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Mental health facility visits before and after the outbreak of COVID-19: The role of walkable built environment

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ABSTRACT

Introduction: Before the COVID-19 pandemic, walkability was linked to improved mental health. However, walkable areas can be more vulnerable to outbreaks of infectious diseases due to increased interaction and proximity between individuals, potentially leading to adverse effects on mental health. Whether walkability maintains its positive association with better mental health during the pandemic remains unclear, especially given mixed findings on whether walkability increases COVID-19 cases.

Methods: This study integrates Walk Score®, mental health facility visit frequencies from mobile phone GPS trajectories, and COVID-19 case rates to explore how the relationship between walkability and mental health evolves across three periods: before the pandemic, during its early stages, and in the later stages. Additionally, it examines the role of COVID-19 case rates in this dynamic using mediation analysis.

Results: Our findings indicate that Walk Score® consistently associates with reduced frequency of mental health facility visits at all three time points, despite a reversal in the relationship between walkability and COVID-19 case rates from the early to later stages of the pandemic. Mediation analysis revealed that walkability has only direct effects on mental health in the early stages of the pandemic when walkability was found to be correlated with increased COVID-19 case rate. However, both indirect and direct effects were observed when walkability was associated with reduced COVID-19 case rate in the later stages.

Conclusions: The study demonstrates that walkable environments consistently offer mental health benefits throughout different pandemic stages. These findings underscore the importance of integrating walkability into urban planning strategies.

1. Introduction

The relationship between the characteristics of the built environment and health outcomes has been the subject of extensive research. Built environment features commonly associated with walkable neighborhoods, including residential density, street connectivity, mixed land use, and access to everyday destinations, have been linked to numerous health benefits including improved mental health. Living in walkable neighborhoods has been conjoined with increased levels of physical activity, which have “beneficial effects on depression symptoms that are comparable to those of antidepressant treatments” (Dinas et al., 2010, p. 319). Walkable

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neighborhoods are also linked with increased walking and use of sustainable active mobility options (Chatziioannou & Luis Alvarez-Icaza, 2017; Kyriakidis et al., 2022), greater social cohesion (Kaczynski and Henderson, 2007; McNeill et al., 2006; Sallis et al., 2016), a stronger and sense of community (Li et al., 2021), all of which contribute to improved mental health outcomes (Murray et al., 2004; Astell-Burt et al., 2013).

However, the COVID-19 pandemic may have complicated this relationship (Hong and Chakrabarti, 2022). It has long been believed that denser and walkable areas can be more vulnerable to outbreaks of infectious diseases due to increased interaction and proximity between individuals (e.g., Cox, 2020; Kling, 2020). Core components of walkable urban environments that are typically seen as beneficial, such as building or population density and street connectivity, were perceived as potential risks that may facilitate the spread of the infectious disease (Arbel et al., 2022). Also, many studies have reported higher infection and death rates in dense urban centers especially in the early stages of the pandemic (Cox, 2020; Sy et al., 2021). The spread of COVID-19, in turn, caused significant psychological distress in terms of anxiety, depression, and post-traumatic symptoms (Talevi et al., 2020; Newby et al., 2020). These two opposing effects of walkability during the pandemic suggest that the benefits of walkability on mental health may be negated by the psychological distress caused by the higher COVID-19 case rates in walkable areas. This is concerning to urban planners as New Urbanism, Smart Growth, and other planning movements have traditionally advocated for more compact and connected environments as a path to sustainability (Ewing and Cervero, 2010; Smart Growth America, n.d.; Congress for New Urbanism, 2001; Litman, 2023; Chatziioannou & Luis Alvarez-Icaza, 2023). If the health benefits of walkable environments are compromised by higher infection rates, the justification for promoting them may weaken (Choo et al., 2024).

What further complicates our understanding is that some other studies reported insignificant or even negative relationships between walkability and the spread of COVID-19; that is, the spread of COVID-19 reduced with walkability. Hamidi et al. (2020) reported that the combined density of population and employment was not significantly associated with COVID-19 infection rate. Other studies have found that the COVID-19 spread was reduced in more walkable areas (Wang et al., 2022; Oishi et al., 2021; Choi and Denice, 2022). If the spread of COVID-19 virus is unrelated with walkability, walkability is likely to keep having its beneficial impacts on mental health regardless of the pandemic. No consensus, however, seems to have been reached regarding how walkability impacts the spread of the diseases (Zhang et al., 2022).

The conflicting effects of walkability on mental health and the spread of COVID-19 make it difficult to apply the previously established positive relationship between walkability and mental health during the pandemic. This lack of understanding is particularly troubling because events similar to COVID-19 pandemic does not appear to be as rare as previously thought, with an annual probability of 2–3 percent, which translates to once every 33–50 years (Madhav et al., 2023). Pandemics similar to COVID-19 are expected to be considerably more frequent in coming decades (Marani et al., 2021).

This study aims to unpack the relationship between walkability and mental health across three time points: before the pandemic, during its early stages, and in the later stages, by treating COVID-19 case rates as a mediator. Three specific research questions are (**R1**) How does the relationship between walkability and COVID-19 case rates change in different stages of the pandemic? (Arrow a in Fig. 1B), (**R2**) Is walkability consistently associated with better mental health outcomes before and in different stages of the COVID-19 pandemic? (Arrow c in Fig. 1A for pre-pandemic; arrows a, b, c' during the pandemic in Fig. 1B), and (**R3**) How does COVID-19 case rates mediate the relationship between walkability and mental health outcomes in different stages of the pandemic (Arrows a, b in Fig. 1B)?

Section 2 provides a brief overview of the findings and gaps in the literature. Section 3 details the data and analytical methods of the

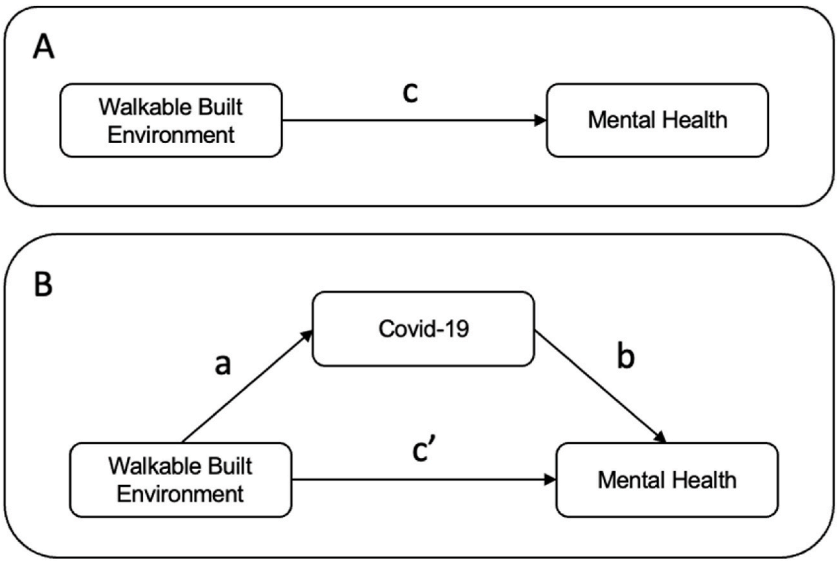

Fig. 1. The mediating impact of COVID-19 on the relationship between walkable environments and mental health.

study, and Section 4 presents the results from correlation, regression, and mediation analyses. Section 5 provides discussions, planning implications, and Section 6 concludes the study.

