An Analysis of Walking Frequency Before and After the Pandemic

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Abstract
This paper is concerned with understanding the factors that contribute to walking frequency and the reasons for changes in walking frequency that occurred during the pandemic period. During the pandemic, people adopted new activity-travel patterns characterized by an elevated level of walking frequency. Using data from the COVID Future Panel Survey, that gathered longitudinal data from a large national sample in the U.S., this study analyzes the factors that contributed to different walking frequency levels and the reasons for increased walking levels in the pandemic era. A bivariate ordered probit model of before- and after-pandemic walking frequency that accounts for fixed effects and pandemic-era shift effects is estimated to determine effects of socio-economic, demographic, and built environment attributes on walking frequency. In addition, a multivariate probit model is estimated to identify reasons for increased walking frequency among different socio-economic and demographic groups. Overall, it is found that individuals with greater resources and flexibility are able to increase their walking frequency in the wake of a disruption. Built environment attributes are significant predictors of walking frequency. Some groups (e.g., households with children) elevated walking frequency due to a realization of the enjoyment afforded by walking, thus offering a glimmer of hope that higher levels of walking may persist (at least for some groups) even after the pandemic is a distant memory.

Keywords: physical activity, walking frequency, COVID impacts, active travel, multivariate models

1. Introduction

Walking is a cost-effective and healthy mode of transport and physical activity. Walking offers numerous physical health benefits, including reducing the risk of chronic diseases (Lee and Buchner, 2008), and enhancing bone density (Krall and Dawson-Hughes, 1994). Additionally, regular walking has been shown to positively impact mental well-being by reducing anxiety and depression levels (Vetrovsky et al., 2017). Further, replacing motorized trips with walking reduces vehicular traffic and associated fossil fuel consumption while improving air quality (Xia et al., 2013). Despite the many advantages of physical activity, including walking, more than half of the U.S. population (53.1%) did not meet the U.S. Department of Health's physical activity guidelines in 2020 (Elgaddal et al., 2022). With regards to walking, National Household Travel Survey (NHTS) 2017 data reveal that almost 27% of the population did not engage in any walking trips, primarily due to the absence of nearby sidewalks, paths, and other pedestrian walkways, as well as inadequate lighting at night (Federal Highway Administration, 2017).

In the realm of transportation, studies have been conducted to analyze the impacts of walking on transportation systems and land use patterns (see, for example, Lee and Moudon, 2006, Duncan et al., 2010, and McConville et al., 2011). There have also been numerous empirical studies examining the effect of sociodemographic characteristics and BE attributes on the adoption of walking for travel. From a sociodemographic perspective, these investigations examine how factors such as age, gender, income, education, and employment status relate to walking behavior (see Wasfi et al., 2013, Adams et al., 2017, Aliyas, 2020a, 2020b, and Evans et al., 2022). Empirical studies have also investigated the impact of neighborhood BE factors, such as land use patterns, street connectivity, pedestrian-oriented infrastructure, parks, and destinations like schools, workplaces, and retail areas on individuals' propensity to walk (see, for example, Mumford et al., 2011, Wilson et al., 2012, Adlakha et al., 2015, Van Heeswijck et al., 2015, and Quinn et al., 2017).

Walking behavior and attitudes were further affected by the disturbance in mobility and lifestyle caused by the outbreak of COVID-19. With restrictions imposed on indoor activities and reduced public transportation services, the pandemic era witnessed an increase in walking as a means of transportation and exercise (Kellermann et al., 2022). Even as the total number of trips in the U.S. decreased to a low of 62.1% of pre-pandemic levels at the height of the pandemic in April 2020 (Titlow, 2023), and the number of transit riders decreased to the lowest level since the 1930s (Bureau of Transportation Statistics, 2023, and Ziedan et al., 2023), which can cause decrease in utilitarian walking trips, available data suggest that recreational outdoor walking trips did not decrease during the lockdown (Hunter et al., 2021). Furthermore, as the stay-at-home orders were lifted, a notable increase in walking levels was observed (Doubleday et al., 2021), which is largely attributed to new participants engaging in outdoor walking/recreational activities (Outdoor Foundation, 2022, and Taff et al., 2021). These findings underscore the adaptability and appeal of walking as a mode of transportation and physical activity during times of restricted mobility and point to the emergence of a growing interest in outdoor activities.

Although the health threats of the COVID-19 pandemic have diminished, walking habits continue to be impacted by the persisting safety concerns related to the virus, daily trip reductions resulting from the adoption of remote work and online shopping modalities (Javadinasr et al., 2022), and the continuance of new (activity/mode choice) routines adopted during the pandemic. However, the overarching effects of the pandemic, both in the short and long term, are expected to differ among individuals and various groups due to a range of sociodemographic, economic, and BE factors, as highlighted in previous research (Dali et al., 2020, and Kleinman, 2020). These

varying impacts are expected to also extend to walking habits. While specific changes in walking and physical activity that occurred during the pandemic have been extensively studied, the majority of these studies were predominantly descriptive, without applying rigorous statistical analyses to draw robust inferences. Additionally, there has been limited research exploring the underlying reasons for shifts in walking frequency and the extent to which these changes will persist in the future.

The above discussion motivates the current research. We contribute to the earlier investigations of walking behavior in a pandemic-altered world, but using multivariate econometric models that accommodate multiple demographic and BE variables at once rather than simple univariate or bivariate descriptive correlations of determinant factors with walking behavior. In addition, we seek to identify the determinants that contribute to any stated increase in walking frequency in the after-COVID period relative to the before-COVID period. In particular, the study uses a bivariate ordered response probit model to jointly model an individual's walking frequency before the pandemic and expectations of walking frequency in the after-COVID period. While some factors affect walking frequency during both periods with the same magnitude, the effects of some other factors on the frequency of walking may have shifted after the pandemic. The model is structured to explicitly present the extent of expected shift occurring in the after-COVID period. This model is estimated using data on walking habits obtained from the COVID Future Panel Survey which gathered detailed information from April 2020 to November 2021 on walking frequency, sociodemographic factors such as education level and household composition, built environment (BE) factors based on residence zip code, and personal attributes for a large national sample of respondents (Chauhan et al., 2021). In doing so, the current study not only reveals how walking habits have shifted and how the impacts of individual and environmental factors have changed over time, but also provides insights to promote a long-term increase in walking levels customized to specific population groups.

2. Walking Activity and the COVID-19 Pandemic

Several studies have focused on tracking changes in walking behavior during pandemic-induced lockdowns and the subsequent transition back to normalcy. During the COVID-19 pandemic, Schmidt et al. (2021) found an increase in the willingness to walk and the frequency of walking, while use of all other modes decreased (with the exception of bicycling, which also increased in usage). A few studies compared walking and mobility trends over several phases of the pandemic. Hunter et al. (2021) distinguished leisure and utilitarian walking trends using mobile phone mobility data and assessed the reduction in walking following the implementation of lockdown measures and the declaration of a national emergency on March 13, 2020. They also tracked the recovery trend once the lockdown restrictions were lifted. During the critical lockdown period, *utilitarian* walking distance decreased by more than 72%; and even in July 2020 when severe lockdown measures were lifted, *utilitarian* walking distances remained 39% lower than pre-pandemic levels. In contrast, *leisure* walking did not significantly decrease in distance and, by July 2020, had actually experienced an increase in distance relative to before the pandemic.

