IMPACTS OF COVID-19 INDUCED ACTIVE TRANSPORTATION DEMAND ON THE BUILT ENVIRONMENT AND PUBLIC HEALTH

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16. Abstract

COVID-19 had a significant impact on people's mobility. According to observational studies, the number of people bicycling and walking increased considerably during the social distancing orders. Various reasons may have contributed to this surge in bicycling and walking activities during the lockdown period, such as limited opportunities for physical and social activities due to COVID-19 and increased concerns about staying healthy. These changes in the demand had subsequently led to changes in built environment resulting in temporary deign and countermeasures to accommodate active transport users. However, pedestrians and bicyclists sharing streets with motorized traffic are often exposed to other traffic risks such as crashes and air pollution. Traffic risks involving non-motorized road users are serious threats that can outweigh the many health benefits in certain locations and populations. The objective of this study was to assess the secondary health outcomes of COVID-19 pandemic on active transport users through various health pathways such as physical activity, air quality, traffic crash and mental health and wellbeing. We conducted literature review and sentiment analysis to explore the secondary health effects of the pandemic on active transport users. The results of this project indicate that the pandemic had negative effects on active transport related sentiments (mainly due to other risks from built environment and traffic), however the changes in natural and built environment such as improved air quality and temporary planning and design measures may have had positive impacts on active transport users' health. Despite these improvements the traffic crashes and fatalities remained stable potentially due to aggressive driving behaviors and reduced congestion.

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Executive Summary

COVID-19 had a significant impact on people's mobility. According to observational studies, the number of people bicycling and walking increased considerably during the social distancing orders. The objective of this study was to assess the secondary health outcomes of COVID-19 pandemic on active transport users through various health pathways such as physical activity, air quality, traffic crash and mental health and wellbeing. We conducted a literature review and sentiment analysis to explore the secondary health effects of the pandemic on active transport users. The results of this project indicate that the pandemic had negative effects on active transport related sentiments (mainly due to other risks from built environment and traffic), however the changes in natural and built environment such as improved air quality and temporary planning and design measures may have had positive impacts on active transport users' health. The findings of this project can have both short and long-term impacts. Short-term recommendations are temporary planned measures and actions for promoting active transportation during the pandemic. Long-term recommendations aim to keep the quick increased active transportation users and improve the walkability and bikeability of cities.

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Background and Introduction

QUICK FACTS

Active Transport such as walking and bicycling are the most popular means of getting a healthy dose of physical activity, which can bring numerous health benefits both directly and indirectly through the changes in transportation related health outcomes.

Walking and bicycling are the most popular means of getting a healthy dose of physical activity, which can bring numerous health benefits by reducing the risks of premature death, obesity, cardiovascular diseases, type II diabetes, depression, certain cancers, etc. Physical activity continues to be on top of our national public health objectives and is included in Healthy People 2030 as one of the national priorities (U.S. Department of Health and Human Services, 2014). In recent years the pedestrian and bicycle trips have been increasing. A study examining the actual count data from 13 metropolitan areas shows a significant annual increase of 2–6 percent for bicycle and 2–3 percent for pedestrian counts (Le et al., 2019).

COVID-19 related mobility restrictions and social-distancing interventions has led to significant changes in active transportation demand (Buehler & Pucher, 2021; Hunter et al., 2021; Nikiforiadis et al., 2020; Y. Pan et al., 2020). Public transport is perceived to be the least safe mode of transportation during COVID-19, leading to a shift to safer alternatives such as bicycling and walking, especially for those with limited access to private automobiles. Meanwhile, with the limited opportunities for physical activities in indoor locations and the shutdown of many outdoor recreational facilities during the pandemic, people may choose to walk or ride a bike more often to stay healthy and cope with the pandemic. Both factors have affected the demand for active transportation during COVID-19 (Fuller et al., 2021; Padmanabhan et al., 2021).

However, pedestrians and bicyclists sharing streets with motorized traffic are often exposed to other traffic risks such as crashes and air pollution. Traffic risks involving non-motorized road users are serious threats that can outweigh the many health benefits in certain locations and populations. Active transportation users are more prone to injuries and deaths when involved in collisions. According to the National Highway Traffic Safety Administration (NHTSA), active transportation user fatalities accounted for 1.9–2.3 percent of total roadway fatalities between 2008 and 2017 (National Center for Statistic and Analysis, 2019). Factors such as risky driving behaviors are among the significant crash-contributing factors affecting bicyclist safety (Dai & Dadashova, 2021). During COVID-19, reckless driving behaviors were observed to increase, namely, speeding, driving under the influence, and a lower seat belt usage rate (NHTSA, 2021). Such risky behaviors of road users can expose active transport users to higher risks of being involved in crashes and suffering from severe injuries and fatalities from crashes. In fact, the NHTSA report also found that despite the reduction in the number of road crashes, the severity of crashes in the United States increased during COVID-19 (NHTSA, 2021).

Other potential health risks are from exposure to air pollution. However, with the reduced traffic volume during COVID-19, the level of air pollutants may have decreased, reducing their harmful health effect on active transportation users (Li et al., 2020; Ma & Kang, 2020). A pre-COVID-19 systematic review comparing air pollution exposures in active versus passive travel modes in European cities found that pedestrians were the least exposed group for many air pollutants, including particulate matter 2.5 (PM2.5), ultrafine particles, and carbon monoxide, compared to other road users (e.g., cyclist, bus riders, and car users). Pedestrians were exposed to black carbon (BC) more than bus users on average but remained less exposed than cyclists and car users (Nazelle et al., 2017). Although cyclists may be more exposed to air pollution than pedestrians and similarly exposed compared to bus and car users, many studies have shown that the health impacts of cycling, mainly due to increased physical activity, well outweigh the exposure risks to air pollution. In most scenarios, studies concluded that the benefits of physical activity from active transportation outweigh the risks from air pollutants. Only in cities where air pollution levels are unusually high, physical activity benefits may be offset by the increased risk of air pollution. For example, in Delhi (153 µg/m3 PM2.5), an individual could bike for up to 45 minutes each day before health risks from air pollution exposure surpassed physical activity benefits (Tainio et al., 2016).

The exposure and safety of active transportation users are heavily dependent on the built environment (e.g., sidewalks, bike lanes, trails, proximate destinations). Responding to the increased demand for active transportation during COVID-19, various built environment modifications have been implemented to accommodate and promote active transportation, which may have also contributed to the changes in active transport demand. Although there have been many publications documenting COVID-19 impacts on transportation and health, no study has synthesized the rapidly accumulating evidence on the impacts of COVID-19 on active transportation users' health outcomes by comprehensively considering travel mode shifts, air quality changes, and built environmental responses/modifications. In this paper, we have conducted a scoping review of the literature to fill in this critical knowledge gap. Figure 1 illustrates the conceptual framework used for conducting the scoping review. It graphically illustrates how the three health pathways due to COVID-19-induced changes in active transportation may impact public health. Increasing active transportation activities during COVID-19 can help improve public health by increasing physical activity. On the other hand, increasing exposure to traffic may negatively affect the health of active transport users by increasing the risks of crashes and air pollution exposures. This framework provides the evidence base to guide future decision-making responding to the increasing demand changes and promoting active transportation to create a healthy and sustainable built environment.

