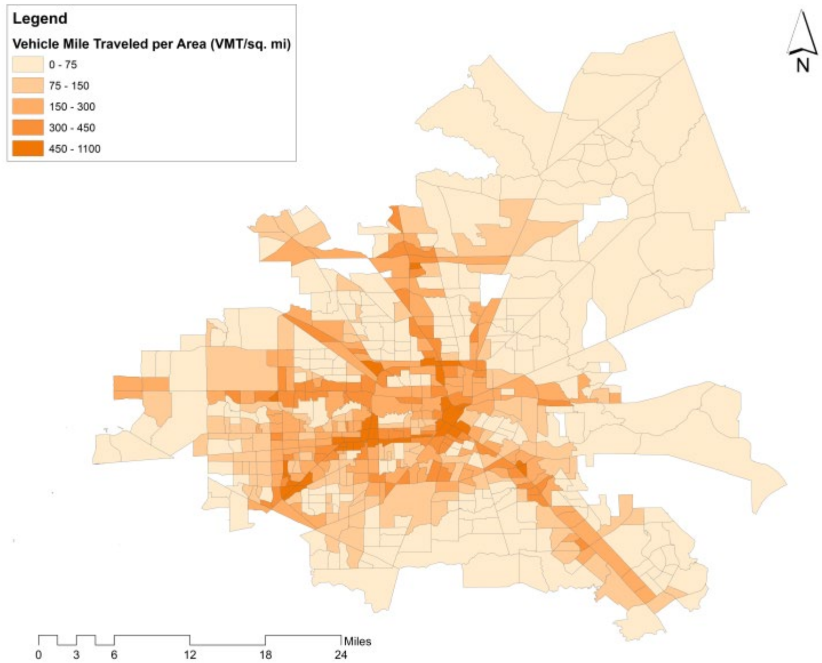

**Figure 14. Range and Distribution of Estimated Premature Deaths Attributable to PM2.5 and NO2 as a Percentage from All-Cause Deaths for Zero-Exposure Scenario.**


Legend
Premature Deaths Attributable to PM2.5 (% of All-cause Deaths)
0.0% - 6.0%
6.0% - 7.0%
7.0% - 7.5%
7.5% - 8.0%
8.0% - 8.5%
N
Miles
0
3
6
12
18
24

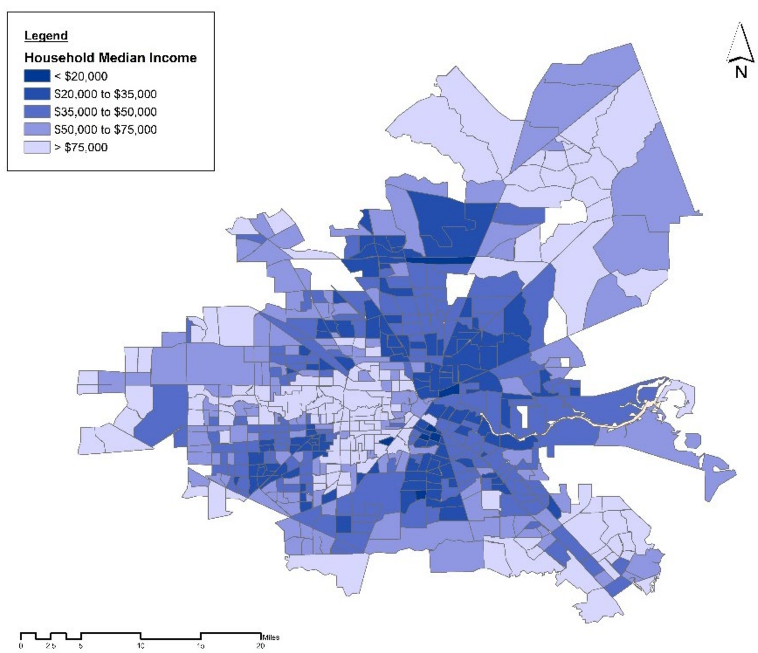
(**a**)


Legend
Premature Deaths Attributable to NO2 (% of All-cause Deaths)
0.0% - 1.5%
1.5% - 2.5%
2.5% - 3.0%
3.0% - 3.5%
N
Miles
0
3
6
12
18
24

(**b**)




(**c**)



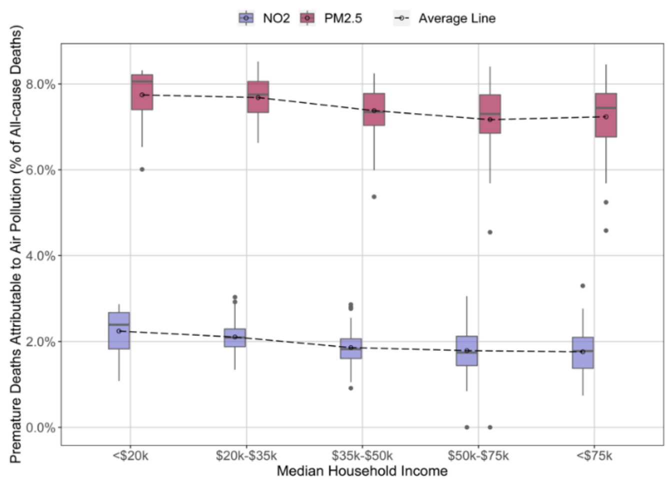

(**d**)

**Figure 15. Spatial Variation of (a) Percentage of Premature Deaths Attributable to PM2.5 from All-Cause Deaths, (b) Percentage of Premature Deaths Attributable to NO2 from All-Cause Deaths across Houston at the Census Tract Level in 2010, (c) VMTA, and (d) Median Household Income across Houston at the Census Tract Level in 2010.**

