

Why Active Travel Remains Infrequent: A Joint Model of Participation and Perceived Barriers

Ifratul Hoque

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: ih6446@my.utexas.edu

Dale Robbennolt

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: dar4836@utexas.edu

Chandra R. Bhat (corresponding author)

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Tel: 512-471-4535; Email: bhat@mail.utexas.edu

ABSTRACT

Walking, bicycling, and using micromobility modes (collectively, active modes) confer well-documented mobility, environmental, and health benefits. Yet, a substantial share of adults never or rarely uses these modes. Using data from the nationwide Transportation Heartbeat of America Survey, combined with residential built-environment measures from the U.S. Environmental Protection Agency's Smart Location Database, this study examines the prevalence and determinants of infrequent active travel in the U.S. and the perceived barriers to using these modes. The analysis adopts a joint modeling framework comprising a binary Never or Rare Active Traveler (NRAT) indicator and seven perceived barriers, accounting for interdependencies among these eight outcomes while controlling for a range of socio-demographic, household, and built-environment factors. Infrequent use is most prevalent among women, older adults, non-employed individuals, and members of vehicle-sufficient households, with trip distance a dominant obstacle for this last group. Personal security is particularly salient among women and renters, who report far greater concerns about loitering or threatening behavior. Built-environment characteristics also substantially shape the reported barriers, with (a) denser areas reducing infrastructure complaints even as they intensify concerns about aggressive drivers and loitering or threatening behavior, (b) walkable areas heightening concerns about insufficient lighting and distracted driving, and (c) a well-connected pedestrian and bicycling network lowering concerns across the widest range of barriers. The findings underscore the need for a differentiated policy agenda in which intervention instruments to promote active travel are matched to the populations and barriers they are best suited to address.

Keywords: Active Transportation, Perceived Barriers, Active Travel, Micromobility, Built Environment, Joint Modeling

1. INTRODUCTION

Walking, bicycling, and the growing array of low-powered micromobility options (such as e-bikes and e-scooters) offer direct and widely accessible alternatives to private vehicle travel for short urban trips. Despite differing in the level of physical exertion required, these modes share a common operating envelope. Each relies on pedestrian- and bicycle-scale infrastructure, substitutes for short motorized trips, and sustains a level of physical activity well above that of vehicular travel even when the ride is electrically assisted. For these reasons, in the rest of this paper, for presentation ease, we will refer to these modes as “active modes” and the corresponding travel as “active travel”.

The societal value of active travel is well documented across transportation and public-health literatures (see, for example, Brand et al., 2021; Ding et al., 2024; Millard-Ball et al., 2025). Each short private-vehicle trip these modes displace yields a small but cumulative reduction in traffic-caused delays (Wang and Zhou, 2017; Hamilton and Wichman, 2018) and greenhouse-gas emissions (Neves and Brand, 2019). In the context of public health, especially the case of human-powered walking and bicycling, active travel has also been strongly linked with tangible mental and physical health benefits (Berrie et al., 2024; Baran et al., 2024). Yet, despite this established linkage between active travel and its beneficial effects related to traffic congestion reduction, air quality and environmental sustainability, and mental/physical health improvement, the most recent national travel-survey evidence shows that private vehicles account for roughly 87% of all person trips in the U.S. (Bricka et al., 2024). And, even with significant growth in shared-micromobility ridership in the U.S., which reached an all-time high of approximately 171 million trips in 2024 (a 32% increase over the previous year and the second consecutive record-setting year; North American Bikeshare and Scootershare Association, 2025), micromobility modes still account for only a small minority of total urban trips. Together, these patterns point to a broader need to understand why active travel uptake remains so limited, even in contexts where walking, bicycling, and micromobility should be viable options. Several structural conditions may help explain this persistent gap, such as the increasing sprawl of many U.S. metropolitan areas, which can reduce the practicality of active travel (Hamidi and Ewing, 2014; Hamidi et al., 2026), as well as long-standing transportation planning priorities that have often emphasized motorized infrastructure over active transportation investments (Loo, 2021). These structural conditions form the backdrop against which travel decisions are made, but the decision to use an active mode for a given trip is also impacted by more immediate environmental and perceptual barriers unique to each individual traveler.

A particular area of importance that has emerged, at least in part due to historical underinvestment in active travel infrastructure, is safety (Buehler and Pucher, 2021; Bland et al., 2024). Inadequate sidewalks, disconnected bicycle networks, poorly designed crossings, and limited traffic-calming measures can all increase objective safety and security risks for active travelers. In this context, objective walkability and bikeability matter, and have been the emphasis of many earlier studies on the use of active modes (see, for example, reviews of such studies by Cerin et al., 2017; Aldred, 2019; Pearson et al., 2025). But objective walkability and bikeability do not, on their own, reliably predict active travel behavior. In fact, perceptions of the same physical environment vary substantially across individuals (being shaped by psychological characteristics and by the traveler’s own understanding of travel needs, abilities, and surroundings), and these subjective perceptions can influence use of active modes as much as objective barriers (Ma et al., 2014; Lättman et al., 2018; van der Vlugt et al., 2022; De Vos et al., 2023). Despite their importance, subjective factors of this kind have received less attention than

objective built-environment (BE) measures, particularly in studies that extend beyond walking to cover bicycling and emerging micromobility modes.

The above discussion motivates the current study. In particular, unlike the relatively vast literature on the effects of objective environment characteristics on active mode use, the emphasis in our study is on the subjective perceptions and considerations that drive the low use of active modes. In so doing, we focus on the perceptions of non-users and rare users of active modes, rather than on current frequent users as has been the case in most earlier active travel studies. Indeed, in many ways, understanding the barriers to “first entry” or the reasons for not going beyond that “one-off” instance is at least as important as understanding the barriers to frequent repeated use, a point also emphasized by Dill and McNeil (2016) and Biehl et al. (2018). We also include an expansive set of demographic variables in our analysis to capture variations across demographic groups in their perceptions of active mode use barriers.

The data used in the current analysis are part of the Transportation Heartbeat of America (THA) Survey conducted in February and March 2026 by the Center for Understanding Future Travel Behavior and Demand (TBD), a National University Transportation Center. This comprehensive survey dataset provides detailed individual- and household-level (IH) characteristics. To these we add BE attributes, drawn from a secondary data source, that represent several supply-side conditions of the active travel environment at the individual’s residential location. The IH characteristics and BE attributes serve as exogenous variables in the analysis. Further, the survey data identify those individuals who report never or rarely using active travel modes (grouped in the four categories of walking, manual bicycling, e-bike/e-scooter, and other micromobility modes). The “rare” use of active travel modes is defined as a usage frequency of “less than one day per month” for each of the four categories of active travel modes. The survey then solicits seven reasons from any individual who never or rarely uses active travel modes, as classified in four groups:

Perceived infrastructural deficiencies in active travel networks

- (1) a lack of sidewalks or bicycle lanes, and
- (2) insufficient lighting;

Perceived traffic-safety concerns

- (3) drivers behaving aggressively, and
- (4) distracted drivers;

Perceived personal-security concerns

- (5) loitering or threatening behavior from others; and

Practical and situational constraints

- (6) adverse weather conditions, and
- (7) the perception that these modes are inappropriate for the trip lengths needed to reach destinations.

The above grouping of the seven barriers into four categories facilitates the presentation of the literature review in the next section as well as the discussion of policy implications in Section 5. Of course, there is a certain degree of subjectivity in the grouping, since several barriers could reasonably fall into more than one category. For instance, a lack of sidewalks or bicycle lanes could be viewed as a traffic-safety concern, and insufficient lighting as a personal-security concern. We retain both under infrastructural deficiencies because they describe specific physical characteristics of the pedestrian and bicycling environment, while the barriers grouped under

traffic-safety and personal-security concerns relate to the behavior of drivers and of other people rather than fixed infrastructure.

We employ a multivariate binary probit framework that jointly models whether respondents never or rarely use active travel modes (who are labeled as Never or Rare Active Travelers, or, for conciseness, NRATs) alongside the aforementioned seven binary outcomes representing the specific barriers that NRATs identify (for a total of eight binary endogenous outcomes). Focusing on NRATs is critical because they represent the segment of the population whose adoption, or more than that “one-off” use of active modes, remains contingent on overcoming their specific perceived barriers. At the same time, by jointly modeling whether an individual is an NRAT with the specific barriers that contribute to being an NRAT, we can generalize the perceived barriers to the broader population (NRATs and non-NRATs alike) after accounting for unobserved differences between these groups (as discussed in more detail in Section 2.2). This is an important step, allowing us to identify individuals who may use active travel somewhat regularly but still face barriers or be more susceptible to reducing their active travel usage in the future.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the determinants of, and barriers to, active travel use. Section 3 presents the characteristics of the dataset and the methodological framework employed in the analysis. Section 4 presents the model estimation results and their interpretation. Section 5 discusses the implications of the findings for active transportation planning, policy, and infrastructure development. Finally, Section 6 concludes with a summary of key findings and identifies directions for future research.

2. LITERATURE OVERVIEW AND THE CURRENT PAPER

The wide range of barriers to active travel, as identified in existing research, is mapped to the four groupings of barriers as identified in the current study. Within each category we also discuss how barrier salience varies across socio-economic and demographic characteristics, since the four categories of barriers do not weigh equally across the population. Throughout this review we remain agnostic to trip purpose. While the relative importance of the barrier factors has been shown to vary across, for example, recreational and utilitarian active travel, the absolute importance of each of these factors is not in question (see Heinen et al., 2010; Porter et al., 2020).

2.1 Determinants of Active Travel and Perceived Barriers

2.1.1 Perceived Infrastructural Deficiencies in Active Travel Networks

Perceptions of the active travel environment do not form in a vacuum. They are shaped by the objective characteristics of the BE, which are also typically the more direct levers for policy action. A substantial body of work documents robust associations between active travel behavior and objective BE features such as residential density, land-use diversity, street connectivity, pedestrian and bicycle infrastructure, and destination access (Tao and Cao, 2023; Tao et al., 2023; Ito et al., 2024). This literature, however, has largely treated objective measures as direct determinants of active mode use, leaving underexamined the subjective pathway through which objective conditions are perceived and experienced as barriers. Because it is this subjective translation, rather than the objective conditions alone, that shapes active mode use decisions at the individual level, a smaller but growing body of work (see, for example, Kerr et al., 2016; Ma and Dill, 2017; Brüchert et al., 2022) has turned to investigating perceived suitability for active travel. This is important for at least two reasons. First, objective and perceived measures are neither redundant

nor reliably interchangeable, since perceptions of the same environment vary substantially across individuals. For example, older adults, parents of young children, those with less formal education or lower income, and infrequent bicyclists tend to perceive the same bicycling environment as less hospitable for bicycling than their respective counterparts (Ma and Dill, 2017). At a broader scale, perceived accessibility does not correlate strongly with objectively measured accessibility, with bicycle users reporting substantially higher perceived accessibility than car or transit users in the same areas, contrary to standard place-based accessibility assumptions (Lättman et al., 2018). Second, perceptions related to the active travel environment connect directly to active mode use. Again, taking the bicycling active travel mode, across the literature, perceived safety has been established as a key determinant of bicycling behavior, even outweighing objective measures of safety (Dill and McNeil, 2016; Biehl et al., 2018; Gössling and McRae, 2022). This pattern is not unique to bicycling. Walking shows a parallel pattern, with perceived walking accessibility directly predicting behavior, while objectively measured accessibility exerts only relatively weak direct effects once perceptions are included as determinants (van der Vlugt et al., 2022). Overall, while there is a growing recognition of the importance of accounting for perceived infrastructural deficiencies, rather than just objective conditions, the subjective pathway through which objective environment characteristics are translated into actual perceived barriers to active travel warrants further investigation.