Methodology

Conceptual Framework

This study aims to assess the potential changes in health outcomes resulting from COVID-19-induced active transportation activities through four health pathways: physical activity, traffic crashes, air pollution, and mental health. To explore these effects, we conducted a literature review and sentiment analysis. Figure 1 provides the conceptual framework for this approach.

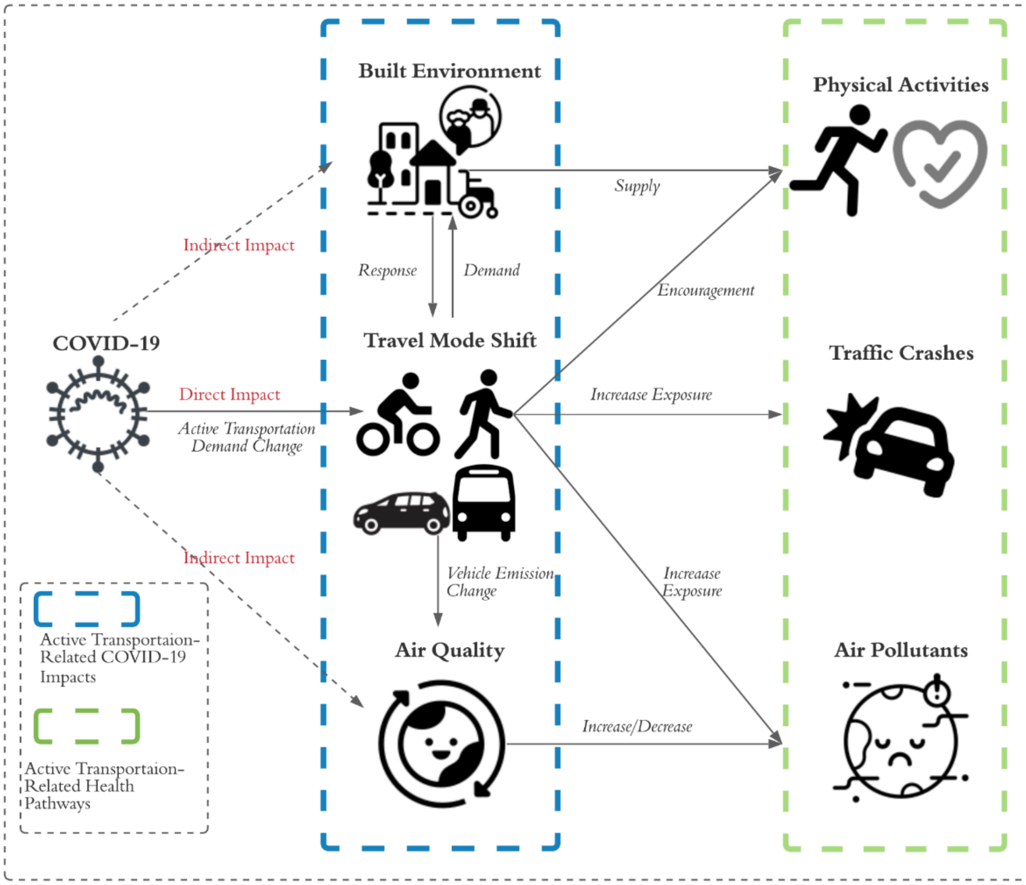


Figure 1. Conceptual framework of the health pathways for COVID-19-induced changes in active transportation.

Literature Review Methods

In this study, we only included the publications written in English to ease the burden of translating non-English publications. All the reviewed articles and reports were published in the years 2020 and 2021. Meanwhile, we defined two inclusion criteria to select the most relevant studies. The selected studies needed to address the impacts of COVID-19 on active transportation volume/demand change or on active transportation users through the three proposed health pathways. We then retrieved relevant research evidence from the five research databases, including Google Scholar, Web of Science, Embase, EBSCO, and Transport Research International Documentation and conducted the scoping review of literature based on the framework proposed by Arksey & O'Malley (2005). A scoping review is commonly used to examine emerging evidence and facilitate discussion on a topic (Munn et al., 2018), which fits the purpose of this research. The scoping review process included four steps: identification, screening, eligibility, and inclusion (see Figure 2).

First, a professional librarian conducted the search based on the proposed keywords from the five selected databases. This search was performed in March 2021. A total of 2,888 publications were identified. Meanwhile, we also identified 79 additional articles while reviewing the selected papers, bringing the number of initially identified articles to 2,967. After identification, duplicated articles were removed, resulting in 2,367 articles kept after this step. Next, two reviewers independently performed a more thorough screening process. They went through the titles and abstracts of the 2,367 articles independently and labelled each article as “Relevant,” “Irrelevant,” or “Maybe.” After this process, we included articles labelled as “Relevant” by both reviewers and excluded articles labelled as “Irrelevant” by either reviewer. A third reviewer screened the articles labelled as “Maybe” to make the final decision. After this process, 303 articles were selected. In the next step, the reviewers carefully read the abstract of each article and selected 85 articles that met our eligibility criteria. Two reviewers reviewed the full text of the selected 85 articles independently to assess their relevance to the scope of the paper. Finally, 46 articles were included in this review.

Among the 46 selected articles, 14 of them specifically examined the COVID-19 impacts on active transportation in Europe, 12 in North America, nine in Asia, two in South America, and one in Australia. Meanwhile, eight of the reviewed articles assessed the COVID-19 impacts at the international level across multiple countries.

