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Designing pandemic resilient cities: Exploring the impacts of the built environment on infection risk perception and subjective well-being

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ABSTRACT

Since the beginning of the COVID-19 pandemic, authorities around the world explored ways to slowdown the spread of the disease while maintaining the physical and mental health of individuals. They redistributed the street space to promote physical activity and non-motorized travel while meeting the social distancing requirements. Although the statistics showed significant increases in walking and bicycling trips during the pandemic, we have limited knowledge about the associations between built environment characteristics, COVID-19 infection risk perception while traveling, and subjective well-being. This study assesses the impacts of the built environment on subjective well-being and infection risk perception while traveling during the pandemic. It uses data collected from the residents of Columbus, Ohio, through a multi-wave survey conducted at different time points during the COVID-19 outbreak. By employing a structural equation modeling approach, it explores the associations between residential neighborhood characteristics, individuals’ subjective well-being, and perceived infection risk while using non-motorized modes and shared micromobility. The findings show that those living in more compact, accessible, and walkable neighborhoods are less likely to perceive active travel and shared micromobility as risky in terms of COVID-19 infection. Our results also show that built environment characteristics have an indirect positive effect on the subjective well-being of individuals. The findings of our study demonstrate that built environment interventions can help promote physical activity and support mental health of individuals at this critical time. Our study also indicates that designing compact neighborhoods will be a crucial element of pandemic resilient cities in the post-COVID-19 era.

1. Introduction

The COVID-19 outbreak caused enormous global challenges, namely millions of hospitalizations and deaths, interruption of global supply chains, business bankruptcies, and overwhelmed health systems (Ekwebelem et al., 2020; Filho et al., 2020; Thoradeniya and Jayasinghe, 2021). According to the World Health Organization (WHO), there have been 259,502,031 confirmed cases of COVID-19, including 5,183,003 deaths globally as of November 26, 2021 (WHO, 2021). All these changes resulted in significant disruptions to individuals’ daily activities and travel frequencies worldwide (Budd and Ison, 2020; De Vos, 2020). This is expected considering the mandates implemented by local governments to slowdown the spread of the disease (Budd and Ison, 2020) and individual concerns regarding the risk of potential exposure to coronavirus (De Vos, 2020). Earlier this year, the rapid administration of COVID-19 vaccines helped the reopening processes and reduced the anxiety of individuals to a certain level around the world. However, the stagnation in vaccine uptake in many countries in summer and the emergence of new variants that are more contagious caused the transmission rates to increase once again (Hawkins et al., 2021; Kluge, 2021). Consequently, the unprecedented effects of the pandemic on daily travel and out-of-home activity participation persist to a certain level.

COVID-19 unveiled many transportation-related problems in our cities, such as lack of access to open and green spaces, insufficient transportation infrastructure, and lack of reliable transit services (Ahmadpoor and Shahab, 2021; Dailey et al., 2020; ITDP (Institute for Transportation & Development Policy), 2020; Kyriazis et al., 2020; Tirachini and Cats, 2020). As a result, researchers and media paid special attention to the mobility-related changes and disruptions created by COVID-19 (Budd and Ison, 2020; De la Graza, 2020; Goldbaum, 2020). Studies that were conducted early in the pandemic showed that many...
individuals experienced significant travel reductions during this time, particularly with shared modes that may increase the risk of contact with other users (De Haas et al., 2020; Gao et al., 2020; Klein et al., 2020; Wang et al., 2020). While the world experienced a reduction in travel in general, most individuals reported substantial increases in virtual activities such as teleworking and online shopping (Mouratidis, 2021; Riggs, 2020). This new mostly home-based lifestyle created additional problems for individuals, such as health anxiety, feeling of loneliness, and limited daily physical activity that are all crucial elements of subjective well-being and physical health (Flanagan et al., 2020; Son et al., 2021; Tull et al., 2020). As a response to these new challenges posed by the pandemic, various local governments introduced open street policies worldwide to create safe urban environments and promote non-motorized transportation (Kraus and Koch, 2021; NACTO, 2020). Opening the streets to pedestrians and bicyclists was intended to support individuals’ physical and mental health (Combs and Pardo, 2021; Hamblin, 2020). For future planning and policymaking, it is essential for urban planners to evaluate the links between built environment characteristics and physical/mental health at this critical time. Empirical studies that provide evidence about the impacts of the built environment on individuals’ mental health and physical activity during the pandemic can help make our cities more pandemic resilient in the post-COVID-19 era.

This study analyzes the associations between the built environment, subjective well-being, and COVID-19 infection risk perception while walking, bicycling, and using shared micromobility. Exploring these associations is imperative to be better informed about the impacts of the built environment improvements on physical activity and mental health of the individuals during the pandemic (De Haas et al., 2020; Handy, 2020; Li et al., 2020a). We employ a structural equation modeling approach to assess the associations between the built environment, subjective well-being, and infection risk perception while walking, bicycling, and using shared micromobility. We include socio-demographic characteristics, attitudinal factors, and infection risk perception while traveling with other modes as control variables in the analyses.

2. Literature review

The COVID-19 infection risk perception while traveling characterizes out-of-home activity frequency and individual travel behavior during the pandemic (Parady et al., 2020; Rahimi et al., 2021). Prior to the COVID-19 crisis, researchers conducted several studies on the impacts of exposure risk perception on travel behavior during virus outbreaks (e.g., seasonal influenza, SARS, etc.). These studies show that perceived infection risk impacts travel preferences and mobility behavior (Brug et al., 2004; Høtte et al., 2020). The substantial reduction in travel (particularly with the shared modes) during the COVID-19 pandemic (Klein et al., 2020; Rahimi et al., 2021; Transit App, 2021; Wang et al., 2020) supports previous findings on the negative effects of infection risk perception on mode choice and travel frequency. Additional studies are needed to better understand the impacts of COVID-19 infection risk perception on daily mobility and travel preferences of individuals.

There is limited but growing literature on the impacts of COVID-19 on risk perception, travel behavior, and subjective well-being (Budd and Ison, 2020; De Vos, 2020; Fuller et al., 2021; Ozbilen et al., 2021a; Parady et al., 2020; Rahimi et al., 2021). These studies examine the effects of the pandemic and subsequent restrictions on travel frequency, infection risk perception while traveling, and subjective well-being. Considering the dynamic nature of the pandemic and differences between various geographies, researchers call for additional studies that will explore the travel and mental health implications of the pandemic. The assessment of these implications requires revisiting previous literature assessing the factors affecting individuals’ travel behavior and subjective well-being. In the remainder of this section, we will present a brief summary of the determinants of travel behavior and subjective well-being to establish a comprehensive framework for the analysis. Following this summary, we will conclude the section with a discussion on the daily mobility challenges caused by the COVID-19 pandemic and the research needs for post-pandemic policymaking.