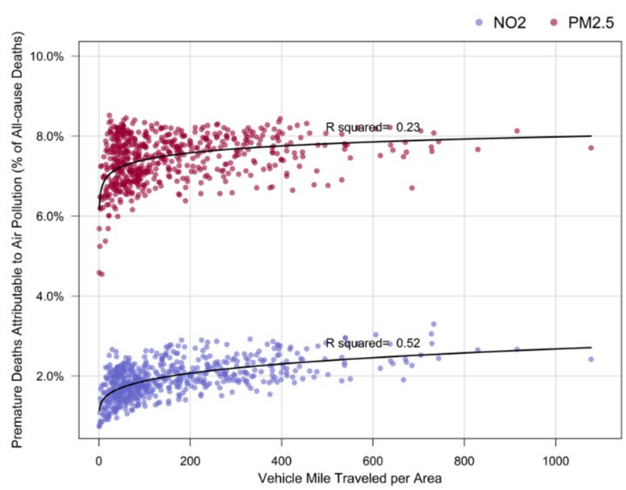
## Premature Mortality Attributable to Air Pollution by Household Income and Road Traffic

Figure 15d shows the spatial variation of median household income across the city. The relationship between median household income at each census tract and premature deaths attributable to air pollution was further explored. The comparison showed an inverse correlation between median household income at the census tract level and the ratio of premature deaths attributable to air pollution from all-cause premature deaths (the average lines in Figure 16a). In other words, it is expected that the ratio of premature deaths attributable to $PM_{2.5}$ and $NO_2$ reduces with an increase in household income from \$20,000 to \$75,000.

Per Figure 14, the ratio of premature deaths attributable to $PM_{2.5}$ and $NO_2$ at the census tract level can vary from 0.0 percent to 3.3 percent and 0.0 percent to 8.6 percent, respectively. A closer look at the spatial distribution of the ratio of premature deaths across the city showed a relationship between VMTA and the ratio of premature deaths attributable to air pollutants (Figure 16b). This relationship is consistent with the similarity between the spatial variation of the premature deaths attributable to air pollutants, especially $NO_2$ and VMTA, indicated in Figure 15d. The relation between the ratio of premature deaths and VMTA is stronger for the deaths estimated due to $NO_2$ compared to $PM_{2.5}$ (R-squared of the best-fitted curve for $NO_2$ is 0.52 versus 0.23 for $PM_{2.5}$).




**(a)**




**(b)**

**Figure 16. Variation of the Percentage of Premature Deaths Attributable to Air Pollution from All-Cause Deaths by (a) Median Household Income, and (b) Road Traffic.**

### Sensitivity Analyses

The most conservative estimation of premature deaths attributable to $NO_2$ resulted in zero deaths. The most extreme estimation resulted in 609 deaths (Table 9). The most conservative and most extreme estimations for premature death attributable to $PM_{2.5}$ resulted in 366 and 809 deaths (Table 9).

Results of the uncertainty analyses of the lower and upper 95$^{th}$ CI of each variable is depicted in Figure 17. The 95 percent CI of ERFs had the largest role in the uncertainty of estimated attributable premature deaths, wherein the estimated attributable premature deaths due to $NO_2$ and $PM_{2.5}$ could be changed by up to 276.1 percent and 41.0 percent, respectively. The uncertainties in the mortality rates resulted in up to 2.1 percent deviation in the estimated attributable premature deaths. Overall, more uncertainty was associated with premature death attributable to $NO_2$ than attributable to $PM_{2.5}$.

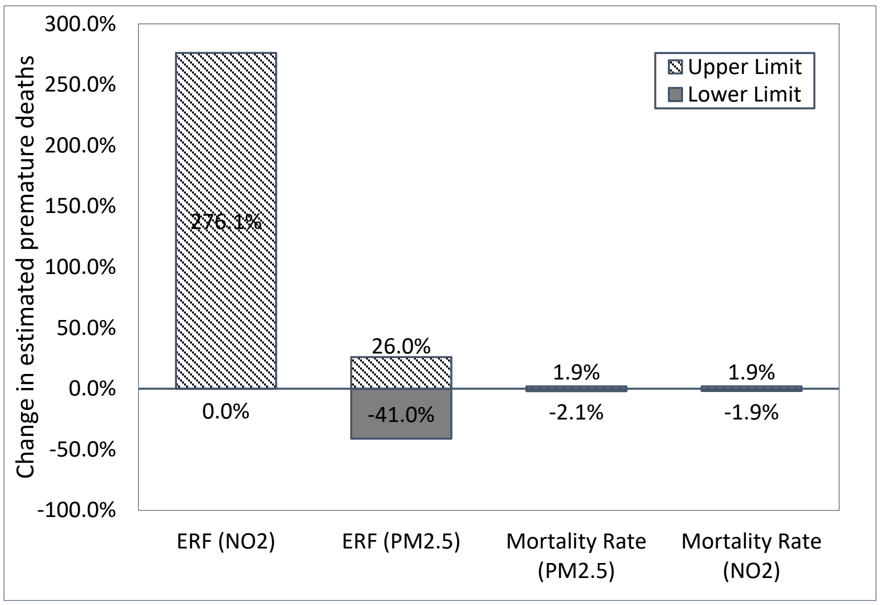



**Figure 17. Uncertainty Analysis Results.**

# Discussion and Recommendations

## Work Package 1: The Conceptual Model and Literature Review Results

### Overview and Added Value

A conceptual model explaining the relationship between transportation and public health was developed and is considered significant in explaining how the transportation and public health fields are intertwined and for devising appropriate strategies to protect and promote the public's health. The aggregation of the existing literature has established that the health burden attributable to transportation systems, infrastructure, facilities, and activities is significant but modifiable. Several of the pathways connecting transportation and public health are well recognized and researched in the literature, including physical activity, road travel injuries, air pollution, and GHGs, and, to a lesser extent, green spaces, blue spaces, aesthetics, access, noise, and heat. However, other pathways are new additions in this work or have been understudied in the literature and require further research to better understand their health impact. Also, researchers' understanding of the extent by which multiple pathways are influenced by transportation planning and policy is limited. These pathways include mobility independence, contamination, social exclusion, community severance, EMFs, and stress.