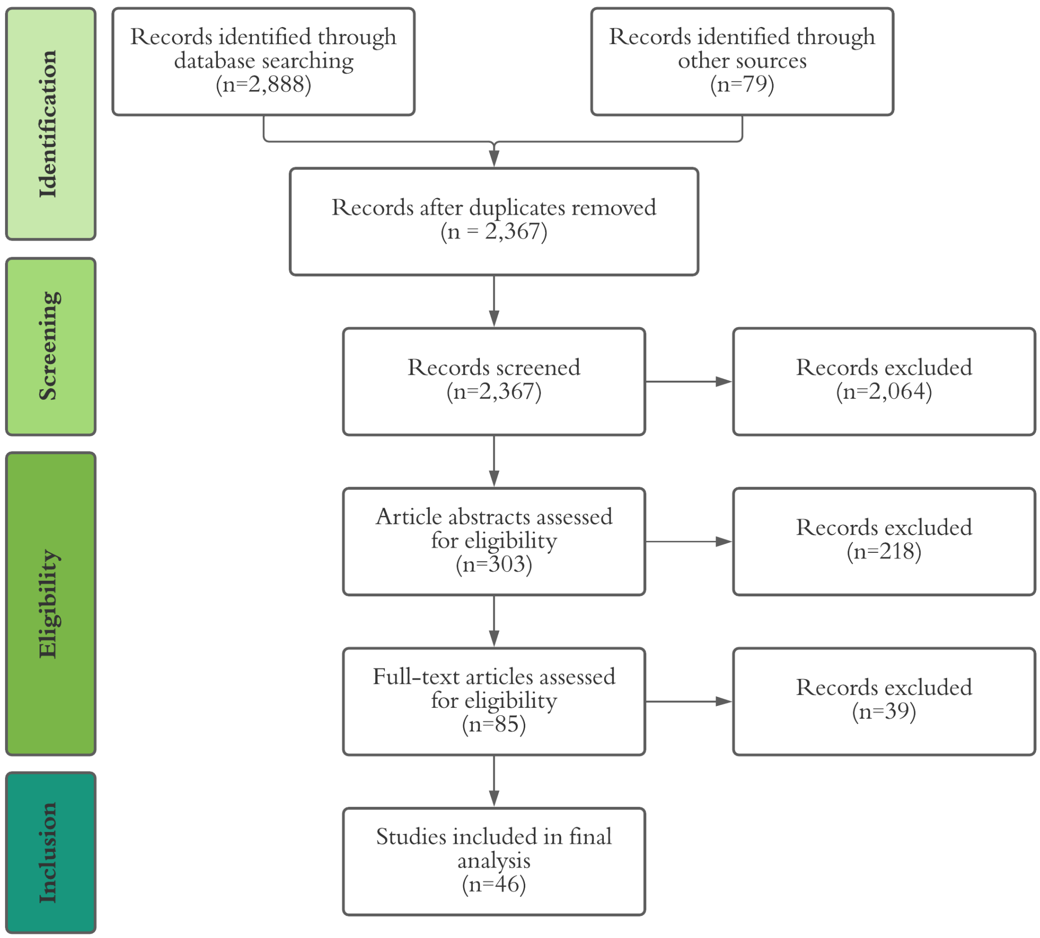


Figure 2. Scoping review procedure for literature identification and inclusion.

Sentiment Analysis Methods

To assess the mental health and sentiments towards active transport, we performed a sentiment analysis of social media data (Twitter at the time). We first determined a list of search terms including but not limited to “jog” or “run” or “biking” or “cycling” or “sidewalk” or “walk lane” or “pedestrian” or “walking” or “walk” or “bike” or “walkway” or “walk way” or “bikelane” or “bike lane” or “footpath” or “foot path” or “pedway” or “ped way” or “running” or “pavement” or “footway” or “disability” or “bicycle” or “jogging” or “bike share” or “bike sharing” or “shared bike lane” or “active transport” or “trail” or “shared use path” or “micromobility” or “e-scooter” or “bike route” to describe the transport mode and infrastructure type. We collected the Twitter data spanning four distinct periods within the Texas area, as illustrated in Table 1. Recognizing January 20, 2020, as the onset of COVID-19 in the United States (Li et al., 2020c), we identified March to April 2020 as the pandemic’s early stage. This period was chosen based on the escalating awareness and testing rates observed during these months.

Additionally, aligning with Texas's official vaccination commencement period (Texas Department of State Health Services, 2022), March to April 2021 was also identified as a critical time frame for analyzing pandemic severity. The selected periods reflect significant milestones in the pandemic's trajectory, offering a comprehensive view of the evolution of public sentiment regarding active transportation.

Table 1. COVID-19 Periods and Number of Tweets

Period	Date	Number of Tweets
Pre-COVID	March to April, 2019	103,381
Early COVID	March to April, 2020	87,130
Early COVID Prevention	March to April, 2021	87,947
Post-COVID	March to April, 2022	118,117

Sentiment Analysis Using TextBlob

First, we conducted a TextBlob-based sentiment analysis. Sentiment analysis is a typical application of the natural language processing (NLP) method. It is a method of analyzing, processing, summarizing, and subjective reasoning text with emotion color and using some emotion score indicators to quantify qualitative data (Liu and Zhao, 2022). TextBlob is an open-source text processing library written in Python. It can perform many natural language processing tasks, such as speech tagging, nominal component extraction, emotion analysis, and text translation (Krylova et al., 2020; Saura et al., 2022; Umair and Masciari, 2022). It is a simple model that utilizes a build-in lexicon to calculate the polarity, subjectivity, and intensity. In this research, we selected polarity as output results. Polarity lies between [−1, 1], where −1 refers to negative sentiment, and +1 refers to positive sentiment (Rustam et al., 2021).

Emotion Analysis Using DistilBERT-Base-Uncased

With the development of the NLP pre-training model in recent years, the number of parameters is getting larger and larger but is limited by the computational power and brings difficulties in the actual landing and online. BERT is a pre-training model proposed by the Google AI research institute in October 2018. The full name of BERT is bidirectional encoder representation from transformers. BERT showed terrific results in the machine reading comprehension top-level test SQuAD1.1. BERT comprehensively surpassed human beings in both measurement indicators and achieved state-of-the-art performance in 11 different NLP tests, including pushing the glue benchmark to 80.4 percent (absolute improvement of 7.6 percent) and the accuracy of Multi-Genre Natural Language Inference (MultiNLI) to 86.7 percent (absolute improvement of 5.6 percent), which became a milestone model achievement in the history of NLP development (Guo et al., 2022). BERT adopts the model of transformer encoder as the language model, altogether abandoning recurrent/convolutional neural networks (CNN) and other structures, and ultimately adopts the attention mechanism to calculate the relationship between input and output, in which the model includes two sublayers (Le et al., 2022). For the most popular and recent BERT pre-training model, DistilBERT was proposed. On the premise of retaining 97 percent performance, the size of the model is reduced by 40 percent, and the operation speed of influence is faster by 60 percent (Sanh et al., 2019). Mahumud et al. (2022) conducted a sentiment analysis in the Google Play Store to assess users' sentiments based on reviews using CNN, Long short-term memory (LSTM), and DistilBERT. Results indicated that the DistilBERT model outperformed the other models with the highest accuracy of 98.84 percent. Compared with the traditional BERT model, it has fewer layers with almost the same accuracy and 40 percent fewer parameters. It promises to run 60 percent faster while preserving 97 percent of its performance. (Liu et al., 2022). The DistilBERT-base-uncase model is pre-trained using raw texts without human labeling and employs a stimulated Google's BERT-uncased model.

Association Rules Mining

Association rule mining finds interesting connections hidden in large data sets. The discovered patterns are usually expressed as association rules or a frequent itemset. Association rules reflect the interdependence and relevance between one thing and others. If there is a specific correlation between two or more items, the occurrence of one of them can predict the occurrence of other things associated with it (Lei et al., 2010). Association rule mining is used for knowledge discovery, not prediction, so it is an unsupervised machine learning algorithm. Ariori algorithm uses prior knowledge of the properties of a frequent itemset and uses the iterative method of layer-by-layer search.

Results

In this section we present the findings of (1) the literature review related to changes in health pathways, including physical activity, air quality, and traffic crashes, and (2) health pathways related to sentiments.

Literature Review Findings

At the time of the search, no study was found directly reporting on the changes in health-related outcomes associated with active transportation (e.g., diseases caused by air pollution or injuries and fatalities for pedestrians and cyclists) induced by the pandemic. Therefore, we first reviewed and summarized the observed and estimated changes in active transportation demand, air quality, and built environment during the pandemic. We analyzed these changes through the three specified pathways to health and discussed the potential health consequences of these COVID-19-induced changes in active transportation. In this report we provide the summary of findings related to health outcomes. More detailed analysis of literature resulting from this activity can be found in Li et al. (2022).