2.1. Determinants of travel behavior and subjective well-being

There is well-established literature on the determinants of travel behavior. Individuals’ mode choices and travel frequencies are affected by ‘hard factors’ such as built environment characteristics and socio-demographics, and “soft factors,” namely individual attitudes, subjective well-being, and perceptions (De Vos et al., 2013; Klinger and Lanzendorf, 2016; Park and Akar, 2019). Previous studies demonstrate that all these factors influence travel behavior. However, it is also important to acknowledge that some of these factors influence each other (De Vos et al., 2013; Ettema et al., 2010; Singleton, 2019). It is essential to understand the associations between these hard and soft factors for a comprehensive analysis of travel preferences and mental health during the COVID-19 pandemic. As a result, we will delve into the determinants of travel behavior and the interrelationships between these determinants in the following subsections.

2.1.1. Socio-demographics

Socio-demographic characteristics of individuals are significantly associated with travel behavior. Previous studies show that age, gender, employment status, educational attainment, race, household income, and vehicle ownership impact transportation mode choice and trip frequencies (Barajas, 2019; Chen and Akar, 2017; Klinger and Lanzendorf, 2016; Mauch and Taylor, 1997; Tal and Handy, 2010). For example, women, non-Hispanic Whites, and those who are older are less likely to use non-motorized transportation options as compared to the others (Akar et al., 2013; McDonald, 2008; Noland et al., 2011; Shen et al., 2017). Additionally, earlier studies show that household income level and vehicle ownership negatively influence active travel frequency and duration (Böcker et al., 2017; McDonald, 2008; Plaut, 2005; Rajamani et al., 2003). The literature also shows significant relationships between socio-demographic characteristics and individuals’ overall subjective well-being and travel domain specific subjective well-being (Boarini et al., 2012; Singleton, 2019). For instance, those with higher household income and educational attainment report greater subjective well-being scores (Boarini et al., 2012; Pinquart and Sorensen, 2000). In brief, socio-demographic characteristics, particularly those related to socio-economic status (e.g., household income, employment status, educational attainment, etc.), are significantly associated with both physical mobility and mental health of individuals. As a result, researchers need to account for these individual and household level factors while analyzing travel behavior during the COVID-19 pandemic.

2.1.2. Attitudes and perceptions about various travel modes

Attitudinal factors and perceptions are also associated with travel behavior and subjective well-being. Previous studies show that travel satisfaction, positive perceptions about walking/bicycling, and pro-environmental identity positively impacts active travel and subjective well-being (Clark et al., 2016; Namgung and Akar, 2015; Ozbilen et al., 2021b; Zawadski et al., 2020). A recent study by Barajas (2019) shows that perceptions of bicycling and social relationships with bicyclists are significant predictors of bicycling. Another study on the effects of perceptions on travel behavior shows that pro-environmental attitudes are negatively associated with driving (Kahn and Morris, 2009). These two studies demonstrate that individuals’ perceptions regarding

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1 Micromobility is a novel terminology that covers small, lightweight human-powered or electric vehicles that operate at low speeds (McQueen et al., 2020). Micromobility modes include docked/dockless bike share systems and electric scooters.
environment and active travel modes impact their travel behavior. According to Ettema et al. (2010), travel domain specific subjective well-being and overall subjective well-being are influenced by satisfaction with travel experience. The relationship between travel and subjective well-being can be two-directional. In their study, De Vos et al. (2013) indicate that while those more satisfied with their travel can have greater well-being, the opposite may be true in some circumstances. They suggest further empirical research to clarify the direction of the association between travel satisfaction and subjective well-being.

### 2.1.3. Built environment characteristics

A considerable body of work demonstrates that built environment factors have significant impacts on travel behavior, especially travel with non-motorized options (e.g., bicycling and walking) (Cao et al., 2007; Ewing and Cervero, 2010; Handy et al., 2002; Kerr et al., 2012; Namgung and Akar, 2015). Built environment characteristics that are influential on travel behavior can be grouped under five categories that are also known as five s-variables or 5Ds (Ewing and Cervero, 2010):

1. **density** (variable of interest (e.g., population, housing, employment, etc.) per unit area),
2. **diversity** (number of different land-uses in a specific area (e.g., land-use mix or entropy)
3. **design** (street network characteristics (e.g., number of intersections, sidewalk coverage, etc.) in a given area),
4. **destination accessibility** (ease of access to major trip attractions (distance to the central business district, number of jobs reachable within a given travel time)
5. **distance to transit** (average of the shortest routes from residences to the nearest transit stop)

The characteristics of a neighborhood are measured through these 5Ds in travel behavior research. Neighborhoods with higher scores in these categories are relatively more compact, walkable, and accessible and can help reduce private car use (Ewing and Cervero, 2010). There are numerous empirical studies that demonstrate positive associations between five s-variables and active travel frequency and durations (Barajas, 2019; Cheng et al., 2019; Yang et al., 2019). A dense, diverse, well-designed, accessible, and pedestrian-friendly built environment can also impact individuals’ subjective well-being. An increasing number of empirical studies present evidence on the positive association between a well-designed built environment and subjective well-being in different contexts and geographies (Guo et al., 2021; McCarthy and Habib, 2018; Yin et al., 2019). In a recent review study, Mouratidis (2021) identifies seven pathways linking the built environment to subjective well-being, namely travel, leisure, work, social-relationship, residential well-being, emotional responses, and physical health. According to Mouratidis (2021), built environment interventions can be used to improve subjective well-being of individuals.

### 2.2. Daily mobility and the COVID-19 Pandemic: Challenges and needs

The COVID-19 pandemic still affects the daily mobility and travel behavior of billions of people. Researchers from all around the world conducted studies on the effects of perceived infection risk and COVID-19 restrictions on daily mobility (De Haas et al., 2020; Gao et al., 2020; Kim et al., 2021; Ozbilen et al., 2021a; Parady et al., 2020; Rahimi et al., 2021). Some of these studies focus on the impacts of the pandemic on different groups and demonstrate that these impacts are not distributed evenly (Brough et al., 2020; Hamidi et al., 2020; Shamshiripour et al., 2020). These unbalanced effects are expected considering the socio-economic disparities between different groups and built environment variations across different neighborhoods (Brough et al., 2020; Dabelko-Schoeny et al., 2021; Kryzius et al., 2020; Rollston and Galea, 2020). The upheaval created by the pandemic call for policies that can address the challenges created by this outbreak.