2.1.2 Perceived Traffic-Safety Concerns

Beyond concerns relating to the actual infrastructure environment, the perceived risk of interacting with motor-vehicle traffic is a central determinant of active travel behavior. Again, these perceptions are clearly shaped by objective conditions, but subjective and perceptual factors play a large role in shaping how individuals respond to a given physical environment (Winters et al., 2011; Sanders, 2015; Soto et al., 2022). Perceived traffic safety, in particular, has been shown to be an important determinant of active travel adoption and usage, with even objectively favorable features (including green spaces and active travel infrastructure) losing much of their beneficial effect when the active travel environment is perceived as unsafe in the presence of motor traffic (Ogilvie et al., 2010; Sundling and Jakobsson, 2023). In this context, fear and perceived risk can directly constrain active travel behavior even when objective danger is limited, with individuals reporting multiple distinct sources of traffic-related fear (including aggressive driving behavior, distracted drivers, high vehicle speeds, and vehicle interactions caused by poor roadway infrastructure), each of which may discourage active travel for different reasons and through different mechanisms (Schneider et al., 2022; Duren et al., 2023). But the underlying pattern of perceived danger from motor traffic as a primary barrier to active mode use is robust across many studies (for example, Heinen et al., 2010; Sanders et al., 2020; Soto et al., 2022; Badia and Jenelius, 2023), even as the intensity of traffic-safety concerns varies across demographic groups. Thus, traffic-safety risks weigh especially heavily on women, suppressing bicycling tendency (Garrard et al., 2008; Prati et al., 2019). Such safety concerns, along with comfort and physical accessibility, also become more salient with age (Van Cauwenberg et al., 2012; Brüchert et al., 2022). Further, parental traffic-safety concerns are a documented barrier to children walking to school (Oluyomi et al., 2014; Bruner et al., 2023).

2.1.3 Perceived Personal-Security Concerns

Personal-security concerns refer to the perceived risk of harassment, intimidation, or harm from other people in the active travel environment. These concerns are conceptually distinct from

traffic-safety concerns and, albeit not as extensively studied as the safety considerations, have been shown to operate through their own pathways. Perceived neighborhood safety from crime, social disorder, and threatening encounters is associated with higher rates of walking and bicycling, while individuals who feel less secure in their neighborhood are significantly less likely to walk than those who report feeling more secure (Evenson et al., 2012; Foster et al., 2021). Antisocial behaviors and personal-security concerns along active travel routes have also been identified as barriers to walking and bicycling (Mason et al., 2013; Ravensbergen et al., 2020a). These concerns are not experienced uniformly across the population. Women consistently report substantially higher personal-security concerns than men in active travel contexts, which directly influence their intended and manifested active travel behaviors (Stark and Meschik, 2018; Graystone et al., 2022).

2.1.4 Practical and Situational Constraints

Beyond infrastructure quality and safety perceptions, a range of practical and situational factors determines whether active travel is even a feasible option for a given individual in a particular context. Mobility limitations, time constraints, daily responsibilities, weather, and the need to carry goods or accompany others may all cause walking, bicycling, or using e-scooters to be perceived as less practical (Heinen et al., 2010; Belloc et al., 2025). Among these factors, inclement weather conditions and trip-purpose complexity have been found to be particularly limiting factors for active travel adoption and use. For instance, bicycling intensity is substantially suppressed by precipitation, adverse temperatures, and high wind speeds, with weather sensitivity varying across facility types and being more pronounced for recreational than for utilitarian bicycling (Nosal and Miranda-Moreno, 2014; Böcker and Thorsson, 2014). Trip-purpose complexity poses a similar constraint, since daily trip chains that combine work commutes with childcare drop-offs, household errands, and other obligations into single multi-stop tours are particularly difficult to accomplish on foot or by bicycle, even when individual travel-leg distances are short (McGuckin and Murakami, 1999; McGuckin et al., 2005; Habib et al., 2021).

Other individual-specific factors also affect active travel adoption and use. For instance, having a driver's license and high levels of car ownership are strongly associated with lower rates of walking and bicycling (Buehler, 2011; Buehler and Pucher, 2024). This relates back to individual travel needs and context, as some trips are much more easily undertaken with motorized alternatives, particularly over longer distances. At the systemic level, bicycling in the U.S. has been concentrated in the central neighborhoods of a few metropolitan areas, with very low levels in the South and in suburbs (Pucher et al., 2011), and e-scooter use exhibits a parallel within-city pattern, clustering heavily in downtowns and university districts (Caspi et al., 2020). These aggregate patterns highlight the importance of compactness of activity destinations for promoting active travel (Kärmeniemi et al., 2019; Fang et al., 2022).

2.2 Study in Context

Our study contributes to the existing literature on active travel barriers, as discussed above, in five important ways. First, we examine the factors that deter active travel behavior using individual-level survey data in which respondents directly report the specific concerns behind their non-use or rare use of active travel modes. While a rich body of literature has examined the BE correlates of active travel behavior at an aggregate level (e.g., Caspi et al., 2020; Ghaffar et al., 2023; Millard-Ball et al., 2025), the existing literature on individual-level perceived barriers has been sparse and, even when studied, is largely descriptive, considering the influence of one exogenous variable at a time without simultaneously controlling for others (e.g., Porter et al., 2020; Sanders et al., 2020;

Soto et al., 2022; Zaganjor et al., 2025). To our knowledge, this is the first study to jointly model an individual’s propensity to be an NRAT together with the specific perceived barriers underlying that limited use. Second, we incorporate a comprehensive set of socio-economic and demographic characteristics, enabling us to characterize how the salience of each perceived barrier varies across population subgroups. This specification moves beyond aggregate prevalence to identify which segments of the population, defined by attributes such as gender, age, educational attainment, income, household structure, and vehicle access, are most likely to experience each specific barrier, and how the relative importance of the barriers differs across these groups. Third, we append objective residential BE measures to each respondent’s record, enabling us to examine how objective environmental conditions are translated into subjectively perceived barriers. Linking measured BE exposure to perceived barriers allows us to identify which types of infrastructure improvements are most likely to reduce specific perceived barriers. This provides a direct mapping from perceived barriers back to actionable infrastructure levers and supports the geographic customization of active transportation infrastructure investments. For example, in our empirical findings later, we note that personal-security concern (perception of loitering or threatening behavior from others) is the barrier most sharply intensified in high-population-density areas, suggesting the use of crime-prevention-through-environmental-design principles (see, for example, Lee et al., 2023) as a potentially effective intervention strategy to increase active travel in high-density residential areas. Fourth, we model whether an individual is an NRAT or not and the barriers to active travel jointly within a multivariate binary probit framework that accounts for unobserved correlations. This is methodologically important because NRATs may be different in unobserved ways from non-NRATs, and these same unobserved differences may also shape the barriers they identify. For instance, an individual with a heightened sensitivity to personal-security concerns due to an unobserved characteristic (such as, say, past assault experiences) may be more likely to be an NRAT and more likely to identify loitering or insufficient lighting as barriers to active travel. Ignoring this common unobserved factor (as would be the case if the NRAT outcome and the stated barriers to being an NRAT are modeled independently) would lead to an overestimation of the importance of security-related barriers for a randomly selected individual from the general population. But, by estimating the NRAT and barrier outcomes jointly, we are able to generalize our estimates to the broader population, rather than being applicable only to the NRAT sample from whom the stated barriers are elicited in the survey. Finally, we translate the estimated model into average treatment effects (ATEs) that quantify, in directly interpretable terms, how shifting a given characteristic changes the prevalence of low active travel use and of each perceived barrier. Because these effects are recovered for specific population subgroups and BE contexts, they convert the estimated relationships into concrete, subgroup-specific evidence that pinpoints which barriers weigh most heavily on which populations and in which settings. This, in turn, supports the design of customized infrastructure and policy interventions tailored to the groups and contexts they are most likely to benefit.

3. METHODOLOGY

3.1 Data Description

The data analyzed in this paper originate from the second wave of the THA Survey, fielded across the U.S. between February and March 2026. The sampling frame relied on a long-standing address panel maintained by the Qualtrics survey platform. A survey administration procedure was structured to facilitate the collection of a nationally representative sample of the U.S. adult population using this sampling frame (see Robbennolt et al., 2025, for a detailed discussion of the

THA Survey design and administration procedures). In particular, the recruitment process applied quota controls on a comprehensive set of socio-economic and demographic characteristics (race, ethnicity, age, gender, educational attainment, household income, area type of residence, and census division of residence) intended to approximate the distributions observed along each of these dimensions in the general U.S. adult population. Eligibility was restricted to adults aged 18 or older residing in the U.S., and a series of attention checks and timing-based quality filters were embedded throughout the instrument to safeguard response quality. The dataset captured detailed coverage of attitudes regarding transportation, mobility, and urban living; current activity-travel behaviors and mode use; safety experiences across travel modes; commuting patterns and telework arrangements; online shopping and delivery behaviors; and knowledge and opinions about emerging transportation technologies and infrastructure investments. Additional residential BE attributes were appended to the survey records based on the respondent's residential zip code using the Environmental Protection Agency (EPA) Smart Location Database (Chapman et al., 2021). This database compiles its measures at the census block-group (CBG) level. To assign these measures to respondents, whose residential location is identified by zip code, the CBG-level values were aggregated to the zip-code level. Specifically, each zip code was assigned a weighted average of the values of all block groups overlapping it, with each block group weighted in proportion to the land area it contributes to the zip code. The specific BE measures appended to the survey records are described in Section 3.1.2. After basic cleaning and screening, and dropping observations that could not be matched, the final estimation sample comprised 8,273 respondents (from the original sample of 8,567 respondents).

3.1.1 Endogenous Outcomes

The distribution of the eight endogenous outcomes is presented in Table 1. The first outcome is a binary variable indicating whether an individual is an NRAT or not. To define this variable, individuals were asked about their frequency of use (for both leisure purposes without a fixed destination and for utilitarian purposes to reach activity destinations) of each of (1) walking, (2) using a manual bicycle (that they own or share), (3) using an e-bike or an e-scooter (that they own or share), and (4) using another micromobility mode (including skateboard, e-skateboard, hoverboard, unicycle). Then, each individual was classified as an NRAT if, for every one of these four active modes, they reported a usage frequency of either “never” or “less than one day per month”. The threshold defining an NRAT is chosen to identify individuals whose engagement with active travel is minimal and unlikely to reflect a meaningful mobility choice, in line with the frequency bands used in prior active travel and micromobility studies (see Sanders et al., 2020; Blazanin et al., 2022; Baquero Larriva et al., 2024; Aguilera-García et al., 2024). At very low levels of use (less than one day per month), active travel typically amounts to an incidental or “one-off” instance rather than a developing behavioral pattern, placing these individuals at the early, pre-adoption stage through which regular active travel develops. It is this population of very rare users, along with non-users of active travel modes, whose uptake of active modes hinges on overcoming the “first entry” barriers that this study examines. Such NRATs comprised 17.8% (1,476 individuals) of the sample (see the top panel of Table 1).

