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Do changes in the residential location lead to changes in travel attitudes? A structural equation modeling approach

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Abstract

Numerous studies have found that travel attitudes might not only affect travel behavior, but also the residential location choice as people might choose a residential location based on their travel preferences and needs (i.e. transport-related residential self-selection). However, it might also be possible that the residential location and travel behavior influence attitudes towards travel. In this study—using quasi-longitudinal data—we analyze how a change in the residential environment affects attitudes towards specific modes, both directly and indirectly through changes in mode frequency (of commute and leisure trips). Using a structural equation modeling approach on 1650 recently relocated residents in the city of Ghent, Belgium, this study indicates that moving to a more urban type of neighborhood improves attitudes towards public transport and active travel. Especially for leisure trips the effects from changes in the built environment on attitudes are partly indirect through changes in mode frequency. This study offers new insights into the links between the built environment, travel behavior and attitudes. We provide further evidence that the built environment influences travel attitudes, but also indicate that these effects are partly mediated by travel mode frequency.

Keywords Travel behavior · Residential self-selection · Attitudes · Built environment · Structural equation modeling

Introduction

Numerous studies have indicated that the built environment—and the residential location in particular—has an important impact on how people travel. People living in compact, mixed-use neighborhoods with access to public transport and a design stimulating active travel frequently use modes other than the car. People living in more suburban-style neighborhoods (i.e. with low density and diversity) with limited public transport and active travel facilities mainly travel by car and have relatively long travel distances (see Ewing

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and Cervero 2010, for an overview of studies). Varying travel patterns according to the residential location can be partly explained by differences in household car ownership (e.g. Ding et al. 2017; Van Acker and Witlox 2010). People living in sprawled, single-use areas might be forced to own one or more cars (as public transport is often lacking and destinations are mostly not within walking or cycling distance), therefore stimulating even more car use (even to nearby destinations). People living in urban-style neighborhoods often do not own a car (or more than one car per household) since destinations are often nearby, therefore stimulating active travel and public transport use.

Multiple travel behavior studies have demonstrated that besides the built environment, travel attitudes also have an important impact on people's travel behavior (e.g. Bagley and Mokhtarian 2002; Handy et al. 2005; Kitamura et al. 1997). However, travel attitudes might also influence the residential location choice, as people may consciously choose to live in a neighborhood stimulating their preferred way of travelling (e.g. Handy et al. 2005; Schwanen and Mokhtarian 2005). As a result, it might be difficult to know the extent to which varying travel patterns in different types of neighborhoods can be attributed to the built environment itself, as opposed to attitude-induced residential self-selection (Cao et al. 2009a). In case of self-selection, attitudes can be regarded as a stronger predictor of travel behavior than the built environment (Bagley and Mokhtarian 2002; Kitamura et al. 1997). Not taking into account travel attitudes might consequently result in an overestimation of the effects of the built environment on travel behavior. However, most studies still find statistically significant effects of the built environment after controlling for self-selection (e.g. Cao et al. 2006, 2009b; Handy et al. 2005, 2006; Næss 2009). Since the residential location choice is affected by a wide range of elements (e.g. dwelling and neighborhood characteristics, distance to work, budget limitations), travel attitudes might not always play a decisive role in the choice of where to live. Some studies consequently found that people do not always live in a neighborhood consistent with their travel preferences and needs (e.g. De Vos et al. 2012; Frank et al. 2007; Schwanen and Mokhtarian 2005).

Most travel behavior studies analyzing the links between the built environment, travel behavior and attitudes focus on effects from attitudes to behavior. Some of these studies are inspired by the theory of planned behavior (Ajzen 1991), indicating that behavioral intention is strongly affected by attitudes and considering attitudes to be stable constructs, partly determined by genetic factors. However, other psychological theories indicate that attitudes can change. Both the cognitive dissonance theory (Festinger 1957) and the balance theory (Heider 1958) state that people might change their attitudes so they will better match with their behavior, partly because a dissonance between attitudes and behavior is an undesired situation resulting in psychological discomfort. People might change their attitudes by (subconsciously) attributing positive elements to chosen alternatives and negative elements to non-chosen alternatives, in order to justify the made decision. However, travel behavior studies focusing on the effects of travel behavior and the built environment on travel attitudes are scarce. As a result, possible links between the built environment, travel behavior and attitudes are underexplored.