Researchers underline the need to redesign our cities based on the lessons we learned throughout the pandemic (Aboukorin et al., 2021; Florida and Storper, 2021). To plan and design pandemic resilient cities and prepare urban environment for possible future pandemics, transportation scholars should clearly understand the associations between built environment factors, subjective well-being, and travel behavior. Developing a framework that analyzes the factors affecting infection risk perception while walking, bicycling, and using shared micromobility can help transportation scholars develop policies and strategies that can promote these options during and after the pandemic. Previous studies show that walking, bicycling, and shared micromobility have the potential to contribute to the overall sustainability efforts by minimizing the environmental and economic costs as well as supporting individuals’ physical and mental health (Bassett et al., 2008; Fitt and Curl, 2019; Neun and Haubold, 2016; Pae and Akar, 2020; San Francisco Municipal Transportation Agency, 2019). Promoting sustainable travel alternatives is also vital to slowdown the rapidly growing Climate Change crisis and to reduce its negative impacts (Black, 2010; Litman, 2019; Stone et al., 2010).

Within these considerations, our study contributes to the literature by (i) assessing the effects of the built environment on the COVID-19 infection risk perception while walking, bicycling, and using shared micromobility; (ii) analyzing the association between the built environment and subjective well-being during the pandemic.

### 3. Data and methodology

As part of a larger study assessing the impacts of recent transportation infrastructure investments and travel behavior variations across different neighborhoods (Ozbilen et al., 2021a), the data for this study were collected through a multi-wave survey with respondents from the Columbus Metropolitan Area in Ohio. Columbus is the largest metropolitan area in Central Ohio and the 32nd most populous metropolitan area in the nation (Statista, 2021). It has a diverse representation of age groups, cultures, and ethnicities. Columbus Metropolitan Area has a sprawled urban form, a well-connected highway system, and a relatively sparse transit network (Vyas et al., 2019; Wang and Chen, 2015). Since Columbus is a major Midwestern city that is more car-dependent than coastal cities such as New York, San Francisco, and Boston, our findings offer valuable insights to numerous U.S. cities with a similar urban form and transportation network.

#### 3.1. Data

We conducted multiple waves of surveys at different phases of the pandemic to account for the spread, variation in the number of hospitalizations and deaths as well as the public perceptions about the pandemic. We argue that public perception regarding the transmission rates affects perceived risk of infection and travel decisions differently throughout the pandemic due to the ever-changing nature of the outbreak. Therefore, we administered the four surveys at different time points. The surveys were distributed among those who live in the Columbus Metropolitan Area (the city of Columbus and the surrounding suburbs). The surveys included questions about infection risk perceptions associated with COVID-19 regarding different transportation modes, subjective well-being, overall travel satisfaction, pro-environmental identity, and personal and household characteristics.

Survey responses were collected through mailed surveys and the Qualtrics Online Panel, an online sample recruitment service. The Online Panel distribution feature allows researchers to send their surveys to a targeted population of respondents. The researchers can select respondents based on age, gender, race, location, etc. (Qualtrics, 2021). We targeted respondents who live in the Columbus Metropolitan Area and are 18 years or older for our study. The Qualtrics Online Panel provides a high-quality sample. However, it does not give a reliable response rate for the surveys because the participants are recruited from...
To explore the impacts of built environment characteristics, we merged these survey responses with the United States Environmental Protection Agency (U.S. EPA)’s Smart Location Database (SLD) that is published in May 2021 (version 3.0). SLD is a nationwide geographic data resource for measuring location efficiency, and it includes more than 90 attributes summarizing characteristics such as household and employment density, diversity of land use, design of the built environment, access to destinations, and transit accessibility (Chapman et al., 2021). The database is developed in a way that it can reflect the five D-variables based on respondents’ home address information provided by the respondents differed in terms of geographic accuracy, we used the CBG level built environment measures from SLD rather than calculating the five D-variables based on respondents’ activity space. Prior to running the further analyses, we removed those without the home address information. We also removed those who did not answer the infection risk perception question. All mailer survey respondents provided valid responses to all questions, including those related to their addresses and risk perceptions while traveling. Those respondents that are removed from the final sample are randomly and evenly distributed in the three online surveys. We merged the responses in the final sample with SLD variables. Table 2 presents the descriptive statistics of the final sample, including 1,171 respondents.

Fig. 1 shows the distribution of the respondents across the study area. As can be seen in the figure, respondents are evenly distributed in the Columbus Metropolitan Area. This even distribution provided us with the opportunity to account for the variation across different neighborhoods in terms of compactness, walkability, and accessibility. Since our study aims to assess the associations between built environment characteristics, COVID-19 infection risk perception, and subjective well-being, having a diverse set of respondents from different neighborhoods is crucial for a comprehensive analysis.

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### Table 1
Details of the Multi-wave Survey.

| # | Survey Method     | Survey Period                  | Valid Responses |
|---|-------------------|--------------------------------|-----------------|
| 1 | Online            | Apr 30 - May 7, 2020           | 436             |
| 2 | Online            | Nov 10 - Dec 9, 2020           | 413             |
| 3 | Mailer            | Nov 30, 2020 - Feb 5, 2021     | 688             |
| 4 | Online            | Feb 5 - Feb 20, 2021           | 435             |
| 5 | Total, Online + Mailer | From Apr 30, 2020 to Feb 20, 2021 | 1,972 |

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### Table 2
Descriptive Statistics of the Variables Included in the Analyses (N = 1,171).

| Categories            | Variable (SEM Code)* | Values | %     |
|-----------------------|----------------------|--------|-------|
| Perceived infection risk while walking (RISKWALK) | Not at all | 55.51 |
| Perceived infection risk while scootering (RISKSCTR) | Slightly | 27.50 |
| Perceived infection risk while bicycling (RISKBICYCLE) | Moderately | 11.19 |
| Perceived infection risk while using shared micromobility | Very | 3.33 |
| Perceived infection risk while using shared micromobility | Extremely | 2.48 |
| Perceived infection risk while using shared micromobility | Not at all | 57.47 |
| Subjective well-being | The conditions of my life are excellent (SWB1) | Strongly disagree | 5.21 |
| Socio-demographics | Age (AGE,CAT) | 18–34 | 20.50 |
| Socio-demographics | Age (AGE,CAT) | 35–49 | 28.44 |
| Socio-demographics | Age (AGE,CAT) | 50–64 | 27.41 |
| Socio-demographics | Age (AGE,CAT) | 65+ | 22.03 |
| Socio-demographics | Employment status (WORKING) | Working | 58.84 |
| Socio-demographics | Employment status (WORKING) | Not working | 41.16 |
| Socio-demographics | Educational attainment (EDUCATE) | Undergraduate | 58.24 |
| Socio-demographics | Educational attainment (EDUCATE) | Graduate | 23.40 |
| Socio-demographics | Employment status (WORKING) | Prefer not to say | 2.14 |
| Socio-demographics | Gender (FEMALE) | Male | 42.78 |
| Socio-demographics | Employment status (WORKING) | Prefer not to say | 5.38 |
| Socio-demographics | Race (RACE) | White | 15.12 |
| Socio-demographics | Employment status (WORKING) | Prefer not to say | 8.85 |
| Socio-demographics | Educational attainment (EDUCATE) | Highschool or less | 16.23 |
| Socio-demographics | Education (EDUCATE) | Undergraduate | 58.24 |
| Socio-demographics | Race (RACE) | Non-White | 17.85 |
| Socio-demographics | Educational attainment (EDUCATE) | Prefer not to say | 3.93 |
| Socio-demographics | Race (RACE) | White | 15.12 |
| Socio-demographics | Educational attainment (EDUCATE) | Prefer not to say | 8.85 |
| Socio-demographics | Race (RACE) | Non-White | 17.85 |
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| Socio-demographics | Educational attainment (EDUCATE) | Prefer not to say | 3.93 |
| Socio-demographics | Race (RACE) | White | 15.12 |
| Socio-demographics | Educational attainment (EDUCATE) | Prefer not to say | 8.85 |
| Socio-demographics | Race (RACE) | Non-White | 17.85 |
| Socio-demographics | Educational attainment (EDUCATE) | Prefer not to say | 3.93 |
| Socio-demographics | Race (RACE) | White | 15.12 |
| Socio-demographics | Educational attainment (EDUCATE) | Prefer not to say | 8.85 |
### Table 2 (continued)