The next set of outcomes is related to the set of barriers that lead NRATs to avoid active travel. Specifically, the survey elicited information on eight barriers from individuals who characterized themselves (as per the definition discussed earlier) as NRATs. However, from among the eight barriers, one barrier was excluded from our analysis because only a very small

share of respondents selected it.¹ The descriptive statistics for the seven retained barriers are shown in the lower panel of Table 1, with percentages based on the number of individuals selecting each barrier within the group of NRATs. It is important to note that because the survey permits multiple selections of the seven barriers, the percentage across the seven barriers exceeds 100%. In fact, the 1,476 NRATs register 1,863 barrier selections, an average of 1.26 barriers per NRAT. The perception that active modes are inappropriate for the trip lengths needed to reach destinations is the single most cited concern (38.1%), followed by a lack of sidewalks or bicycle lanes (24.3%), adverse weather (17.0%), and the two traffic-safety concerns of aggressive and distracted driving, which cluster in the middle at nearly identical rates (16.5% and 16.3%, respectively). At the lower end, insufficient lighting (7.9%) and loitering or threatening behavior (6.2%) are the least frequently cited as reasons for the low frequency of active mode use. Aggregate prevalence, however, is only one dimension of barrier salience, and a barrier reported by relatively few NRATs can still weigh heavily on the subgroups who experience it. This is the reason for developing a multivariate modeling approach, as undertaken in this paper, so that heterogeneity across specific demographic groups residing in specific BE contexts may be teased out.

Table 1. Descriptive Statistics of the Endogenous Outcomes

Outcome Variable	Count	Percentage
<i>Frequency outcome (out of N = 8,273 full sample)</i>		
Never or Rare Active Traveler (NRAT)	1,476	17.8%
<i>Perceived barriers (asked of NRATs only; n = 1,476)</i>		
Infrastructural deficiencies in active travel networks		
A lack of sidewalks or bicycle lanes	359	24.3%
Insufficient lighting	116	7.9%
Traffic-safety concerns		
Drivers behaving aggressively	244	16.5%
Distracted drivers	240	16.3%
Personal-security concerns		
Loitering or threatening behavior from others	91	6.2%
Practical and situational constraints		
Adverse weather conditions	251	17.0%
These modes are inappropriate for the trip lengths needed to reach destinations	562	38.1%

3.1.2 Exogenous Variables

The exogenous variables may be grouped into four categories. These include (1) individual-level demographic characteristics, (2) household-level attributes, (3) geographic context represented by the respondent's census division of residence, and (4) residential BE characteristics. Sample shares for the survey-derived attributes, alongside 2024 American Community Survey (ACS) 5-year estimates (U.S. Census Bureau, 2026) for those variables that have direct ACS counterparts, are reported in the upper left and right panels of Table 2.

¹ This barrier relates to concerns about interactions with law enforcement or security officers, which we removed because of the low number of respondents citing it (44, or 2.98% of the 1,476 NRATs and 0.53% of the entire sample), which was insufficient to support reliable estimation of any determinant of this specific barrier. Still, we recommend that future data collection efforts consider this type of barrier too, as it raises substantively distinct policy and equity implications.

Table 2. Descriptive Statistics of the Analysis Sample

<i>Individual-level demographic characteristics</i>			<i>Household-level attributes</i>		
Variable	Sample (%)	ACS (%)	Variable	Sample (%)	ACS (%)
Gender			Annual household income		
Female	53.0	51.2	Less than \$25,000	19.1	14.6
Male	47.0	48.8	\$25,000-\$49,999	20.3	19.7
Age			\$50,000-\$99,999	26.6	29.1
18 to 24 years	10.2	11.9	\$100,000-\$149,999	19.6	18.6
25 to 44 years	30.8	34.3	\$150,000-\$199,999	9.3	9.6
45 to 64 years	30.4	31.8	\$200,000 or more	5.1	8.4
65 to 74 years	17.6	12.8	Household size		
75 years or older	11.0	9.2	One	21.4	28.7
Employment status			Two	34.2	33.8
Full-time	40.6	45.6	Three or more	44.4	37.5
Part-time	9.3	14.6	Housing unit type		
Retired/not employed	50.1	39.8	Single-family	67.7	62.4
Educational attainment			Apartment	27.1	32.4
High school or less	32.3	36.4	Other†	5.2	5.2
Some college	32.6	27.9	Homeownership status		
Bachelor's degree(s)	17.3	21.6	Own	60.8	60.0
Graduate degree(s)	17.8	14.1	Rent	39.2	40.0
Race			Presence of children		
White	63.3	61.0	One or more	32.0	28.5
Black	16.0	12.2	None	68.0	71.5
Asian/Pacific Islander	7.9	9.8	Vehicle ownership		
Other*	12.8	17.0	None	10.9	8.4
Ethnicity			One	44.0	33.1
Hispanic	19.2	19.3	Two	32.9	36.6
Non-Hispanic	80.8	80.7	Three or more	12.2	21.9
<i>Geographic context represented by the respondent's census division of residence*</i>					
New England	7.2	4.7	East South Central	9.0	5.8
Middle Atlantic	13.5	12.8	West South Central	13.6	12.1
East North Central	13.2	14.2	Mountain	7.4	7.6
West North Central	7.7	6.4	Pacific	13.6	16.0
South Atlantic	14.8	20.4			
<i>Residential built-environment (BE) characteristics</i>					
Variable Group	Variable	Description	Mean	SD	
Socio-economic variables	No-vehicle households	Share of households with no motor vehicle	0.10	0.13	
	Low-wage workers	Low-wage worker share	0.24	0.04	
	Medium-wage workers	Mid-wage worker share	0.34	0.08	
Development density measures	Population density	Persons per acre	11.32	22.98	
	Activity density	Employment and housing units per acre	13.06	59.09	
Local activity mix attributes	Employment mix	Eight-tier employment entropy	0.54	0.11	
	Jobs-per-household ratio	Ratio of jobs to households	2.25	11.66	
	Land-use mix	Employment and household entropy	0.50	0.11	
Network design measures	Pedestrian network density	Pedestrian facility-miles per sq-mi	12.07	6.84	
	Intersection density	Weighted street intersections per sq-mi	81.78	62.78	
	Pedestrian 3 leg intersections	Pedestrian 3 leg intersections per sq-mi	60.76	46.81	
	Pedestrian 4+ leg intersections	Pedestrian 4+ leg intersections per sq-mi	22.42	24.60	
Walkability	National Walkability Index	EPA composite walkability score	9.78	3.61	

* Other race includes Native American, Middle Eastern or North African, and other write-in responses (e.g., Moorish American, multiracial).

† Other housing type includes manufactured homes, group quarters (e.g., dormitories, nursing and assisted-living facilities), and other non-standard arrangements (e.g., shelters, hotels).

[‡] Census divisions comprise the following states: New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont); Middle Atlantic (New Jersey, New York, Pennsylvania); East North Central (Illinois, Indiana, Michigan, Ohio, Wisconsin); West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota); South Atlantic (Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia); East South Central (Alabama, Kentucky, Mississippi, Tennessee); West South Central (Arkansas, Louisiana, Oklahoma, Texas); Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming); and Pacific (Alaska, California, Hawaii, Oregon, Washington).

The analysis sample diverges from the ACS estimates along a few notable dimensions. The most prominent divergences appear in the age and employment distributions, with older adults aged 65 or older and “retired/not employed” respondents both over-represented. At the household level, apartment residents and households owning three or more vehicles are each under-represented relative to their national shares. These divergences are consistent with patterns documented for online opinion panel-based databases, which, even when recruitment is governed by demographic quotas, draw on a pool of individuals who have self-selected into the panel and so tend to differ from the general population along certain dimensions (Wang et al., 2023). Those with more available time, such as older adults and individuals outside the labor force, tend to be more readily recruited, while harder-to-reach higher-income and apartment-dwelling groups tend to be under-represented. The sample includes broad geographic coverage across all census divisions, as shown in the central panel of Table 2. Overall, despite some differences in the distributions of exogenous variables in the current sample and the ACS data, there is substantial variation across all the variables considered. Given this variation in exogenous variables and the fact that the sample was collected exogenously (rather than being targeted towards NRATs specifically), an unweighted estimation approach is preferred to a sampling-weighted one for the purpose of estimating the individual-level relationships between exogenous variables and active transportation outcomes (Solon et al., 2015; Robbennolt et al., 2026).

Finally, the residential BE context for each respondent is summarized through thirteen measures drawn from the EPA Smart Location Database (Chapman et al., 2021) and reported in the lower panel of Table 2. As indicated earlier, these measures correspond to the zip code of the respondent’s residence (for presentation ease, we will refer to the zip code of the respondent’s residence as the respondent’s neighborhood or simply “neighborhood”). Three of these are socio-economic shares (ranging from zero to one). The share of no-vehicle households gives the fraction of neighborhood households owning no motor vehicle, while the shares of low- and medium-wage workers give the fraction of resident workers earning low-tier wages (\$1,250 per month or less) and middle-tier wages (\$1,251 to \$3,333 per month), respectively. Together, these three measures characterize the motorization and broader socio-economic profile of the neighborhood. Two measures capture development density, with population density measuring persons per acre of developable land (land not protected from development) and activity density measuring jobs and housing units per acre of developable land. Three further measures capture local activity mix attributes as follows: (1) the employment mix is captured through an eight-tier employment entropy index (which ranges from zero to one, with zero indicating that all local jobs fall within a single employment sector and one indicating jobs distributed evenly across all eight sectors)², (2) the jobs-per-household ratio (an unbounded measure of zero or greater) indexes the local balance

² The eight employment sectors considered in this index are retail, office, industrial, service, entertainment, education, health care, and public administration. Please see Chapman et al. (2021) for further details of how the entropy index is computed.

between jobs and residences³, and (3) the land-use mix is captured through an index of the entropy of employment and households (which similarly ranges from zero to one, with zero indicating a single category of activity, such as entirely residential, and one indicating an even balance of households and employment across categories).⁴ The next four measures capture network design at the neighborhood level as follows: (1) pedestrian network density measuring the facility-miles of pedestrian-oriented links per square mile, (2) intersection density measuring street intersections per square mile as a weighted count that excludes auto-oriented intersections, and (3) the pedestrian three-leg intersection density and (4) the four-or-more-leg intersection densities, the last two measuring the count of each intersection type per square mile. The final measure, the National Walkability Index, is a composite score summarizing BE support for walking, formed as a weighted sum of the ranked values of the employment mix, the land-use mix, intersection density, and proximity to the nearest transit stop. It ranges from 1 (least walkable) to 20 (most walkable), which the EPA Smart Location Database groups into four tiers, namely least walkable (1.0-5.75), below average (5.76-10.50), above average (10.51-15.25), and most walkable (15.26-20.0).