In this study we will analyze—using quasi-longitudinal data—how a change in people's residential location might affect changes in mode-specific attitudes, both directly and indirectly through changes in mode frequency. A structural equation modeling approach will be performed using 1650 recently relocated residents from the city of Ghent (Belgium). Doing so results in new insights in the links between the built environment, travel behavior and attitudes; i.e. we further examine the (potential) effect of the built environment on travel attitudes, but also take into account the unexplored indirect effects through travel mode frequency. This paper is organized as follows. "Direct and indirect effects of the built environment on travel attitudes" section gives an overview of studies that have analyzed possible effects from the built environment and travel behavior on travel attitudes. "A structural equation modeling approach" section describes the used methodology, while the data is explained in "Data" section. The main results are provided in "Results" section. "Re-evaluating the links between the built environment, travel behavior and attitudes" section discusses the implications of the found results on the links between the built environment, travel behavior and attitudes. A conclusion is provided in "Conclusion" section.

Direct and indirect effects of the built environment on travel attitudes

The effect of travel behavior on travel attitudes

Although most travel studies have—partly based on the theory of planned behavior (Ajzen 1991)—nalyzed the effects of attitudes on behavior, some studies (often performed before Ajzen's study) have also looked at potential changes in attitudes. These studies indicate that travel-related attitudes and mode choice are mutually dependent on each other and that attitudes both affect, and are affected by, choices (Dobson et al. 1978; Golob et al. 1979; Tardiff 1977). Some studies even state that travel behavior influences attitudes more than vice versa (Golob 2001; Kroesen et al. 2017). A number of studies focused on specific travel modes. In a relatively old study, Reibstein et al. (1980) found that the frequency of bus use positively affects attitudes towards buses. Abou-Zeid et al. (2012) and Fujii and Kitamura (2003) found improved attitudes towards public transport of habitual car users switching to public transport (due to receiving a temporary free public transport pass). They indicate that original negative attitudes towards public transport (possibly caused by misperceptions concerning public transport) were corrected by information gained through direct experience of using public transport. Fujii et al. (2001) found that increased public transport ridership—due to a temporary freeway closure—improved attitudes towards public transport, due to changes is perception of commute time. Bagley and Mokhtarian (2002) found that car attitudes are positively affected by car use and negatively affected by walking and cycling. These studies indicate that travel attitudes are more subject to change than often assumed. Based on the existing literature it can be expected that a cyclical process between travel-related attitudes and mode choice exists; a positive stance towards a certain mode can increase the use of that mode, while using that mode frequently might improve the attitude towards that mode.

The effect of the built environment on travel attitudes

Many studies have found that people's travel attitudes are mostly consistent with their residential neighborhood, assuming that people try to choose a neighborhood stimulating their preferred travel mode(s) (i.e. residential self-selection). However, it might also be possible that people change their travel attitudes so they better match with the travel patterns stimulated by the residential location. Some studies analyzing the effects of travel attitudes on the built environment have acknowledged that opposite effects might also be feasible (Bohte et al. 2009; Cao et al. 2009a; Chatman 2009; Handy et al. 2005; Kitamura et al. 1997; Næss 2009). However, studies have not yet reached a consensus on whether the built environment exerts an (important) effect on travel attitudes. Bagley and Mokhtarian (2002), for instance, did not find significant effects of respondents' residential location on