2. Literature review

2.1. Walkable built environment and mental health

While there is no universally agreed-upon definition of walkability and its measurement, the literature commonly viewed walkability as the combination of proximity and connectivity between origins and destinations of daily activities (Saelens et al., 2003). While there are variations, some of the most widely used indicators of proximity and connectivity include residential density, street connectivity, mixed land use, access to daily destinations and public transit (Ewing and Cervero, 2010; Frank et al., 2010; Shashank and Schuurman, 2019).

These aspects of the urban form determine the ease of navigating urban environments, allowing individuals to easily reach various daily destinations. For example, the presence of a diverse mix of land uses—integrating residential, commercial, and recreational spaces—often leads to increased walking because it provides individuals with different kinds of destinations in close proximity (Frank et al., 2004; Lee and Moudon, 2006; Saelens and Handy, 2008). Areas characterized by higher residential densities not only shorten the distance between destinations but also ensure a richer array of services and amenities, naturally promoting walking (Ewing and Cervero, 2010; Handy, 1996; McCormack and Shiell, 2011). A grid-like street network enhances connectivity, making it easier for individuals to walk between points without unnecessary detours, as opposed to the limited movement in hierarchical or cul-de-sac patterns (Dill, 2004; Moudon et al., 2006; Sallis et al., 2012).

Walk Score® is a database of a pre-calculated, intuitive, well-validated walkability index with a wide geographic coverage (Duncan et al., 2011). Walk Score® quantifies the network distance from a given location to various nearby amenity categories (e.g., grocery stores, coffee shops, restaurants, bars, movie theatres, schools, parks, libraries, bookstores, fitness centers, drug stores, hardware stores, clothing/music stores), weights them based on the distance, and summarizes them into a score (Carr et al., 2010). It also reflects pedestrian friendliness such as population density, block length, and intersection density (Walk Score®). Its effectiveness as a predictor of walking and physical activity has been demonstrated in multiple research and it is used extensively in urban planning, transportation, and public health literature (Harvey et al., 2015, 2017; Yin and Wang, 2016; Duncan et al., 2011)

An increasing number of studies are using these indicators to examine how a walkable built environment can benefit mental health (Cooney et al., 2013; McPhie and Rawana, 2015; Morey et al., 2015; Ma et al., 2023). Recent studies suggest that walkability can help alleviate stress by providing accessible spaces that encourage daily physical activity and promote relaxation through exposure to the built and natural environment (Finucane et al., 2022; Ma et al., 2023), producing strong antidepressant effects (Dinas et al., 2010). Some even reported the health effects of a walkable neighborhood can exceed the effect of individual-level physical activity, with walkability functioning as a proxy measure of other benefits such as being more socially connected (Berke et al., 2007). This social connection can be a mediator that connects walkability and mental health (Sun et al., 2024). Walkable neighborhoods can also facilitate social cohesion (Lund, 2002) and the sense of community (Leyden, 2003), enhancing mental wellbeing (Li et al., 2021). Older adults living in walkable neighborhoods are also less likely to have cognitive impairment (De Almeida Siqueira et al., 2022), which may co-occur with depression (Steffens and Potter, 2007).

2.2. COVID-19 pandemic on walkability-mental health relationship

While the literature well-documented the benefits of walkability and mental health (arrow ***c*** in Fig. 1A), little is understood about how this relationship can be modulated by the COVID-19 pandemic.

On one hand, higher density often corresponds with an increased rate of disease transmission. Walkable urban areas tend to be more densely populated (Smith et al., 2008) and have the potential to be more vulnerable to outbreaks of infectious diseases because of the heightened interaction and proximity between individuals (Oishi et al., 2021). Studies by Martins-Filho (2021), Nguimkeu and Tadadjeu (2021), and Mansour et al. (2021) corroborate this assertion, indicating that neighborhoods with higher densities have reported elevated rates of disease contraction compared to their less densely populated counterparts.

In addition, in areas with high density and better connectivity, the mere perception of a higher risk of COVID-19 could impact mental health. This perception of risk, whether it accurately reflects the actual risk or not, can affect an individual's behavior, stress levels, and overall psychological well-being (Xiong et al., 2020). The presence of perceived risk, coupled with the factual risk of disease transmission due to higher interpersonal contact, can dissuade individuals from using spaces designed to be walkable and accessible, thus forfeiting the associated mental health benefits derived from social interactions, physical activity, and exposure to natural environments (Hartig et al., 2014). For example, urban green spaces, which have been proven to provide stress relief and improve mood (Nutsford et al., 2013), might be underutilized due to fears of contracting the virus in areas where people gather.

On the other hand, some studies reported a negative or insignificant relationship between walkability and the spread of COVID-19 (Oishi et al., 2021; Hamidi et al., 2020; Kim et al., 2021). Oishi et al. (2021) found that higher Walk Score® was associated with lower prevalence of COVID-19 in New York City. Residents in zip code with higher Walk Score® can reach daily destinations like grocery stores and restaurants within shorter distances, potentially minimizing their exposure to the virus and containing its spread between neighborhoods. Another study from New York City also reported that the percentage of land zoned as low-density residential zones (R1-R5 zones) is negatively associated with higher COVID-19 cases (Kim et al., 2021). Hamidi et al. (2020) examined 913 U.S. metropolitan counties and reported an insignificant relationship between county density and COVID-19 infection rate. They also found that high-density counties have lower COVID-19 mortality rates, potentially due to better health care systems. Using 72 cities in Massachusetts, USA, Wang et al. (2022) also found that higher Walk Score®, Bike Score, Transit Score were associated with lower COVID-19 transmission.

Furthermore, numerous studies underscore the complex relationship between walkable urban form and the propagation of COVID-19 (Hamidi et al., 2020; Khavarian-Garmsir et al., 2021; Boterman, 2020; Federgruen and Naha, 2021; Perone, 2021). These studies advocate for a more sophisticated comprehension of various factors at play, including urban design, socioeconomic conditions, public behavior, and policy responses. The collective insights derived from these studies indicate that attributing the spread of COVID-19 solely to urban form risks oversimplifying the multifaceted nature of pandemic dynamics (Hamidi et al., 2020; Khavarian-Garmsir et al., 2021; Boterman, 2020; Federgruen and Naha, 2021; Perone, 2021).