3.2 Analytic Framework

The modeling framework takes the form of a multivariate binary-response probit system with eight outcome dimensions. The first dimension is a binary NRAT indicator. The remaining seven dimensions correspond to binary perceived barrier outcomes, each indicating whether an NRAT cited a specific reason as a barrier. Because participants were able to cite any combination of these seven reasons, each barrier is modeled as a separate binary outcome rather than as a multinomial choice. Note also that the barrier outcomes are observed for only the 1,476 NRATs; the remaining 6,797 respondents in the analysis sample contribute information only regarding the NRAT binary outcome.

The eight outcome dimensions are modeled jointly to accommodate two distinct sets of unobserved correlations. The first set of seven correlations arises between the NRAT outcome and each of the seven barrier outcomes, while the second set of 21 correlations arises across the barrier outcomes themselves. The mathematical formulation of this joint multivariate binary-response probit model is presented in Section 3.3.

3.3 Model Formulation

In the multivariate binary probit framework, let q ($q = 1, 2, \dots, Q$) index respondents in the analysis sample and let i ($i = 1, 2, \dots, I$) index the binary outcomes that each respondent contributes. In our application, $Q = 8,273$. Of these, the 1,476 respondents identified as NRATs contribute the full set of $I = 8$ outcomes, comprising the single outcome for the usage indicator and the seven perceived barriers to active travel. The remaining 6,797 frequent active mode users contribute only to the NRAT outcome ($I = 1$) and so only contribute to the total likelihood through this single outcome.

The following presentation of the model structure will focus on the 1,476 NRATs who provide the full vector of eight binary outcomes. For the remaining respondents, the formulation is simply marginalized to become a simple binary probit model with a single binary outcome.

³ This ratio is computed as total neighborhood employment divided by the number of neighborhood households (again, please see Chapman et al., 2021 for details).

⁴ This land-use mix is based on six categories of activity, namely occupied housing units together with the five employment sectors of retail, office, industrial, service, and entertainment (please see Chapman et al., 2021 for details).

Suppressing the index for the individual, simply for the ease of notation, the latent propensity (y_i^*) underlying each binary outcome may be written as the difference between the utility of the second alternative (U_i^2) and the utility of the first alternative (U_i^1) for that outcome:

$$y_i^* = U_i^2 - U_i^1 = \beta_i' \mathbf{x} + \varepsilon_i \quad (1)$$

In Equation (1), $\mathbf{x}$ is an $(L \times 1)$ vector of exogenous variables (including a constant); β_i is the corresponding $(L \times 1)$ coefficient vector to be estimated; and ε_i is a standard-normal error term assumed to be independent and identically distributed across respondents in the sample. The latent propensities (y_i^*) are not observable in the data. Instead, the analyst observes only the binary realization (y_i), which equals 1 when $y_i^* \leq 0$, and 2 when $y_i^* > 0$. Thus, if m_i ($m_i \in \{1, 2\}$) is the actually realized alternative for outcome i , each respondent's response may be expressed as $y_i = m_i$ if $\theta^{m_i-1} < y_i^* < \theta^{m_i}$, for $\theta^0 = -\infty$, $\theta^1 = 0$, and $\theta^2 = \infty$.

Next, to accommodate the joint nature of the eight outcomes, and in particular to allow unobserved factors that simultaneously influence the propensity of being an NRAT and the propensity of citing specific barriers, we treat the stacked error vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_I)'$ as following a multivariate normal distribution with a mean vector of zeros and a general correlation matrix $\boldsymbol{\Sigma}$ given by:

$$\boldsymbol{\Sigma} = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1I} \\ \rho_{12} & 1 & \rho_{23} & \cdots & \rho_{2I} \\ \rho_{13} & \rho_{23} & 1 & \cdots & \rho_{3I} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{1I} & \rho_{2I} & \rho_{3I} & \cdots & 1 \end{pmatrix}. \quad (2)$$

The off-diagonal elements ρ_{ij} of the correlation matrix capture error correlations among the latent propensities, accommodating shared unobserved heterogeneity across the joint outcome system. To express the system compactly, we stack the I lower thresholds for each respondent into a vector $\boldsymbol{\theta}_{low} = (\theta^{m_1-1}, \theta^{m_2-1}, \dots, \theta^{m_I-1})'$, the corresponding I upper thresholds into a vector $\boldsymbol{\theta}_{up} = (\theta^{m_1}, \theta^{m_2}, \dots, \theta^{m_I})'$, the latent propensities for each of the outcomes into the vector $\mathbf{y}^* = (y_1^*, y_2^*, \dots, y_I^*)'$, and the I parameter vectors into $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_I)'$. As noted above, for estimation, these stacked vectors must be marginalized for individuals who do not contribute the full vector of outcomes (the 6,797 frequent active mode users). Using these stacked vectors, the complete model system can be written in matrix form as:

$$\mathbf{y}^* = \boldsymbol{\beta}' \mathbf{x} + \boldsymbol{\varepsilon}, \boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{up}, \text{ where } \mathbf{y}^* \sim MVN_I(\boldsymbol{\beta}' \mathbf{x}, \boldsymbol{\Sigma}), \quad (3)$$

with $MVN_I(\boldsymbol{\beta}' \mathbf{x}, \boldsymbol{\Sigma})$ denoting the I -dimensional multivariate normal distribution with mean $\boldsymbol{\beta}' \mathbf{x}$ and correlation matrix $\boldsymbol{\Sigma}$. To complete the parameterization, we collect all parameters to be estimated into a single vector $\boldsymbol{\delta} = ([\text{Vech}(\boldsymbol{\beta})]', [\text{Vechup}(\boldsymbol{\Sigma})]')'$, where the operator “Vech(.)” row-vectorizes the non-zero elements of the matrix or vector on which it operates and the operator “Vechup(.)” row-vectorizes the upper-triangular elements of a square matrix.

The likelihood contribution of an individual then takes the form:

$$L(\delta) = \Pr[\boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{up}] = \int_{D_r} f_I(\mathbf{r} | \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma}) d\mathbf{r} \quad (4)$$

where the integration domain $D_r = \{\mathbf{r} : \boldsymbol{\theta}_{low} < \mathbf{r} < \boldsymbol{\theta}_{up}\}$ is the multivariate region of $\mathbf{y}^*$ truncated by the lower and upper threshold vectors, and $f_I(\mathbf{r} | \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Sigma})$ is the I -dimensional multivariate normal density with mean $\boldsymbol{\beta}'\mathbf{x}$ and correlation matrix $\boldsymbol{\Sigma}$. The full-sample log-likelihood is obtained as the sum of the individual-level log-likelihoods, with the contribution of the 6,797 frequent active mode users reducing to that of a univariate binary probit model comprised solely of the NRAT indicator. The integral in Equation (4) is up to eight-dimensional in our application and is evaluated using the matrix-based analytic methods of Bhat (2018).

4. MODEL RESULTS

4.1 Model Specification

The selection of variables in the final model was based on a combination of insights drawn from prior literature and theory as well as statistical tests for model fit. For naturally discrete and bracketed individual and household socio-demographic variables, dummy variables were created and tested in their most disaggregate form, and progressively combined based on statistical tests. For the continuous BE attributes drawn from the EPA database, each variable was first tested in its original linear form. Two measures performed well in continuous form and were retained accordingly: the share of no-vehicle households and the share of medium-wage workers in the respondent's zip code area. For the remaining BE variables, the variables were tested in several additional forms and the best in each case was found to be in the form of dummy variables based on bracketed bins. Finally, the t-statistic threshold for inclusion was set at 1.00, corresponding to a 0.32 level of significance or 68% confidence level. This level of significance was selected because the seven barriers were available for only a small portion of the overall sample and (even among the retained seven barriers) some had very unequal shares of selection and non-selection, leading to a relatively inefficient model. Thus, we prefer to be slightly more inclusive in our retention of marginally significant variables to help inform future efforts.⁵ The final estimation results are shown in Table 3.

⁵ Further justification for this threshold is warranted. Choosing a significance level always entails some trade-off between the risk of retaining a variable that has no genuine effect and the risk of discarding one that does. In this regard, the conventional 95% confidence level carries no special status that makes it the right resolution of that trade-off in every setting. As the American Statistical Association has emphasized, the level should instead be matched to the data and situation at hand rather than defaulting to a fixed cutoff (Wasserstein and Lazar, 2016; Wasserstein et al., 2019). In our current empirical context, we elect to retain variables using a somewhat more permissive threshold, since the seven barrier outcomes are elicited only from the NRAT subsample and several of them are selected by a small and highly unbalanced share of those respondents, which leaves limited information for pinning down barrier-specific effects with precision. Under these conditions we would rather tolerate a modestly elevated risk of retaining a spurious effect than discard variables that are plausibly informative and can guide future work built on larger or more balanced samples. In practice, the reported findings do not hinge on this decision, as removing the more marginally significant coefficients left the sign, magnitude, and significance of the remaining coefficients essentially unchanged, as did re-estimation under a range of alternative specifications. The stability of the estimates across these checks supports the robustness of the reported results (Lu and White, 2014; Srivastava et al., 2018; Brennan et al., 2021) and bolsters the consideration and inclusion of the retained variables.

Table 3. Model Estimation Results

Explanatory Variables (base category)		NRAT		Infrastructural deficiencies in active travel networks				Traffic-safety concerns				Personal- security concerns		Practical and situational constraints			
				Lack of sidewalks / bicycle lanes		Insufficient lighting		Aggressive drivers		Distracted drivers		Loitering / threatening		Adverse weather		Trip-length mismatch	
				Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constants		-1.08	-7.58	-1.34	-4.93	-2.11	-5.49	-0.37	-1.73	-0.81	-3.35	-2.13	-10.61	-0.85	-3.62	-0.12	-0.42
Individual-level demographic characteristics																	
Gender (male)	Female	0.21	5.75	0.10	1.27	—	—	—	—	—	—	0.29	2.46	0.09	1.04	-0.17	-2.07
Age (18 to 24 years)	25 to 44 years	—	—	—	—	—	—	—	—	—	—	—	—	—	—	-0.24	-2.64
	45 to 64 years	0.37	7.73	—	—	—	—	-0.11	-1.44	—	—	—	—	—	—	-0.24	-2.64
	65 to 74 years	0.57	10.01	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	75 years or older	0.74	11.19	—	—	-0.50	-2.88	—	—	-0.21	-1.78	—	—	—	—	—	—
Employment status (not employed)	Full-time	-0.31	-6.26	—	—	—	—	—	—	—	—	-0.41	-2.45	—	—	—	—
	Part-time	-0.23	-3.55	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Retired	—	—	—	—	—	—	-0.26	-2.72	-0.13	-1.38	—	—	—	—	0.13	1.24
Educational attainment (high school or less)	Some college	-0.08	-1.78	—	—	0.18	1.60	—	—	—	—	0.22	2.07	0.26	2.67	0.25	3.12
	Bachelor's degree(s)	-0.29	-5.67	0.37	3.99	0.30	1.91	—	—	—	—	—	—	0.46	3.75	0.38	3.51
	Graduate degree(s)	-0.29	-5.67	0.37	3.99	—	—	0.28	2.10	0.33	2.58	—	—	0.46	3.75	0.38	3.51
Race (White)	Black	—	—	—	—	-0.22	-1.11	0.10	1.20	—	—	—	—	—	—	-0.34	-2.77
	Asian/Pacific Islander	0.12	1.87	—	—	—	—	—	—	—	—	—	—	—	—	0.34	2.61
	Other	—	—	—	—	0.17	1.15	0.10	1.02	0.14	1.35	—	—	0.24	2.08	—	—
Ethnicity (non-Hispanic)	Hispanic	-0.11	-2.12	—	—	0.29	1.83	0.33	3.20	0.16	1.23	0.22	1.34	—	—	—	—
Household-level attributes																	
Annual household income (less than \$25,000)	\$25,000-\$49,999	—	—	—	—	—	—	—	—	—	—	—	—	-0.14	-1.50	—	—
	\$50,000-\$149,999	-0.14	-3.23	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	\$150,000-\$199,999	-0.14	-3.23	—	—	—	—	—	—	-0.32	-2.12	—	—	—	—	—	—
	\$200,000 or more	-0.14	-3.23	—	—	—	—	—	—	-0.32	-2.12	—	—	—	—	-0.20	-1.15
Household size (one)	Two	-0.11	-2.40	—	—	—	—	—	—	—	—	-0.21	-1.85	—	—	-0.11	-1.48
	Three or more	-0.11	-2.40	—	—	—	—	—	—	—	—	-0.21	-1.85	—	—	—	—
Housing unit type (single-family)	Apartment	-0.20	-3.78	-0.20	-1.94	—	—	—	—	—	—	—	—	—	—	—	—
	Other	—	—	—	—	—	—	—	—	0.12	1.22	—	—	—	—	0.11	1.14
Homeownership (owner)	Renter	0.10	2.22	0.28	3.43	0.19	1.66	—	—	—	—	0.31	2.80	0.31	3.46	—	—
Vehicle ownership (vehicle-sufficient)	Vehicle-deficient	-0.13	-2.44	—	—	—	—	—	—	—	—	—	—	-0.13	-1.10	-0.35	-3.11