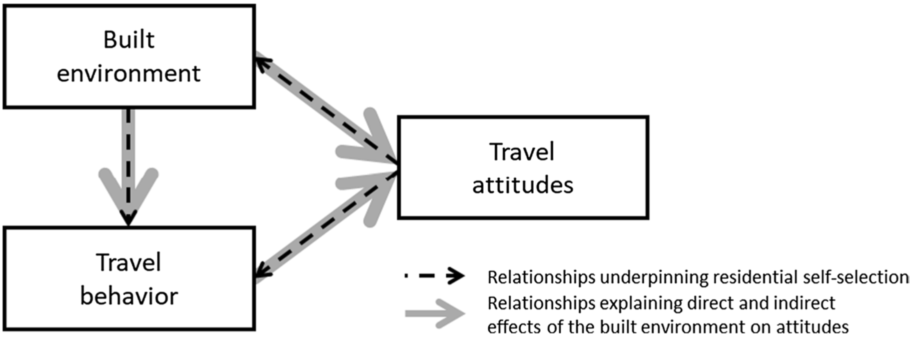

Fig. 1 Relationships between the built environment, travel behavior and attitudes

their travel attitudes. Other studies, using cross-sectional structural equation models to analyze links between travel behavior, the built environment and attitudes, did find significant bidirectional relationships between the built environment and travel preferences (de Abreu e Silva 2014; Ewing et al. 2016; Van Acker et al. 2014). In a Dutch study, van de Coevering et al. (2016)—using two-wave panel data—indicate that distance to public transport (i.e. living far away from a railway station) has a positive effect on car attitude and a negative effect on public transport attitude. Another Dutch study using (different) panel data indicates that those living close to a railway station are—over time—more likely to state that short distances (to public transport, shops and workplace) were an important reason for their current residential location choice (Kroesen 2019). Lin et al. (2017)—using cross-sectional data from Beijing, China—found that the residential environment can affect travel mode preferences, especially when the residential location choice was not based on travel attitudes. Finally, two studies focusing on recently relocated residents found that attitudes towards travel modes significantly changed after respondents moved, becoming more in line with travel stimulated by the new built environment (De Vos et al. 2018; Wang and Lin 2019). The built environment might not only affect travel attitudes directly, but also indirectly through travel patterns stimulated by the built environment. A person living in an urban environment might have positive attitudes towards active travel since the built environment might stimulate this person to frequently walk or cycle. However, none of the above-mentioned studies have explicitly focused on direct and indirect effects of the built environment on travel attitudes. As a result, the nature and extent of the effect of the built environment on travel attitudes is up till now poorly understood.

Figure 1 gives an overview of the links between the built environment, travel behavior and travel attitudes. The relationships underpinning residential self-selection (black, dashed line arrows) have frequently been measured in previous studies. In this paper we focus on the (less-studied) direct and indirect effects of the built environment on attitudes (bold, grey line arrows). Some studies refer to these effects as the 'reverse causality' hypothesis (Kroesen 2019; van de Coevering et al. 2016, 2018; van Wee et al. 2019). However, since we do not assume that the effects of the built environment and travel behavior on attitudes are a reaction of—or stronger than—the effects of travel attitudes on the built environment and travel behavior, we will not use this term in the current study. We will not focus on the built environment, travel behavior and attitudes itself, but on changes in these elements. Respondents in this study have recently relocated to selected neighborhoods in the city of Ghent (Belgium), therefore changing their residential environment, and possibly also their travel behavior and attitudes. These dynamics in built environment, travel behavior and attitudes result in an interesting case study to analyze direct and indirect effects of the built environment on travel attitudes.

A structural equation modeling approach

In this study we will apply a structural equation modeling approach. Such an approach is useful for representing multiple relationships among a set of variables, in which a certain variable can be the outcome (dependent variable) in one set of relationships, and a predictor of outcomes (explanatory variable) in other relationships. Unlike regression, a structural equation model (SEM) can measure both direct effects between variables and indirect effects through mediating variables. Since we want to analyze the effect of the built environment on travel attitudes, both directly and indirectly through travel behavior, a SEM approach is an appropriate methodology. Two types of SEMs—which can be combined—exist, i.e. a measurement model and a structural model. A measurement model (also known as confirmatory factor analysis) specifies the relationships between latent variables and their observed indicators, while in the structural model relationships between the latent variables are modelled (Golob 2003; Mokhtarian and Ory 2009). Since our variables are directly observed (manifest variables) a measurement model has not been specified, and we only estimate a structural model.