In summary, existing studies show mixed findings about how walkability is associated with the spread of COVID-19 virus, with no clear consensus so far (Zhang et al., 2022). Inconsistent conclusions are found even amongst review papers as well, as shown between Zhang et al. (2022) and Choo et al. (2024). This makes it challenging to anticipate how walkability is linked with mental health outcomes during the pandemic. These missing insights translate to the lack of understanding about whether we can keep expecting walkability to provide the mental health benefits under COVID-19-like pandemics in the same way and magnitude as reported before the pandemic.

There are only a few studies that examine the relationship between the neighborhood environment and mental well-being during the COVID-19 pandemic. Finucane et al. (2022) conducted a study on predominantly Black urban neighborhoods in Pittsburgh to explore how social isolation and neighborhood walkability influenced the relationship between COVID-19 experiences and mental well-being. Using a longitudinal cohort of Black residents, the study revealed that individuals living in more walkable neighborhoods experienced lower levels of distress from COVID-19 closures, suggesting that access to walkable infrastructure provided psychological resilience during the pandemic.

Additionally, conducted in Greater Melbourne, Australia, Ma et al. (2023) utilized a self-administered survey collected during the COVID-19 lockdown period. They measured the 'psychological resilience' of participants using a Likert scale, capturing how the pandemic affected their mental health. Using a multinomial logit model, the study reported that high levels of walkability and access to green space were associated with a mitigated negative impact of pandemic on mental health, even after considering individuals' sociodemographics, residential locations, and housing types. Also, their structural equation model results revealed that walkability indirectly alleviated the negative mental health impacts of the pandemic by enhancing the neighborhood satisfaction during the lockdown.

Given the prolonged pandemic with multiple critical waves, further research is needed to explore the evolving dynamics of mental health impacts over time within the same location. The epicenter of COVID-19 shifted from the urban areas at the beginning of the pandemic to suburban and rural areas in the latter stages (Cuadros et al., 2021; Frey, 2020; Wu et al., 2023). Furthermore, changing risk perceptions and vaccine dissemination may have complicated the relationship. This study directly addresses this gap by

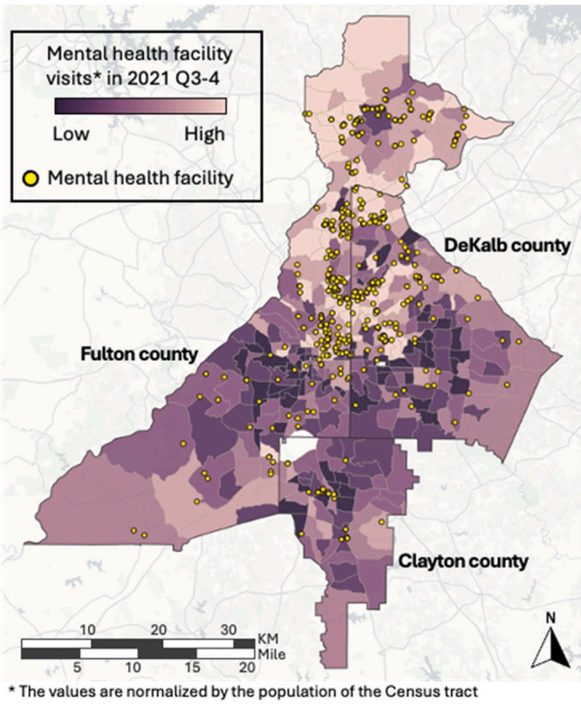

Fig. 2. Map of Dekalb, Fulton, Clayton county, Georgia.

comparatively examining the relationship between mental health and walkability both immediately before and during the COVID-19 pandemic within the same study area. By doing so, it contributes to the broader discourse on whether walkability's well-documented mental health benefits remain consistent during pandemics.

3. Data and methods

3.1. Data

3.1.1. Dependent variable: the number of mental health facility visits

This study was conducted in Fulton, DeKalb, and Clayton Counties in Georgia, USA - the three counties that contain and surround the City of Atlanta (Fig. 2). The unit of analysis was Census Tracts (see Table 2 for data sources). We obtained data from SafeGraph, a provider of weekly foot traffic data collected from anonymized smartphones. This dataset includes locational information of Point of Interests (POIs) and from which block group their visitors originated. The origin Census Block Group is determined based on the duration and number of consecutive overnight stays in a particular location. Each POI in SafeGraph data has a North American Industry Classification System (NAICS) code, which provides unique identifiers for its industry type. This study used 622210 ″Psychiatric and Substance Abuse Hospitals," 621112 ″Offices of Physicians, Mental Health Specialists," and 621330 ″Offices of Mental Health Practitioners (except Physicians) to extract only mental health facilities within the three counties (See Table 1).

It is important to note that mental health facility visits should not be considered a direct measure of mental health status. Some individuals with mental illnesses may face constraints that prevent them from physically visiting mental health facilities. Moreover, the availability of telehealth services and private counseling options allows individuals to access mental health support remotely. Hence, we acknowledge that the data on mental health facility visits should be interpreted with caution, recognizing that it may not capture the full spectrum of mental health needs within the population.

The dependent variable of this study—the total number of mental health facility visits during a specific time window from each Census Tract—was calculated by adding up the numbers of visits to mental health facilities generated within each Census Tract and normalizing it by the population of the Census Tract to avoid bias due to varying population sizes. While this study initially acquired all monthly data between July 2019 and April 2022, it is further narrowed down to 3 periods to enable comparison between visit patterns to mental health facilities before and during the COVID-19 pandemic. The first window spanned from July to December of 2019 (i.e., six-month time window before the pandemic) and the second and third window spanned from January–June, and July to December of 2021, respectively (i.e., six-month time windows during the pandemic).

Fig. 3 presents the weekly trend in visits to mental-health-related POIs throughout the study period. These visits have experienced a significant decline since the outbreak of the COVID-19 pandemic. The data indicate that the visitation rates have remained relatively consistent during the entire study duration.

3.1.2. Independent variable: neighborhood walkability

This study used Walk Score® as a measure of neighborhood walkability. Collecting Walk Score® data for each neighborhood was done through the following steps: First, 10 locations were randomly selected within each Census Tract. Second, the XY coordinates of the selected locations are used in the Walk Score® API to retrieve the Walk Score® of those locations. Third, the Walk Score® of each neighborhood was calculated by taking the average of the locations in each neighborhood.

3.1.3. Control variables: neighborhood characteristics

The following variables were collected from the 2019 American Community Survey (ACS) 5-year estimate: the number of persons below the poverty level, the number of workers in service or natural resources and construction industries, the number of one-person households, the number of senior-aged persons, the median age, the number of minority population (i.e., non-white population), and the number of persons without insurance.