Table 3. Model Estimation Results (Continued)

Explanatory Variables (base category)			NRAT		Infrastructural deficiencies in active travel networks				Traffic-safety concerns				Personal- security concerns		Practical and situational constraints			
					Lack of sidewalks / bicycle lanes		Insufficient lighting		Aggressive drivers		Distracted drivers		Loitering / threatening		Adverse weather		Trip-length mismatch	
			Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Geographic context represented by the respondent's census division of residence																		
Census division (New England)	Middle Atlantic		—	—	0.22	1.95	—	—	—	—	—	—	—	—	—	—	0.15	1.30
	East North Central		—	—	-0.11	-1.01	—	—	—	—	—	—	—	—	—	—	—	—
	West North Central		-0.11	-1.68	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	South Atlantic		—	—	—	—	—	—	—	—	—	—	—	—	-0.48	-3.98	-0.24	-2.48
	East South Central		—	—	—	—	—	—	—	—	—	—	—	—	-0.46	-3.14	—	—
	West South Central		—	—	—	—	—	—	—	—	—	—	—	—	-0.65	-4.89	—	—
	Mountain		—	—	—	—	—	—	—	—	—	—	—	—	-0.62	-4.01	—	—
Pacific		—	—	—	—	—	—	—	—	—	—	—	—	-0.78	-4.95	—	—	
Residential built-environment characteristics																		
Socio- economic variables	No-vehicle households		-0.87	-3.76	—	—	—	—	—	—	—	—	—	—	—	—	—	—
	Medium-wage workers		0.84	3.26	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Development density measures	Population density (Not low, > 10)	Low (≤ 10)	—	—	0.29	1.95	0.64	3.01	-0.22	-3.38	—	—	-0.18	-1.31	—	—	—	—
	Activity density (Not low, > 6)	Low (≤ 6)	—	—	0.16	1.63	-0.39	-2.46	—	—	—	—	—	—	-0.15	-1.20	—	—
Local activity mix attributes	Employment mix (Not low, > 0.50)	Low (≤ 0.50)	—	—	—	—	-0.20	-1.80	—	—	-0.09	-1.19	—	—	—	—	—	—
	Jobs-per-household ratio (Low, < 0.50)	Medium (0.50-2.00)	—	—	—	—	—	—	—	—	—	—	—	—	—	—	-0.11	-1.45
		High (> 2.00)	—	—	—	—	—	—	0.13	1.49	—	—	—	—	—	—	—	—
	Land-use mix (Not low, > 0.30)	Low (≤ 0.30)	-0.07	-1.57	-0.13	-1.62	—	—	—	—	—	—	—	—	—	—	—	—
Network design measures	Pedestrian network density (Not low, >5)	Low (≤ 5)	—	—	0.10	1.16	0.23	1.42	—	—	—	—	0.67	1.80	0.23	1.49	—	—
	Intersection density (Not low, > 100)	Low (≤ 100)	0.12	2.35	0.22	2.00	—	—	—	—	—	—	—	—	0.25	1.67	—	—
	Pedestrian 3 leg intersections (Not low, > 40)	Low (≤ 40)	-0.10	-1.99	—	—	—	—	—	—	-0.14	-1.81	-0.39	-1.69	—	—	-0.14	-1.36
	Pedestrian 4+ leg intersections (Not low, > 5)	Low (≤ 5)	—	—	—	—	—	—	—	—	—	—	-0.45	-1.31	-0.32	-2.02	0.28	2.59

Table 3. Model Estimation Results (Continued)

Explanatory Variables (base category)			NRAT		Infrastructural deficiencies in active travel networks				Traffic-safety concerns				Personal- security concerns		Practical and situational constraints			
					Lack of sidewalks / bicycle lanes		Insufficient lighting		Aggressive drivers		Distracted drivers		Loitering / threatening		Adverse weather		Trip-length mismatch	
					Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Walkability	National Walkability Index (Least walkable, ≤ 5.75)	Below average (5.76-10.50)	-0.15	-2.60	—	—	0.32	1.73	—	—	—	—	—	—	—	—	—	—
		Above average (10.51-15.25)	-0.29	-3.96	-0.14	-1.28	0.32	1.73	—	—	—	—	—	—	—	—	-0.21	-2.18
		Most walkable (> 15.25)	-0.39	-2.62	-0.14	-1.28	0.32	1.73	—	—	0.55	2.36	—	—	—	—	-0.21	-2.18
Correlations (only upper diagonal shown)																		
NRAT			1.00		-0.16	-1.31	—	—	-0.32	-2.78	—	—	0.52	2.64	—	—	—	—
Lack of sidewalks / bicycle lanes			—	—	1.00		0.71	11.32	0.74	17.87	0.70	16.90	0.45	5.02	0.57	11.82	0.31	5.79
Insufficient lighting			—	—	—	—	1.00		0.68	8.99	0.63	10.54	0.61	6.10	0.56	8.26	0.27	3.97
Aggressive drivers			—	—	—	—	—	—	1.00		0.88	22.07	0.48	4.58	0.64	11.72	0.20	2.87
Distracted drivers			—	—	—	—	—	—	—	—	1.00		0.56	6.00	0.56	10.86	0.11	1.94
Loitering / threatening			—	—	—	—	—	—	—	—	—	—	1.00		0.42	4.68	0.21	2.15
Adverse weather			—	—	—	—	—	—	—	—	—	—	—	—	1.00		0.24	4.32
Trip-length mismatch			—	—	—	—	—	—	—	—	—	—	—	—	—	—	1.00	

Note: The category cut-points for the BE characteristics are expressed in each measure's natural units (as mentioned in Table 2 and described in Section 3.1.2).

A “—” entry in the table indicates that the exogenous variable does not have a significant effect (at the 68% confidence level) on the column endogenous outcome. In cases where multiple variables have the same coefficients, the implication is that the variables did not have statistically different effects. The constants in the first row are estimated to reproduce the observed shares selecting each outcome, conditional on exogenous variables, and so do not have any substantive interpretations. Regarding the vehicle ownership variable, households are classified based on vehicle sufficiency rather than the raw vehicle count reported in Table 2. A household is considered vehicle-sufficient if the number of household vehicles equals or exceeds the number of licensed drivers in the household, and vehicle-deficient if the number of vehicles falls short of the number of licensed drivers. The remainder of the variables are discussed in the following section, followed by a discussion of correlations and model fit.

4.2 Main Estimation Results

4.2.1 *Effects of Individual-Level Demographic Characteristics*

Table 3 indicates that, compared with men, women are more likely to be NRATs. This pattern is consistent with the well-documented gender gap in bicycling participation and the broader literature linking women’s daily mobility to greater household-management responsibilities, more complex trip-chaining behaviors, and heightened concerns about personal security in public spaces (for example, Ravensbergen et al., 2020a; Ravensbergen et al., 2020b; D’Agostino et al., 2024). These differences are also reflected in the reported barriers. Women are more likely to cite personal-security concerns related to loitering or threatening behavior as a barrier, while being less likely to identify trip-length mismatches, suggesting that personal security weighs more heavily than travel distance in their active travel decisions. Women also report somewhat greater concerns about deficiencies in sidewalks and bicycle lanes as well as adverse weather, although these effects are only very marginally significant.

Age exhibits the strongest relationship with NRAT status. Adults older than 44 years are progressively more likely to be NRATs, consistent with the increasing physical limitations associated with aging and the resulting decline in active lifestyles (Buehler et al., 2024). The perceived barriers, however, vary much less by age. Adults aged 25 to 64 are less likely to report trip-length mismatch as a barrier than either younger or older adults, possibly reflecting more settled residential and activity patterns. Those aged 75 years and older are less likely to cite insufficient lighting or distracted drivers, potentially because their more discretionary travel enables them to avoid nighttime and peak-period travel. Adults aged 45 to 64 are also somewhat less likely to report aggressive drivers as a barrier, a finding that warrants further investigation.

Employment status primarily influences the likelihood of being an NRAT rather than the specific barriers reported. Both full-time and part-time workers are less likely to be NRATs than non-employed individuals, consistent with active commuting serving as an important source of daily physical activity (Sahlqvist et al., 2012). Full-time workers are less likely to cite loitering or threatening behavior, while retired individuals are less likely to identify aggressive or distracted drivers, possibly because they travel more frequently during quieter, off-peak periods (Jones et al., 2018). Retired individuals are, however, somewhat more likely to identify trip-length mismatch as a barrier, consistent with travel that is more discretionary and less anchored to nearby workplaces.

In terms of formal education status, respondents with higher educational attainment are less likely to be NRATs, aligning with research linking education to more frequent active travel through greater leisure-time physical activity and heightened sensitivity to the health and environmental benefits of active modes (Cerin et al., 2009; Hudde, 2024). At the same time, more

highly educated respondents tend to report a broader range of perceived barriers, including concerns related to infrastructure, safety, adverse weather, and trip-length mismatch. One possible explanation is that these individuals hold higher expectations regarding the quality of the active travel environment.