In the travel behavior field, SEMs have regularly been used since the 1980s (Golob 2003), although most studies using this approach have been performed in the past two decades. Studies have used the SEM approach to analyze relationships between travel behavior, built environment, car ownership, travel distance and travel attitudes. Some studies have used this approach to examine the indirect effect of the built environment on car use, through car ownership (Aditjandra et al. 2012; Ding and Lu 2016; Van Acker and Witlox 2010). De Abreu e Silva et al. (2006, 2012) analyzed the effects of land use characteristics on travel behavior, directly and indirectly through commuting distance. Ding et al. (2017) measured the effect of the built environment on travel mode choice considering the mediating effects of both car ownership and travel distance. SEMs have also been applied for measuring self-selection effects. Both Bagley and Mokhtarian (2002) and Cao et al. (2007) found that travel attitudes have a significant effect on travel behavior, both directly and indirectly through the residential location choice. Some studies also included direct links from the built environment to travel attitudes in their SEMs (Bagley and Mokhtarian 2002; de Abreu e Silva 2014; Ewing et al. 2016; Lin et al. 2017; Van Acker et al. 2014; see Sect. 2.2). Other transport studies using a SEM approach have focused on elements such as travel satisfaction (De Vos 2019; De Vos et al. 2019b; Gao et al. 2017), transport-related social exclusion (Currie and Delbosc 2010), perceived public transport service quality (de Oña et al. 2013; Lai and Chen 2011), or analyzed the relationship of travel-related elements with activity participation (Kuppam and Pendyala 2001; Lu and Pas 1999; Maat and Timmermans 2009), e-shopping (Cao et al. 2012; Farag et al. 2007), and information and communication technologies (Choo and Mokhtarian 2007; Ren and Kwan 2009; Wang and Law 2007).

Data

For this study we use data from a 2017 online survey on travel behavior (changes) of recently relocated residents. Within the city of Ghent (Belgium; 258,000 inhabitants), we selected multiple urban and suburban neighborhoods. Approximately 101,300 people (situation 2017) reside in the selected neighborhoods, accounting for 39.3% of all residents in the city of Ghent (https://gent.buurtmonitor.be). The urban neighborhoods are located directly around the central business area and are characterized by a relatively high average population density (8000 inhabitants per km^2), highly mixed land uses and can be regarded as a low-traffic area with good public transport services. The suburban neighborhoods are located around 3–6 km from the city center, have a considerably lower average density (1800 inhabitants per km^2), lower diversity, and limited public transport services. In February 2017, 9979 survey invitations were distributed among all the households within the selected neighborhoods that relocated in the last two years (i.e. between January 2015 and December 2016). Addresses of residents relocating to the set of selected urban and suburban neighborhoods in 2015 and 2016 were obtained from the city of Ghent administration. Respondents are evenly distributed according to how long before filling out the survey they moved (49.1% indicates to have moved in 2015, versus 50.9% in 2016). In the end, 1842 adults participated, of which 1650 respondents completed the survey, resulting in a response rate of 16.5%.

Table 1 shows the socio-demographic characteristics of the respondents. Most respondents are highly educated (77.2%), live in urban neighborhoods (67.4%) and are—mainly full-time—employed (83.5%). There are somewhat more men than women in the sample (52.1% versus 47.9%) and most respondents live together as a couple without children living at home (37.3%), or are single (29.9%). Somewhat more than half of the respondents (53.2%) lives in a household with a monthly net income lower than €2500. Respondents in our sample are noticeably young, as almost half of them (49.5%) are younger than 30 years old. This is, however, not that surprising since young adults are—compared to older adults—more likely to relocate due to a considerable amount of life events taking place during early adulthood (e.g. entry into the labor market, formation of a household with partner, having children). In contrast to young adults being overrepresented, other socio-demographics of our respondents (e.g. income, gender, household composition) are comparable to the total population of the selected neighborhoods (https://gent.buurtmonitor.be). We cannot claim to have a fully representative sample of the total population of selected neighborhoods. However, since all recently relocated residents in the selected neighborhoods were invited to participate, our sample is probably representative for the group of people relocating to these neighborhoods (although we cannot make a statement on representativeness since we do not have information on the socio-demographics of all movers). Anyhow, we do have a relatively large sample size, making it possible to estimate relationships with ample confidence (e.g. Groves 1989). For more details on the neighborhood selection and sampling recruitment, see De Vos et al. (2018, 2019a).