The Urban Institute provided the estimated loss of low-income jobs, which was incorporated in this study as a proxy of the negative economic impact of the COVID-19 pandemic. This variable was included because we assumed that the extent of job loss can help assess the potential stressors experienced by individuals in the community and their subsequent impact on mental health.

3.1.4. Mediating variable: COVID-19 confirmed case rates

The Georgia Department of Public Health provided data on weekly COVID-19 confirmed case rates for each Census Tract. This variable represents the accumulated sum of COVID-19 confirmed case counts divided by population between July to December 2020 and the same period in 2021.

Table 1
POI types by NAICS code related to mental health.

NAICS code	POI Type	Count
622210	Psychiatric and Substance Abuse Hospitals	9
621112	Offices of Physicians, Mental Health Specialists	32
621330	Offices of Mental Health Practitioners (except Physicians)	1,444

Table 2
Data summary.

Description		Source
Dependent variable		
Mental Health Facility Visits	809,527 visits to 1,485 mental-health-related POIs, Origin block groups, and destination POIs	SafeGraph
Independent variables		
Walk Score®	Continuous Walkability Index (0.0–100.0)	Walk Score® API
Facility	Number of mental health facilities within 2 miles from residing census tract	SafeGraph
COVID-19 Case Rate	Weekly confirmed case rate (case/population)	Georgia Department of Public Health
Demographic	● Persons below the poverty level (%) ● Service worker (%) ● Natural resources & construction worker (%) ● One person household (%) ● Senior-aged person (%) ● Median age ● Minority population (non-white persons) (%) ● Persons with no insurance (%)	2019 ACS 5-year estimate
	● Number of Estimated Low-income Job Loss	Urban Institute (2021)

Note1. Geographic Boundaries: Fulton, Dekalb, Clayton County.
Unit of analysis: Census Tracts.
Study Period.
1) July 2019–December 2019 (pre-pandemic).
2) January 2021–June 2021 (early-pandemic).
3) July 2021–December 2021 (mid-pandemic).

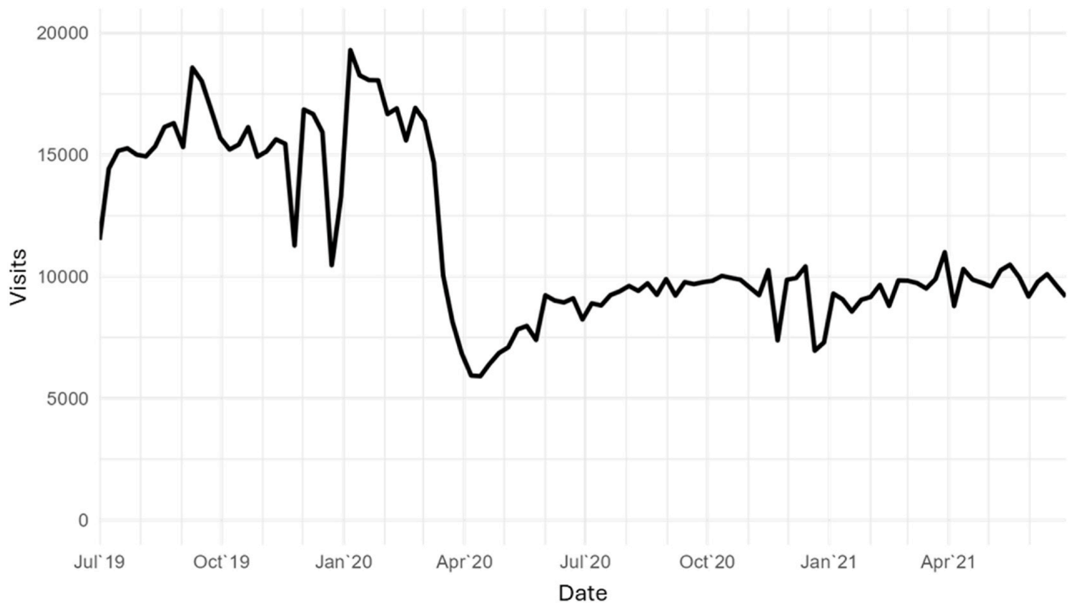

Fig. 3. Weekly mental health facility visits between July 2019 and July 2021 (Source: SafeGraph).

3.2. Statistical analysis

This study aims to answer three research questions utilizing the following statistical methods (workflow illustrated in Fig. 4). **R1** *How does the relationship between walkability and COVID-19 case rates change in different stages of the pandemic?* To address the first question, we implemented correlation analysis using Walk Score® and COVID-19 case rate data across two time periods: July and December 2020 (i.e., "Early-pandemic" period) and January to June 2021 (i.e., "Mid-pandemic" period) (See Table 3).

R2 *Is walkability consistently associated with better mental health outcomes before and in different stages of the COVID-19 pandemic?* For this question, we run three log-linear regressions. The first model examines the relationship between walkability and mental health facility visits in the pre-pandemic period between July 2019 and December 2019 (i.e., "Pre-pandemic Model"). The second model focuses on the "Early-pandemic" period between July and December 2020 (See Table 3). July 2020 is shortly after the shelter-in-place order in Georgia was lifted (Norder, 2020). The only difference between pre-pandemic and early-pandemic models is, apart from the

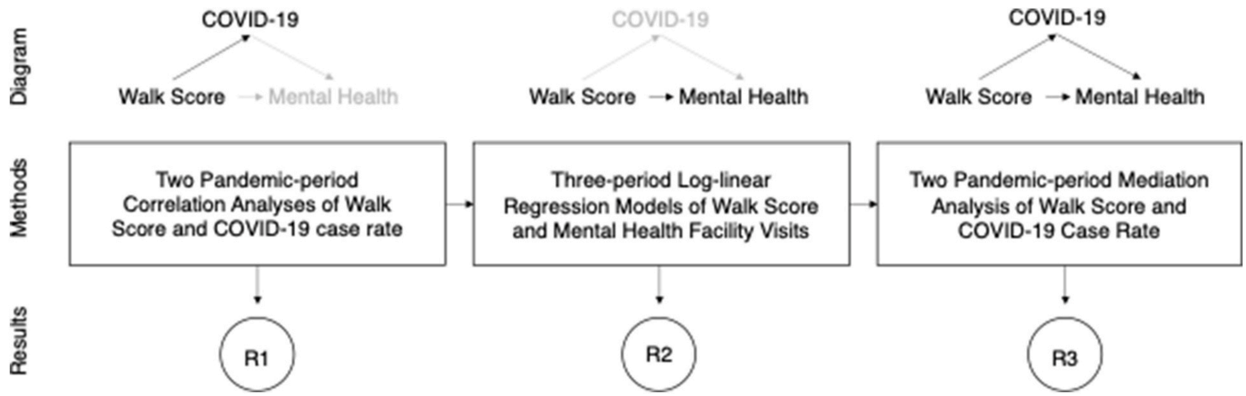

Fig. 4. Illustration of methodology.