Review of Observed Changes

Impacts on Travel Mode Shift

Numerous studies have been conducted to examine the influence of COVID-19 on people's engagement in active transportation, concentrated on walking, cycling, and shared biking. After performing the article screening process, the 20 most relevant research works were included, out of which nine were related to examining the changes in bike-sharing systems (BSS), 10 in walking, and seven in cycling. Since there were a considerable number of studies specifically targeting the BSS changes, we separated BSS from biking in this review.

For BSS, 67 percent of the reviewed studies (six out of nine) observed a drop in the number of BSS users (Bucsky, 2020; Chai et al., 2020a; Firestine, 2021; Padmanabhan et al., 2021; Teixeira & Lopes, 2020; Tokey, 2020). Meanwhile, one survey conducted by Nikiforiadis et al. (2020) in Thessaloniki, Greece, indicated that COVID-19 did not significantly influence BSS use. Some surveys indicated that the change of BSS usage is strongly related to the cyclists' biking frequency and attitudes toward COVID-19. For example, Matson et al. (2021) observed a decrease in BSS usage for infrequent cyclists; however, the frequent cyclists increased BSS usage since the pandemic began. A survey conducted by Jobe and Griffin (2021) in San Antonio indicated that 47.8 percent of their respondents did not change their BSS usage, while 26.1 percent increased their BSS trips, and 21.7 percent decreased or even stopped their BSS usage during the pandemic.

Among the 10 walking-related articles, five of them (50 percent) observed a clear decrease in the number of pedestrians since COVID-19 began (Bucsky, 2020; Ehsani et al., 2021; Hunter et al., 2021; Shakibaei et al., 2021; Szczepanek, 2020). However, three studies observed an opposite trend indicating that walking activities had increased (Abdullah et al., 2020; Anke et al., 2021; Matson et al., 2021). Some studies also suggested that the demand changes in walking also varied across different population groups and locations. For example, Yang & Xiang (2021) found that low-income households increased walking activities during the pandemic. Zecca et al.

(2020) observed that the pedestrian flows were almost completely zeroed in the residential areas, while the pedestrian intensity increased considerably in places close to essential services.

Regarding the changes of bicyclists, three of the seven reviewed articles mentioned that bike trips had significantly increased in their study areas since the pandemic began (Anke et al., 2021; Ehsani et al., 2021; Fuller et al., 2021). One study (Abdullah et al., 2020) did not find obvious changes, and one study (Bucsky, 2020) observed a 23 percent decrease in cycling demand. Kurkcu et al. (2021) found spatial differences in changes in biking trips. They observed a considerable decrease in biking among older adults and people living in high-income areas. Fuller et al. (2021) also found that different trip purposes led to different levels of changes. For example, their study observed that biking trips increased for exercise and wellbeing (recreational) but not for commuting purposes. Habib & Anik (2021) indicated that people made more recreational bike trips during the pandemic to improve their physical and mental health, leading to an increase in bike sales. Some studies revealed an evident shift from public transportation to active transportation to lower virus exposure (Anke et al., 2021; Bucsky, 2020; Habib & Anik, 2021).

Impacts on Air Pollutants

Active transportation is commonly defined as any self-propelled, human-powered mode of transportation. Therefore, while active transportation users do not produce emissions, they are exposed to environmental pollutants. Exposure to pollutants like nitrogen dioxide (NO2), particulate matter (PM), sulfur dioxide (SO2), ozone (O3), BC, and carbon dioxide (CO2) is detrimental to human health. The World Health Organization (WHO) recently reviewed the literature on air pollution effects on human health and accordingly updated its air quality guidelines, bringing the air pollution thresholds down to reflect the latest evidence (WHO, 2021). Air pollution from traffic has been associated with all-cause mortality and a wide spectrum of diseases that include but are not limited to cardiovascular disease, lung cancer, diabetes, adverse birth outcomes, congenital anomalies, neurological disorders, pregnancy-induced hypertensive disorders and preeclampsia, and adverse respiratory outcomes (Khreis et al., 2020). O3 exposure, although not a primary traffic-related pollutant, can cause coughing and a sore or scratchy throat, making it difficult to take a deep breath. It also inflames and damages the airways, making the lungs more susceptible to infection, aggravating lung diseases such as asthma, emphysema, and chronic bronchitis, and increasing the frequency of asthma attacks (U.S. Environmental Protection Agency, 2021). Due to the increased ventilation rate during walking and biking, the inhaled dose of air pollutants can increase; these pollutants can have detrimental impacts on the health of active transportation users with prolonged exposure to traffic pollution. Therefore, exploring the impact of air pollutants on active transportation user health has gained increasing attention in the literature. For the purposes of this study, we reviewed the studies on impacts of COVID-19 on air pollution to make an inference on how these changes may impact the active transport users' health.

In this scoping review, we included a total of 19 articles that estimated changes in air quality by comparing certain pollutants before and during COVID-19. The typical pre vs. during COVID-19 threshold in these studies is the implementation of lockdown policies in the geographical location of each study. Figure 3 illustrates the percent changes of eight air pollutants observed by the reviewed articles, including BC, CO2, NO2, NOx, O3, PM10, PM2.5, and SO2. Each violin plot represents the median value (black line in the bar), the interquartile range (the black bar in the center), and the probability density distribution (the plot shape) of changes for each pollutant. The wider the plot around a value, the more articles report pollutant percent changes at that value. Black dots represent the mean values of changes reported by each article. This review classifies the observed percent changes into three categories: slight change (0–25 percent), moderate change (25–50 percent), and significant change (50–75 percent).

Among the eight pollutants, the changes of NO2 and PM2.5 were most frequently captured by the selected studies. A total of 14 articles assessed PM2.5 changes, with 13 observing a slight to moderate decrease and one observing a slight increase. A total of 14 articles examined NO2 changes, and all of them reported a decrease, with a majority reporting a moderate decrease. Meanwhile, with the implementation of lockdown policies, studies also observed apparent decreases in the levels of BC, CO2, NOx, PM10, and SO2. Five articles examined the changes of PM10, reporting moderate to significant decreases in PM10 levels. Five articles observed slight to moderate decreases of SO2 levels in their study areas. Two articles examined NOx changes, and one showed a moderate change, while the other showed a significant decrease. Two articles studied BC level changes and also reported moderate to significant decreases in their studies. Only one of the reviewed articles examined CO2 changes at the global level and observed a slight decrease in CO2 levels. Different from the aforementioned pollutants, an opposite change was identified by many studies addressing O3. Seven articles reported on the O3 changes, and five of them observed slight to moderate increases in O3 from their study sites, and one observed a significant increase. Studies claimed that the decrease in nitrogen oxide levels could directly lead to an increase in O3 (Dantas et al., 2020; Mahato et al., 2020).