| Categories                        | Variable (SEM Code)* | Values | %     |
|-----------------------------------|----------------------|--------|-------|
| **Environmental identity**        |                      |        |       |
| I see myself as pro-environment   |                      |        |       |
| (ENVID1)                          |                      |        |       |
| Strongly disagree                 | 3.76                 | 14.52  |       |
| Disagree                          | 5.72                 | 21.26  |       |
| Neutral                           | 21.26                | 36.21  |       |
| Agree                             | 42.53                | 23.59  |       |
| Strongly agree                    | 25.96                | 12.13  |       |
| Prefer not to say                 | 0.77                 | 0.44   |       |
| I am pleased to be               |                      |        |       |
| pro-environment (ENVID2)          |                      |        |       |
| Strongly disagree                 | 3.67                 | 20.07  |       |
| Disagree                          | 5.38                 | 67.57  |       |
| Neutral                           | 24.85                | 26.31  |       |
| Agree                             | 16.48                | 7.09   |       |
| Strongly agree                    | 28.78                | 2.39   |       |
| Prefer not to say                 | 1.03                 | 0.06   |       |
| I feel strong ties with           |                      |        |       |
| pro-environment people (ENVID3)   |                      |        |       |
| Strongly disagree                 | 7.09                 | 30.91  |       |
| Disagree                          | 12.81                | 3.59   |       |
| Neutral                           | 37.40                | 40.14  |       |
| Agree                             | 24.85                | 21.86  |       |
| Strongly agree                    | 16.48                | 0.06   |       |
| Prefer not to say                 | 1.37                 | 0.01   |       |
| I identify with                  |                      |        |       |
| pro-environment people (ENVID4)   |                      |        |       |
| Strongly disagree                 | 7.52                 | 3.59   |       |
| Disagree                          | 10.50                | 26.31  |       |
| Neutral                           | 32.88                | 56.21  |       |
| Agree                             | 29.80                | 26.31  |       |
| Strongly agree                    | 18.19                | 26.31  |       |
| Prefer not to say                 | 1.11                 | 0.01   |       |
| Overall travel satisfaction       |                      |        |       |
| Travel time (includes waiting)    |                      |        |       |
| (TRVLSAT1)                        |                      |        |       |
| Very dissatisfied                 | 2.22                 | 3.59   |       |
| Dissatisfied                      | 6.32                 | 12.13  |       |
| Neutral                           | 13.07                | 12.13  |       |
| Satisfied                         | 43.55                | 40.56  |       |
| Very satisfied                    | 32.88                | 12.13  |       |
| Travel distance (TRVLSAT2)        |                      |        |       |
| Very dissatisfied                 | 1.62                 | 26.31  |       |
| Dissatisfied                      | 4.87                 | 3.59   |       |
| Neutral                           | 13.58                | 56.21  |       |
| Satisfied                         | 46.03                | 21.86  |       |
| Very satisfied                    | 32.02                | 26.31  |       |
| Prefer not to say                 | 1.88                 | 0.01   |       |
| Reliability (TRVLSAT4)            |                      |        |       |
| Very dissatisfied                 | 1.45                 | 26.31  |       |
| Dissatisfied                      | 3.07                 | 3.59   |       |
| Neutral                           | 12.38                | 12.13  |       |
| Satisfied                         | 39.45                | 40.56  |       |
| Very satisfied                    | 41.42                | 26.31  |       |
| Prefer not to say                 | 2.22                 | 0.01   |       |
| Simplicity (TRVLSAT5)             |                      |        |       |
| Very dissatisfied                 | 1.28                 | 26.31  |       |
| Dissatisfied                      | 4.10                 | 3.59   |       |
| Neutral                           | 14.01                | 56.21  |       |
| Satisfied                         | 39.80                | 21.86  |       |
| Very satisfied                    | 38.94                | 26.31  |       |
| Prefer not to say                 | 1.88                 | 0.01   |       |
| Flexibility (TRVLSAT6)            |                      |        |       |
| Very dissatisfied                 | 1.45                 | 26.31  |       |
| Dissatisfied                      | 4.95                 | 3.59   |       |
| Neutral                           | 15.97                | 56.21  |       |
| Satisfied                         | 37.23                | 26.31  |       |
| Very satisfied                    | 38.00                | 26.31  |       |
| Prefer not to say                 | 2.39                 | 0.01   |       |
| Comfort (TRVLSAT7)                |                      |        |       |
| Very dissatisfied                 | 2.14                 | 26.31  |       |
| Dissatisfied                      | 3.59                 | 3.59   |       |
| Neutral                           | 14.35                | 56.21  |       |
| Satisfied                         | 37.66                | 26.31  |       |
| Very satisfied                    | 40.14                | 26.31  |       |
| Prefer not to say                 | 2.14                 | 0.01   |       |
| Safety (TRVLSAT8)                 |                      |        |       |
| Very dissatisfied                 | 1.88                 | 26.31  |       |
| Dissatisfied                      | 4.70                 | 3.59   |       |
| Neutral                           | 14.77                | 56.21  |       |
| Satisfied                         | 36.21                | 26.31  |       |

### Notes:
* SEM Codes presented in parentheses are used in the tables in Results and Discussion section for ease of readability.