The collective health impacts of the 14 pathways have not been quantified yet in any setting. However, quantifications of the health impacts of the separate pathways indicate that the adverse impacts may qualify as a health epidemic. The health burden associated with transportation affects populations globally and disproportionately affects socioeconomically deprived and ethnic minority communities, who are already more susceptible to their exposures due to a host of extrinsic and intrinsic effect modifiers. Based on the simple aggregation of conservative estimates for each pathway as they are documented in the literature, over 4.5 million premature deaths occur each year globally from TRAP, motor vehicle crashes, and physical inactivity—a nontrivial proportion that could be reduced through healthier transportation. The burden of disease attributable to environmental noise (most of which can be traced to transportation-related sources in urban areas) has become better recognized as the volume of relevant research increases. For example, in Western Europe alone, over 1 million DALYs are lost annually due to road traffic noise (WHO, 2011). Quantifying the health burden attributable to transportation across as many pathways as possible will help professionals in transportation and urban planning, public health, and policy to better grasp the magnitude of the health impacts and propose necessary policy recommendations and amendments. However, researchers have yet to better understand and account for the interactions and overlaps between the different pathways and their impacts.

The conceptual model developed in this work presents three unique pathways not previously included in the reviewed transportation and health conceptual models or frameworks. These pathways are contamination, mobility independence, and electromagnetic fields. Although scarce quantitative evaluation of the health effects of transportation-related electromagnetic fields exists, the inclusion of this pathway is meant to prompt a health-conscious dialogue as emergent and disruptive technologies—such as WPT stations—present potential reconfiguration of existing transportation systems and a new urban source for human exposure to electromagnetic fields. Contamination associated with transportation pertains to toxins that humans are exposed to other than ambient air pollutants. Numerous adverse health effects are associated with the exposure to nonairborne pollutants, and this topic warrants a broader discussion of the pollution associated with motor vehicle traffic than is currently available in the literature. Mobility independence is a crucial element of mobility for vulnerable populations such as the elderly and children. Summarizing the health impacts of mobility independence (or lack thereof) may provide the evidence base to justify developing more inclusive and equitable transportation systems. The health effects of mobility independence remain understudied in the literature but are an important area to explore, especially given the potential effects of mobility independence on cognitive function, which is of increasing relevance in rapidly aging global populations (WHO, 2012; Patterson, 2018).

The other frameworks or models reviewed also do not explicitly illustrate the role of equity and intrinsic and extrinsic effect modifiers in influencing the exposures and the severity of transportation-related health impacts. These factors have been explicitly added in the conceptual model to communicate that equity is relevant at all stages of the conceptual model, whether it be in, for example, the unequal distribution or placement of transportation infrastructure; the unequal exposure to air pollution, noise, green space, or aesthetics; and the unequal health impacts. Similarly, different populations will react differently—even to the same exposures—depending on extrinsic or intrinsic factors that increase or decrease susceptibility (known as effect modifiers). These factors are important to consider and account for when studying the health impacts of transportation but also when devising mitigation strategies and allocating scarce resources. Unfortunately, within the transportation and urban planning fields, a history of racist practices can explain some of the inequities that contribute to the disproportionate occurrence of adverse transportation-related exposures for specific demographics (Fuller and Brugge, 2020). Practices that integrate meaningful levels of citizen participation and redefine the role of the professional in community-engagement exercises can improve participation and mitigate the occurrence of inequitable outcomes (Lyles and Swearingen White, 2019; Blue et al., 2019). Highlighting equity and effect modifiers as two important elements in this framework is also meant to raise awareness of these issues and formalize them in the conceptual model and future assessments.

Policy action is required to rectify the existing flaws of transportation and prevent the exacerbation of current health burdens through future transportation development and urban growth. However, efforts to reduce car dependency and unlock the potential health benefits of alternative transportation options have been inconsistent and underwhelming. The conceptual model and literature referenced in this work establish the validity of substantial transportation system changes to benefit public health outcomes at individual, population, and global levels. Global crises also lie ahead with climate change. As the impacts of climate change continue, meeting the timeline proposed by the Intergovernmental Panel on Climate Change (reducing GHG emissions to 50–85 percent of preindustrial levels by the year 2050) requires meaningful changes to transportation systems and urban development patterns that must be pursued immediately and with greater purpose than past initiatives.

The following recommendations may improve the utility of current and future research to better inform practitioners and decision-makers.

## Research Recommendations

Although the evidence base has been significantly expanded and strengthened in recent years, further research is needed to support some preliminary claims made by existing studies that provide conflicting and inconclusive results. Researchers identified several research gaps and needs after reviewing the weaknesses in each key factor and pathway description and outlined these elements in Table 10. This list is not exhaustive.