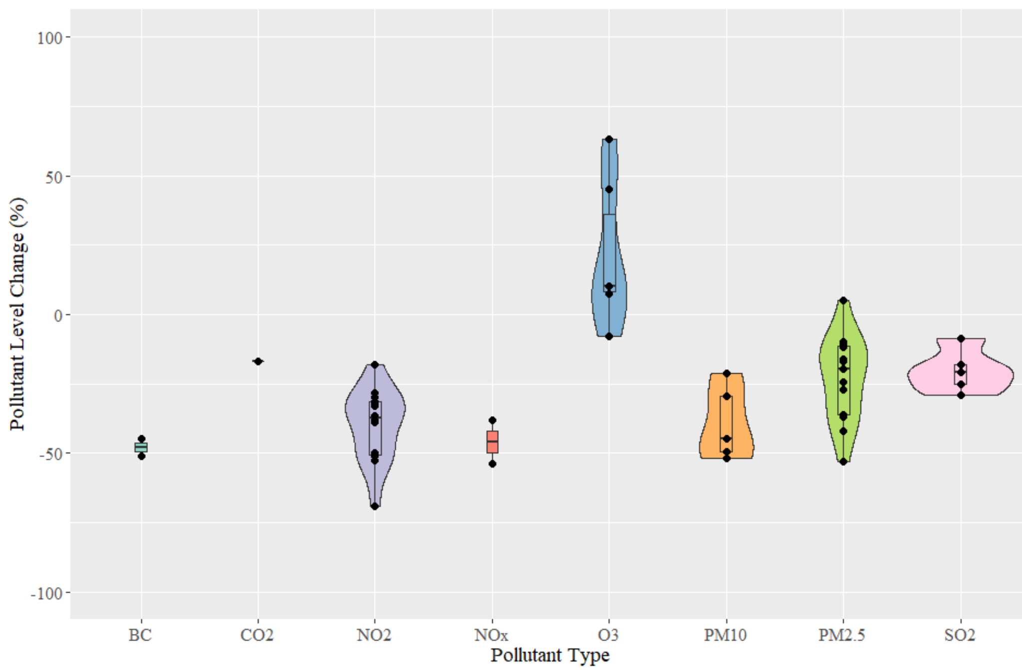


Figure 3. Changes in air pollutants during COVID-19.

Impacts on the Built Environment

Many planning organizations adapted contingency plans to accommodate the changing demand for active transportation. Some of the practices were documented in the reviewed studies. Five studies addressed built/natural environmental strategies responding to COVID-19. These studies extended their discussions from the regional (e.g., England and Wales) and national (i.e., Italy) level to the global perspectives, highlighting the shifting or renewed roles of the urban environments amidst COVID-19. Given the small number of articles addressing the built environment and the unique focus of each article, we provided our review of each study separately for these articles.

Capolongo et al. (2020) explored the broad inquiry on ways to better integrate pandemic-responsive public health strategies into contemporary urban planning practices. They proposed shorter-term action items such as “plan a smart and sustainable mobility network” and “re-think the accessibility to the places of culture and tourism,” as well as longer-term strategies such as "re-think building typologies, fostering the presence of semi-private or collective spaces," "integrate the existing environmental emergency plans with those related to the health emergencies," and "improve stakeholders' awareness of the factors affecting public health in the cities."

Two studies addressed mobility responses to COVID-19. One study addressed specific local strategies implemented in large cities in Italy (Barbarossa, 2020), and the other study inventoried and analyzed a comprehensive list of mobility measures from around the world (Combs and Pardo, 2021). Barbarossa (2020) discussed Italian examples of COVID-19 mobility responses employed by the 10 most populated cities. Their responses covered a wide range of built environment interventions to accommodate the increased demand for walking and cycling, such as temporary and permanent bike lanes, pedestrian and public spaces, restricted areas, and traffic calming zones. The scale of these interventions varied from 22 km of temporary/permanent bike lanes in Florence to 150 km of temporary bike lanes in Rome. Combs and Pardo (2021) developed a database containing 1,109 COVID-19 mobility responses from multiple data sources at a global scale. Most of the COVID-19 mobility strategies involved physical modifications to existing streets. Popularly implemented strategies were re-allocation of vehicular lanes to walking and cycling (13.2 percent, 146 applications), partial street closure (11.0 percent, 122 applications), and full street closure (11.0 percent, 122 applications) to support walking/cycling. Other environmental measures included automated walk signals, re-allocated curb spaces and street parking, re-allocated sidewalks to commerce, and improved bicycle parking facilities. They also found a number of policy/program responses to mobility challenges during COVID-19, such as reduced/free transit fare, reduced speed limit, subsidized bike purchase/maintenance, and revising/creating mobility plans to respond to COVID-19.

Two studies specifically focused on modelling green spaces in urban communities (Shoari et al., 2020; Ugolini et al., 2020). Shoari et al.'s (2020) study of parks and gardens in England and Wales showed that while most people had parks or gardens within a 10-minute walk, disparities existed in terms of accessibility. For example, children had lower levels of accessibility to parks/gardens, and those in high-density living environments (e.g., flat residents) had lower per-capita park/garden spaces. Ugolini et al. (2020) conducted online surveys during the early waves of COVID-19 in six countries, including Croatia, Israel, Italy, Lithuania, Slovenia, and Spain. They found that nearby green spaces such as tree-lined streets and small urban gardens became more important during COVID-19 among respondents from Italy, Spain, and Israel, while respondents from Lithuania reported traveling further outside the city to visit green spaces during COVID-19. Urban green spaces were considered important even without the ability to visit them. Respondents recommended those green spaces be better integrated into the neighborhoods for increased accessibility during pandemics like COVID-19.

Implications of COVID-19-Induced Changes on Active Transportation Users' Health

In this review paper, we explored how the observed changes (discussed in the Results section) may have affected or could potentially affect the health of active transportation users through the following health pathways: physical activity, traffic crashes, and traffic-related air pollution. During the search of the literature (performed in March 2021), we did not find studies concerning traffic crashes involving active transportation users or the potential impacts of air pollution changes on active transportation users' health. However, we performed a non-systematic search to identify relevant studies published since then to support the inferences we made about the potential impacts of observed changes in travel demand, air quality, and the built environment on active transportation users' health.

Physical Activity

Two studies, located in the United Kingdom and Japan, looked at the determinants related to physical activity participation during the COVID-19 pandemic. Spence et al. (2021) conducted a 1,521-respondent survey to examine the impact of the COVID-19 lockdown on the physical activity of U.K. adults and identified potential motivational determinants of behavioral change. Most respondents reported reduced physical activities for commuting to workplaces and activities at recreational facilities compared to the pre-lockdown level. On the contrary, many respondents maintained or increased their physical activities at home and in their local neighborhoods. Meanwhile, significant increases were observed in sedentary behaviors, including sitting, reclining, and using screen-based devices for working, schooling, and leisure. This study also indicated that most adult respondents did not follow the U.K. guidelines on physical activity, and the prevalence of physical activity was much lower than it was before the pandemic.

This study also modelled the relationship between the physical activity changes and three potential determinants: physical opportunity (i.e., access to parks, gyms), social environment (i.e., social cues, social support from friends and family, norms), and reflective motivation (i.e., willingness). The results indicated that the frequency of physical activity during the pandemic was highly determined by the respondents' physical opportunities and their motivation/willingness. The social environment was not influential in their model. The study suggests the importance of the community environment in promoting physical activity during pandemics like COVID-19 and the significant roles of recreational and active transport facilities such as green space and biking/cycling.