Table 3
Temporal scope of each model's data for COVID19 cases and mental health facility visits.

	Model 1	Model 2	Model 3
	"Pre-pandemic"	"Early-pandemic"	"Mid-pandemic"
COVID-19 confirmed case rate	–	Jul.-Dec. 2020	Jan.-Jun. 2021
Mental health facility visits	Jul.-Dec. 2019	Jan.-Jun. 2021	Jul.-Dec. 2021

time difference, that the early-pandemic model includes COVID-19 case rates as one of the independent variables to reflect that fact that the COVID-19 pandemic itself was a major stressor (World Health Organization: WHO, 2022). The third model shares the same specification with the Early-pandemic Model but focuses on the "Mid-pandemic" period, January to June 2021. A notable difference between the Early and Mid-pandemic study periods is the progression of COVID-19 vaccination. On December 14, 2020, the first person in the U.S. outside of clinical trials received a COVID-19 vaccine (CDC Museum COVID-19 timeline, 2023).

R3 *How does COVID-19 case rates mediate the relationship between walkability and mental health outcomes in different stages of the pandemic?* To answer the last question, we conducted two mediation analyses on the Early-pandemic and Mid-pandemic models to examine the direct effects of walkability and the indirect effects of COVID-19 rates on mental health facility visits. Mediation analysis requires two models: (1) a mediator model examining the relationship between Walk Score® and the mediating COVID-19 confirmed case rates and (2) an outcome model examining the relationship between mental health facility visits and the mediating COVID-19 confirmed case rates while controlling for Walk Score® (Van Cauwenberg et al., 2016; Tibbe and Montoya, 2022). Note that this outcome model is identical to the Early-pandemic Model and the Mid-pandemic Model employed to answer the second research question. Both models included all control variables described in Section 3.1.3. The mediator and outcome models were then used as inputs to the "mediate" function in the "mediation" package in R to estimate the direct relationship between Walk Score® and mental health facility visits, as well as the indirect relationship through COVID-19 case rates. Additionally, the proportion of indirect relationships out of the total relationship is calculated. The percentile bootstrap confidence interval (sims = 8,000) was calculated at 95 % confidence level.

Table 4
Descriptive statistics.

Variables		mean	median	sd	min	max
Dependent	Mental Health Facility Visits (2019 Jul-Dec)	150	126	124	0	1,327
	Mental Health Facility Visits (2021 Jan-Jun)	80	64	67	0	520
	Mental Health Facility Visits (2021 Jul-Dec)	75	53	75	0	951
Mediator	Covid-19 case rate (2020 Jul-Dec)	4.1 %	3.9 %	1.2 %	0.6 %	11.2 %
	Covid-19 case rate (2021 Jan-Jun)	3.1 %	3.0 %	0.8 %	1.0 %	6.1 %
Explanatory	Walk Score®	34	30	22	1	93
	# Mental Health Facilities within 2 miles	14.9	7.0	17.3	1.0	83.0
	# Job Loss	39	35	19	3	142
	Below Poverty Level (%)	21 %	22 %	8 %	0 %	56 %
	Occupation: Service (%)	17 %	16 %	9 %	0 %	53 %
	Occupation: Natural Resources, Construction (%)	5 %	4 %	5 %	0 %	38 %
	One-person Household (%)	36 %	34 %	14 %	3 %	88 %
	Senior-aged Population (%)	12 %	11 %	7 %	0 %	90 %
	Median Age	36.1	35.3	6.6	14.5	67.8
	Non-White Population (%)	62 %	67 %	31 %	3 %	100 %
	Without Insurance (%)	13 %	13 %	9 %	0 %	60 %

The R 'mediate' function returns estimates of the Average Causal Mediation Effect (ACME) and the Average Direct Effect (ADE), which are crucial for interpreting mediation analysis (Tingley et al., 2014). ACME represents the average effect of the independent variable on the dependent variable that is mediated through the mediator variable. In other words, it quantifies the indirect pathway. ADE, on the other hand, measures the average effect of the independent variable on the dependent variable that is not mediated, representing the direct pathway. The total effect is the sum of the direct (ADE) and indirect (ACME) effects. Additionally, the 'proportion mediated', calculated as the ratio of the indirect effect to the total effect, indicates the extent to which the mediator explains the relationship between the independent and dependent variables.

4. Results

4.1. Descriptive statistics

Table 4 presents descriptive statistics of data with the unit of analysis being Census Tracts and a sample size of 391. Three tracts were excluded as they were considered outliers. All variables employed in the models are continuous. The dependent variable, mental health facility visits across three different periods, showed that the number of in-person visits to these facilities has significantly declined since the outbreak of the pandemic, as previously presented in Fig. 3. The mediator variable, the COVID-19 case rate, was slightly higher in the initial year compared to the first half of the following year.

In our study area, the average Walk Score® was 34. We divided the Walk Score® by 100 before including it in the regression model to improve numerical stability by normalizing the scale. The distribution of mental health facilities within a 2-mile radius of each tract exhibited a skew, with a mean of 14.9 and a median of 7. We applied a logarithmic transformation to this variable in our final linear regression model to address this skewness. Regarding the impact of the pandemic on employment, it was projected that on average, each tract would experience 39 job loss among low-income residents. However, Urban Institute advises interpreting this figure as indicative of relative, rather than absolute, job losses (Urban Institute, 2021). The average poverty rate across the Census Tracts was 21 %. On average, 12 % of the population of a Census Tract were of senior age. The average percentage of non-white population was over 60 %, with a wide spectrum ranging from a minimum of 3 % to a maximum of 100 %. Additionally, an average of 13 % of the population did not have any form of insurance coverage.

4.2. R1: relationship between Walk Score® and COVID-19 case rate

The correlation analysis yielded significant correlations between Walk Score® and Covid-19 case rate, but in opposite directions during the early and mid-pandemic periods (Table 5). In the early pandemic period, Walk Score® had a positive, although small, correlation with the COVID-19 case rate, suggesting that neighborhoods with higher walkability might have experienced higher COVID-19 case rates. However, this relationship flipped to a negative correlation in the Mid-pandemic period, which reflects the current inconclusive debate on how urban density and connectivity are associated with COVID-19 transmission. A similar result during the same period can be found in Wang et al. (2022), in which they reported that higher walkability was associated with lower COVID-19 infection rates in 72 cities in Massachusetts. Notably, most studies have employed data from early stage of the pandemic, making these findings from the later stages particularly significant.