Doubleday et al. (2021) focused on the effects of the pandemic on leisure walking by counting daily bikes and pedestrians in parks and trails in megacities and observed a decreasing trend in biking and walking volumes (which varied across cities). In analyzing general mobility patterns during the recovery phase following lockdowns, Chen and Steiner (2022) found that, in comparison to the baseline of 2019, the total number of trips (regardless of mode) remained lower by 7% in the U.S. in 2021. However, they observed an increase in trips shorter than one mile and

between 50 and 500 miles, suggesting a potential increase in travel within walking distance range and in longer distance recreational travel. In the case of Berlin, Germany, Kellermann et al. (2022) also found a decrease in total trip making, but an increase in very short distance trips that are more conducive to walking.

Research on walking behavior changes during the pandemic has identified variations across different socio-economic groups. Kyan and Takakura (2022), Qu et al. (2022), and Zafri et al. (2021) found that individuals from lower household income and education levels tended to engage in less walking during the pandemic. Furthermore, Qu et al. (2022) reported that the gap between income groups widened during the pandemic. In contrast, Zafri et al. (2021) conducted a survey on the expected change in walking frequency once COVID-19 is no longer a threat and found that individuals in low-income groups expressed a higher propensity to increase walking (relative to pre-pandemic levels). The influence of gender on walking behavior has also been studied. Greier et al. (2021) suggested that during the COVID-19 lockdown, both girls and boys walked less than pre-lockdown, but the decrease is larger for girls among high school students. Additionally, Nikiforiadis et al. (2022) explored the recovery period following the first lockdown in the spring of 2020 and found a greater increase in walking frequency among women and young adults in cities with a more pedestrian-friendly environment. Carr et al. (2021) and Lee et al. (2022) highlighted the positive effects of dog walking on reducing loneliness and enhancing mental health among older adults, especially those who experienced significant negative social interaction consequences due to the pandemic. Similarly, Liu et al. (2022) reported that individuals who believed COVID-19 had a negative impact on their lives were less inclined to engage in walking activities. Ma et al. (2022) investigated perceived racism against Asians during the pandemic and found that Asians exhibited a lower tendency to increase walking during the pandemic lockdown.

This study recognizes that the COVID-19 pandemic has brought about significant disruptions to lifestyles, some of which have persisted and continue to impact mobility patterns. With the COVID-19 pandemic increasingly fading away, it is of value to understand changes in walking behavior in a post-pandemic era. Not only might the significant sociodemographic and BE attributes that affect walking frequency have changed, but the magnitude of influence of these factors on walking habits may have shifted. Most previous studies that investigated walking habits during the pandemic or the recovery period were mostly descriptive, thus presenting key limitations in the ability to draw robust statistical inferences. Unlike previous studies, this study uses the rigorous multivariate model system to how walking frequency has evolved and examine how the impacts of various factors have changed over time. Through this study, we evaluate the changes in the influence of socio-economic and BE factors on walking frequency. Furthermore, we analyze the reasons underlying the increased walking frequency among different sociodemographic groups. This analysis will provide valuable insights for developing strategies and interventions to promote (and retain the increase in) walking in the post-pandemic era.

3. Data and Variable Description

This section presents a description of the data and key variables used in this study.

3.1. Survey

The data used for this study is derived from the COVID Future Panel Survey in the U.S. (Chauhan et al., 2021). The survey consists of three waves and covers a myriad of topics before, during, and after the pandemic. The first wave collected data from 8,723 respondents during the early stages of the pandemic from April to October 2020, the second wave collected 2,877 responses from

November 2020 to May 2021, and the third wave collected 2,728 responses from October to November 2021 representing the period when the restrictions and fears caused by the pandemic had faded. Since our study focuses on analyzing the changes in walking frequency before and after the pandemic, we use the 2,728 responses from those who participated in the first and third waves. After extensive data cleaning and deletion of clearly erroneous data, 2,629 were included in the final sample.

To gather pre-pandemic socio-economic and environmental factors, we utilized data from responses of Wave 1, while post-pandemic information was obtained from Wave 3 data. Certain demographic factors, such as race, remained unchanged during the pandemic, while other factors experienced similar shifts for everyone or exhibited minimal changes within our sample (e.g., age and education). In such cases, we established Wave 1 as the baseline for these factors.

3.2. Exogenous variables

We categorized the explanatory variables into three groups: individual characteristics, household sociodemographic characteristics, and built environment (BE) attributes. Individual characteristics include gender, age, employment status, education level, and work-from-home status (including availability of such an option and frequency). Household characteristics include household composition, household vehicle ownership, and household income. To account for the changes that occurred during the pandemic, we took into consideration both pre- and post-pandemic employment and household income levels. We categorized the shifts in these variables as exogenous variables, allowing us to analyze and understand the impact of these changes on the outcomes of interest. Built environmental factors included population density, walkability index, distance to the nearest transit from the center of the residence zip code, crime rate of the zip code where respondents lived, accessibility to personal or public bikes, and commute time. The walkability index is defined in Smart Location Database Version 3.0 (EPA, 2021) as a function of intersection density, proximity to transit stops, employment mix, and household and employment mix (Champman et al., 2021).

We obtained data from the American Community Survey (ACS) 5-year estimates for 2019 and 2020 to determine sample representativeness as depicted in Table 1 (U.S. Census Bureau, 2019, 2020). Although the sample shows some deviations from census distributions, this is not of any major concern in the context of a multivariate modeling study such as this one because it focuses on individual-level causal effects rather than sample descriptive statistics. The data depict the richness of variation in socio-economic characteristics that is desired in data sets used for modeling purposes and is therefore quite appropriate for accomplishing the objectives of this study.

Table 1 Sample Distribution of Exogenous Variables (N = 2,629)

Variable	Sample (%)	ACS 2020 (%)
Age		
18 to 29 years	6.7	20.8
30 to 49 years	27.8	33.7
50 to 64 years	31.9	24.9
65 years or older	33.6	20.7
Gender		
Female	37.3	50.5
Male	62.7	49.5
Education		
High school or less	12.0	11.1
Some college	60.3	55.2
Bachelor's or higher	27.7	33.7
Employment Status		
Employed	55.1	62.0
Non-employed	44.9	38.0
Ethnicity		
Hispanic	7.4	18.4
Non-Hispanic	92.6	81.6
Race		
Non-White	14.1	25.5
White	85.9	74.5
Household Vehicles		
0	6.7	8.1
1	38.8	32.9
2	39.9	37.1
3 or more	14.6	21.9
Household Income		
Less than $50,000	19.1	36.8
$50,000 to $99,999	46.4	29.6
$100,000 or more	34.5	33.6

3.3. Outcome variables

The main outcome variable of this study is the frequency of walking before and after the pandemic. In the survey, participants were asked about their walking frequency on a five-point scale, ranging from "never" to "everyday", for the pre-pandemic period in Wave 1. In Wave 3, participants were asked to state their likely walking frequency for a future time when COVID-19 no longer presents a threat. For ease in presentation, and to avoid confusion with the statistical use of the term "expected", we will present the rest of this study as though this expectation of walking frequency represents actual walking frequency in the after-COVID period. The responses regarding walking frequency are presented in Table 2. The results indicate that, of the total respondents, 1,203 individuals (45.8%) stated that they expected to maintain the same walking frequency as before the pandemic (sum of the diagonal elements in Table 2). Additionally, 728 respondents (27.7%) expressed that they would walk more frequently (sum of the upper triangular part of Table 2), while 698 respondents (26.5%) indicated that they expected to walk less often than before the pandemic (sum of the lower triangular part of Table 2). It is important to note that the use of ordinal outcome variables, rather than count variables, for modeling walking frequency does not

compromise the validity of the study's results, as casual effects can still be examined. Additionally, regarding temporal considerations, such as the recollection of past events or anticipation of future events, using ordinal scales or categories can be appropriate since soliciting exact numerical frequencies from respondents when dealing with subjective or uncertain events can be challenging.