Sasaki et al. (2021) examined the impacts of COVID-19 on older adults' physical activities in August 2020 based on a survey of 999 participants. Sasaki et al. analyzed associations between several variables such as socioeconomic status, social participation, and physical activity among older populations in northern Japan. The study found that older men in lower socioeconomic status were less likely to be active, while older women with higher social participation (e.g., participating in an exercise program) were more likely to be active during the pandemic. Older adults with a higher socioeconomic status and social participation in pre-COVID-19 were more likely to maintain physical activity levels during the pandemic.

Air Pollution-Related Health Concerns

Not many studies have explored the effect of COVID-19-related transportation changes on air pollution that affect active transportation users. However, based on the rich evidence from the existing air quality literature, their positive impacts can be inferred. Results from our review showed that air pollution levels were reduced up to 78 percent for NO2, 53 percent for PM2.5, and 55 percent for PM10, all of which are regulated air pollutants due to significant adverse health effects. These reductions imply significant health benefits ranging from fewer exacerbations of, for example, asthma attacks, hospital admissions, and cases of stroke and myocardial infarctions as well as other important effects such as reducing the rates of chronic diseases and premature mortality if and where these reductions are sustained. Other pollutants from transport such as BC (Invernizzi et al., 2011) were also reduced during the pandemic. However, maintaining the reduced air pollution level beyond the pandemic through other transportation planning measures or policies remains a challenge.

Traffic Crashes

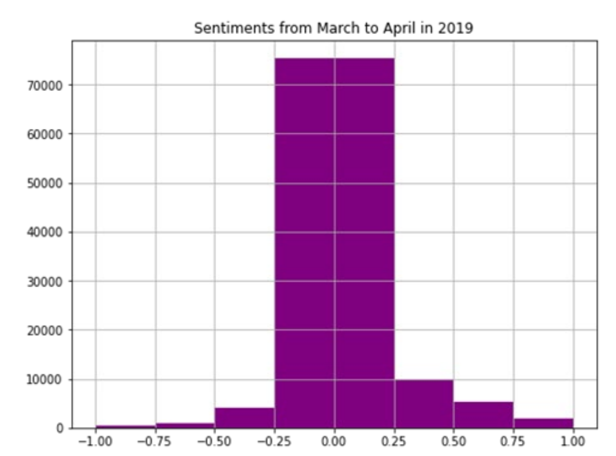
The changes in travel demand and vehicle miles travelled during the pandemic affected traffic safety. NHTSA conducted a comparative analysis of road crashes (NHTSA, 2021). The motor vehicle crash rates per emergency medical services activation was compared between 2019 and 2020 (NHTSA, 2021). The results showed a decrease in the rate of crashes. This trend was observed in Connecticut, United States (Doucette et al., 2021), Tarragona, Spain (Saladié et al., 2020), and Greece and the Kingdom of Saudi Arabia (Katrakazas et al., 2020).

Data from the United States show that despite fewer crashes during the global pandemic, road fatality increased by 7 percent between 2019 and 2020 (NHTSA, 2020). The percentage of all patients severely injured in motor vehicle crashes increased significantly in the 10th week of 2020 when the COVID-19 public health emergency was declared (NHTSA, 2021). The increased severity of crashes was also partly because of the changes in driving behaviors during the global pandemic. The comparison between the number of drivers with a positive drug test in the fourth quarter of 2019 and 2020 shows a 5 percent increase in drug usage (at least one category) among drivers during the pandemic and a 13 percent increase among motorcyclists (NHTSA, 2021). The analysis of data from U.S. roads indicated traffic speed, one of the major contributors to road crash severity, also increased during the pandemic (NHTSA, 2021). In a survey of 3,000 respondents in the United States and Canada that asked about the likelihood of engaging in risky driving during the pandemic as compared to before COVID-19 (Vanlaar et al., 2021), respondents admitted engaging more in speeding (7.6 percent) and drinking and driving (7.6 percent) in the United States, and speeding (5.5 percent) and distracted driving (4.2 percent) in Canada during the global pandemic (Vanlaar et al., 2021).

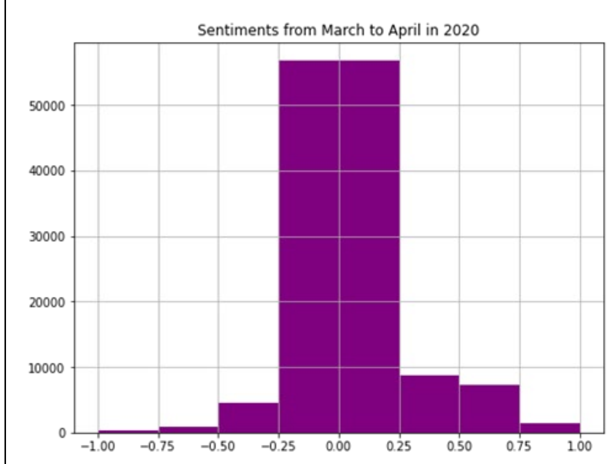
Sentiment Analysis Findings

Sentiment Scores

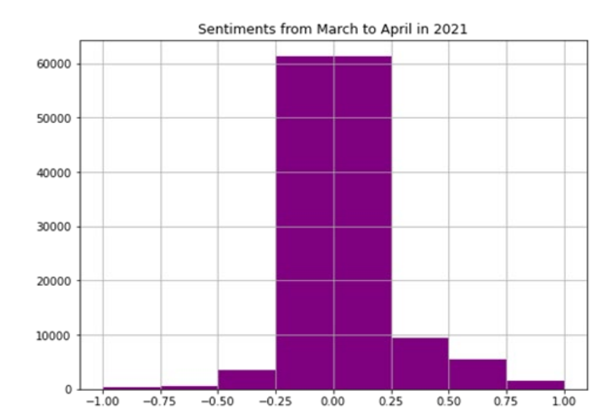
Figure 4 illustrates sentiment scores distribution in four stages from March to April in Texas. Tweets with positive sentiment about active transportation are more prevalent in 2019 compared with 2020, which demonstrates that people's attitude toward active transportation has changed due to the negative impact of COVID-19. There is a small rebound in the comparison of 2020 and 2021 data. The data show that after the vaccine injection in 2021 and the full opening of Texas, people have a more positive attitude towards active transportation. In 2022, the tendency is more obvious.