#### 3.2. Methodology

We employ a structural equation modeling (SEM) approach for the analysis. SEM is a modeling technique that enables the analysis of multiple endogenous and exogenous variables simultaneously (Kline, 2016). It allows the inclusion of latent constructs (e.g., subjective well-being, travel satisfaction, etc.) specified as linear combinations of the observed variables (Delbosc et al., 2020; Golob, 2003). Additionally, SEM allows the assessment of highly collinear built environment variables by summing or averaging them (Bowen and Guo, 2012).

In brief, SEM can serve as an umbrella methodology that encompasses a set of multivariate statistical approaches to empirical data. Some of the widely used concepts that affect travel behavior, such as perceptions toward specific modes, attitudes, and subjective well-being, are complex phenomena that require the use of in-depth and sophisticated analysis techniques. SEM offers a better alternative to traditional linear statistical approaches that evaluate the impacts of these items by summing or averaging them (Bowen and Guo, 2012).

For the analysis, we first developed a confirmatory factor analysis (CFA) model including latent constructs. There are seven latent constructs in this study:

1. Perceived infection risk while walking, bicycling, and using shared micromobility
2. Built environment characteristics (5Ds)
3. Subjective well-being
4. Perceived infection risk while using shared motorized transportation modes
5. Socio-economic status
6. Pro-environmental attitude
Table 2 presents the descriptive statistics of each observed variable associated with the latent constructs. At this point it is important to describe three categories of infection risk perception associated with different transportation modes. Recent studies show that people attribute varying degrees of risk to different transportation modes. Briefly, they attribute lower risk scores to those modes that are used individually (Kim et al., 2021; Ozbilen et al., 2021a; Rahimi et al., 2021). This argument is consistent with the significant reductions in trips with public transit, ridesharing, ride hailing and significant increases in trips with individual modes such as private car, walking,
important to combine all five dimensions of built environment given
spond to different dimensions of 5Ds identified in the literature. It is
fied eight observed variables from the SLD. These eight factors corre
ables of the study.
Under three groups. In Fig. 2, those modes in green represent the
result, we grouped perceived risks associated with different modes
bicycling, and shared micromobility (while e-bikes and e-scooters are
mode since the former two are not sustainable travel options.
individual modes since the latter two to the SES latent variable for further analyses.
The remaining three latent variables, namely subjective well-being, pro-environmental attitude, and overall satisfaction of travel experience utilize responses to specific questions that are pre-determined for the development of these latent variables.
In the multivariate analysis, we first run a CFA for the measurement part of the model and tested the latent variables that are developed based on our literature review. Then, we run an SEM that analyzes the hypothesized associations between all endogenous and exogenous variables.

4. Results and discussion
We use a mean and variance-adjusted weighted least squares (WLSMV) estimator for the analyses due to the presence of ordinal and categorical variables in our hypothesized model. WLSMV enables the use of pairwise deletion when there are only small amounts of missing data. Using pairwise deletion with WLSMV estimator provides more efficient estimates than listwise deletion with WLSMV (Asparouhov and Muthen, 2010). Since we recruited participants at different time points throughout the pandemic, we use a setting in which the responses are clustered under four different survey waves. By clustering we acknowledge that those in the same survey wave may have more similar perceptions about travel and infection risk than those in other waves. All analyses are conducted in the Mplus software.

| Table 3 |
| CFA Standardized Factor Loadings for the Measurement Model. |
| Latent Variable Name | Indicator Code | Std. Estimate* |
|----------------------|----------------|---------------|
| Risk perception associated with walking, bicycling, and scootering | RISKBCYCLE | 0.991 |
| | RISKWALK | 0.723 |
| | RISKSCR | 0.948 |
| | RISKMAR | 0.863 |
| Subjective well-being | SWB1 | 0.846 |
| | SWB2 | 0.913 |
| | SWB3 | 0.928 |
| | SWB4 | 0.854 |
| | SWB5 | 0.650 |
| Built environment characteristics (5Ds)** | BUILTVEN1 | 0.593 |
| | BUILTVEN2 | 0.557 |
| | BUILTVEN3 | 0.102 |
| | BUILTVEN4 | 0.787 |
| | BUILTVEN5 | 0.707 |
| | BUILTVEN6 | 0.562 |
| | BUILTVEN7 | 0.650 |
| Overall satisfaction of travel experience | TRVLSAT1 | 0.837 |
| | TRVLSAT2 | 0.806 |
| | TRVLSAT3 | 0.808 |
| | TRVLSAT4 | 0.912 |
| | TRVLSAT5 | 0.927 |
| | TRVLSAT6 | 0.898 |
| | TRVLSAT7 | 0.965 |
| | TRVLSAT8 | 0.858 |
| Pro-environmental attitude | ENVID1 | 0.902 |
| | ENVID2 | 0.918 |
| | ENVID3 | 0.836 |
| | ENVID4 | 0.942 |
| Socio-economic status | WORKING | 0.331 |
| | EDUCATE | 0.605 |
| | RACE | 0.207 |
| | HHINCOME | 0.884 |
| | VEHOWN | 0.783 |
| Perceived infection risk while using shared motorized modes | RISKOCAR | 0.741 |
| | RISKCAR | 0.896 |
| | RISKBUS | 0.925 |
| | RISKUBER | 0.861 |

Notes: Standardized estimates of factors that are closer to 1 indicate better correlation with the corresponding latent variable.

* All standardized factor loadings are significant at the 1% level.

** Description of built environment variables are (1) BUILTVEN1: Residential density; (2) BUILTVEN2: Employment density; (3) BUILTVEN3: Land-use mix; (4) BUILTVEN4: Multimodal intersection density having three legs; (5) BUILTVEN5: Multi-modal intersection density having four or more legs; (6) BUILTVEN6: Transit service frequency per capita; (7) BUILTVEN7: Regional centrality index; (8) BUILTVEN8: Walkability index. For the details of the calculation of the built environment measures used in the analysis, please see the Methodology section.

bicycling, and shared micromobility (while e-bikes and e-scooters are shared modes, they are used individually) (Abdullah et al., 2020; Bert et al., 2020; De Haas et al., 2020; Handy, 2020; Li et al., 2020a; Zuo et al., 2020). Consequently, we separated individual and shared modes for our study. We also distinguished car and motorcycle and other in
that the total effect of the built environment can be estimated when all relevant measures are combined (Ewing and Cervero, 2010). The variables used for the built environment latent construct are residential density, employment density, land use diversity, multimodal intersection density (two complementary variables), frequency of transit service, regional centrality index, and walkability index.

Socio-economic status (SES) is a latent variable that consists of employment status, educational attainment, annual household income, race, and vehicle ownership. While the first three observed variables are traditional SES measures widely used in previous studies (Feuillet et al., 2021; Yang et al., 2010), race and vehicle ownership are non-traditional measures that are found to be intimately intertwined with the traditional SES measures (APA, 2017; Carroll et al., 2011). Therefore, we included the latter two to the SES latent variable for further analyses.