Furthermore, respondents who indicated that they expected to walk more after the pandemic were asked about their reasons for this response as presented in Figure 1. These findings align with previous research on the reasons for increased walking. For instance, one of the main reasons people reported walking more is for exercise and recreational purposes, which is consistent with patterns observed during the pandemic (Hunter et al., 2021).

Table 2 Responses on Walking Frequency Before and After the Pandemic

After the Pandemic	Before the Pandemic					
	Never	A few times a year	A few times a month	A few times a week	Everyday	Total
Never	313 11.9%	71 2.7%	68 2.6%	85 3.2%	27 1.0%	564 21.5%
A few times a year	38 1.4%	59 2.2%	49 1.9%	42 1.6%	17 0.6%	205 7.8%
A few times a month	48 1.8%	70 2.7%	141 5.4%	121 4.6%	32 1.2%	412 15.7%
A few times a week	84 3.2%	65 2.5%	159 6.0%	321 12.2%	186 7.1%	815 31.0%
Everyday	46 1.7%	15 0.6%	63 2.4%	140 5.3%	369 14.0%	633 24.1%
Total	529 20.1%	280 10.7%	480 18.3%	709 27.0%	631 24.0%	2629 100%

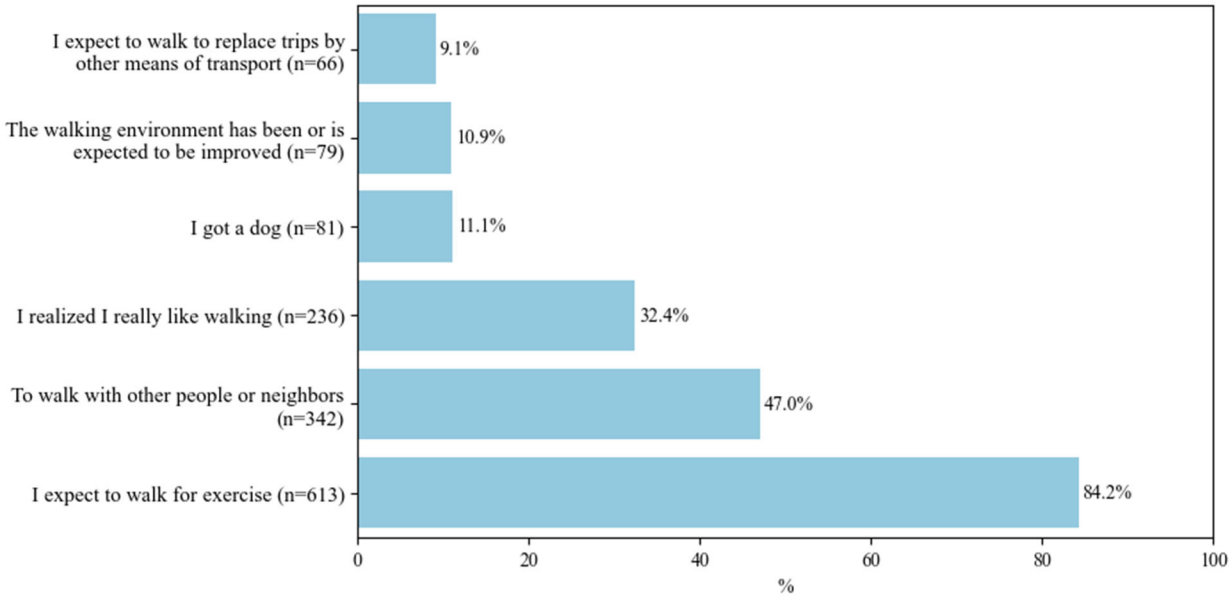

Figure 1. Percent of Respondents Selecting Reasons for Increased Pandemic-Era Walking

4. Model Structure and Framework

The structure of the model is shown in Figure 2. The model aims to estimate walking frequency before and after the pandemic, as well as the possible reasons for an increase in walking frequency. The exogenous variables, representing sociodemographic and built environment attributes that influence the outcome variables, are depicted on the left-hand side of Figure 2. The three outcome variables, including the frequency of walking before the COVID-19 pandemic, the frequency of walking after the COVID-19 pandemic, and the reasons for increasing walking after the COVID-19 pandemic, are shown on the right-hand side of Figure 2.

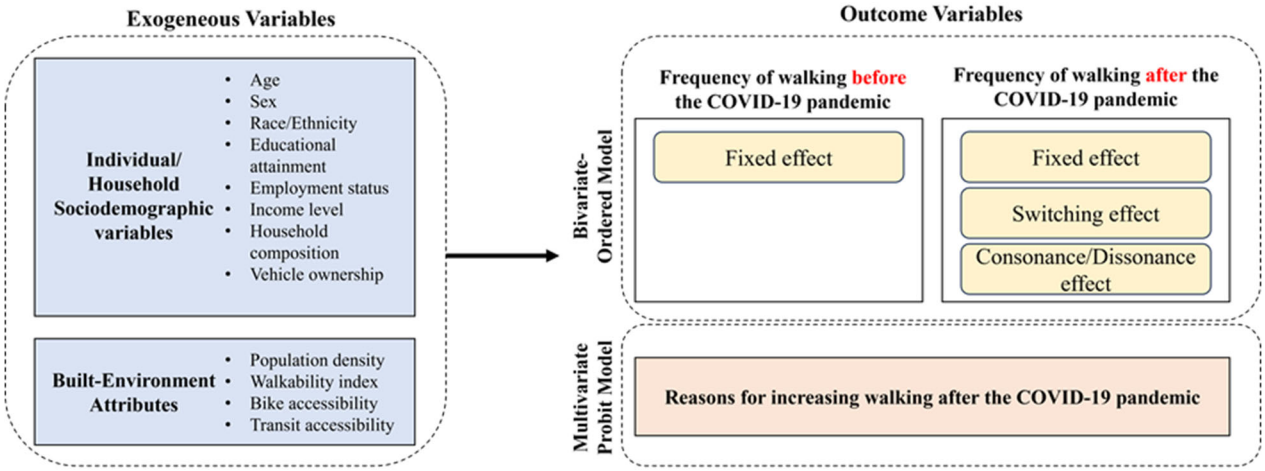

Figure 2. Relationship between Exogenous and Outcome Variables

Given that walking frequency was assessed using ordinal variables, as mentioned in the previous section, and considering the expected correlation between pre-pandemic and post-pandemic walking frequency, we utilize a bivariate ordered response model to estimate this relationship. Specifically, the underlying latent variables representing walking frequency in the before and after-COVID periods (the top block in the outcome portion of Figure 2), and the mapping of these two latent variables to the observed ordinal walking frequency levels, are specified in terms of three effect components: fixed effects, switching effects, and consonance/dissonance effects. The fixed effects part captures the influence of exogenous variables on the latent propensity of walking frequency, regardless of pandemic effects. In other words, the coefficients associated with the exogenous variables remain the same in both the pre-pandemic and post-pandemic walking frequency models. When only considering the fixed portion of the model, changes in the outcome (i.e., latent propensity) are solely attributed to changes in individual factors (e.g., income) rather than *changes in the effect* of the factors on walking frequency. The second part of the walking frequency model represents the switching effects, which represent the influence of the exogenous variables on the frequency of walking after the pandemic – *above and beyond* the fixed effects. For a variable for which only the second effect exists, the implication is that the variable does not affect the underlying latent variable characterizing pre-pandemic walking frequency, but does affect the after-COVID walking frequency latent variable. For a variable for which both effects exist, the first component provides the variable effect in the before-COVID period, while the second component provides the variable effect in the after-COVID period.