**Table 10. Research Recommendations.**

| Pathway | Research Needs |
|---|---|
| Autonomous Vehicles | To understand the impacts that shared AVs will have on total transportation-related emissions, air pollution exposures, health impacts and equity. |
| Community Severance | To quantify the impacts of community severance as related to transportation. |
| Social Exclusion | To clarify the physical health impacts of social exclusion/inclusion as related to transportation. |
| Electromagnetic Fields | To investigate the contribution of transportation technologies and disruptors to electromagnetic fields and the health effects induced by transportation-related electromagnetic fields. |
| Air Pollution | To explore further whether the risk of higher air pollution exposures outweigh physical activity benefits in near-road environments, and in different contexts with different air pollution concentrations and mixtures. |
| Green Space and Aesthetics | To better understand the relationship with transportation and health effects. |
| Heat | |
| Mobility Independence | |
| Electromagnetic fields | |
| **Key Transportation Factors** | **Recommendation** |
| Disruptive or Emergent Technology | To focus on the impacts that shared AVs and EVs will have on total transportation-related emissions, especially non-exhaust and stationary emissions (e.g., electricity generation) from EVs. Health effects from non-exhaust emissions from brake, tire, and road wear and road dust resuspension are also under-researched. |
| Built Environment | To evaluate the impact of urban growth management strategies on shifts to health-promoting transportation modes (active and public transportation) in different contexts. |
| Transportation Mode Choice | To conduct longitudinal studies quantifying the health effects of transportation mode shifts and conduct more studies evaluating the benefit and risk trade-offs of active transportation in near-road environments where air pollution, noise exposures, and risk of road travel injuries can be higher. |

While the conceptual model is meant to be a tool to identify and evaluate the health impacts of transportation in urban areas, potential exists for health benefits if the overlap and interaction between pathways is better understood. Stronger interdisciplinary collaboration may further elucidate these overlaps and interactions and can help devise integrated strategies and solutions that address multiple issues rather than focusing on isolated pathways. This narrow focus has proven harmful because policy makers might induce unintended consequences from solutions targeted at isolated pathways (see, for example, critical discussion of negative consequences of Europe's shift toward the diesel powertrain for GHG emissions objectives and lack of consideration of other pathways) (Cames and Helmers, 2013). Not only should practitioners and policy makers be encouraged to build coalitions with peers from adjacent fields, but researchers should use the conceptual model to explore the specific overlaps between the 14 pathways that can inform practice and policy. Doing so will advance mitigation of transportation issues beyond the *one exposure–one outcome–one intervention* approach and may enable more meaningful, and perhaps accurate, quantifications that can be controlled for the different pathways when estimating their health impacts, therefore avoiding, for example, double-counting benefits and harms.

### Practice and Policy Recommendations

The way transportation and public health is framed emphasizes why collaboration between experts and practitioners in various fields is necessary. Transportation has a huge, yet preventable, impact on many adverse health outcomes, and interdisciplinary approaches in practice and policy are needed to promote healthy transportation practices (Khreis et al., 2016). However, the transportation and health fields have traditionally been separated, with limited collaboration opportunities in education, training, and workforce development (Sanchez and Khreis, 2020). The many health outcomes associated with each pathway are byproducts of previous iterations of innovation that were inconsiderate of public health and driven by various markets. Several of the reviewed pathways are experiencing paradigm shifts due to emergent technologies that are expected to improve the function and efficiency of transportation but whose health impacts are as yet to be determined and are to some extent marginalized.

A growing number of interdisciplinary opportunities are occurring in the transportation and health fields, although there remains untapped potential for further collaboration. Since the value of interdisciplinary knowledge and skills is increasing because they are necessary to solve complex problems, it is necessary to promote interdisciplinary opportunities in education, training, and the workforce across practice and policy. Policy makers must recognize the interconnected relationship between transportation and health because their decisions impact more than just the built environment, infrastructure, transportation mode, and emerging technologies and disruptors.

## Work Package 2: Premature Mortality Attributable to Transportation-Related Noise and Motor Vehicle Crashes and the Role of Socioeconomic Status

### Overview and Added Value

Work Package 2 quantified the health burden attributable to transportation-related noise and motor vehicle crashes in Houston, Texas, in the form of premature deaths. The results showed that, in 2016, 302 (95 percent CI: 185–427) premature deaths were attributable to noise from road traffic and aviation, which accounts for 1.7 percent of all-cause premature deaths in Houston. Three hundred thirty deaths from motor vehicle crashes for individuals younger than 75 years old were reported in 2016, which accounts for 1.9 percent of all-cause premature deaths. These findings, therefore, highlight the significant and less acknowledged role of transportation-related noise in the health burden in Houston, where premature death cases attributable to noise were comparable to motor vehicle crash fatalities. Overall, 632 premature deaths per year were attributed to transportation-related noise and crashes, which can be translated into 3.6 percent of premature deaths in the city, which is higher than the death rate caused by diabetes mellitus in the U.S. (2.9 percent in 2016, according to Xu et al. [2018]) and is comparable to the death rate from Alzheimer's disease (4.2 percent in 2016 [Xu et al., 2018]). In addition, the estimated premature death rate attributable to transportation-related noise is higher than the death rate of influenza, pneumonia, or suicide in the U.S. (Xu et al., 2018).

The ERFs employed in this work were responsible for the largest share of uncertainty in the final estimated health impacts. The researchers also showed that the estimated premature deaths were more sensitive to the following inputs in this order: mortality rate, ERF, and noise exposure level. It was found that the burden of premature deaths from transportation-related noise was higher in the census tracts located in the CBD and in the vicinity of highways and airports. Researchers demonstrated the inverse correlation between the median household income and the ratio of premature deaths attributable to aviation noise, while a more complex relationship was observed between median household income and detrimental health outcomes from road traffic noise. The findings of this study not only provide decision-makers and engineers with more detailed information about the health impacts of transportation-related noise and crashes, but they also underscore the need for implementing noise burden of disease assessments in health impact assessment tools, something that has only been occasionally done so far.