In this study we will estimate the model shown in Fig. 2, and this for both commute trips and leisure trips, and for four different travel modes (i.e. car, public transport, cycling

Table 1 Respondents' socio-demographic characteristics (N = 1650)

Socio-demographics	%
Personal characteristics	
Age distribution	
18–29	49.5
30–44	29.1
45–59	13.4
60 +	8.0
Gender	
Female	47.9
Male	52.1
Education	
High education (University (college) degree)	77.2
Job status	
Full time	72.8
Part time	10.7
Unemployed	6.4
Retired	6.9
Student	3.2
Household characteristics	
Household composition	
Single	29.9
Single parent	5.9
Couple without children	37.3
Couple with children	14.6
Other (e.g. living with parents, with friends)	12.3
Household net income/month	
< €1500	13.5
€1500—€2499	39.7
€2500—3499	19.2
€3500 +	27.6
Residential location	
Urban neighbourhood	67.4
Suburban neighbourhood	32.6
Household car ownership	
0	25.5
1	54.3
> 1	20.2

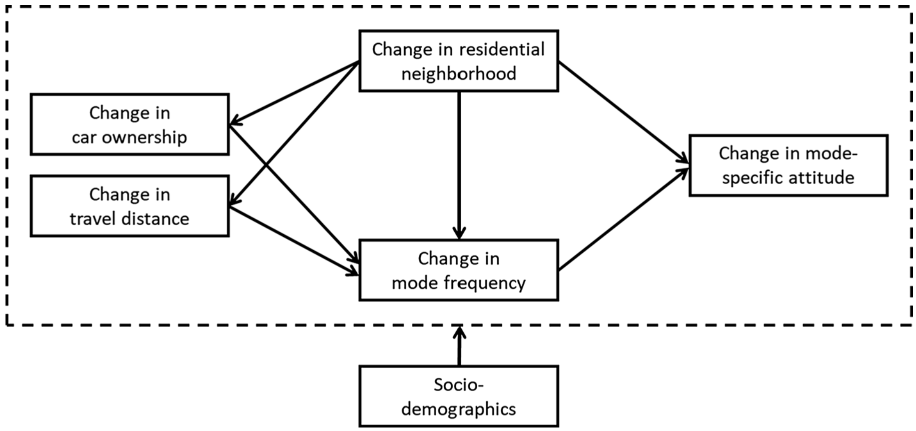

Fig. 2 Conceptual structural model

and walking).[1] As a result, eight models will be estimated.[2] In these models, we will not focus on respondents' current residential neighborhood, travel behavior and travel attitudes, but we will analyze self-reported changes in the type of residential neighborhood, changes in travel patterns and changes in travel attitudes resulting from a residential relocation. Quasi-longitudinal data have the advantage that they can capture (self-reported) changes in people's behavior and attitudes without needing to collect (expensive and time consuming) longitudinal data. Of course, the reported changes might be less reliable than changes measured by data collection using multiple waves. Quasi-longitudinal data are occasionally used in travel behavior studies (e.g. Aditjandra et al. 2012; Cao and Ermagun 2017; Cao et al. 2007; Handy et al. 2005).

A residential relocation is an interesting opportunity to examine potential changes in travel attitudes since a residential move is often accompanied by changes in neighborhood type and travel patterns. The models will measure the effects of changes in the type of residential neighborhood on changes in mode-specific attitudes, both directly and indirectly through changes in the frequency of use of that particular mode. Since distance and car ownership can be affected by the residential location and can in turn affect travel mode choice, we added links from changes in residential neighborhood to changes in car

[1] Since unemployed and retired respondents do not perform commute trips (trips to job/school location), these respondents were not included in the models focusing on commute trips. As a result, the models on commute trips include 1430 respondents, while the models on leisure trips include 1650 respondents.