However, the set of fixed and switching effects, by themselves, do not capture the inevitable intrinsic bivariate clustering due to state dependence (or consonance) in walking frequency. That is, the switching effects component can reflect the number of observations walking at each frequency level after COVID (column totals in Table 2) well, but is not able to reflect the bivariate clustering representing consonance (even after allowing for unobserved correlation between walking frequency before and after COVID). For example, those who never walked in the before-COVID period may "stick" to that behavior in the after-COVID period, and similar effects may exist for the other ordinal walking categories; these are the respondents in the diagonal cells of Table 2. Similarly, intrinsically, it is not very likely that someone who "never" walked in the before-COVID period would start walking "everyday" in the after-COVID period. Such clustering/rare walking frequency combinations would not be adequately recognized by the correlation in the underlying latent variables representing walking frequencies before and after COVID. Therefore, consonance/dissonance effects, the third component of the model, are introduced through the use of threshold shifters to account for specific cross-before and cross-after COVID combinations that are very rare or very likely to occur.

The third outcome variable corresponds to the reasons for increased walking after the COVID-19 pandemic (bottom block in the outcome portion of Figure 2). Six reasons were considered in this study (as shown in Figure 1), and individuals are able to select all that apply. Consequently, a multivariate probit model with six binary dependent variables is formulated for this portion of the study. The detailed formulations and estimation process is based on Anderson et al. (2023).

In the empirical estimation process, we tested different functional forms and combinations of bracketed and continuous explanatory variables. The results discussed in the subsequent sections reflect the most effective and efficient forms for each variable. In addition, we tested interaction effects among variables, however, none of these were statistically significant.

5. Estimation Results for Model of Walking Frequency

This section presents model estimation results. The model components corresponding to walking frequency estimation are presented first, while the model component corresponding to reasons for increased walking in the post-pandemic period are presented second.

5.1. Influence of Variables on Walking Frequency

Table 3 presents the estimation results for the bivariate ordered probit model representing the fixed and switching effects of exogenous variables on the frequency of walking before and after the COVID-19 pandemic. The column labeled "fixed effect" reflects the effects of the variables on the frequency of walking in general (at any time). The column labeled "switching effect" corresponds to the change in the effects of exogenous variables following the pandemic. Thus, any variable in the table that depicts a fixed effect but no additional switching effect has the same effect on walking frequency before and after the pandemic. If a variable depicts a switching effect, it means that the influence of the variable has changed following the pandemic. As discussed previously, various functional forms of explanatory variables were investigated and the final model specification was chosen based on both statistical considerations and behavioral intuitiveness. As such, some variables that are not significant at a 0.05 significance level were retained in the model.

Table 3. Estimates of Exogeneous Variables on Walking Frequency (N=2,629)

Exogenous variables (base)	Fixed effect		Switching effect	
	Coef.	t-stat	Coef.	t-stat
Individual characteristics				
Age (under 29 years old)				
30 to 49 years	-0.245	-2.77	--	--
50 years or older	-0.106	-1.26	-0.06	-1.17
Gender (male)				
Female	-0.164	-4.33	--	--
Education level (high school or lower)				
Bachelor's or some college	0.267	4.69	--	--
Graduate degree(s)	0.354	4.99	0.25	4.18
Household characteristics				
Household composition (one-adult household without children)				
Live with significant other	0.16	3.45	-0.14	-2.79
Live with child	-0.15	-3.16	--	--
Live with three or more related adults	--	--	0.25	1.73
Household vehicles (zero)				
One	-0.37	-4.39	--	--
Two	-0.53	-5.71	0.12	2.14
Three or more	-0.60	-5.96	0.21	2.94
Household income (< $100,000)				
$100,000 or higher	0.19	4.21	--	--
Change in household income during the pandemic (no change or decreased from <$100,000)				
Increased income	--	--	0.15	2.09
Decreased to other levels from $100,000 or higher	--	--	0.19	4.21
Employment status/Job characteristics				
Employment status (non-employed)				
Employed	-0.10	-2.63	--	--
Commute time (< 50min)				
≥50min	0.46	4.76	-0.41	-3.28
Work from home frequency post-Covid				
Number of days per week	--	--	0.06	4.59
Built-environment attributes				
Population density (persons/sq mile)	0.01	3.39	--	--
Walkability index/100	5.70	5.67	--	--
Bike accessibility (no)				
Yes	0.40	10.04	--	--
Distance to nearest transit stop/100 (meter)	-0.06	4.28	--	--

Table 3. Estimates of Exogeneous Variables on Walking Frequency (N=2,629) (Continued)

Exogenous variables (base)	Fixed effect		Switching effect	
	Coef.	t-stat	Coef.	t-stat
Correlations	Pre-COVID walk freq.		Post-COVID walk freq.	
Pre-COVID walking frequency	1.00	--	0.49	16.51
Post-COVID walking frequency	--	--	1.00	--
Thresholds and consonance				
Unadjusted thresholds for pre-pandemic	**Coef.**		**t-stat**	
1|2	-0.57		-3.91	
2|3	-0.20		-1.41	
3|4	0.31		2.13	
4|5	1.10		7.55	
Unadjusted thresholds for post-pandemic				
1|2	-0.49		-3.22	
2|3	-0.27		-1.82	
3|4	0.18		1.22	
4|5	1.09		7.09	
Constant consonance shifts for post-pandemic				
1|2 Consonance Shift	0.32		3.33	
2|3 Consonance Shift	0.31		5.16	
3|4 Consonance Shift	0.24		4.35	
4|5 Consonance Shift	0.31		4.98	
Cross before-after threshold adjustments				
"A few times a year" before to "A few times a week" after	0.09		1.53	
"Never" before to "Everyday" after	-0.45		-5.39	
"Never" before to "A few times a week" after	-0.19		-4.09	
"A few times a week" before to "Never" after	-0.15		-2.88	
Generic consonance shifts for post-pandemic				
Household income (<$100,000)				
≥$100,000	-0.15		-1.31	
Outcome-specific consonance shifts for post-pandemic				
Household income (<$100,000)				
≥$100,000 * Walking every day after	-0.09		-1.59	
Education level (bachelor or lower)				
Graduate degree(s) * Walking every day after	0.12		1.88	
Data fit measures				
Log-likelihood at convergence	*-7271.89*			
Number of parameters	*46*			
Log-likelihood at independence (35 parameters)	*-7720.91*			
Likelihood ratio test	$LR = 898.04 > \chi^2_{(11,0.01)} = 24.727$			