Race and ethnicity effects also emerge. Compared with White individuals, Asian/Pacific Islander respondents are more likely to be NRATs, while Hispanic respondents are less likely to be NRATs compared to non-Hispanic respondents. Previous studies have reported mixed racial and ethnic differences in active travel, partly because these relationships are often confounded with differences in income, vehicle access, and the built environment, all of which are controlled for in the current analysis (Adjaye-Gbewonyo and Briones, 2024; Grengs, 2025). The remaining racial differences may therefore reflect cultural norms and attitudes toward walking and bicycling, including the extent to which active travel is embedded in everyday travel and social activity patterns. In terms of barriers, Black respondents, respondents of other non-White races, and Hispanic respondents are generally more likely (relative to non-Hispanic White respondents) to cite concerns related to aggressive or distracted drivers, while Hispanic respondents also report greater concerns about insufficient lighting and personal security. These findings are consistent with evidence that drivers behave less cautiously toward, and yield less often to, pedestrians of color (Goddard et al., 2015; Ingram et al., 2017; Beliveau et al., 2026). The few remaining race- and ethnicity-specific effects, such as lower concern about trip-length mismatch among Black respondents and higher concern among Asian/Pacific Islander respondents, are comparatively modest.

4.2.2 Effects of Household-Level Attributes

Individuals in households with an annual income of \$50,000 or more are uniformly less likely to be NRATs compared to those in households with an annual income of less than \$50,000, potentially reflecting the time poverty that limits active travel among lower-income groups. Income, however, has relatively little influence on the perceived barriers themselves, with only a few isolated effects. Household composition plays a more consistent role. Individuals living in households with two or more persons are less likely to be NRATs than those living alone and are less likely to cite loitering or threatening behavior as a barrier, while those in two-person households are also less likely to identify trip-length mismatch. These findings are consistent with evidence that social companionship encourages active travel by enhancing perceived personal safety (Ory et al., 2016; Kritz et al., 2020).

The remaining household attributes largely reflect differences in the residential and transportation environments. Apartment residents are less likely to be NRATs and less likely to perceive sidewalk and bicycle lane deficiencies than residents of single-family homes, consistent with the greater activity density and walkability typically associated with multi-family environments (Hegde et al., 2025). In contrast, renters are more likely to be NRATs and more likely to identify infrastructural deficiencies, personal security concerns, and adverse weather as barriers. Finally, individuals in vehicle-deficient households are less likely to be NRATs and less likely to cite trip-length mismatch (and, marginally, adverse weather) as barriers, reinforcing the well-established substitution between private vehicle availability and active travel (Ghimire and Bardaka, 2023).

4.2.3 Effects of Geographic Context

The census division indicators in Table 3 account for broad regional differences across the U.S. While these variables are less straightforward to interpret than the residential BE measures discussed next (because they encompass substantial within-region heterogeneity), they nonetheless capture broad climatic and geographic influences. The dominant regional effect relates to adverse weather. Compared with respondents living in the Northeast and Midwest, those residing in the South and West are consistently less likely to identify adverse weather as a barrier to active travel, a pattern that likely reflects milder winter conditions in the South and West (Carlson et al., 2021). Beyond weather, only a few isolated regional differences emerge, including lower concern about trip-length mismatch in the South Atlantic, somewhat greater concern about sidewalk and bicycle lane deficiencies in the Middle Atlantic, and a marginally lower propensity to be NRATs in the West North Central division.

4.2.4 Effects of Residential Built-Environment (BE) Characteristics

The final set of variables in Table 3 relates to the residential BE. Across our many specification trials, we tested an extensive set of interactions between BE characteristics and individual, household, and geographic variables to examine whether different population groups perceived the same residential environments differently. None of these interactions were statistically significant at the confidence level used for variable retention, suggesting that the influence of the BE on perceived barriers is reasonably consistent across population groups.

Among the socio-economic BE variables, a higher share of no-vehicle households is associated with a lower propensity to be an NRAT, an intuitive result given that such neighborhoods tend to foster both supportive environments and a local culture more conducive to active travel (Mitra and Saphores, 2017). Conversely, a higher share of medium-wage workers is associated with a greater propensity to be an NRAT, possibly reflecting the more suburban, auto-oriented character of these neighborhoods, where longer travel distances reduce the practicality of active travel (Saelens and Handy, 2008; Blumenberg and King, 2024).

Development density produces a consistent pattern. Respondents in low-density neighborhoods are more likely to cite deficiencies in sidewalks, bicycle lanes, and lighting, reflecting the generally less developed pedestrian environment of these areas. At the same time, they are less likely to identify aggressive drivers and loitering or threatening behavior as barriers, since the lower pedestrian and vehicle activity of low-density neighborhoods reduces exposure to these concerns (Morency et al., 2012). Low activity density shows a partly similar pattern, with greater concern about sidewalk and bicycle lane deficiencies but less concern about insufficient lighting and adverse weather. This indicates that busier, activity-rich neighborhoods, which tend to provide better active travel facilities, draw fewer infrastructure complaints even as their greater activity makes lighting and weather concerns more salient.

The local activity mix attributes exhibit more modest effects. Respondents in areas with limited employment diversity are less likely to report insufficient lighting and distracted drivers as barriers, perhaps reflecting quieter neighborhoods with lower traffic volumes. Those living in areas with modest jobs-per-household ratios are somewhat less likely to perceive trip-length mismatches, while residents of employment-rich areas are more likely to report concerns regarding aggressive drivers, consistent with heavier traffic activity. Finally, a low degree of land-use mix is associated with a marginally lower propensity to be an NRAT and somewhat fewer reports of sidewalk and bicycle lane deficiencies, possibly because neighborhoods dominated by a single

land use, typically residential in character, offer quiet streets and continuous local sidewalks that support at least occasional recreational walking close to home.

Network design measures exhibit some of the strongest relationships in the model. Respondents living in areas with low pedestrian network density are more likely to identify deficiencies in infrastructure (sidewalks and bicycle lanes), along with elevated concerns about insufficient lighting, personal security, and adverse weather. The infrastructure effects are expected, while the heightened security concern may reflect reduced informal surveillance in areas where sparse pedestrian networks discourage outdoor activity. Low intersection density tells a similar story, being associated with a higher propensity to be an NRAT, more frequent reports of sidewalk and bicycle lane deficiencies, and greater concern about adverse weather, consistent with the longer, less direct travel paths of poorly connected street networks. Likewise, areas characterized by fewer three-leg intersections and more four-or-more-leg intersections, indicative of traditional connected street grids rather than curvilinear suburban layouts, are associated with lower concern about trip-length mismatches.

Finally, the National Walkability Index reinforces these broader findings. Respondents in more walkable areas are progressively less likely to be NRATs than in the least walkable areas, consistent with the intent of walkable urban design to promote active travel (Watson et al., 2020). At the same time, they are more likely to cite insufficient lighting, and in the most walkable neighborhoods, distracted driving as barriers. One possible explanation is that greater pedestrian activity, especially after dark and in mixed traffic environments, increases exposure to, and awareness of, these issues. In contrast, respondents in more walkable neighborhoods are less likely to report deficiencies in sidewalks and bicycle lanes or concerns about trip-length mismatches, reflecting the more complete pedestrian networks and compact land-use patterns of such environments.

4.3 Correlations

The correlation parameters estimated in the model appear in the final section of Table 3. Consider first the correlations between the NRAT indicator and the seven specific barriers, three of which are statistically significant. The first two significant correlations (corresponding to the correlations between NRAT propensity and the propensity to cite lack of sidewalks or bicycle lanes and aggressive drivers as barriers) are negative. A negative correlation implies that the unobserved factors raising the propensity to identify these barriers are associated with a lower, not higher, propensity to be an NRAT. Equivalently, and interestingly, this also implies that these two barriers are voiced disproportionately by individuals who, in unobserved terms, are closest to being active travelers, a pattern with direct policy relevance, since removing such barriers is what most plausibly converts latent demand into actual active travel. A plausible reading is that both barriers are experiential. Noticing missing sidewalks or bicycle lanes, or encountering aggressive drivers, generally requires being “out and about” in the pedestrian and bicycling environment; yet, precisely because of their greater exposure and attentiveness to on-the-ground conditions, relatively regular active travelers are more likely to perceive and report these infrastructural and traffic-safety deficiencies (Sanders, 2015; Aldred, 2016).

The NRAT indicator is also positively correlated with personal-security concerns related to loitering or threatening behavior, indicating that the unobserved factors predisposing an individual to be an NRAT also heighten this particular concern. In other words, the apprehension about personal security and the tendency to avoid active travel appear to spring from a common unobserved source, consistent with evidence that such concerns deter would-be active travelers

before a trip is ever undertaken (Foster et al., 2014; Rees-Punia et al., 2018). This contrasts with the situation corresponding to the first two barriers just discussed above, which appear to arise from participation, while the correlation with personal-security concerns relates to suppressed participation.

The remaining significant correlations are among the seven barriers themselves, and all are positive. These pervasive positive inter-barrier correlations point to an underlying disposition of general concern that leads some individuals to be more attentive to, and more likely to articulate, barriers across multiple dimensions of the active travel environment. Such a disposition may reflect personality traits, for instance risk aversion or environmental sensitivity, that simultaneously raise or lower concern across all the barriers considered.

4.4 Model Fit

We evaluate the performance of the proposed joint model against an independent model that does not consider the correlations among the eight outcomes. The independent model specification treats all outcome dimensions independently, ignoring the correlation terms discussed in the previous section (and shown at the bottom of Table 3). A variety of disaggregate fit metrics are employed to compare the performance of the two models, as shown in Table 4. The log-likelihood at convergence and the adjusted likelihood ratio index calculated in comparison to both the constants-only log-likelihood and the equal-probability log-likelihood are all larger for the proposed model, supporting the superior fit of this model. Additionally, the proposed model has a smaller Bayesian information criterion than the independent model, suggesting that the proposed model has a better fit after accounting for the number of parameters. Finally, the two models are compared using a formal likelihood ratio test, which is found to be significant at any reasonable level of significance for a chi-square value with 24 degrees of freedom. The proposed model clearly outperforms the independent model based on these disaggregate fit statistics.

Table 4. Model Fit

Metric	Proposed Model	Independent Model
Log-Likelihood at Convergence	-7020.37	-7708.96
Log-Likelihood at Constants	-8417.53	
Log-Likelihood at Zero	-12896.00	
Number of Parameters (including constants)	141	117
Adjusted Likelihood Ratio Index (relative to constants-only model)	0.149	0.070
Adjusted Likelihood Ratio Index (relative to equal-probability model)	0.445	0.393
Bayesian Information Criterion	15312.65	16473.35
Likelihood Ratio Test	$1377.18 > \chi^2_{24, 0.00001} = 65.58$	

4.5 Average Treatment Effects (ATEs)

The coefficients in Table 3 indicate the direction of the effects on the underlying latent propensities, but they do not directly convey the magnitude of those effects on the probability of being an NRAT or of identifying a particular barrier. To provide such an intuitive interpretation, Table 5 presents ATEs, computed as the percentage change in the proportion of individuals experiencing a given outcome when a single exogenous variable is shifted from a baseline level to a treatment level, with all other variables held at their observed sample values.