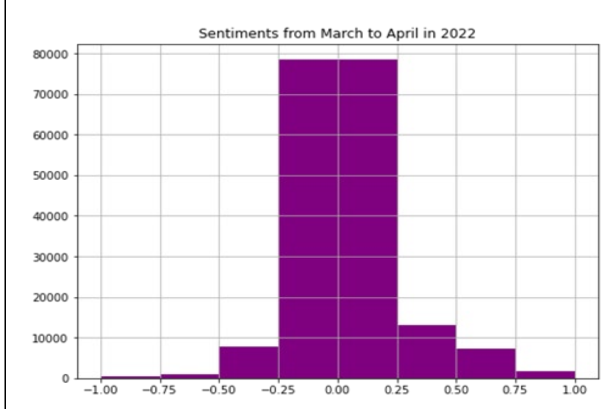
a) Pre-COVID



b) Early COVID



c) Early Prevention

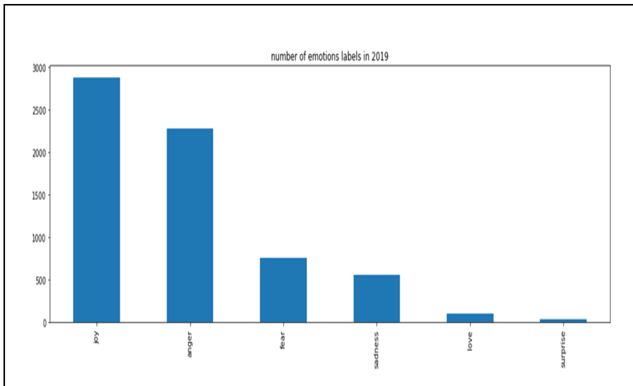


d) Post-COVID

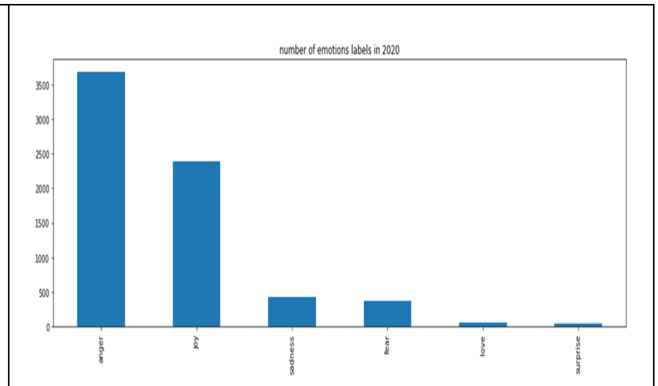
Figure 4. Sentiment distribution from March to April in four stages.

Emotion Analysis

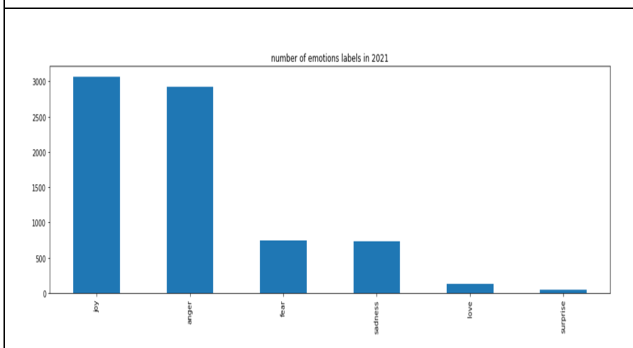
Figure 5 illustrates emotion label frequencies in different study periods using DistilBERT-base-uncased model that outputs six emotion scores including joy, anger, sadness, fear, love, and surprise. We labeled each text with the highest emotion score. In 2019, most of the emotion labels are joy, followed by anger and fear. In 2020, most tweets indicate anger about active transportation, followed by joy and sadness. Compared to 2020, people feel more joy about active transportation in 2021. However, there are still many tweets showing anger towards active transportation. In 2022 the overall sentiment is happier and less angry about active transportation.



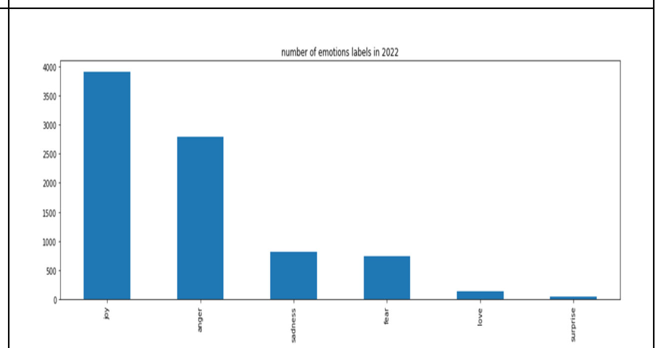
a) Pre-COVID



b) Early-COVID



c) Early Prevention



d) Post-COVID

Figure 5. Emotion labels distribution from March to April in four stages.

Association Rules

The minimum support is the artificially specified threshold, which indicates the itemset's lowest statistical importance. The minimum confidence is also an artificially specified threshold, meaning the most insufficient reliability of association rules. Only when the support and confidence levels reach the minimum support and minimum confidence simultaneously, this association rule will be called a strong one (Lei et al., 2010). For example, the rule bike lane related–other has the highest confidence, which corresponds to our understanding that many other active transportation types, such as e-scooters, use bike lanes. We set a minimum support value of 20 percent and a minimum threshold of 70 percent. The results of association rule mining in Table 2 show examples of association rules ordered concerning their minimum support, confidence, lift, leverage, and conviction.

Table 2. Pre-COVID Association Rules

Rule #	Antecedents	Consequent	Support	Confidence	Lift	Leverage	Conviction
0	(others)	(bike lane related)	0.708	0.671	0.600	0.847	1.261
1	(bike lane related)	(others)	0.671	0.708	0.600	0.893	1.261

2	(joy)	(others)	0.436	0.708	0.314	0.720	1.017
3	(trail related)	(walking)	0.221	0.260	0.211	0.952	3.663
4	(walking)	(trail related)	0.260	0.221	0.211	0.810	3.663
5	(others, anger)	(bike lane related)	0.240	0.671	0.201	0.838	1.248
6	(anger, bike lane related)	(others)	0.227	0.708	0.201	0.887	1.252
7	(others, joy)	(bike lane related)	0.314	0.671	0.266	0.848	1.263
8	(bike lane related, joy)	(others)	0.296	0.708	0.266	0.898	1.268

Table 3 illustrates the association rule mining results in 2020. For example, the rule anger–bike lane related suggests that people would feel angry about bike lane-type roads. Also, the rule anger indicates that people would feel angry about other types of active transportation modes.

Table 3. Early-COVID Association Rules

Rule #	Antecedents	Consequents	Support	Confidence	Lift	Leverage	Conviction
0	(anger)	(bike lane related)	0.412	0.782	1.005	0.002	1.019
1	(anger)	(others)	0.375	0.711	0.992	−0.003	0.979
2	(joy)	(bike lane related)	0.263	0.769	0.988	−0.003	0.961
3	(bike lane related)	(others)	0.661	0.849	1.184	0.103	1.873
4	(others)	(bike lane related)	0.661	0.921	1.184	0.103	2.819
5	(joy)	(others)	0.248	0.725	1.011	0.003	1.029
6	(bike lane related, anger)	(others)	0.347	0.841	1.173	0.051	1.779
7	(others, anger)	(bike lane related)	0.347	0.925	1.189	0.055	2.977
8	(bike lane related, joy)	(others)	0.228	0.866	1.207	0.039	2.107

Table 4 illustrates the association rules results in 2021. There are only four rules in the 2021 data set. For instance, rule other–bike lane related is just like the rule in 2019. The second highest confidence rule joy, others–bike lane related suggests that other types of active transportation are highly associated with the bike lane.