## Strengths and Limitations

In this study, both aviation and road traffic noise, as opposed to focusing on one source of noise (Mueller et al., 2017a; Mueller et al., 2017b), were used to quantify and compare the potential contribution of transportation-related noise to premature deaths in an urban area. The researchers also quantified the burden of disease from transportation-related noise as opposed to ambient environmental noise (Tobías et al., 2015). Therefore, the health impacts of transportation-related noise exposure can be compared to the health impacts attributable to other transportation risk factors in the future, such as TRAP and transportation-related physical activity. To be able to account for the nonlinear ERFs in the burden of disease assessment of noise, researchers estimated $RR_{diff}$ for exposure to different levels of noise within a census tract, which resulted in a more accurate burden of disease analysis than estimating the health outcomes attributable to the averaged noise across the census tracts, which is usually used (Mueller et al., 2017a). The researchers compared the deaths from motor vehicle crashes with the deaths attributable to transportation-related noise to explore the significance of transportation-related noise and also specifically explored the relationship between the median household income and the estimated attributable burden. The U-shaped relationship between the estimated premature deaths attributable to transportation-related noise and median household income was consistent with the recent finding of Alotaibi et al. (2019), who also showed a U-shaped relation between childhood asthma attributable to air pollution and median household income across the contiguous U.S.

This work, however, has many limitations that are mainly related to the input data. One of its aims was to show a clear and easy-to-grasp contrast between a transportation-related exposure that received significant policy attention and financial mitigation resources—motor vehicle crashes—and one whose health impacts are only emerging—transportation-related noise. To do that, the study employed an easy-to-grasp metric: premature death. This metric, however, does not account for the number of years lost due to premature death, nor does it measure the time lived with disability, as opposed to DALYs. Quantifying the health impacts of noise and motor vehicle crashes using DALYs can provide better insight—for example, by considering the effect of youngsters' deaths from motor vehicle crashes—but it is a metric that is more difficult to interpret by professionals outside public health. Future work can benefit from using DALYs in similar burden of disease comparisons. This study also focused on estimating CVD premature deaths attributable to transportation-related noise, and other detrimental health impacts of noise were not quantified. Although a contrast was observed in the spatial distribution of premature deaths from motor vehicle crashes and premature deaths attributable to transportation-related noise, further analysis is required before drawing any conclusions from this contrast, given the uncertainties in the methodology of assigning local crashes.

The extracted ERFs were estimated for adults older than 30 years, so the potential mortality in the younger population was not quantified. Therefore, this approach is likely to result in underestimating the overall impacts of transportation-related noise in Houston. The noise exposure data were deployed from the transportation-related noise modeling tools developed by the U.S. Department of Transportation. The map was produced in 2014, and the researchers assumed that the noise estimations were applicable to this study's time period, which was 2016. Similar to any model, the transportation-related noise models were based on several simplifying assumptions, which were discussed in the Methodology section, such as (a) the assumption that soft ground for modeling noise will result in underpredicting sound levels for large areas with acoustically hard grounds (e.g., water or pavement), and (b) the assumption that average road pavement material and texture may under-/overpredict the sound levels depending on the road pavement type in place. The ERFs selected for the burden of disease analysis were estimated for road traffic noise exposures above 35 dB $L_{den}$ and aviation noise exposures above 30 dB $L_{den}$. The NTNMT only predicted noise exposure levels above 35 dB $L_{Aeq}$, which is equal to 38.6 dB $L_{den}$, according to Brink et al. (2018). Therefore, the number of premature deaths was only possible to estimate for noise exposures above 38.6 dB $L_{den}$, for both road traffic and aviation noise. Consequently, the premature deaths attributable to noise in the studied area are likely underestimated.

The number of mortalities at the census tract level was approximated based on the variation of population counts across the census tracts located within a county. In short, the number of mortalities were weighted based on the population size of each census tract by assuming constant mortality rates across the county. However, the rates of mortality were shown to be higher in communities with lower socioeconomic characteristics (Anderson et al., 1997; Wilkinson and Pickett, 2008; Pickett and Wilkinson, 2015). Unfortunately, the researchers had no other source of mortality data with a finer spatial resolution, and this limitation is commonly seen in most health impact and burden of disease assessment studies. Consequently, this approximation may result in underestimating the number of premature deaths attributable to noise at census tracts with lower households' median income. The homogeneous distribution of the population across census tracts was also assumed. Although this assumption may be valid in a dense urban area, it may lead to underestimating the burden of disease in suburban areas, especially for traffic noise since higher population densities and levels of exposure may occur in the vicinity of high-speed roads.

## Research and Practice Recommendations

Further studies are needed to examine the assumptions and limitations of this study, including the ERF limitations, transportation-related noise exposure uncertainties, and limitations in the availability and spatial assignment of motor vehicle crashes. Given the significant contribution of transportation-related noise to Houston's premature death burden, the researchers suggest equipping health impact assessment tools with a noise burden of disease analysis function.

The estimated premature deaths can be considered to be preventable by enacting policies and implementing efficient urban and transportation designs to improve traffic safety and control transportation-related noise emissions and exposures. Decreasing traffic flows, improving the roadway design, equipping vehicles with safety features, and incorporating new technologies (e.g., connected and automated vehicles) are some of the strategies that have been suggested to improve traffic safety (Goniewicz et al., 2016). Decreasing traffic volumes and speeds (Ögren et al., 2018), using low-noise tires (Heutschi et al., 2016), electric motors (Tobollik et al., 2016), and quiet pavements (Praticò and Anfosso-Lédée, 2012) are some of the strategies that have been suggested to reduce transportation-related noise emissions. Distancing people further away from noise sources (Moudon, 2009; Ögren et al., 2018); implementing noise barriers, including acoustic walls (Moudon, 2009); and increasing vegetation, including green walls (Peng et al., 2014; Jang et al., 2015; Khreis et al., 2020), are some of the noise exposure abatement strategies.