[2] We also estimated these models for urban and suburban residents separately (i.e. 16 models in total). However, direct effects from (i) socio-demographics on change in neighborhood and (ii) change in neighborhood on the other endogenous variables (i.e. change in car ownership, distance, mode frequency and attitudes) are considerably less strong in the separate models. This can – most likely – be explained by the limited variance in the variable 'change in neighborhood' when dividing the sample in urban versus suburban respondents (i.e. urban residents mainly moved to more urban neighborhoods and suburban residents mainly moved to less urban neighborhoods). As a result, we do not present the separate models for urban and suburban residents in this study. The models were also measured for all travel modes and mode-specific attitudes combined (i.e. two models in total, one for commute trips and one for leisure trips). However, this resulted in unsatisfactory goodness-of-fit measures, probably caused by the increased level of complexity (both models have eleven endogenous variables).

ownership and changes in distance, and links from changes in car ownership and changes in distance to changes in mode frequency. Previous studies using a SEM approach have also included car ownership (changes) and distance (changes) as mediating variables in the effects of (a change in) residential location on (changes in) mode frequency (e.g. Aditjandra et al. 2012; Cao et al. 2007; de Abreu e Silva et al. 2012; Ding et al. 2017; Van Acker and Witlox 2010).[3] Finally, we also took into account respondents' socio-demographic characteristics by including them as exogenous variables in the models. In the end, the following variables were included in the SEMs:

- Change in residential neighborhood: Respondents were asked to indicate to what extent their current neighborhood is less or more urbanized compared to their previous neighborhood, on a scale from −2 (far less urbanized) to + 2 (far more urbanized).[4]
- Change in car ownership: We asked respondents to report their current household car ownership and the household car ownership just before they relocated. The change in car ownership is measured by subtracting the previous car ownership from the current car ownership.
- Change in travel distance: For commute trips and leisure trips respectively, we asked respondents to what extent the distance to their job/school location and the average distance to out-of-home leisure activities changed after they moved, on a scale from −2 (a lot shorter) to + 2 (a lot longer).
- Change in mode frequency: For both commute trips and leisure trips, we asked respondents to what extent their frequency of car use, public transport use (bus, tram, train), cycling, and walking changed after their residential location, on a scale from −2 (far less frequent) to + 2 (far more frequent).
- Change in mode-specific attitude: Respondents were asked to indicate to what extent their attitude towards car use, public transport use, cycling and walking changed after they moved, on a scale from −2 (far more negative) to + 2 (far more positive).
- Socio-demographics: Respondents' age (in years), gender (0 = male; 1 = female), educational level (0 = low education (secondary school degree or less); 1 = high education (college or university degree)), household net income/month (0 = low income (< €2500); 1 = high income (€2500 +)), and non-adult children living at home (0 = no; 1 = yes).

Table 2 shows how respondents' residential neighborhood, travel patterns and attitudes have changed due to their residential relocation. In general, a considerable share

[3] Although bidirectional effects between changes in car ownership and travel distance can be expected (i.e. longer average travel distances resulting in a possible purchase of a car, and owning a car resulting in longer travel distances), we did not include these in the models, in order not to unnecessarily complicate the models.

[4] Change in residential neighborhood could also have been measured using spatial attributes (e.g. density, diversity, and distance to city center) of both the previous and current residential location. However, since we were afraid that a considerable share of the respondents would not have been inclined to give detailed information on their previous and current residential location, we decided to directly ask them to what extent their current neighborhood differs from their previous one in terms of urbanization. Since it is possible that respondents interpret urbanization differently from each other and different from our view on urbanization, we tried to reduce this potential difference in interpretation by adding the following clarification in the survey: "In this study, the level of urbanization is interpreted as the extent to what an environment is characterized by a high density of buildings and a high diversity of amenities such as shops, dwellings, hotel and catering, offices and schools.".