Table 5. Average Treatment Effects (ATEs) of Exogenous Variables

Variable	Base	Treatment	NRAT	Infrastructural deficiencies in active travel networks		Traffic-safety concerns		Personal-security concerns	Practical and situational constraints	
				Lack of sidewalks / bicycle lanes	Insufficient lighting	Aggressive drivers	Distracted drivers	Loitering / threatening	Adverse weather	Trip-length mismatch
Individual-level demographic characteristics										
Gender	Male	Female	31.89	11.81	-0.02	-0.03	0.00	94.96	11.84	-15.15
Age	18 to 24 years	25 to 44 years	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-20.58
		45 to 64 years	72.77	0.12	0.11	-10.82	0.09	0.87	0.12	-20.58
		65 to 74 years	123.11	-0.06	-0.02	-0.22	0.14	1.22	-0.05	-0.07
		75 years or older	171.49	-0.38	-61.56	-0.51	-25.47	0.53	-0.48	-0.35
Employment status	Not employed	Full-time	-34.57	0.14	0.10	0.22	0.06	-62.10	0.09	0.06
Educational attainment	High school or less	Graduate degree(s)	-32.03	49.03	0.39	31.47	52.00	-0.23	79.14	46.20
Ethnicity	Non-Hispanic	Hispanic	-13.52	-0.09	63.17	38.04	23.22	62.42	0.06	-0.11
Household-level attributes										
Homeownership	Owner	Renter	13.67	35.39	38.91	-0.12	0.16	104.10	45.98	-0.16
Vehicle ownership	Vehicle-sufficient	Vehicle-deficient	-15.76	0.14	-0.06	0.24	-0.17	-0.27	-15.24	-30.94
Residential built-environment characteristics										
Population density	Not low, > 10 persons per acre	Low (≤ 10)	0.16	41.33	224.38	-20.55	0.08	-33.65	0.11	-0.09
Pedestrian network density	Not low, > 5 facility-miles per sq-mi	Low (≤ 5)	0.28	11.62	46.93	-0.06	0.08	278.82	31.48	-0.10
National Walkability Index	Least walkable, ≤ 5.75	Below average (5.76-10.50)	-17.02	0.00	79.37	0.05	-0.06	-0.28	-0.01	0.00
		Above average (10.51-15.25)	-31.20	-14.73	79.37	0.08	-0.08	-0.55	0.00	-18.64
		Most walkable (> 15.25)	-40.28	-14.73	79.37	1.16	90.91	-1.20	0.97	-18.64

For compactness, Table 5 reports ATEs only for the variables with the largest substantive effects. For most categorical exogenous variables, the treatment corresponds to the highest category relative to the lowest, with intermediate categories also shown for age and walkability. For population density and pedestrian network density, the base is instead the not-low (higher-supply) category and the treatment is the low category, so that these built-environment measures are expressed in the same direction as the other supply variables. For example, the ATE of 31.89 for gender indicates that women are 31.89% more likely to be NRATs compared to men.⁶ The corresponding gender-related ATE of 11.81 for sidewalk and bicycle lane deficiencies indicates that women (regardless of whether they are NRATs or not) are 11.81% more likely than men to identify this as a barrier. The remaining entries may be similarly interpreted.⁷

In the following section, the ATEs in Table 5 are discussed in more detail in the context of specific implications and policy interventions that may be used to increase active travel uptake.

5. POLICY IMPLICATIONS

The policy implications are organized into five sections. Section 5.1 focuses primarily on the ATEs related to perceived infrastructural deficiencies in active travel networks (this corresponds to the first group of barriers as identified in Section 1), with particular emphasis on the role of the residential built environment. Section 5.2 discusses the implications of perceived traffic-safety concerns (the second barrier group), and Section 5.3 turns to perceived personal-security concerns (the third barrier group). Section 5.4 considers the practical and situational constraints that discourage active travel (the fourth barrier group). Finally, Section 5.5 focuses specifically on older adults, particularly those aged 65 years and above. We devote a separate section to this group for two reasons. First, the share of older adults in the U.S., as in many other countries, has increased substantially in recent years (World Health Organization, 2015; Vespa et al., 2020). Second, active living has been widely recognized as an important contributor to maintaining physical and mental health and quality of life in later life (Bauman et al., 2016; World Health Organization, 2020).

5.1 Connected Pedestrian and Bicycling Networks

A critical policy lever that emerges from the ATEs corresponding to the objective residential BE characteristics relates to the population density and pedestrian network density ATEs. While the NRAT ATEs corresponding to these two neighborhood BE characteristics show little variation

⁶ To be precise, based on the coefficient estimates in Table 3, and if each respondent were to identify as a woman (with other explanatory variables held at their sample values), the share of NRATs is estimated to be 19.85%. The corresponding proportion if each respondent were to identify as a man (with other explanatory variables held again at their sample values) is estimated to be 15.05%. The ATE is then computed as the percentage change in the NRAT share in moving from the male case to the female case, that is, $(19.85 - 15.05) / 15.05 \times 100$, which equals 31.89%. In other words, women are estimated to be 31.89% more likely than men to be NRATs.

⁷ A note here about the ATEs in Table 5, which may seem counter-intuitive for some entries relative to the estimation results in Table 3. For example, Table 3 does not indicate any effect of gender on the “aggressive drivers” barrier. However, Table 5 shows a small ATE of -0.03 for “aggressive drivers”. This is because the ATEs are computed considering the correlation terms discussed in Section 4.3. In the case of the “female” variable, women are more likely to be NRATs than men, and the correlation between NRAT propensity and the propensity to cite “aggressive drivers” is negative. That is, as explained in Section 4.3, unobserved factors that make a person more likely to be an NRAT also decrease the probability that the individual will cite “aggressive drivers”, which contributes to the small negative entry for the “female” ATE corresponding to “aggressive drivers” in Table 5. In general, the correlations in Section 4.3 may act in different directions for different variables, which may get manifested as non-zero ATEs in Table 5 even with a corresponding “zero” entry (that is, a “—” entry) in Table 3. However, any such ATEs will tend to be relatively small in Table 5.

based on these density measures, there are clear ATE differences for the barriers. As may be noticed, residents of low-density neighborhoods (both in terms of population density and pedestrian network density) report the lack of sidewalks/bicycle lanes and insufficient lighting more often than residents of “not low” density neighborhoods, with the contrast especially observed for insufficient lighting (see Table 5). These perceptions align with the objectively thinner supply of pedestrian and bicycling infrastructure in such neighborhoods, suggesting that the two perceived infrastructural-deficiency barriers point to a concrete, buildable policy target. Walkability follows the same pattern for sidewalks and bicycle lanes, with residents of more walkable neighborhoods reporting fewer such deficiencies. For insufficient lighting, however, they report more concerns. This is likely because the heavier foot traffic of walkable areas, especially after dark, makes poor lighting more noticeable. The same two barriers also vary considerably across population groups, though for different reasons. Respondents with graduate degrees report the lack of sidewalks/bicycle lanes markedly more often than those with a high school education or less, a pattern that likely reflects higher expectations regarding the quality of the active travel environment (see Section 4.2) rather than objectively worse conditions. Renters, by contrast, report both the lack of sidewalks/bicycle lanes and insufficient lighting notably more often than homeowners, and Hispanic respondents report insufficient lighting far more often than non-Hispanic respondents. The concentration of these concerns among renters and Hispanic respondents adds an equity dimension to infrastructure investment decisions.

In terms of interventions, a caveat is in order before translating these findings into action. The results only indicate that respondents perceive a lack of sidewalks or bicycle lanes, but do not reveal the specific form of deficiency each respondent has in mind, which may range from missing segments along otherwise served routes to the absence of any facilities at all. What the results do establish is that this perception, along with several other barriers, is more prevalent where the pedestrian network is sparse. Because pedestrian network density is measured as pedestrian-oriented facility-miles per square mile (see Section 3.1.2), raising this density amounts to progressively adding facility-miles. An effective approach to doing so would be to join existing fragments into a continuous network, a process that we refer to as network completion. Expanding the extent of pedestrian and bicycle networks is associated with substantially higher rates of walking and bicycling across cities worldwide, along with sizable emissions and health co-benefits (Millard-Ball et al., 2025). Building on this evidence, jurisdictions can pursue completion by maintaining an inventory of sidewalk and bicycle lane gaps and prioritizing gap segments for construction based on their contribution to overall network connectivity rather than on construction cost alone, with particular weight on links that connect residential areas to transit stops, schools, and everyday destinations. Given the elevated concerns among renters noted above, corridors serving neighborhoods with high shares of rental housing also deserve explicit weight in this prioritization. Complete Streets policies, which require that roadways be designed and operated to provide safe access for users of all modes, including pedestrians and bicyclists (McCann, 2013), offer a complementary instrument by ensuring that routine resurfacing and reconstruction projects add missing pedestrian and bicycling facilities as a matter of course rather than as discretionary extras (Chahine et al., 2025; Pearson et al., 2025). A dedicated share of the capital improvement program may further be reserved for closing gaps in the highest-need corridors. Insufficient lighting calls for a complementary effort on a different logic. Because it is cited both in sparse, low-density neighborhoods and in busy, highly walkable ones, lighting investment should reach both settings, correcting objectively deficient illumination in the former while bringing the heavily used pedestrian environments of the latter up to the standard their users expect, particularly along

routes traveled after dark. Because renters and Hispanic respondents report insufficient lighting most acutely, neighborhoods with high shares of these residents warrant explicit priority in lighting investment. Finally, low pedestrian network density is associated with heightened concern across a wider range of barriers than any other residential BE characteristic in Table 5, extending beyond the two infrastructural deficiencies to the personal-security and practical constraints considered in Sections 5.3 and 5.4. This breadth reinforces network completion, in the specific sense of raising pedestrian network density, as a primary consideration for easing the conditions that constrain active travel.

5.2 Targeting Investments in Traffic Safety

Concern about aggressive and distracted drivers stands apart from the other barriers in where it clusters. Unlike the infrastructural deficiencies, which are reported most often in sparse, low-density neighborhoods, traffic-safety concern is greatest where walking and bicycling are most common. Distracted-driver concern is reported more often in the most walkable neighborhoods than in the least walkable ones, and aggressive driver concern is more common in denser neighborhoods than in low-density ones, both places where pedestrians and vehicles share the same streets and so cross paths far more often. The same holds among the individuals most engaged in active travel. Respondents with graduate degrees, who are among the least likely to be NRATs and thus among the most active, nonetheless report both aggressive and distracted drivers as barriers considerably more often than those with a high school education or less, and Hispanic respondents report elevated concern on both traffic-safety dimensions. Taken together, these concerns weigh most on the people already out walking and bicycling, wearing on their everyday experience and discouraging further active travel in the very places best suited to it.

Because these concerns concentrate where pedestrian activity is highest, traffic-safety investment should be directed there first, while not neglecting the areas where pedestrians are currently rare. In the busiest walking environments, lower speed limits (Hu and Cicchino, 2024), leading pedestrian intervals at signalized crossings (Zadey et al., 2025), daylighting of intersections by removing parking near crosswalks, and enforcement campaigns aimed at distracted driving can each reduce the hazards active travelers encounter. Ensuring an adequate supply of crosswalks and signals, pedestrian-appropriate signal timing, and dedicated bicycling infrastructure is likewise important in these areas to reduce friction between active travelers and motorists. Lower-activity neighborhoods deserve similar attention as well. Where few people walk, each pedestrian tends to face a higher per-person risk, plausibly because drivers are less accustomed to encountering people on foot, a pattern known as the safety-in-numbers effect (Elvik and Bjørnskau, 2017). Extending driver-awareness and enforcement efforts into these areas therefore helps protect the pedestrians who do travel there.