## Work Package 3: Quantifying Premature Mortality Attributable to Ambient Air Pollution and the Role of Socioeconomic Status

### Overview and Added Value

Work Package 3 expanded on Work Package 2 and quantified the health burden attributable to air pollution in Houston, also in the form of premature deaths. The results showed that, in 2010, 631 (95 percent CI: 366–809) premature deaths were attributable to $PM_{2.5}$, and 159 (95 percent CI: 0–609) premature deaths were attributable to $NO_2$. The estimated number of premature deaths attributable to $PM_{2.5}$ and $NO_2$ can be translated into 7.3 percent and 1.8 percent of all-cause premature deaths in the city, respectively. The ratio of premature deaths attributable to $PM_{2.5}$ was, therefore, higher than the death rate caused by diabetes mellitus, Alzheimer's disease, or motor vehicle crashes in the U.S. (2.8 percent, 3.4 percent, and 4.9 percent, respectively, in 2010, according to Murphy et al. [2013]), while the ratio of premature deaths from $NO_2$ is comparable to the death rate from suicide and influenza and pneumonia (1.6 percent and 2.0 percent, respectively, in 2010, according to Murphy et al. [2013]). Complying with the annual WHO air quality guideline values for $PM_{2.5}$ (10 μg/m$^3$) and the NAAQS criteria for $PM_{2.5}$ (12 μg/m$^3$) was estimated to potentially prevent 82 (95 percent CI: 42–95) and 8 (95 percent CI: 6–10) premature deaths in Houston in 2010.

The researchers found that the burden of premature deaths from air pollution was higher in the census tracts located in the CBD. In addition, a similar spatial pattern was observed between road traffic variation and the ratio of premature deaths attributable to air pollutants, which was more prominent for $NO_2$. Researchers showed an inverse correlation between the median household income and the ratio of premature deaths attributable to air pollution. The ratio of premature deaths attributable to air pollution decreases by 10 percent when the household's median income increases from $20,000 to $75,000, which is likely due to the higher exposure to air pollutants in census tracts with lower median household income. In other works, the baseline rates of mortality were also shown to be higher in communities with lower socioeconomic characteristics (Anderson et al., 1997; Pickett and Wilkinson, 2015; Wilkinson and Pickett, 2008). Unfortunately, the researchers had no other source of mortality data with a finer spatial resolution, which is a common limitation in similar burden of disease assessment studies, including the results shown in Work Package 2. In addition, a positive relation between road traffic and premature deaths attributable to air pollution was shown: the more vehicles passing through a squared mile of a census tract, the higher the risk of deaths from air pollution. The stronger relationship between the ratio of premature deaths attributable to $NO_2$ and VMTA compared to the ratio of premature deaths attributable to $PM_{2.5}$ and VMTA agrees with the fact that road traffic is responsible for a more significant portion of $NO_2$ than $PM_{2.5}$ (Hao et al., 2001; Bhanarkar et al., 2005; Sundvor et al., 2012; U.S. EPA, 2019). A higher level of uncertainty was observed in the $NO_2$ burden of disease analysis, which is in line with the less precise association between premature deaths and $NO_2$ in epidemiological studies. This factor implies that the evidence on premature mortality attributable to $PM_{2.5}$ is more reliable than evidence for $NO_2$, given the stronger association between $PM_{2.5}$ and mortality and the stronger case for biological plausibility not discussed in this work.

### Strengths and Limitations

In this work, the premature deaths attributable to air pollutants at the census tract level were estimated, which enabled investigation of the spatial distribution of attributable deaths and their correlations to the spatial distribution of traffic. The air pollution concentrations were estimated at a relatively high resolution—the census block—and then converted to a lower resolution—the census tract—to match the other dataset used for the burden of disease assessment. The researchers explored premature deaths attributable to $NO_2$ and $PM_{2.5}$ by the level of road traffic (represented by VMTA) passing through the census tracts and in the catchment area around the census tract, where traffic is expected to be most influential on ambient air pollution level. This approach, although relatively rudimentary, can be considered a more feasible alternative than full-chain modeling, and to a lesser extent, it still represents the role of TRAP in public health. Researchers also compared the reliability of the premature death estimates attributable to $NO_2$ and $PM_{2.5}$ and found that the $PM_{2.5}$ estimates are more precise.

However, this work has many limitations. Researchers assumed the air pollution concentrations do not spatially vary within a census tract, which implies that all populations living in a census tract are exposed to the same average concentration level. To assign the mortality data, which were only available at the county level, to a census tract, researchers assumed that the mortality rate was constant across the census tract located within a county. Based on that, the mortality cases were distributed between the census tracts according to their population. The extracted ERFs were estimated for adults older than 30 years, so potential deaths in the younger population could not be estimated. This approach may therefore result in underestimating the health impacts of air pollution in Houston, which is similar to the limitations in Work Package 2.