A host of socio-economic and demographic variables exhibit fixed and/or switching effects on walking frequency. Older individuals tend to walk less in general as depicted by the negative fixed effects, consistent with findings in the literature (e.g., Paul et al., 2015). Although not statistically significant at the 0.05 significance level, those 50 or older depict a negative switching effect that is noteworthy and behaviorally intuitive. It is likely that older individuals reduced their outdoor activities, including walking, more than other age groups to minimize exposure during the pandemic and subsequently continued with these behaviors after the pandemic. Women have a lower walking propensity than men, a finding also reported in the literature (e.g., Gul et al., 2019), and depict no switching effect. Those with a higher education level show a higher propensity for walking (fixed effects). Berrigan and Troiano (2002) have reported a similar finding and explained that higher-educated individuals may be more aware of the benefits of walking-related physical activity and Van Der Vlugt et al. (2022) also explained that they have the flexibility to use public transit, which leads to walking for access. The positive switching effect associated with the highest education level suggests further amplified walking activity in that group during the pandemic.

In terms of household composition, living with a partner is generally associated with higher walking propensity (fixed effect), findings also reported by Aliyas (2020a) and Kramer et al. (2013). However, the negative switching effect suggests a reduced walking propensity among couples after the pandemic, presumably to decrease their exposure to the virus during the pandemic. Those living with a child exhibit a lower propensity for walking, possibly due to busy schedules and childcare responsibilities (Aliyas, 2020b, and Berge et al., 2011). Conversely, the results reveal that members of larger households generally increased their propensity after the pandemic – presumably to facilitate social interaction and healthy physical activity (during a time of lingering concerns about conducting activities in indoor spaces).

Vehicle ownership and income were found to affect the underlying latent variables characterizing walking frequency as well, with the change in income experienced during the pandemic having additional effects. Car ownership is generally associated with lower walking propensity, as documented in prior research (Sehatzadeh et al., 2011). However, the presence of multiple vehicles (two vehicles or three or more vehicles) is associated with a positive switching effect, suggesting that individuals in households with more vehicles may have consciously increased their propensity for walking during the pandemic upon realizing the negative health outcomes associated with sedentary car-oriented lifestyles. Those in higher-income households exhibit a higher propensity for walking (positive fixed effect), consistent with findings reported by Cerin et al. (2009) and Lachapelle and Noland (2012). While household income itself does not exhibit a switching effect, both a decrease and an increase in income result in positive shifts in walking frequency propensity after the pandemic. Those experiencing an increase in income are likely to have shifted their lifestyle to more closely mimic that of higher-income households. Those experiencing a decrease in income may have suffered a loss of employment; this reduces available monetary resources, increases available time, and creates stress and lower mental well-being. Increased walking propensity may have been a result of all three contributing factors.

Employment characteristics play a role in shaping walking frequency. Employed individuals exhibit a lower walking propensity (negative fixed effect) presumably due to time constraints (Chen et al., 2013, and Li et al., 2019). Additionally, the findings indicate that those with long commutes are likely to walk more frequently, largely because they use public transit more than those with short commutes (De Vos et al., 2022; Morris and Guerra, 2015). Long commutes are associated with a negative switching effect, suggesting a decrease in walking propensity in the COVID era (because of the dramatic drop in transit commuting during and after

COVID). Those who adopted a high level of telework were likely to increase their walking frequency, most likely because of greater time availability and the need for relief from isolation (Batur et al., 2023).

Lastly, built environment attributes exhibit a significant influence on the propensity for walking in ways that are consistent with expectations and prior research. Population density, walkability index, and bicycle access (obtained as the response to a simple binary question of "do you own or have access to a bicycle") are found to contribute positively to walking propensity, consistent with results reported by Liu et al. (2021), Yin et al. (2023), Ewing and Cervero (2010), and Watson et al. (2020). Similarly, living closer to transit stops is associated with increased walking, as reported by Lachapelle and Noland (2012), likely due to walking for access/egress purposes. None of these BE variables exhibited a switching effect, indicating that the pandemic did not bring about any change in BE impact on walking frequency.

5.2. Correlations, Shifts, and Goodness-of-Fit

In addition to variable coefficient estimates, Table 3 presents the resulting correlation terms and consonance/dissonance effects. The significant positive correlation suggests the presence of several correlated unobserved factors that influence walking frequency both before and after the pandemic in the same direction. For example, attitudinal factors and personality traits (health conscious, outdoor/active lifestyle propensity, extrovert personality) may contribute positively to walking frequency regardless of the pandemic.

The unadjusted thresholds do not have any substantive interpretation; they simply map the underlying latent propensities and the actual observed outcomes across the sample. The consonance shifts are all positive and significant, clearly pointing to the substantial presence of consonance. That is, those who are more prone to walk before the pandemic are more prone to walk after the pandemic as well, and vice-versa. This consonance is evidence of the presence of considerable state dependence (after accounting for unobserved heterogeneity through correlation effects), where the current or future state is highly correlated with and dependent upon the past or current state.

To accommodate before-after COVID walking frequency combinations that are unlikely or very likely to occur, cross-threshold adjustments are estimated. These adjustments enable the model to better replicate observed outcome combinations in the sample. Four parameters were found to be statistically significant, with a positive parameter having the effect of pushing thresholds toward the right (reducing the probability of a specific combination occurring) and a negative parameter having the effect of pushing thresholds toward the left (increasing the probability of a specific combination occurring). The positive and negative signs on the cross-threshold adjustment parameters are consistent with the patterns seen in Table 1.

The generic consonance shift parameters suggest that high-income individuals depict a low level of consonance (per the negative shift parameter). It is plausible that these individuals recovered considerable commute time during the pandemic with greater work-from-home. While they used to engage in social interactions in the office and had no time to walk before the pandemic, the pandemic era allowed them to use commute time savings to walk more and combat isolation.

The outcome-specific consonance shift effects indicate the threshold for the "everyday" category in the post-COVID case shifts to the left for high-income individuals (regardless of their pre-COVID walking frequency), thus elevating walk propensity among high-income individuals in the post-COVID case. On the other hand, highly educated individuals are less likely to walk every day after COVID regardless of their pre-covid walking frequency (which is a finding that

warrants further investigation). Finally, the goodness-of-fit measures show that the joint model presents a statistically superior fit when compared with the model with constants only. The significant error correlation also justifies the estimation of a joint bivariate model that accounts for error covariances.

6. Estimation Results for Model of Reasons for Increased Walking

Of the 2,623 respondents in the analysis sample, 729 indicated that they increased their walking during the pandemic period. The multivariate binary probit model of reasons for increased walking is estimated on this subsample of respondents and presented in Table 4. This section offers a discussion of the model estimation results to draw insights on reasons for increased walking, and infer whether the increased walking will persist in the long term.