For the built environment characteristics latent variable, we identified eight observed variables from the SLD. These eight factors correspond to different dimensions of 5Ds identified in the literature. It is important to combine all five dimensions of built environment given

Overall satisfaction of travel experience

- Frequency of transit is the aggregate frequency of transit service per capita. It uses data from transit agencies across the U.S. in GTFS format (Chapman et al., 2021).

- Regional centrality index is a relative regional accessibility measure. Regional accessibility is calculated by determining the level of access to jobs and working age population via transit. This relative measure is the ratio of the accessibility of the corresponding census block group to the census block group with the highest access values in the metropolitan region (Chapman et al., 2021).

- Walkability index comprised of weighted sum of 1) employment and household entropy, 2) employment entropy, 3) street intersection density (auto-oriented intersections eliminated), and 4) distance to nearest transit stop. Walkability is characterized by components of the built environment that influence the likelihood or feasibility of walking as a form of utilitarian transportation (Chapman et al., 2021).

N = 1,171

Residential density is the number of housing units per acre on unprotected land (Chapman et al., 2021).

Employment density is the number of jobs per acre on unprotected land (Chapman et al., 2021).

Land-use diversity is equal to employment and household entropy in a census block group. It is calculated based on trips production and trip attractions including 4 employment categories, namely (Chapman et al., 2021).

Multimodal intersection density measure consists of two complementary variables: intersection density in terms of multi-modal intersections having three legs per square mile and intersection density in terms of multi-modal intersections having four or more legs per square mile. It is calculated as the multimodal intersections per square mile (Chapman et al., 2021).

Frequency of transit is the aggregate frequency of transit service per capita. It uses data from transit agencies across the U.S. in GTFS format (Chapman et al., 2021).

Regional centrality index is a relative regional accessibility measure. Regional accessibility is calculated by determining the level of access to jobs and working age population via transit. This relative measure is the ratio of the accessibility of the corresponding census block group to the census block group with the highest access values in the metropolitan region (Chapman et al., 2021).

Walkability index comprised of weighted sum of 1) employment and household entropy, 2) employment entropy, 3) street intersection density (auto-oriented intersections eliminated), and 4) distance to nearest transit stop. Walkability is characterized by components of the built environment that influence the likelihood or feasibility of walking as a form of utilitarian transportation (Chapman et al., 2021).
4.1. Confirmatory factor analysis (CFA)

We employ a confirmatory factor analysis (CFA) to detect latent variables based on the literature review, as consistent with the principles of SEM (Van Acker et al., 2007). Since we use observed variables that are already examined extensively in the literature, our CFA performs well and provides significant factor loadings at the 1% level. Our model has a good statistical fit to the data. The CFA model fit results are: comparative fit index or CFI = 0.965 (recommended fit criteria > = 0.95); Tucker-Lewis index or TLI = 0.962 (recommended fit criteria > = 0.95); and Root mean square error of approximation or RMSEA = 0.024 - C.I.s 0.022 to 0.027 (recommended fit criteria <= 0.05) (Bowen and Guo, 2012; Hadiuzzaman et al., 2017).

Table 3 presents the standardized factor loadings for CFA. Standardized factor loadings are presented for the analyses for ease of interpretation. Unstandardized factor loadings can be found in Appendix Table A2. Most of the standardized factor loadings are large (0.30 < |λ|), except those for land-use diversity (0.102) and race (white dummy variable) (0.207). Since these variables are extensively examined in the literature and found to be significantly associated with the corresponding latent constructs, we keep these variables in the final analysis. Standardized factor loadings demonstrate that factors correlate well with their corresponding indicators (observed variables). Since all latent constructs are hypothesized based on the literature review, this is expected.

4.2. Structural equation model (SEM)

Now that the factors have been identified, we analyze how they affect the infection risk perception while walking, bicycling, and using shared micromobility and subjective well-being. Fig. 3 depicts the final SEM structure (please see Appendix Table A2. for full model results). As the figure depicts, we include four additional measures that are age, gender (female dummy variable), perceived infection risk while driving a personal car, and perceived infection risk while riding a motorcycle as exogenous variables. The model performs well according to common model fit statistics: CFI = 0.967 (recommended fit criteria > = 0.95); TLI = 0.964 (recommended fit criteria > = 0.95); and RMSEA = 0.025 - C.I.s 0.023 to 0.027 (recommended fit criteria <= 0.05) (Bowen and Guo, 2012; Hadiuzzaman et al., 2017).

The results show that living in neighborhoods that are more compact, walkable, and accessible reduces the infection risk perception associated with shared micromobility and active travel. As the COVID-19 infection risk characterizes individuals’ travel behavior (Parady et al., 2020; Rahimi et al., 2021), this finding demonstrates the potential of built environment improvements in promoting walking, bicycling, and scootering at this critical time. Since higher scores in these built environment characteristics are also positively associated with active travel frequency and durations (Barajas, 2019; Cheng et al., 2019; Yang et al., 2019), the interventions that will improve the built environment quality have the potential to contribute to active travel in multiple ways. We analyze both direct and indirect links between built environment characteristics and individuals’ subjective well-being. While the built environment is positively associated with subjective well-being in recent studies (Guo et al., 2021; McCarthy and Habib, 2018; Yin et al., 2019), we do not find a direct and significant association between them. However, there is an indirect link from built environment characteristics to subjective well-being through infection risk perception while walking, bicycling, and scootering. This indirect link shows that the built environment positively affects subjective well-being by reducing the infection risk perception associated with active travel and shared micromobility. In other words, living in more compact, accessible, and walkable neighborhoods reduces the perceived infection risk perception of individuals and promotes active travel, and this indirectly improves individuals’ subjective well-being. Based on this finding, we can argue that built environment improvements can contribute to the physical health (by reducing perceived risk regarding physical travel) and mental health (by improving the subjective well-being) of individuals during the COVID-19 pandemic. Our finding on the impacts of the built environment on subjective well-being is consistent with the growing literature on the positive relationship between a well-designed physical environment and better mental health (Guo et al., 2021; McCarthy and Habib, 2018; Mouratidis, 2021). Lastly, the increase in perceived infection risk while using shared micromobility and active travel reduces individuals’ subjective well-being. We believe this is because those with higher infection risk perception are more likely to experience health anxiety or concerns related to their daily physical activity and thus, report lower subjective well-being scores (Flanagan et al., 2020;
Socio-demographic characteristics included in the analysis are the socio-economic status latent variable and two exogenous variables, age and gender. These three variables are significantly associated with both perceived risk of infection while walking, bicycling, and scootering and individuals’ subjective well-being. Those with higher socio-economic status attribute lower infection risk to travel with shared micromobility and active travel. This is consistent with previous studies that show people with higher socio-economic status are less likely to take preventative actions and reduce their out-of-home activity and travel during virus outbreaks (Brug et al., 2004; Hotle et al., 2020; Li et al., 2020b). This is expected for two reasons. First, those with lower socio-economic status are more likely to lack health insurance and have limited access to healthcare (Khatana and Groeneveld, 2020; Rollston and Galea, 2020). Second, studies show that the COVID-19 pandemic mainly ravaged the jobs in service industries, and those with lower socio-economic status faced layoffs (Enriquez and Goldstein, 2020; Rothwell, 2021). Since the health insurance system is tied to the employment in the U.S. (Enthoven and Fuchs, 2006), those with lower socio-economic status may be more concerned about the negative impacts of the COVID-19 exposure. Our analysis shows a positive association between the socio-economic status and subjective well-being, consistent with the previous findings (Boarini et al., 2012; Pinquart and Sörensen, 2000). Those respondents who are older are less likely to perceive active travel and shared micromobility options as risky compared to the others. This finding is not expected given that the probability of severe illness with COVID-19 increases with age, particularly among unvaccinated individuals. Females are more likely to perceive walking, bicycling, and scootering as risky in terms of COVID-19 exposure. This finding is consistent with recent COVID-19 and travel behavior studies that show females are more concerned about potential exposure to coronavirus (Abdullah et al., 2020; Rahimi et al., 2021). Older participants and males have higher subjective well-being than the others. The positive association between age and subjective well-being is not expected. COVID-19 studies show that contracting the disease causes a greater risk of severe illness for older adults as compared to the others (Centers for Disease Control and Prevention, 2021). Due to their greater coronavirus concern, older adults reduced their physical activity and social interaction more than the other groups, which is expected to negatively impact their mental health and subjective well-being (Son et al., 2021).