4.3. R2: relationship between Walk Score® and mental health facility visits

The three log-linear regression analyses showed a significant negative relationship between Walk Score® and mental health facility visits in all models, both before and in different stages of the pandemic (Table 6). This suggests that higher neighborhood walkability was consistently associated with fewer visits to mental health facilities. The coefficient estimates of Walk Score® in the pre-pandemic and early-pandemic models were nearly identical (-0.357 and -0.354, respectively). The coefficient estimate of Walk Score® decreased in the mid-pandemic model, down to -0.225. In the pre-pandemic and the early-pandemic periods, a 10-point increase in Walk Score® was associated with approximately 3.51 % and 3.48 % in the number of mental health facility visits, respectively. In the mid-pandemic period, the same increase in Walk Score® was associated with a 2.23 % decrease in the number of mental health facility visits.

The COVID-19 case rates of the preceding half-year were positively associated with more frequent mental health facility visits in the following half-year in both early and mid-pandemic periods.

Many of the control variables showed changes in their statistical significance since the beginning of the pandemic. The number of mental health facilities within 2 miles, the percentage of one-person households, the percentage of senior-aged population, the percentage of population working in natural resources and construction industry, and median age were significant predictors before the

Table 5
Correlation coefficient between Walk Score® and COVID-19 case rate.

	Correlation Coefficient
Early-pandemic	0.117*
Mid-pandemic	−0.163**

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 6
Model results summary.

Dependent Variable	Pre-pandemic	Early-pandemic	Mid-pandemic
	2019 July-Dec Visits	2021 Jan-Jun Visits	2021 Jul-Dec Visits
Walk Score®	−0.357**	−0.354**	−0.225*
	(-0.581, -0.132)	(-0.567, -0.141)	(-0.442, -0.008)
COVID-19 Case Rate		4.752***	4.469*
		(2.167, 7.336)	(0.554, 8.384)
# Mental Health Facilities within 2 miles (log)	0.056**	0.024	0.028
	(0.016, 0.096)	(-0.015, 0.062)	(-0.011, 0.066)
# Job loss	−0.0002	−0.0001	0.001
	(-0.002, 0.002)	(-0.002, 0.002)	(-0.001, 0.003)
Below Poverty Level (%)	0.409	0.127	0.454
	(-0.165, 0.983)	(-0.423, 0.677)	(-0.097, 1.005)
Occu. Service (%)	−0.148	−0.522*	−0.555*
	(-0.670, 0.374)	(-1.024, -0.020)	(-1.056, -0.055)
Occu. Natural Resources, Construction (%)	−1.421**	−1.065*	−0.85
	(-2.337, -0.505)	(-1.947, -0.182)	(-1.728, 0.029)
One-person Household (%)	0.848***	0.288	0.394*
	(0.494, 1.203)	(-0.056, 0.633)	(0.049, 0.738)
Senior-aged Population (%)	−1.620***	−0.005	−0.177
	(-2.346, -0.893)	(-0.702, 0.692)	(-0.873, 0.520)
Median Age	0.018***	0.002	0.005
	(0.009, 0.027)	(-0.007, 0.010)	(-0.004, 0.014)
Non-white population (%)	−0.472***	−0.343***	−0.551***
	(-0.645, -0.300)	(-0.512, -0.175)	(-0.716, -0.385)
Without Insurance (%)	0.132	−0.039	0.055
	(-0.518, 0.781)	(-0.662, 0.584)	(-0.567, 0.678)
Constant	−3.789***	−3.701***	−3.902***
	(-4.262, -3.316)	(-4.156, -3.246)	(-4.367, -3.437)
Observation (N)	391	391	391
R2	0.392	0.314	0.383
Adjusted R2	0.374	0.292	0.364
Residual Std. Error	0.305 (df = 379)	0.293 (df = 378)	0.292 (df = 378)
F Statistic	22.173*** (df = 11; 379)	14.403*** (df = 12; 378)	19.564*** (df = 12; 378)

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

pandemic but were no longer so after the pandemic. The opposite case was the percentage of population working in the service industry: this variable was not associated with the mental health facility outcome pre-pandemic but became a significant predictor since the beginning of the pandemic. One consistent control variable throughout the three models was the percentage of minority population with a negative association with the mental health facility visits.

The pre-pandemic model had the highest R-square of 0.392 (Adjusted R-square: 0.374). This drops to 0.314 in the early pandemic model, which includes the lockdown period. However, it recovered to around 0.383 in the mid-pandemic period.

4.4. R3: mediation analysis on the relationship between Walk Score® and COVID-19 case rate

We first present the mediator models in Table 7 (i.e., the models representing the relationship between Walk Score® and the COVID-19 case rates) and the mediation analysis in Table 8 (i.e., the model that estimates the direct, indirect, and total effects between Walk Score® and mental health outcome using COVID-19 case rates as the mediator). As mentioned in the methods section, for the mediation analysis, we utilize the mediator models and the outcome models from the previous section (Early-pandemic and Mid-pandemic models) as input.

In the Early-Pandemic period of the mediator model (Table 7), the coefficient of Walk Score® was not statistically significant. However, in the Mid-Pandemic period, they show a minimal but significant negative relationship. With a Walk Score® increase of 10, the COVID-19 case rate is likely to decrease by approximately 0.0008.

In the Early-pandemic period, although the correlation between Walk Score® and COVID-19 case rates was significant and positive (Table 5), the mediator model in Table 7 showed that Walk Score® does not have a significant relationship with COVID-19 case rates after the inclusion of control variables. The ACME is also not significant in Table 8. In Mid-pandemic period, however, the mediator model showed that Walk Score® has negative associations with COVID-19 rates (i.e., path 'a' in Fig. 1B), which in turn positively associates with the frequency of mental health facility visits as shown in Table 6 (i.e., path 'b' in Fig. 1B). The product of the negative and positive associations is negative, which indicates an indirect effect where a higher Walk Score® leads to a decrease in COVID-19 rates, subsequently decreasing mental health facility visits. Additionally, the comparison of the absolute values of direct effect (ADE) and indirect effect (ACME) in the mediation analysis in Table 8 reveals that the direct effect of Walk Score® on mental health facility visits is more pronounced than its indirect effect via COVID-19 rates ($|ADE| > |ACME|$ in Table 8).

In summary, while Walk Score® consistently showed significant and negative relationship with the frequency of mental health facility visits in both early and mid-pandemic periods, the mediation effect of COVID-19 case rates was observed only in mid-pandemic

Table 7
Mediator model analyzing the relations of Walk Score® with COVID-19 case rate.