Compared to those below 50 years of age, those 50-64 years were more likely to increase walking for exercise. Those 65 and older were also more likely to increase walking for exercise; this group also pursued more walking to meet social needs. They were less likely to walk more to replace other modes and due to any new recognition of enjoyment derived from walking. It seems clear that the older age groups walked more for leisure rather than for utilitarian purposes before the pandemic (Deka and Brown, 2020) and increased their walking for exercise and/or social needs during the pandemic when indoor recreational facilities, restaurants, and other establishments were operating at limited capacity and presented a threat of contagion. When compared with men, women were less likely to increase walking due to a desire to replace other modes, suggesting that their increase in walking constitutes a net increase in walking as opposed to a mere substitution of one mode for another. Those with the highest education levels (higher than a Bachelor's degree) seemed to increase walking levels due to the acquisition of a dog during the pandemic, but less so because of the need for social interactions. These individuals tended to have positive social affiliation (Hommerich and Tiefenbach, 2018) and low levels of loneliness during the pandemic (Hoffart et al., 2020) as they are more likely to use technology and virtual mechanisms to interact with others (Şar et al., 2012).

Individuals living alone have fewer household and other obligations and are therefore able to increase walking as a means of replacing other modes. On the other hand, those living with a child adopted more walking because of a realization of the enjoyment afforded by walking; in the wake of many indoor establishments being closed or restricted during the height of the pandemic, households with children may have explored outdoor activities and realized the benefits and joy of such pursuits. Those with one or more vehicles are less likely to walk more as a means of replacing other modes of travel; in other words, if individuals in households with cars walk more, they are not substituting car travel with walking.

The ability to work from home is significantly associated with reasons for walking more. Employed individuals who had the option to work from home after COVID, were more likely to walk more because of acquiring a dog, to fulfill social needs, and to get exercise. Prior to COVID, they may not have had a dog (because of work obligations) and fulfilled social needs at the workplace. It is possible that they also got some exercise at the workplace (compared to the scenario of working at home all day). With the option to telework, they were able to acquire a dog and began to walk more, not only for the dog but also for social interactions and exercise. On the other hand, those who already worked from home before COVID were less likely to walk more for exercise; they are likely to have had a pre-COVID routine for exercise and simply continued that regimen during COVID. As such, these individuals were less likely to choose exercise as the reason for increased walking post-COVID.

Table 4. Model Estimation Results for Reasons for Increased Walking Frequency (N=729)

Exogenous variables (base)		Recognized enjoyment		Environment improvement		Dog acquisition		Social needs		Replace other modes		Exercise	
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Individual characteristics													
Age (<50 years)	50 to 64 years	--	--	--	--	--	--	--	--	--	--	0.30	2.20
	65 years or older	-0.19	-1.59	--	--	--	--	0.19	1.68	-0.81	-3.65	0.46	2.70
Gender (male)	Female	--	--	--	--	--	--	--	--	-0.26	-1.70	--	--
Education level (≤ bachelor)	Graduate degree	--	--	--	--	0.27	1.84	-0.13	-1.20	--	--	--	--
Household characteristics													
Household composition (multiple adults with no child)	Living alone	--	--	--	--	--	--	--	--	0.31	1.96	--	--
	Living with child	0.21	1.64	--	--	--	--	--	--	--	--	--	--
Household vehicles (none)	One or more	--	--	--	--	--	--	--	--	-0.61	-2.42	--	--
Employment status/job characteristics													
WFH availability (unavailable both pre- and post-COVID)	Available post-covid	--	--	--	--	0.18	1.33	0.22	2.03	--	--	0.33	1.80
	Available pre-covid	--	--	--	--	--	--	--	--	--	--	-0.36	-1.95
Commute time (≥ 15 min)	<15 min	--	--	-0.15	-1.15	--	--	--	--	--	--	--	--
Built-environment attributes													
Walkability index/100 (range: 0.015-0.186)		--	--	2.39	1.18	--	--	--	--	10.02	4.10	-2.95	-1.57
Housing type (non-apartment)	Apartment	--	--	--	--	-0.25	-1.31	--	--	--	--	--	--
Thresholds	1|2	0.45	6.46	1.43	5.75	1.38	12.44	0.17	2.06	1.73	3.91	-1.12	-4.62
Correlations													
Recognized enjoyment		1.00	--										
Environmental improvement		0.15	0.81	1.00	--								
Dog acquisition		0.11	0.61	0.03	0.10	1.00	--						
Social needs		0.30	2.27	0.04	0.17	0.17	0.90	1.00	--				
Replace other modes		0.28	1.39	0.27	0.81	-0.15	-0.36	0.16	0.67	1.00	--		
Exercise		-0.11	-0.57	-0.46	-2.08	-0.28	-1.05	0.13	0.64	0.09	0.34	1.00	--
Data fit measures													
Model		Multivariate model								Independent model			
Log-likelihood at convergence		-1893.07								-1945.27			
Log-likelihood at constants		-1998.67											
Number of parameters		35								20			
Likelihood ratio test (between joint/indep. models)		$LR = 104.4 > \chi^2_{(15,0.01)} = 30.58$											

Among BE attributes, the walking environment played a key role. An improved walking environment and the desire to replace other modes motivated an increase in walking frequency for those in areas with higher walkability indices. However, those in more walkable neighborhoods were less likely to walk more for exercise; it is likely that individuals in walkable areas already walked for utilitarian purposes (and derived exercise as a secondary benefit) and hence they did not feel the need to increase walking frequency for exercise. Those living in an apartment were less likely to increase walking due to the acquisition of a dog, presumably because of pet restrictions in apartments.

The table also presents error correlations of the multivariate binary probit model. It is found that most error correlations are statistically insignificant, perhaps suggesting that the factors contributing to the choice of different reasons for increased walking frequency are largely uncorrelated and are captured by the observed variables included in the model specification. However, there are a few statistically significant error correlations. First, the error correlation corresponding to "Social Needs" and "Recognized Enjoyment" is positive and significant, suggesting the presence of correlated unobserved factors affecting both. This is consistent with expectations as personality traits and attitudes (e.g., desire for social interactions and active lifestyle) may motivate the selection of these reasons for increased walking (but are unobserved in the model specification). Also, the error correlation between "Exercise" and "Environment Improvement" is significant and negative. Those who increase walking for exercise (i.e., engage in recreational walking as opposed to utilitarian walking) are likely to do so regardless of any improvements to the walking environment. The walking environment is likely to have a greater impact on the frequency of utilitarian walking trips. The presence of significant error correlations calls for the estimation of a multivariate model formulation as opposed to an independent model system that ignores error correlations. Indeed, the data fit measures show that the joint multivariate model provides a statistically significant superior goodness-of-fit compared to the independent model.

7. A Closer Look into Shifting Walking Habits

The estimation results for the bivariate ordered response model in the previous section do not provide information on the direction and magnitude of actual effects of the variables on the ordinal walking frequency decision before and after COVID, primarily due to the non-linear and ordinal nature of the model. To determine the directionality and magnitude of these effects, the estimated underlying propensities for walking frequency need to be translated to actual outcome effects. This transformation considers that the effect of any variable change on outcomes will vary based on the current level of the variable as well as the levels of other variables but an average effect of a change in the variable on the frequency of walking in the before- and after- COVID period can be computed, using average treatment effects or ATEs. Specifically, for each exogenous variable, we consider all sample individuals to be at a particular state of the exogenous variable (e.g., under 29 years old), then compute the probability of each individual having a specific level of walking frequency (Level 1=Never; Level 2=A few times a year; Level 3=A few times a month; Level 4=A few times a week; Level 5= Every day). By averaging the results for each level across all individuals, we obtain the expected population distribution associated with each level of walking frequency. Subsequently, we repeat the same process by assuming that all individuals are 50 years or older. The final step involves computing the Percentage ATE change in walking frequency. This is determined by calculating the difference in the population distribution of walking frequency across the two age groups and dividing it by the distribution of the youngest age group for each

level of walking. Overall, the ATE procedure can be applied to compute the impact of altering an antecedent variable's state on downstream variables of interest.