5.3 Designing Out Personal-Security Concerns

Personal-security concerns tell a different story, one that a glance at aggregate shares would badly misread. Loitering or threatening behavior is the least frequently cited barrier overall (see Table 1), which might suggest it is a minor consideration. Yet the ATEs reveal it to be among the most sharply concentrated of all the barriers. Women report it roughly twice as often as men, and renters roughly twice as often as homeowners, while Hispanic respondents also report elevated concern. At the other end, full-time workers report it far less often, plausibly because their travel falls in daytime periods when more people are about. It is strongly patterned by place as well, rising steeply in neighborhoods with sparse pedestrian networks, where quiet, lightly traveled streets can

feel less secure than busier, more active ones. None of this is visible in the population-wide average. For the specific groups and places where the concern is acute, it plausibly shapes whether active travel is undertaken at all, and it likely colors the daily experience of those who already travel actively. Overlooking personal security because of its low aggregate share would therefore miss a barrier that weighs heavily on some of the very populations active travel policy most hopes to reach.

Addressing this concentrated concern calls for targeted rather than evenly spread investment, directed to the neighborhoods and groups where the concern looms largest. In practice, this means (a) adopting pedestrian-scale lighting standards and conducting systematic lighting audits along high-use walking corridors (Chalfin et al., 2022), which also advance the infrastructural lighting improvements discussed in Section 5.1, and (b) applying crime-prevention-through-environmental-design principles such as trimmed vegetation, unobstructed sightlines, active ground-floor frontage, and the cleanup and greening of vacant or degraded lots (see, for example, Branas et al., 2018; Lee et al., 2023). Because sparse pedestrian activity is itself part of the problem, measures that draw more people onto the street, including the network completion advanced in Section 5.1 and support for ground-floor activity, reinforce these efforts by restoring natural surveillance. Given that women and renters carry the concern most heavily, safety audits that involve them directly as participants in the design process should be built into the routine review of corridor designs, so that the populations most affected shape the remedies (Jauregui et al., 2025). Partnerships with property managers, housing authorities, and neighborhood organizations extend these measures onto the private edges of the public realm, since much of the lighting and vegetation bordering a sidewalk sits on private property beyond the direct reach of public works.

5.4 Easing Practical and Situational Constraints

Distance is the barrier that active travel policy might find hardest to build its way around. The perception that active modes are unsuited to the trip lengths needed to reach everyday destinations is the single most cited barrier in the sample (see Table 1), and unlike the infrastructural and safety barriers, it concerns the length of the trip rather than the quality of the route. Adverse weather, the other practical and situational constraint, shares this character, since it concerns the conditions under which a trip is made rather than the facilities along the way. The two barriers also pattern together in a telling way. Individuals in vehicle-deficient households cite trip-length mismatch nearly a third less often, and, more marginally, adverse weather less often, than those in vehicle-sufficient households, suggesting that active travel undertaken out of necessity is less deterred by either consideration. For those with a car readily available, who are also more likely to be NRATs, both loom larger, since every walking or bicycling trip is weighed against an easy driving alternative. Encouragingly, trip-length mismatch is cited notably less often in more walkable neighborhoods, where homes, jobs, and services already sit close together, a sign that compact, mixed-use development might bring everyday destinations within realistic reach of active modes. Weather concerns, in turn, are somewhat elevated where pedestrian networks are sparse, consistent with the broad reach of sparse networks noted in Section 5.1. The sharpest divide for weather, however, is regional, with residents of the South and West citing it far less often than those of the Northeast and Midwest, pointing to winter conditions as the dominant seasonal obstacle (see Section 4.2).

Because the constraints are the trip and its conditions rather than the route, the policy response works along three lines: (1) bringing destinations closer, (2) extending the range that

active travelers can comfortably cover, and (3) blunting the exposure that weather imposes. On the land-use side, zoning reforms that permit neighborhood-serving retail within residential districts, encourage infill development along existing corridors, and bring everyday services closer to homes can shorten the distances that make active travel impractical for some trips (as established in Ewing and Cervero, 2010, and reaffirmed by Tuffour et al., 2025). On the vehicle side, electric-assist modes extend a traveler's comfortable range. E-bike purchase-rebate programs of the kind now operating in a growing number of U.S. cities, secure bicycle parking and charging at homes, workplaces, and transit stations, and the integration of electric-assist options into shared-micromobility fleets all widen the set of destinations reachable without a car. That this widening actually shifts trips away from driving is already evident where rebate programs operate, with recipients consistently reporting that e-bike trips replace car travel (Johnson et al., 2023; Meng et al., 2025). On the weather side, policy cannot change the climate, but it can shrink the number of days on which conditions rule active travel out. Clearing snow and ice from sidewalks and bicycle lanes with the same priority given to roadways, planting street trees that shade summer routes, and providing covered bicycle parking and sheltered waiting areas extend the season over which active travel remains comfortable. Local planning and zoning commissions, public works departments, employers, transit agencies, and shared-micromobility operators are the key implementation partners. Together, these measures reach a group that better sidewalks and bicycle lanes alone cannot.

5.5 Supporting Older Adults Through Age-Friendly Mobility Design

As highlighted at the opening of this section, older adults represent a rapidly growing share of the worldwide population, and active living is among the most important contributors to physical and mental health and quality of life in later life. For many older adults, walking is a principal source of daily physical activity, supporting the strength, balance, and cognitive engagement that underpin independent living (Bauman et al., 2016). The stakes of inactivity are also higher at older ages. Reduced mobility and safety concerns, particularly the fear of falling or getting hurt, can trigger a self-reinforcing cycle in which less walking diminishes physical capability, which in turn leads to even less walking (Freiberger et al., 2020). Keeping older adults engaged in active travel is therefore not simply a matter of mode choice, but a means of interrupting this downward spiral before it takes hold.

Our ATE results underscore how steep the age gradient is. Age has the largest effect on the probability of being an NRAT of any exogenous variable in the model. The prevalence of NRAT status is essentially unchanged between adults aged 25 to 44 and the youngest adults, but is roughly 73% higher among those aged 45 to 64, more than twice as high among those aged 65 to 74, and nearly three times as high among those aged 75 and older. In sharp contrast, the prevalence of the specific barriers varies little with age. Adults aged 25 to 64 cite trip-length mismatch about a fifth less often than the youngest adults, while those aged 75 and older cite insufficient lighting and distracted drivers substantially less often, consistent with the more discretionary schedules that allow older adults to avoid nighttime and peak-period travel (see Section 4.2). The implication, then, is that what holds older adults back is not any single perceived feature of the travel environment, but rather the broader erosion of physical capability and mobility-related self-efficacy that accompanies aging. Older adults, therefore, may be better served by broad mobility support and age-friendly design than by any one infrastructure fix.

The appropriate actions accordingly span three fronts: (1) physical design, (2) social support, and (3) technology, paralleling the strategies identified in Hwang et al. (2025). On the

physical design front, agencies can extend pedestrian signal times to accommodate the slower walking speeds documented among older adults (Duim et al., 2017; Western et al., 2025), add median refuge islands at wide crossings, place benches and rest points at regular intervals along routes serving senior housing and medical destinations, maintain smooth walking surfaces free of tripping hazards, ensure adequate lighting, and locate everyday services near concentrations of older residents so that trip distances remain within comfortable walking range (Cerin et al., 2017; Stearns et al., 2023). Similar attention to parks and community spaces, with flat and well-maintained paths, gentle inclines, and ample seating, provides secure and inviting settings for recreational walking (Veitch et al., 2020). On the social support front, group walking programs and buddy systems, organized through partnerships among senior centers, parks and recreation departments, and healthcare providers, directly address the confidence and security concerns that discourage walking alone, while providing the companionship, guidance on safe and accessible routes, and accountability that sustain an active routine (Hwang et al., 2025). Travel-training and escorted-trip programs can further ease the transition to active and transit modes for those uncertain about navigating them alone (Mwaka et al., 2026). On the technology front, wearable devices that detect falls and summon help can ease the safety fears that keep some older adults indoors, and device-lending or subsidy programs can put them within reach of those who would not otherwise acquire them. Senior centers, area agencies on aging, healthcare providers, and transit agencies are well positioned to deliver these measures, and the age-friendly community frameworks already adopted by many U.S. jurisdictions offer a ready institutional vehicle for coordinating them (Forsyth and Lyu, 2024).

6. CONCLUSION

This study has investigated why a substantial segment of the U.S. adult population never or rarely uses active modes for travel, and the specific perceived concerns that underlie this non-use or low use. The analysis draws on the second wave of the THA Survey, fielded in February and March 2026 with quota controls designed to approximate the composition of the U.S. adult population, yielding a final estimation sample of 8,273 adults after appending residential BE measures from the EPA Smart Location Database. A multivariate binary probit model is employed to identify the population groups who are more likely to be NRATs, as well as the specific barriers that lead to low levels of active travel uptake among these groups. We consider seven different barriers spanning infrastructural deficiencies, traffic safety, personal security, and practical constraints. The joint estimation accommodates unobserved correlations between the propensity to be an NRAT and the propensity to cite each barrier, allowing barrier propensities to be recovered for the population as a whole rather than only for the self-selected group that reports them, and ATEs translate the estimates into policy-relevant magnitudes.

The findings suggest that infrequent use of active travel is concentrated among women, older adults, non-employed individuals, and members of vehicle-sufficient households. The prevalence of the specific barriers, however, varies substantially across the population, and in ways that aggregate shares conceal. Women and renters, for example, report far greater concern about loitering or threatening behavior than their counterparts despite the low aggregate prevalence of that barrier, and Hispanic respondents report elevated concerns related to insufficient lighting and personal security. Residential BE characteristics, with the exceptions of the neighborhood socioeconomic profile and the National Walkability Index, have a modest influence on whether someone is an NRAT, but they substantially shape the barriers that are reported. The findings underscore the need for a differentiated policy agenda in which intervention instruments are

matched to the populations and barriers they are best placed to address. By tailoring interventions in this way, planners and policymakers can make active travel a realistic option for those who currently rarely use active modes, while also improving the everyday experience of those who already use active modes despite the barriers they perceive.

The research in this study may be advanced in several directions. First, the barrier outcomes record the concerns respondents report rather than their measured environmental exposures, and future studies that pair the two, for example by matching reported concerns to audited or GPS-derived conditions along the routes respondents actually face, would sharpen the link between perceived barriers and the infrastructure and policy levers meant to address them. Second, data collected at a single point in time cannot reveal whether specific interventions of the kind proposed in the paper actually shift the barrier perceptions they target. Such evaluations will require before-after intervention data, followed by analysis with very careful controls for other evolving conditions between the before and after periods. Third, a security-related barrier involving interactions with law enforcement or security officers was cited by too few respondents to estimate reliably and was set aside despite its distinct equity implications, so future data collection should deliberately reach the populations most likely to experience it. Finally, the data reveal which barriers accompany infrequent use but not how active travelers adapt to them, and surveys that directly measure coping behaviors, such as rerouting, retiming trips, or traveling with companions, would show how active travel is sustained under conditions this study can only show to be present.

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