As shown in Fig. 3, we do not find any significant impact of the overall satisfaction of travel experience and pro-environmental attitude on the infection risk perceptions associated with active travel and shared micromobility. However, we find significant associations between these two variables and subjective well-being. Those who are satisfied with their overall travel experience and those with a more pro-environmental identity report a greater subjective well-being score. This is expected considering the positive influences of travel satisfaction and pro-environmental attitude on overall subjective well-being (De Vos et al., 2013; Kahn and Morris, 2009).

Lastly, we find that infection risk perception associated with shared modes and individual motorized modes (personal car and motorcycle) significantly impact perceived risk of infection while walking, bicycling, and using shared micromobility. Those who attribute higher risks to shared transportation options such as bus, carshare, and Uber, and to private cars and motorcycles attribute higher risk to active travel and shared micromobility options, as expected.

5. Conclusion and limitations

The COVID-19 pandemic changed the mobility behavior substantially, particularly because of the perceived risk of exposure to coronavirus and the restrictions implemented to slowdown the spread of the disease (De Vos, 2020). These fundamental changes started many discussions regarding the effects of built environment characteristics on the spread of the disease, out-of-home activity behavior, and mental and physical health. Urban planners and transportation engineers conducted many studies to test these associations in different settings (Aboukorin et al., 2021; Parady et al., 2020; Rahimi et al., 2021; Wang et al., 2020). It is imperative to continue studying these links at different times during the pandemic due to the ever-changing nature of the coronavirus and the transmission rates.

This study employs a structural equation modeling approach to assess the associations between the built environment, subjective well-being, and infection risk perception while walking, bicycling, and using shared micromobility. Considering the variation in the public perceptions about the exposure risk to coronavirus throughout the pandemic, we conducted the analyses using survey data collected in four waves in 2020 and 2021. We accounted for the clustering of the survey responses under these different waves in our final analyses. This provided us with the opportunity to calculate more robust final estimations by adjusting for correlated residuals among clustered responses in each survey wave (Bowen and Guo, 2012). The findings show that living in more compact, accessible, and walkable neighborhoods reduce the perceived infection risk associated with while walking, bicycling, and using shared micromobility. Additionally, there is a negative association between infection risk perception while walking, bicycling, and using shared micromobility and subjective well-being. This means those who are more concerned about exposure to coronavirus while traveling are also the ones who report lower subjective well-being scores. While we do not find a direct effect of built environment characteristics on subjective well-being, our study demonstrates an indirect effect of the built environment on subjective well-being through infection risk perception. Briefly, we can argue that living in more pedestrian and bicyclist friendly neighborhoods reduces the risk perception associated with walking, bicycling, and shared micromobility and thus, increases the frequency and duration of active travel. As a result, individuals can exercise and interact with others and feel better. Therefore, well-designed neighborhoods indirectly improve individuals’ subjective well-being.

Our paper advances our understanding of the effects of built environment characteristics on physical activity and subjective well-being, with an emphasis on COVID-19. Designing more compact, diverse, walkable, and accessible neighborhoods has the potential to contribute to both the mental and physical health of individuals during pandemics like COVID-19. When we also consider the well-known positive effects of these built environment characteristics on non-motorized travel, the benefits of these investments would be amplified. Based on this understanding, we encourage authorities to invest in the built environment and infrastructure to be prepared for future public health crises. Experts underline that increasing contact between humans and animals due to deforestation, habitat fragmentation, and intensive animal husbandry augments the risk of future pandemics (Thoradeniya and Jayasinghe, 2021). As a result, it is imperative to prepare our cities for these potential risks. As it is very well put by Florida and Storper (2021), we are in a period of extended social experimentation about the effects of a pandemic on our cities in the 21st century. While these are challenging times, there are numerous lessons that we can learn from the scholarly efforts that aim to understand COVID-19 and its impacts on individual behavior and everyday life in our cities. A number of studies indicate that the pandemic highlighted the social and spatial inequalities in our cities (Brough et al., 2020; Hamidi et al., 2020; Shamshiripour et al., 2022; Tai et al., 2021). Post-pandemic resilience requires radical policy changes that can address these inequalities. Since built environment improvements take time, opening streets to pedestrians and bicyclists can be the first step of addressing the spatial disparities. Yet still, it is critical to further improve infrastructure and design features, particularly in lower-income neighborhoods, to address environmental injustice issues.