Table 4. Early-Prevention Association Rules

Rule #	Antecedents	Consequents	Support	Confidence	Lift	Leverage	Conviction
0	(bike lane related)	(others)	0.588	0.885	1.349	0.152	2.985
1	(others)	(bike lane related)	0.588	0.898	1.349	0.152	3.270
2	(bike lane related, joy)	(others)	0.276	0.890	1.358	0.073	3.141
3	(joy, others)	(bike lane related)	0.276	0.898	1.349	0.071	3.269

Table 5 illustrates the association rules results in 2022. The rule others, anger–bike lane related with the highest confidence value indicates that people using other types of active transportation potentially feel upset about the bike lane. The second highest rule, others–bike lane related, suggests that people using different types of active transportation are more likely to use the bike lane as their road.

Table 5. Post-COVID Association Rules

Rule #	Antecedents	Consequents	Support	Confidence	Lift	Leverage	Conviction
0	(anger)	(bike lane related)	0.283	0.742	1.011	0.003	1.030
1	(joy)	(bike lane related)	0.294	0.735	1.001	0.000	1.004
2	(others)	(bike lane related)	0.606	0.877	1.195	0.099	2.162
3	(bike lane related)	(others)	0.606	0.825	1.195	0.099	1.770
4	(others, anger)	(bike lane related)	0.235	0.888	1.209	0.041	2.369
5	(anger, bike lane related)	(others)	0.235	0.830	1.201	0.039	1.814
6	(others, joy)	(bike lane related)	0.243	0.875	1.192	0.039	2.128

Conclusions and Recommendations

This scoping review examined potential health impacts of induced active transportation activities during the COVID-19 pandemic through the three health pathways, physical activity, air quality, and traffic crashes, while sentiment analysis was implemented to assess the mental health effects of COVID-19 on active transport users. We summarized the study findings as follows:

Physical activity: The evidence from the United Kingdom and Japan demonstrated that the frequency of physical activities decreased while sedentary-related behaviors increased compared to the pre-pandemic frequency. These changes were directly related to the respondents' physical opportunities and motivation/willingness. Meanwhile, the respondents' socioeconomic status could also influence physical opportunities and willingness to participate in and maintain physical activity during the pandemic.

Air quality: The air pollution reductions achieved during the pandemic were unprecedented, beyond what is feasible with more incremental measures. Although not many studies quantified the health impacts of these changes, they are expected to be large and span across reductions in adverse short-term health effects such as the exacerbations of respiratory symptoms as well as longer-term positive effects such as reduced premature mortality and improved respiratory and cardiovascular health. Further efforts are needed to quantify and document these impacts using methods like health impact assessments.

Traffic Crashes: Our review of the literature showed a decrease in the number of crashes after the emergence of the global pandemic. However, the severity of crashes increased due to riskier driving patterns and behaviors including speeding, failing to wear seat belts, and driving under the influence of drugs or alcohol, all of which have a significant impact on active transportation users' safety. The understanding of the COVID-19 impacts on non-motorized crashes is still in its infancy, and mixed conclusions were drawn in the limited literature. Therefore, this topic requires further investigation to better understand the non-motorized traffic safety in the era of the global pandemic and the underlying mechanism behind the potential associations.

Sentiments and Associate Mental Health: We applied TextBlob-based sentiment analysis at first. The results show that COVID-19 impacts people's sentiment about active transportation. At the very beginning of the pandemic, people felt less positive about active transport due to the grim situation of the epidemic. As the epidemic was gradually controlled, people's sentiment tendencies became more positive. Moreover, a DistilBERT-base model was applied to analyze human emotion changes in different study periods. In our four study periods, the joy label had the highest value in three periods except for 2021, indicating that COVID-19 restrained people from going out for walking and biking-related activities. After a rapid increase of anger labels in 2020, the anger label was continuously decreasing. It occupies second place, suggesting that people's emotional tendencies toward active transportation in Texas relate to COVID-19.

Outputs, Outcomes, and Impacts

This study brings various broader impacts on public health and urban planning research. For example, it can help to inform the metropolitan planning organizations and other policymaking agencies to revisit strategies and priorities for supporting and promoting active transportation. Furthermore, there is an urgent need to assess the health outcomes of COVID-19-induced active transportation demand change, which can help transportation, planning, and public health agencies at multiple governmental levels make informed decisions about the critical needs to accommodate and further support active transportation. However, the effectiveness of policy and built environmental interventions relies heavily on the physical and population contexts. Both the COVID-19 impacts and the availability/benefits of supportive environmental features are not equally distributed across populations and locations. For example, children and residents of high-density residential communities had lower access to green spaces (Shoari et al., 2020). While collective findings from the reviewed studies suggest the importance of being able to walk and bike safely during the pandemic, it is even more important for those who rely on transit for their daily travel needs, called "captive" transit riders, as transit services became less available and less safe. Planning efforts should consider tailored and targeted approaches to ensure that the programs (e.g., reduced/free transit fare, reduced speed limit, subsidized bike purchase/maintenance) and built environmental modifications (e.g., temporary/permanent bike lanes and sidewalks, public spaces, traffic calming or restricted zones, automated crossing signals, re-allocated street spaces, and improved bicycle parking facilities) are best suited for the local context. Further, more efforts are needed to measure these planning interventions' health and transportation effects in both the short-term and the long-term (Capolongo et al. 2020). The unprecedented public health challenges of COVID-19 have accompanied unprecedented opportunities for urban planning to revisit and reprioritize its policy objectives to create healthy cities that are more resilient and adaptable to pandemics like COVID-19 in the future.

Research Outputs, Outcomes, and Impacts

The results of the literature review were published in Li et al. (2022).

The research team is currently developing a research paper based on the sentiment analysis: Hu, N., Zhang, Z., Dadashova, B. and Li, X. Exploring Sentiment Changes About Active Transportation During COVID-19 Using Social Media Data Mining (In Preparation).

Additionally, the research team developed a travel survey as part of the initial work plan. However, due to constant changes during the COVID-19 pandemic this survey was not administered. We plan to use this survey for future research purposes.

Technology Transfer Outputs, Outcomes, and Impacts

The research team built a strategic partnership with the following agencies: Sun Metro, El Paso Metropolitan Planning Organization, County of El Paso Planning Development, Texas Department of Transportation, Horizon City Town, and El Paso Public Works. We conducted a stakeholder meeting to discuss the stakeholders' expectations and feedback on the project. The participants discussed several initiatives in the El Paso region (e.g., Vision Zero, Bike Plan, etc.) regarding the safety and health of active transport users.

Education and Workforce Development Outputs, Outcomes, and Impacts

The following students were involved in this project:

- Nanzhou Hu, (current) PhD student of Geography, Department of Geography, Texas A&M University.
- Minaal Farrukh, (former) MS student of Public Health, Department of Public Health, Texas A&M University.
- Soham Sarda, (former) MS student of Civil Engineering, Department of Civil Engineering, Texas A&M University.
- Amaryllis Park, (former) PhD student of Urban Planning, Department of Landscape Architecture and Urban Planning, Texas A&M University.

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