Additionally, we use a similar procedure to evaluate how such changes affect consonance levels. The consonance levels are calculated as follows:

$$\text{Consonance} = \frac{1}{Q}\sum_{q=1}^{Q}\sum_{k=1}^{K=5} P(y_{q1} = k, y_{q2} = k), \tag{1}$$

where y_{q1} and y_{q2} reflect the walking level of individual *q* in the period before and after COVID, respectively. *Q* is the total sample size, and *K* represents the five levels of walking frequency. The percentage ATE value corresponding to consonance is calculated as the percentage change in the overall consonance value between the base and treatment levels of the exogenous variable of interest.

The results of the ATE analysis are presented in Table 5. The table is organized into several broad columns for clarity. The first three broad columns display the variable name and base and treatment levels. The fourth broad column labeled "%ATE" presents the percent ATE values for each of the five walking frequency levels and the consonance measure. For a more detailed interpretation, each exogenous variable's ATE evaluation is presented in two rows, separated by a dotted line. The upper row represents the %ATE values before the pandemic, while the lower row represents the %ATE values after the pandemic. For example, consider the first numeric row corresponding to the age variable: Before the pandemic (upper sub-row), if all sample individuals transitioned from the "less than 30 years old" category to the "50 years or more" category, the percentage of individuals who never walked (Level 1) would increase by 15.5%, those who walked a few times a year (Level 2) would increase by 7.5%, those who walked a few times a month (Level 3) would increase by 3.2%, those who walked a few times a week (Level 4) would decrease by 2.5%, and those who walked every day (Level 5) would decrease by 11.3%. In the post-COVID period (lower sub-row), if all sample individuals transitioned from the "less than 30 years old" category to the "50 years or more" category, the percentage of individuals who walk at Level 1 would increase by 23.7% (higher than the pre-COVID %ATE of 15.5%), Level 2 would increase by 11.8%, Level 3 would increase by 6%, Level 4 would decrease by 3.1%, and Level 5 would decrease by 16.4%. Furthermore, in the consonance column, it is noted that if all sample individuals were moved from the "less than 30 years old" category to the "50 years or more" category, the percentage of the population walking at the same frequency before and after COVID would decrease by 1.6%.

Table 5 Average Treatment Effect (ATE) on Endogenous Variables

Variable	Base Level	Treatment Level	%ATE					Consonance
			1*	2*	3*	4*	5*	
			Before the pandemic					
			After the pandemic					
Individual Characteristics								
Age	Less than 30 years	50 years or more	15.5	7.5	3.2	-2.5	-11.3	-1.6
			23.7	11.8	6.0	-3.1	-16.4	
Gender	Male	Female	24.3	11.0	4.2	-4.7	-17.7	-1.4
			24.3	11.5	4.7	-4.3	-17.4	
Education Level	Lower than college	Higher than bachelor	-58.2	-24.1	1.8	53.8	196.1	-4.6
			-60.6	-30.3	-7.4	43.5	111.8	
Household Characteristics								
Household Composition	Single adult	Couple, no children	-15.3	-7.8	-3.3	3.8	16.7	0.9
			-4.0	-2.1	0.2	1.1	2.7	
	Single Adult	Adults > 3	-4.1	-1.6	-0.3	1.4	3.7	-1.4
			-26.6	-15.5	-10.0	3.4	30.7	
	Couple, no children	Couple, with children	16.1	7.7	3.1	-3.2	-12.9	0.1
			19.9	9.0	3.6	-4.3	-16.1	
Number of Vehicles	0	2 or more	300.2	77.8	-38.5	-36.8	-76.5	-2.6
			192.7	62.2	14.9	-23.9	-61.5	
Income Low: <$50,000 High: >$100,000	Remains at low	Remains at high	-21.9	-11.2	-4.7	5.5	24.5	-0.5
			-26.3	-10.9	-4.1	-1.1	40.7	
	Remains at low	Increases from low to high	0.0	0.0	0.0	0.0	0.0	-4.8
			-37.9	-18.9	-11.8	-1.1	63.8	
	Remains at high	Decreases from high to low	0.0	0.0	0.0	0.0	0.0	2.4
			-4.4	-6.0	-4.3	8.0	-2.2	
Employment Status/Job Characteristics								
Employment Status/ Commute time	Unemployed	Employed and commute Time <50	13.9	6.2	2.2	-3.2	-11.4	-0.6
			8.2	2.5	-0.5	-3.0	-4.0	
	Unemployed	Employed, commute time >50	-40.4	-24.6	-13.7	4.9	45.8	-2.1
			-3.6	-4.8	-0.1	0.2	4.7	
	Employed, commute time <50 before COVID	Employed, commute time >50 after COVID	0.0	0.0	0.0	0.0	0.0	0.0
			-5.4	-2.6	-1.5	1.2	5.9	
Employment Status/ Work From Home Frequency	Unemployed	Employed, no work from home	11.8	4.9	1.4	-3.0	-8.8	-0.5
			13.3	5.9	2.2	-3.1	-11.2	
	Employed, no work from home	Employed, work from home for 3 days	0.0	0.0	0.0	0.0	0.0	0.2
			-18.0	-9.2	-5.5	4.3	22.4	
	Employed, no work from home	Employed, work from home for 5 days	0.0	0.0	0.0	0.0	0.0	-0.6
			-28.8	-16.0	-10.1	5.9	38.8	
Built-environment Attributes								
Walkability	Low (≤ 0.08)	High (> 0.12)	-25.6	-12.6	-4.6	8.3	32.8	1.2
			-25.6	-13.2	-5.2	7.6	32.2	
Accessible to Bikes	No	Yes	-41.7	-23.0	-9.9	12.7	61.7	3.7
			-42.0	-24.2	-11.2	11.6	61.2	
Distance to transit (/100)	0 (10th percentile)	5.25 (90th percentile)	48.7	20.3	7.3	-8.9	-30.6	-2.1
			48.4	20.9	8.0	-8.1	-30.1	

* Level 1=Never; Level 2=A few times a year; Level 3=A few times a month; Level 4=A few times a week; Level 5= Every day

The findings highlight a substantial difference in walking frequency between age groups. Both before and after the pandemic, older individuals (aged 50 and above) exhibited lower walking frequencies. Interestingly, the pandemic widened this age-related gap, with older individuals showing a more significant decrease in their walking frequency compared to the younger group. This is indicated by the significant increase in the absolute value of %ATEs corresponding to both ends of the walking frequency spectrum (from 15.5% to 23.7% at Level 1 and from -11.3% to -16.4% at Level 5). Additionally, older individuals were more likely to change their walking habits during the pandemic (%ATE for consonance is -1.6%), possibly indicating a greater adaptability among this demographic group. On the other hand, the pandemic did not appear to have a significant impact on gender-based differences in walking frequency. It is important to consider this persistent gender discrepancy in promoting physical activity and pedestrian-friendly urban planning, as women may face unique barriers to regular walking such as feeling less safe in public spaces, resulting in lower perceived walkability than men (Rišová and Sládeková Madajová, 2020). Additionally, the gap in walking frequency between those with lower and higher educational attainment narrowed during the pandemic. Interestingly, the difference in the population share of individuals walking everyday (Level 5) between low and high-educated individuals, while still high, shrinks significantly from 196.1% to 111.8%, while the difference in those who walk less than a few times a week (Levels 1-3) deteriorates slightly. The negative %ATE related to the consonance measure (-4.6%) also indicates that individuals with higher educational levels are more flexible in their walking habits, suggesting a willingness to adapt to changing circumstances.