We acknowledge that there are several limitations to our study. First, this study uses built environment variables at the census block group
level for the analysis. This may limit our findings due to the ecological fallacy and modifiable areal unit problem (Hankey et al., 2021; Kaza et al., 2016). Future studies may address this limitation by collecting survey data that provide better geographic accuracy about respondents’ home addresses and developing built environment measures that offer finer spatial granularity. Second, our paper makes the case that the residential neighborhood characteristics impact infection risk perception associated with shared micromobility and active travel, but it does not account for primary travel mode of respondents. While our dataset consists of variables related to pre-COVID primary travel modes of the respondents, these variables did not provide statistically significant results in the analyses. As a result, we did not include them in the final model. Previous studies show that the primary travel mode is significantly associated with individuals’ out-of-home activity behavior and travel patterns (Daniels and Mulley, 2013; Farrell et al., 2010; Kroesen, 2014). As the COVID-19 infection risk characterizes travel behavior during the pandemic (Parady et al., 2020; Rahimi et al., 2021), individuals’ primary mode may impact their risk perceptions associated with different travel alternatives. The removal of variables related to individuals’ primary travel modes from the final analyses may limit what we can conclude related to the impacts of the built environment on individuals’ travel behavior and mode preferences during and after the pandemic. Third, our study is based on a multi-wave survey conducted at different time points during the COVID-19 outbreak, and thus our findings should be interpreted with caution in terms of long-term consequences of the pandemic. With the ever-changing nature of COVID-19, the implications of the pandemic on out-of-home activity behavior may change. As a result, it is still early to determine if the pandemic will be a substantial change for the mobility patterns of individuals (Carrie et al., 2021; Mouratidis and Peters, 2022; Van Crannenburgh et al., 2012) or the current trends related to COVID-19 will be temporary as in the SARS outbreak (Li and Ito, 2021; Van Crannenburgh et al., 2012). To address this limitation, post-COVID studies should explore potential transportation demand management strategies (e.g., street space allocation to promote active travel, mixed-use development, teleworking policies, etc.) to identify the implications of these interventions on individuals’ out-of-home activity behavior and travel patterns in the long-run. Understanding the long-run implications of travel behavior interventions on activity-travel patterns may also provide insights to policymakers and transportation researchers in making our cities more pandemic resilient.

There is a need for more research in different contexts to fully understand the association between the built environment and travel behavior during the pandemic. We encourage researchers to use data that are collected at different time points during the pandemic to be able to capture the variations in travel behavior based on the changes in public perception. It would also be informative if future researchers investigate the impacts of built environment factors on travel domain specific subjective well-being. While we did not find a direct link between the built environment and overall subjective well-being, there may be an indirect positive association between living in more compact, accessible, and walkable neighborhoods and overall subjective well-being through travel domain specific subjective well-being. We asked for the risk perception information from all participants and analyzed the data all participants combined. Future studies can investigate the differences between the risk perception for both actual users and non-users of specific modes (e.g., transit users, bicycle users, etc.) Finally, we encourage future studies to include subjective measures of the built environment (e.g., residents’ perceptions about transportation infrastructure, access to basic needs) in the analyses. While objective built environment measures can explain the variation in travel behavior and individual perceptions to a certain level, the inclusion of both objective and subjective measures helps to capture the true associations, particularly for specific groups such as older adults, immigrating, etc. (Cerin et al., 2017; Loukaitou-Sideris et al., 2019).

CRediT authorship contribution statement

Basar Ozbilen: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. Gulsah Akar: Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1

CFA Unstandardized Factor Loadings for the Measurement Model.

| Latent Variable Name | Factor Code | Unstandardized Estimate* |
|----------------------|-------------|--------------------------|
| Risk perception associated with walking, bicycling, and scootering | RISKBICYCLE | 1.000 |
| | RISKWALK | 0.730 |
| | RISKSCTR | 0.957 |
| | RISKHAR | 0.870 |
| Subjective well-being | SWB1 | 1.000 |
| | SWB2 | 1.080 |
| | SWB3 | 1.098 |
| | SWB4 | 1.009 |
| | SWBS | 0.769 |
| Built environment characteristics (5Ds) | BUILTVEN1 | 1.000 |
| | BUILTVEN2 | 4.653 |
| | BUILTVEN3 | 0.014 |
| | BUILTVEN4 | 10.537 |
| | BUILTVEN5 | 7.703 |
| | BUILTVEN6 | 0.003 |
| | BUILTVEN7 | 0.066 |
| | BUILTVEN8 | 1.625 |
| Overall satisfaction of travel experience | TRVLSAT1 | 1.000 |
| | TRVLSAT2 | 0.963 |
| | TRVLSAT3 | 0.966 |
| | TRVLSAT4 | 1.089 |
| | TRVLSAT5 | 1.108 |
| | TRVLSAT6 | 1.073 |
| | TRVLSAT7 | 1.153 |
| | TRVLSAT8 | 1.037 |
| Pro-environmental attitude | ENVID1 | 1.000 |
| | ENVID2 | 1.018 |
| | ENVID3 | 0.927 |
| | ENVID4 | 1.044 |
| Socio-economic status | WORKING | 1.000 |
| | EDUCATE | 1.829 |
| | RACE | 0.628 |
| | HHINCOME | 2.673 |
| | VEH_OWN | 2.369 |
| Perceived infection risk while using shared motorized modes | RISKOCAR | 1.000 |
| | RISKCARS | 1.209 |
| | RISKBUS | 1.247 |
| | RISKUBER | 1.162 |

Notes: *All unstandardized factor loadings are significant at the 1% level.

\[ N = 1,171 \]

The first indicator of each latent construct has an estimate value of 1.000. This is the loading at 1 for scaling the latent variable.
Table A2

| Variable | Perceived infection risk while using shared mobility and non-motorized transportation | Subjective well-being |
|----------|-------------------------------------------------------------------------------------|------------------------|
|          | Unstandardized Estimate | p-value | Standardized Estimate | p-value | Unstandardized Estimate | p-value | Standardized Estimate | p-value |
| Built environment characteristics (SDs) | -0.035 | 0.013 | -0.042 | 0.007 | - | - | - | - |
| Perceived infection risk while using shared mobility and non-motorized transport | - | - | - | - | -0.121 | 0.000 | -0.185 | 0.000 |
| Pro-environmental attitude | - | - | - | - | 0.114 | 0.001 | 0.120 | 0.001 |
| Overall satisfaction of travel experience | - | - | - | - | 0.290 | 0.000 | 0.273 | 0.000 |
| Socio-economic status | -0.509 | 0.000 | -0.182 | 0.000 | 0.458 | 0.000 | 0.249 | 0.000 |
| Age | -0.067 | 0.036 | -0.055 | 0.055 | 0.087 | 0.000 | 0.108 | 0.000 |
| Female | 0.134 | 0.000 | 0.051 | 0.000 | -0.140 | 0.006 | -0.062 | 0.004 |
| Perceived infection risk while using shared motorized modes | 0.732 | 0.000 | 0.350 | 0.000 | - | - | - | - |
| Perceived COVID-19 infection risk while driving personal car | 0.188 | 0.023 | 0.123 | 0.014 | - | - | - | - |
| Perceived infection risk while riding a motorcycle | 0.778 | 0.000 | 0.681 | 0.000 | - | - | - | - |
| The indirect effect of built environment characteristics on subjective well-being | - | - | - | - | -0.004 | 0.036 | 0.008 | 0.031 |

N = 1,145

Chi-square = 1,328.042

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