Table 2 Changes in respondents' residential neighborhood, travel patterns and attitudes (PT = public transport)

Change in neighborhood	Far less urban	Less urban	Remained stable	More urban	Far more urban
	6.3%	15.0%	32.7%	21.8%	24.2%
Change in mode freq. (commute—leisure)	Far less frequent	Less frequent	Remained stable	More frequent	Far more frequent
Car frequency	19.0—16.2%	10.1—16.9%	53.0—48.8%	9.0—12.7%	9.0—5.4%
PT frequency	15.5—7.5%	10.6—12.7%	55.9—52.1%	12.9—22.1%	5.2—5.6%
Cycling frequency	11.9—7.2%	8.7—11.2%	49.8—48.2%	14.0—21.4%	15.7—12.1%
Walking frequency	13.1—5.3%	7.1—9.9%	56.2—44.3%	13.5—25.7%	10.0—14.8%
Change in household car ownership	Decreased by two or more	Decreased by one	Remained stable	Increased by one	Increased by two or more
	4.5%	15.0%	68.7%	11.3%	0.6%
Change in distance (commute—leisure)	A lot shorter	Shorter	Remained stable	Longer	A lot longer
	22.7—14.7%	16.7—22.1%	34.6—40.5%	17.1—18.9%	8.8—3.9%
Change in mode-specific attitude	Far more negative	More negative	Remained stable	More positive	Far more positive
Car attitude	1.9%	8.8%	72.0%	13.2%	4.1%
PT attitude	1.6%	10.1%	66.6%	17.9%	3.8%
Cycling attitude	1.5%	7.4%	58.3%	23.4%	9.4%
Walking attitude	1.0%	5.0%	53.9%	28.8%	11.3%

of respondents moved to a more urban-style neighborhood and travels shorter distances then before the move. This can be partly explained by the fact that we have a large share of urban respondents and that a considerable share of respondents relocated to live closer to their job (27.9%) or indicated that proximity of leisure activities was important in the choice of where to live (48.3%). Although mode frequency and mode-specific attitudes remained stable for a large share of respondents, car frequency regularly decreased while walking and cycling frequency often increased (mainly for leisure trips). Attitudes towards active travel improved for a considerable share of respondents, while attitudes towards car use and public transport use mostly remained stable. Household car ownership did not change for most respondents, although a decrease in car ownership occurs more often than an increase in car ownership.

The used variables are ideal for measuring the effects of the built environment and travel behavior on travel attitudes since they measure changes in residential neighborhood, travel behavior and attitudes after respondents relocated. As a result, they would not have been suited to test effects from attitudes to the residential location (since attitudes before the relocation affect residential location choice). A reciprocal relationship between (changes in) travel behavior and attitudes is plausible and can potentially be measured using our data. However, such a non-recursive model turned out not be identifiable, making it impossible to estimate it. A plausible model with unidirectional effects from changes in mode-specific attitudes to changes in mode frequencies is identifiable, and is presented and described in detail in a parallel study (De Vos et al. 2020).[5]

Most variables included in the models (except for socio-demographics and changes in car ownership) capture self-reported, retrospective changes in residential neighborhood, behavior and attitudes measured by a five-point Likert scale. As a result, these (directly observed) manifest variables are ordinal in nature and can be regarded as subjective and rather crude measurements, making it difficult to truly capture the magnitude of (relationships between) changes in the built environment, changes in travel behavior, and changes in attitudes. Ideally, more precise and continuous measures, preferably longitudinal and latent (unobserved) variables should be used. Retrospectively measuring changes in attitudes is not common in travel behavior studies. Some studies argue that it is infeasible or unreliable to retrospectively measure travel attitudes (Bohte et al. 2009; Cao et al. 2007; Mokhtarian and Cao 2008). However, we found three studies that measured cycling attitudes retrospectively. Underwood et al. (2014) analyzed childhood and teenage experiences with and attitudes towards cycling as seen in retrospect from adulthood, while Thigpen (2019a,b) asked undergraduate juniors and seniors to recall their cycling attitudes in their previous years at University of California, Davis. Although retrospectively measuring attitudes remains subject to debate—as it is vulnerable to memory and consistency biases (i.e. unreliable attempts to recall one's attitudes and confounding previous attitudes with current one's, respectively)—this measurement method can be considered as reliable since studies have indicated that results are often similar with longitudinal measurements of attitude change (Haggard et al. 1960; Jaspers et al. 2009), a result that also has been found for cycling attitudes (Thigpen 2019a,b).