Dependent Variable	Early-pandemic	Mid-pandemic
	2020 Jul-Dec COVID-19 Case Rate	2021 Jan-Jun COVID-19 Case Rate
Walk Score®	−0.001	−0.008**
	(-0.009, 0.007)	(-0.013, -0.002)
# Mental Health Facilities within 2 miles (log)	−0.001	−0.001
	(-0.002, 0.001)	(-0.002, 0.0002)
# Job loss	0.0001	0
	(-0.00002, 0.0001)	(-0.00005, 0.00005)
Below Poverty Level (%)	−0.019	−0.005
	(-0.040, 0.002)	(-0.020, 0.009)
Occu. Service (%)	−0.008	−0.002
	(-0.027, 0.012)	(-0.015, 0.011)
Occu. Natural Resources, Construction (%)	0.027	0.004
	(-0.008, 0.061)	(-0.018, 0.027)
One-person Household (%)	0.020**	0.014**
	(0.006, 0.033)	(0.005, 0.023)
Senior-aged Population (%)	−0.009	−0.002
	(-0.036, 0.018)	(-0.020, 0.016)
Median Age	0.0002	0.0001
	(-0.0001, 0.001)	(-0.0001, 0.0003)
Non-white population (%)	−0.012***	0.0002
	(-0.018, -0.005)	(-0.004, 0.004)
Without Insurance (%)	0.015	0.006
	(-0.009, 0.039)	(-0.011, 0.022)
Constant	0.037***	0.027***
	(0.019, 0.054)	(0.015, 0.038)
Observation	391	391
R2	0.129	0.098
Adjusted R2	0.103	0.072
Residual Std. Error	0.011	0.008
F Statistic	5.083***	3.737***

*p < 0.05; **p < 0.01; ***p < 0.001.

Table 8
Mediation analysis.

Model	Early-pandemic			Mid-pandemic		
	Estimate	95 % CI Lower	95 % CI Upper	Estimate	95 % CI Lower	95 % CI Upper
ACME	−0.009	−0.099	0.09	−0.117**	−0.239	−0.03
ADE	−0.695**	−1.169	−0.24	−0.539*	−1.156	0.00
Total Effect	−0.704**	−1.174	−0.25	−0.656*	−1.293	−0.14
Prop. Mediated	0.013	−0.148	0.20	0.179*	0.039	0.67

*p < 0.05; **p < 0.01; ***p < 0.001.
*ACME: Average Causal Mediation Effects (ACME).
*ADE: Average Direct Effects (ADE).
*Total Effect: combined indirect and direct effects.
*Prop. Mediated: The ratio of these estimates.

period. In the early-pandemic period, almost all the effect of Walk Score® on mental health was through direct effect. Meanwhile, about 18 % of the effect of Walk Score® was through the indirect effect mediated by the COVID-19 case rates in the mid-pandemic period.

5. Discussion

5.1. Summary of analysis

This study explored the relationship between neighborhood walkability and the frequency of residents' mental health facility visits before and during the COVID-19 pandemic. The findings can be summarized as below to answer the three research questions posed in the Introduction.

First, how does the relationship between walkability and COVID-19 case rates change in different stages of the pandemic (R1)? Table 5 presented that the correlation between Walk Score® and COVID-19 case rates was positive in the early pandemic phase but then became negative in the mid-pandemic phase. The association between Walk Score® and COVID-19 transmission may be spurious, potentially influenced by a third factor not considered in this and other previous cross-sectional studies. One possible example of the third factor is social distancing practice: While a walkable environment may have contributed to the spread of the pandemic in its early stage, it may have later played a role in mitigating the spread as more people adopted social distancing practices.

Second, is walkability consistently associated with better mental health outcomes before and in different stages of the COVID-19 pandemic (R2)? Our data indicated that mental health outcomes were consistently better with higher walkability in all three time points. The three regression models in Table 6 indicate a consistent and significant negative association between Walk Score® and the frequency of mental health facility visits. This implies that walkability may maintain its mental health benefits regardless of the pandemic. High walkability, as indicated by higher Walk Score®, likely reduced the need for mental health services by providing better walking access to employment, amenities, and leisure spaces (Murray et al., 2004), greater social cohesion, and sense of community (Li et al., 2021).

Third, how does COVID-19 case rates mediate the relationship between walkability and mental health outcomes in different stages of the pandemic (R3)? The two mediation analyses showed that, when COVID-19 case rates increased with Walk Score® in the early stages of the pandemic, the direct effect (ADE) of Walk Score® on the frequency of mental health facility visits is statistically significant and negative, contributing significantly to the total effect. However, the indirect effect (ACME) is small and not statistically significant as shown in Table 8. In contrast, when Walk Score® is negatively correlated with the case rates in the mid-pandemic stages, both the direct (ADE) and indirect (ACME) effects are significant, with the indirect effect showing a significant mediating effect. The proportion of the total effect mediated (Prop. Mediated) is also significant during this period. Around 18 % of the total influence of Walk Score® on mental health facility visits is explained by its indirect pathway through COVID-19 case rates.

5.2. *Planning and policy implications*

Since the pandemic, numerous studies have argued that more compact, denser, and well-connected cities are associated with increased COVID-19 infection rate (Choo et al., 2024; Mouratidis, 2022; Wong and Li, 2020; Zhang et al., 2022; Kwon et al., 2022). With the prospect that the events similar to COVID-19 pandemic are likely to become more frequent in coming decades (Marani et al., 2021), these findings seem to be increasingly more relevant. This is troubling because New Urbanism, Smart Growth, and other major planning discourses have long been promoting walkable environments as a way toward more sustainable future (Ewing and Cervero, 2010; Smart Growth America, n.d.; Congress for New Urbanism, 2001; Litman, 2023). If the benefits of such walkable environments were negated by the increased infection rate and led to worse health outcomes, it may weaken the rationale and momentum for promoting walkable environments. For example, Choo et al. (2024) argues "This synthesized meta-analysis demonstrated that population density, road density (as one component of the urban built environment), and human mobility may influence the onset of a potential epidemic or pandemic … Thus, policy implementation aimed at adjusting the density and mobility of urban settings becomes essential in the pursuit of rendering cities more resilient and sustainable and as part of preparedness strategies for future infectious disease disasters" (p.9). However, this study, along with a few other studies (Murray et al., 2004; Li et al., 2021), found that the health-related benefits of walkability, such as better access to amenities and leisure spaces and more opportunities for physical activity, greater social cohesion, and sense of community, may still play a significant role *despite the possibility of increased infection*.

There are two points to highlight from this study on this. First, the direct effect of Walk Score® to the frequency of mental health facility visits was consistently stronger and negative. This implies that even when considering the potential for increased COVID-19 transmission, the benefits of walkable environments in terms of mental health remain significant. This direct positive impact may outweigh the potential risks associated with increased infection rates. Second, during periods when the Walk Score® was positively correlated with COVID-19 case rates, the mediation effect of COVID-19 on the relationship between walkability and mental health outcomes was insignificant. This means that the indirect pathway through COVID-19 case rates did not significantly alter the positive direct effect of walkability on mental health. Essentially, while higher walkability may initially have been associated with higher infection rates, this did not substantially diminish the mental health benefits derived from walkable environments. The resilience of the direct effect suggests that promoting walkable environments remains beneficial for mental health, even amidst concerns about infectious diseases.