It is also critical to note that the health impacts of $PM_{2.5}$ and $NO_2$ cannot be added up because of the overlap in their biological pathways to adverse health outcomes, including premature mortality investigated in this work. Although researchers showed a relationship between road traffic and deaths attributable to air pollution, no conclusion can be drawn as to the contribution of TRAP to the premature mortality burden since an approach that allows source apportionment was not used. In addition, while the LUR model used predicts air pollution with fairly high accuracy, it considers all sources of air pollution, and researchers could not parse out the exact contribution of traffic from other sources in the exposure and associated burden of disease. The researchers also used the median household income at the census tract level to stratify the burden of disease estimates. This socioeconomic indicator can be a proxy for different factors which not only affect the exposure to air pollution but also the susceptibility and human response to those exposures. These factors include ethnicity, diet, stress and violence exposures, and access to health care, wherein ethnicity is particularly important in U.S. (Fuller and Brugge, 2020). Previous work using the same air pollution models showed that ethnicity is indeed an important factor explaining the disparities in $NO_2$ concentrations across the contiguous U.S., which were larger by race/ethnicity than by income (Clark et al., 2017). Finally, because of the limitations in the availability of ADT data, 2011 data were used, and the researchers assumed that the spatial variation of traffic did not change from 2010 to 2011.

## Research and Practice Recommendations

A number of strategies have been discussed in the literature to improve air quality and consequently reduce adverse health impacts—for example, imposing regulations for air pollution levels, reducing road traffic-related emissions, and controlling energy generation-related emissions as well as greenhouse gas emissions (Wang et al., 2016). Among others, traffic-related emissions have been shown to have the most significant impacts on air quality and subsequent health impacts (Wang et al., 2016). Therefore, travel demand management policies to control the traffic passing through air pollution hotspots in cities, such as census tracts with a higher level of exposure and detrimental health impacts, can be efficient solutions to improve public health. Improving public transport, improving infrastructure for active transportation, parking control, road pricing, and prohibiting car traffic are some of the travel demand management policies that have been implemented in cities (Gärling and Schuitema, 2007). The results of both Work Package 2 and 3 underscore the importance of conducting burden of disease and health impact assessments of transportation-related projects and designs. The results of such studies can contribute to the cost-benefit analysis of the transportation project and help the city to make more informed decisions to protect and promote the public's health.

To estimate the contribution of TRAP more accurately, future research is encouraged to conduct a full-chain burden of disease assessment comprising transportation modeling, emission modeling, dispersion modeling, and exposure assignment and then assess the attributable health impacts, which should also include the burden of disease and not only premature mortality. Similar studies can be conducted to evaluate the air pollution and health impacts of new technologies (e.g., electric and hybrid vehicles with less emission rates and AVs with different driving patterns). In addition, the comparison between air pollution health impacts and other health risk factors in cities is needed. Although this assessment has been conducted for three pathways (air pollution, noise, and motor vehicle crashes), the remaining 11 are yet to be quantified.

## Outputs, Outcomes, and Impacts

### Outputs

- Developed a new conceptual model to frame and assess transportation impacts on human health through all known pathways (Khreis et al., 2019).
- Developed new methodology to account for the overlap in the attributable health burden from the different transportation-related noise exposures: aviation and road (Sohrabi and Khreis, 2020).
- Developed new methodology to assign population exposures to transportation-related noise based on varying noise levels/surfaces within the same census tracts (Sohrabi and Khreis, 2020).
- Proposed an easy practice to assess the correlation between VMTA and the ratio of premature deaths attributable to air pollutants in urban areas, to provide insight into the role of transportation (Sohrabi et al., 2020).

### Outcomes

None known.

### Impacts

None known.

## Research Outputs, Outcomes, and Impacts

- Khreis, Haneen; Glazener, Andrew; Ramani, Tara; Zietsman, Josias; Nieuwenhuijsen, Mark J.; Mindell, Jennifer S.; Winfree, Gregory D.; Fox, Mary A.; Wunderlich, Robert; and Burke, Thomas A. (2019). Transportation and Health: A Conceptual Model and Literature Review. College Station, Texas: Center for Advancing Research in Transportation Emissions, Energy, and Health, May 2019. Available at: https://www.carteeh.org/14-pathways-to-health-project-brief/.
- Sohrabi, S. and Khreis, H., 2020. Burden of disease from transportation noise and motor vehicle crashes: Analysis of data from Houston, Texas. Environment International, 136, p.105520.
- Sohrabi, S., Zietsman, J. and Khreis, H., 2020. Burden of Disease Assessment of Ambient Air Pollution and Premature Mortality in Urban Areas: The Role of Socioeconomic Status and Transportation. International Journal of Environmental Research and Public Health, 17(4), p.1166.
- Glazener, Andrew; Sanchez, Kristen; Ramani, Tara; Zietsman, Josias; Nieuwenhuijsen, Mark J; Mindell, Jennifer S; Fox, Mary and Khreis, Haneen (2021). Fourteen Pathways between Urban Transportation and Health: A Conceptual Model and Literature Review. Journal of Transport & Health 21, p. 101070.
- Nieuwenhuijsen, Mark J.; Khreis, Haneen (2020). Introduction to Transport and Health. Book Chapter, Advances in Transportation and Health, 1st Edition, Tools, Technologies, Policies, and Developments. Editors: Nieuwenhuijsen, Mark J., Khreis; Haneen. Elsevier, 2020.
- Sanchez, Kristen and Khreis, Haneen (2020). The Role of Education, Training and Workforce Development. Book Chapter, Advances in Transportation and Health, 1st Edition, Tools, Technologies, Policies, and Developments. Editors: Nieuwenhuijsen, Mark J., Khreis; Haneen. Elsevier, 2020.
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- Khreis, Haneen (2019). Potential Health Implications of New Mobility. Health Effects Institute 2019 Annual Conference, Seattle, USA, 5–7 May 2019.
- Khreis, Haneen (2019). Integrating human health into urban transport planning. The Mansueto Institute Colloquium Series, University of Chicago, Chicago, USA, 15 April 2019.