Similarly, the difference in walking frequency between those living alone and those living with a partner but without children is substantially reduced, as evidenced by the low post-COVID %ATE values. In contrast, couples with children showed lower walking frequency both before and after the pandemic, with the gap between these groups increasing during the pandemic. High vehicle ownership levels were associated with reduced walking frequency, a trend observed both before and after the pandemic. Interestingly, the impact of vehicle ownership on walking habits decreased during the pandemic, with individuals who owned multiple vehicles walking more frequently after COVID. This shift may suggest a reconsideration of transportation choices during the pandemic, where individuals opted for more active forms of mobility and continued to do so after the pandemic. Conversely, the disparity between high and low-income groups widened. Interestingly, individuals whose income increased from low to high were more likely to change their walking frequency (-4.8% ATE for consonance), while those whose income decreased from high to low showed less tendency to change their walking habits (2.4% ATE for consonance). This finding underscores the dynamic nature of income-related influences on physical activity. Employment status and commute time played a complex role, with different effects based on commute duration. Those employed, working from the in-person physical office, and commuting less than 50 minutes walked less than the unemployed, but this gap decreased during the pandemic. Conversely, those employed with commutes exceeding 50 minutes walked more than the unemployed, with the disparity narrowing during the pandemic. The flexible work arrangements implemented in response to the COVID-19 pandemic had a significant impact on walking frequency. Specifically, individuals who worked from home, for three to five days a week, showed increased walking frequencies. The %ATE, reflecting the percentage of individuals walking every day, saw a notable increase, ranging from 22.4% (for 3 days working from home) to 38.8% (for 5 days working from home).

Residing in highly walkable neighborhoods and having bicycle accessibility consistently maintained a positive impact on walking frequency, and this relationship remained largely unaffected by the pandemic. However, the distance to transit had a contrasting effect, contributing to a decrease in walking frequency, particularly for individuals residing farther from transit, regardless of the time period. Notably, while the distance to transit negatively affected walking frequency, the ATE of consonance indicated that people living far from transit exhibited a greater tendency to alter their walking habits (less consonance) in response to the pandemic. This stands in contrast to the effect of bike accessibility, where the introduction of bike access (going from no access to having access) increased the probability of consonance by 3.7%. This highlights the nuanced relationship between location-based factors and the adaptability of walking behavior.

8. Implications and Conclusions

This study focuses on the change in walking that occurred during the pandemic. In the face of lockdowns, indoor restrictions, and threat of contagion, people engaged in higher levels of walking during the pandemic. This study aimed to identify the factors that contribute to walking levels and the extent to which the effects of different variables may have changed during the pandemic. While the amount of walking may be influenced by a host of socio-economic and demographic variables, built environment attributes, and employment modalities, the shift in the amount of walking may have occurred due to a change in the effects of these variables on walking frequencies. In other words, in the context of a pandemic when behaviors are changing and adapting to conditions, some variables may exhibit a fixed effect on walking frequency (i.e., the effect on the amount of walking regardless of the pandemic), some may exhibit a switching effect (i.e., an effect contributing to a shift/change in the amount of walking during COVID circumstances), and some may exhibit both a fixed effect and a switching effect. In addition, those who increased their walking during COVID may have done so for different reasons; insights derived from a knowledge of underlying factors that motivated increased walking during COVID may help shape future policies that encourage continued walking long after the pandemic has faded.

Overall, this study finds strong relationships between socio-economic and demographic characteristics, BE attributes, and walking frequency, both before and after a pandemic-induced disruption. Specifically, our study identified groups that typically engage in less walking, including older individuals, those from low-income households, those with access to multiple vehicles, and residents of areas with limited walkability. Furthermore, we identified groups that were disproportionately affected by the pandemic, such as those required to work in person. To address these disparities, policymakers should prioritize strategies aimed at enhancing accessibility to walking opportunities for these groups and promoting increased walking participation among them. As indicated by our results, investments in walking infrastructure and land use density do contribute significantly to walking frequency. Additionally, given the significant variations in the underlying reasons for the observed increases in walking frequency, policymakers can leverage these outcomes to tailor interventions more effectively. For instance, the establishment of social neighborhood walking groups could effectively encourage older individuals to walk more, satisfying their social needs while promoting physical activity. Implementing child-friendly streets can inspire families with children to increase their walking habits and relish outdoor time with their youngsters. Organizing dog adoption events can further stimulate walking among pet owners. In addition, enhancing the built environment by implementing “Healthy” streets and fostering a more comprehensive, walkable urban landscape will undoubtedly play a pivotal role in incentivizing increased walking in the future.

The sustainability of increased walking levels across various groups remains uncertain and largely dependent on the reasons underlying the increase. As a result of the pandemic, certain groups increased their walking due to the desire for exercise and combating isolation. Some experienced a newfound enjoyment of walking, while others were motivated by changes in the walking environment or the acquisition of a dog. With many establishments and recreational opportunities returning to normal, the motivation for elevated walking levels may wane. However, those who embraced higher levels of walking because of a new realization, an improvement in walking environment, or an acquisition of a dog may continue to do so in the longer term as those reasons are not short-lived in nature. In other words, campaigns and interventions that bring about greater awareness and realizations (of the benefits of walking), provide enhanced walking environments, and afford people time and flexibility to engage in walking activities are likely to yield long-term positive results – bringing about benefits to public health and the environment.

Furthermore, several areas warrant further exploration regarding changes in walking behaviors in the post-pandemic landscape. First, there is a valid concern about the long-term sustainability of the changes discussed in this study once daily life returns to its pre-pandemic state. While the immediate effects and perceptions brought by the pandemic are likely to wane over time, lifestyle adaptations, such as remote work and online shopping, are expected to have long-term effects. Given that the survey we utilized was conducted in the final stages of the pandemic, it was unable to capture the full extent of behavioral changes that actually occurred after the official end of the COVID-19 pandemic in 2023 (World Health Organization, 2023). Second, because of the inherently different characteristics between utilitarian and recreational walking, a separate model for each type of walking would be more beneficial for informing policy implications. Finally, when considering walking as a form of physical activity, both frequency and duration affect the health benefits of walking. Therefore, considering both these dimensions together will provide a better indication of physical activity.

Acknowledgements

This research was partially supported by the Center for Understanding Future Travel Behavior and Demand (TBD), a National University Transportation Center sponsored by the U.S. Department of Transportation under grants 69A3552344815 and 69A3552348320, as well as by the Center for Teaching Old Models New Tricks (TOMNET), a Tier 1 University Transportation Center sponsored by the US Department of Transportation under grant 69A3551747116. The authors are grateful to Lisa Macias for her help in formatting this document.

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