Similar findings have been reported elsewhere: Hamidi et al. (2020) found that, while the population and activity density was positively correlated with higher infection rates in a simple correlation analysis, it was associated with lower death rate. The authors suspect that the lower death rate in denser areas is due to better access to health care facilities in such areas. Arifwidodo and Chandrasiri (2024) found that residents living in walkable neighborhoods were more likely to engage in sufficient physical activity during the pandemic. Because people with more active lifestyles have lower risk of chronic diseases, they are more likely to survive illness from COVID-19 (Frank and Wali, 2021).

In summary, while the pandemic has highlighted potential risks associated with compact, dense, and well-connected urban environments, the enduring mental health benefits of walkability should not be overlooked. For planners and policymakers, this highlights the need for strategies that balance the mental health and social advantages of walkable neighborhoods with measures to mitigate health risks during infectious disease outbreaks.

To achieve this balance, urban planners can prioritize urban design approaches that promote physical distancing and mitigate crowding (Choo et al., 2024), while maintaining the accessibility to Point-of-Interests (POI). Street-level approaches can be effective in this regard: Features such as wider sidewalks, pedestrianized streets, and outdoor seating can facilitate social interactions while maintaining physical distance during health crises (Psyllidis et al., 2023). Several major cities have implemented such measures to support both public health and social well-being through partially closing roads and expanding pedestrian spaces. Seattle's "Healthy Streets", Chicago's "Open Chicago" initiatives and Vancouver's Slow Streets project each repurposed road space to expand pedestrian spaces. Seattle partially closed streets to encourage outdoor activities, while Chicago collaborated with local artists to redesign pedestrianized streets for distanced outdoor activities (Seattle.gov, n.d.; City of Chicago, n.d.). Similarly, Vancouver installed signage and temporary barriers to improve routes for walking and biking to facilitate peoples' exercising and access to businesses in the neighborhood (City of Vancouver, n.d.). Similar approaches, such as pop-up bike lines, parklets, and mini plazas can also promote walking by expanding pedestrian outdoor spaces.

While this study used WalkScore for its wide acceptance and availability, the walkability literature discusses other aspects of the built environment that encourage walking. Urban design features that offer a sense of safety (e.g., well-maintained greenery, streetlights), protection from traffic (e.g., crosswalk, walk signal, and buffered sidewalks), and pleasurability (e.g., public parks and street greenery) can also promote walking (Ki and Lee, 2021; Koo et al., 2023; Kim et al., 2023), potentially leading to improved mental health. Improving physical features of the immediate neighborhood may, particularly during lockdowns, improve residents' satisfaction and overall well-being (Finucane et al., 2022). Additionally, improving access to green infrastructure such as parks, green roofs, and pocket parks can enhance both walkability and mental health, providing spaces for physical activity and stress relief (Hazlehurst et al., 2022). These spaces can also serve as gathering points during emergencies, fostering community resilience (Svensson and Elntib, 2021), while contributing to environmental sustainability.

Transit-oriented development (TOD) remains essential strategies for supplementing walkability that ensures access to essential services during emergencies when mobility restrictions are in place (Ma et al., 2023). Investments in high-quality active transportation infrastructure further support these goals, enabling safe transportation options for residents (Kyriakidis et al., 2022).

Furthermore, to address health risks while preserving the benefits of walkable environments, urban planners can leverage smart city technologies to create more adaptive urban spaces. One promising approach is pedestrian flow monitoring, which uses sensors, cameras, or AI-driven analytics to detect crowd density in real time and adjust access to public spaces or traffic signals dynamically (Choo et al., 2024; Han et al., 2024; Seshadri et al., 2024). This can help prevent overcrowding, particularly in high-footfall areas such as transit hubs, commercial districts, and entertainment zones, reducing the likelihood of virus transmission while maintaining accessibility. For example, Tokyo's crowd behavior analysis technology monitors crowd congestion and flow in Toshima (Nishiyama, 2018), while Singapore's Smart Urban Mobility initiative uses real-time crowd monitoring for adaptive transit scheduling (Das and Kwek, 2024).

One key consideration for planners is the equitable distribution of these interventions. As mentioned earlier, the COVID-19 pandemic prompted many cities to implement street reallocation programs to increase space for walking and cycling. However, as highlighted by Firth et al. (2021), these interventions sometimes had unintended negative consequences. In Seattle and Vancouver, street reallocations primarily occurred in neighborhoods with historically marginalized populations, which could have been more beneficial if guided by a mobility justice framework. However, many interventions lacked community engagement, leading to adverse effects on essential workers who rely on car-based travel (Firth et al., 2021). While reallocations improved pedestrian accessibility, they also reduced transit and vehicular access for those who still needed to commute daily.

This highlights another critical consideration, which is the role of community characteristics in shaping the effectiveness of walkability interventions (Wen et al., 2006) and the importance of participatory planning. Socioeconomic diversity and varying levels of access to resources may influence how different neighborhoods benefit from walkability improvements. Planners should engage with local communities to identify specific needs and co-create solutions that address disparities (Kyriakidis et al., 2022). Equitable distribution of these interventions ensures that the benefits are accessible to all residents, particularly in underserved areas.

In brief, while the pandemic has introduced risks associated with walkable environments, the enduring benefits for mental health provide a rationale for continued investment in walkability. By adopting context-sensitive approaches, planners and policymakers can create neighborhoods that are not only walkable but also resilient and equitable.

6. Conclusion

In conclusion, while there may be concerns that walkability could increase COVID-19 transmission, we observed consistent and significant mental health benefits of walkable environments. The findings advocate for the continued promotion of walkable environments, highlighting their essential role in fostering healthier, more resilient communities. By prioritizing walkability in urban planning, we can ensure that cities support both mental health and public health of individuals.

Future research should explore a more comprehensive approach to understanding mental health service utilization during the pandemic by integrating data on both in-person and digital health services, such as telehealth, online counseling, and community support programs. This expanded scope would provide a more complete view of how individuals accessed mental health resources. Additionally, the geographic focus of this study on three counties surrounding Atlanta highlights the need for further research in diverse urban contexts. Urban environments differ significantly in terms of population density, infrastructure, cultural practices, and public health responses, which can influence the relationships between walkability, COVID-19 case rates, and mental health outcomes. To enhance the generalizability of these findings, future studies should replicate this analysis in diverse urban settings, considering variations in urban form and policy responses.

CRediT authorship contribution statement

Chaeyeon Han: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Bon Woo Koo:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Uijeong Hwang:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

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