- Khreis, Haneen (2020). Health Impacts of Transportation. Harvard Medical School and University of Leeds Institute for Transport Studies. Mobility and Health: Impacts and Implication of Travel Choice on Health. Online Meeting, 18 July 2020.
- Khreis, Haneen (2019). Health and the Urban Environment. World Health Organization Climate, Environment and Health Symposium, Seoul, South Korea, 20–21 June 2019.
- Glazener, Andrew; Ramani, Tara; Zietsman, Josias (Joe); Nieuwenhuijsen, Mark J; Lucas, Karen; Mindell; Jennifer and Khreis, Haneen (2018). Mobility and Public Health: A Conceptual Model and Literature Review. LAUNCH at Texas A&M University, College Station, Texas, USA, 1 August 2018.
- Glazener, Andrew; Ramani, Tara; Zietsman, Josias (Joe); Nieuwenhuijsen, Mark J; Lucas, Karen; Mindell; Jennifer and Khreis, Haneen (2018). Mobility and Public Health: A Conceptual Model and Literature Review. Transportation, Air Quality and Health Symposium, Austin, Texas, USA, 18–20 February 2019.
- Sohrabi, Soheil and Khreis, Haneen (2018). Assessing the Health Impact of Transportation Systems: A Burden of Disease Analysis. Transportation, Air Quality and Health Symposium, Austin, Texas, USA, 18–20 February 2019.

## Technology Transfer Outputs, Outcomes, and Impacts

None known.

## Education and Workforce Development Outputs, Outcomes, and Impacts

Two students primarily worked on this project, with others involved as described next. Andrew Glazener, who is currently a master's of community and regional planning candidate at the School of Architecture at The University of Texas at Austin, was initially employed as a CARTEEH intern in 2018 to further the development of the conceptual model and assist in reviewing the underlying literature. Andrew stayed on with CARTEEH as a research assistant throughout 2019 and continues to collaborate with the researchers. Besides the outputs outlined above, Andrew produced further deliverables, as follows, that built on the work discussed in this report:

- Glazener, A. and Khreis, H., 2019. Transforming our cities: best practices towards clean air and active transportation. Current Environmental Health Reports, 6(1), pp.22–37.
- Glazener, A. and Khreis, H., 2020. Best practices for air quality and active transportation. In Traffic-Related Air Pollution (pp. 405–435). Elsevier.

Andrew mentioned that his contributions as an undergraduate student to the 14 Pathways framework inspired him to pursue additional transportation-related research opportunities and enroll in his master's graduate degree program. As a graduate student, he has contributed to other related research projects outside this research group, including evaluating the impact of state-level growth management policies on transportation behavior and developing land use strategies that support public transportation ridership.

Soheil Sohrabi, who is currently a PhD candidate at the Zachery Department of Civil Engineering at Texas A&M University, was initially employed as a graduate research assistant in 2018 to perform analysis for the two Houston case studies and further the development of the burden of disease assessment methodology. This project was well beyond the transportation engineering curriculum and helped the student gain a multidisciplinary perspective at the intersection of transportation and health. In addition, the project enabled Soheil to get hands-on experience in health impacts assessments and develop his geographical information system, data management, and analytics skills as he worked with multiple databases on mortality, air quality, noise, and motor vehicle crashes. Soheil is still a PhD candidate and works with the Principal Investigator (Haneen Khreis) on another project that was awarded to the Texas A&M Transportation Institute in 2019 by the Robert Wood Johnson Foundation, titled "Quantifying the Benefits and Harms of Connected and Automated Vehicle Technologies to Public Health and Equity," which also employs burden of disease assessment methodology that Soheil has trained in during this project's period. Soheil also used the 14 Pathways framework in other work, including the development of his PhD proposal and thesis, and plans to continue his research on the health implications of transportation projects and technologies in the future. Besides the outputs outlined above, Soheil produced further deliverables, as follows, that built on the work overviewed in this report:

- Sohrabi, S., Khreis, H. and Lord, D., 2020. Impacts of Autonomous Vehicles on Public Health: A Conceptual Model and Policy Recommendations. Sustainable Cities and Society, 63, p.102457.
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Other students were peripherally involved in this work too. Kristen Sanchez, who is currently a graduate research assistant at the Texas A&M Transportation Institute and is pursuing a Master of Public Health degree in the Department of Epidemiology and Biostatistics at Texas A&M University's School of Public Health, assisted in the literature review for Work Package 1 and produced outputs that used the 14 Pathways framework, which are as follows:

- Sanchez, K. and Khreis, H. (2020). The Role of Education, Training and Workforce Development. Book Chapter, Advances in Transportation and Health, 1st Edition, Tools, Technologies, Policies, and Developments. Editors: Nieuwenhuijsen, Mark J., Khreis; Haneen. Elsevier, 2020.

The work conducted in this project was also used for the development of some lecture slides for the CARTEEH Curriculum for Transportation Emissions and Health, which can be found at https://www.carteeh.org/education/carteeh-curriculum-for-transportation-emissions-and-health/curriculum/#basics.

It also played an instrumental role in the development of the "Healthy People through SMART Infrastructure" initiative, in which the 14 Pathways to Health were used as the Healthy Transportation Infrastructure Objectives (detailed here: https://www.carteeh.org/healthy-people-through-smart-infrastructure/) and are the basis for developing the Transportation Health Enhancement Toolkit, including the Performance Measures, some Methods and Models, Case Studies and Practitioner Guidance.

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