[5] In this parallel study, we analyze the effects of changes in residential neighborhood on changes in mode frequency, both directly and indirectly through changes in car ownership, travel distances and travel attitudes. Results indicate that the built environment has strong direct effects on active leisure trips and car use, while distance (for car use) and attitudes (for active travel) were found to be important mediating variables (De Vos et al. 2020).

Results

Multivariate normality and goodness-of-fit

The maximum likelihood estimation (MLE) approach—by far the most commonly used estimation technique—was chosen to develop the SEMs. MLE is based on normal theory and is therefore not strictly theoretically appropriate when the data are not multivariate normal. However, it is quite common to find that observed variables in SEMs are not multivariate normal (Cao et al. 2007; Mokhtarian and Ory 2009). The variables we used in the eight models also do not have the multivariate normal distribution. The critical ratio, which is supposed to be lower than 1.96 in order to signify departure from multivariate normality with 95% confidence, is between 6.97 and 15.30 in our models, which can be considered as moderate non-normality (Mokhtarian and Ory 2009; Ory and Mokhtarian 2010). We tried several approaches (such as transforming certain variables or removing some observations (i.e. outliers))[6] to reach multivariate normality, but none of them produced satisfactory results. Although our models deviate from the multivariate normality assumption, the influence of non-normal data is reduced when using MLE with a large sample size, i.e. approximately a ratio between sample size and the number of observed variables of at least 15, or a sample size larger than 500 (Cao et al. 2007). In our model the ratio between sample size and variables is clearly higher than 15 (i.e. 143 for the commute models and 165 for the leisure models) and our sample size is around three times as large as recommended (i.e. 1430 for the commute models and 1650 for the leisure models). Furthermore, estimates resulting from an MLE approach are mostly found to be robust under violations of multivariate normality (Boomsma 1987). As a result, we do not expect that the non-normality of the data will be a serious problem in our case.[7]

We analyzed how well the models fit the used data by examining various goodness-of-fit measures. Since the values of these measures were not satisfactory, we decided to remove insignificant paths (i.e. paths with a p-value larger than 0.1) from socio-demographics to the endogenous variables in the models.[8] As a result, we still measure the essence of the model as shown in Fig. 2, while discarding insignificant paths from socio-demographics to

[6] Multivariate normality can be improved by transforming variables which have high kurtosis values (e.g. by taking the natural log or square root) (Bagley and Mokhtarian 2002; Mokhtarian and Ory 2009). However, in our models, only the variable 'change in car ownership' had a high kurtosis value (i.e. 3.7 in the commute models and 4.0 in the leisure models). Transforming this variable did not significantly improve the outcomes, so we decided to keep the original variable. We also tried to improve multivariate normality by removing outliers (based on the Mahalanobis distance) ten at a time. However, in all the eight models, multivariable normality was still not achieved after removing 100 cases. Since removing more than 100 cases would result in a considerable loss of information and model power (Gao et al. 2008), we have chosen not to remove outliers.

[7] A possible alternative for the MLE approach – not requiring multivariate normality – is the asymptotic distribution free (ADF) estimation technique. Activity-travel behavior studies demonstrated that model coefficients estimated by MLE are mostly identical to those obtained by an ADF approach (Golob and McNally 1997; Kuppam and Pendyala 2001). However, ADF requires at least 1,000 cases, and preferably more than 2,500 cases (Mokhtarian and Ory 2009; Ory and Mokhtarian 2010). As a result, our sample can be considered rather small for using the ADF technique. Furthermore, the literature suggests that ADF is often difficult to use in practice and often does not perform well (Ory and Mokhtarian 2010). We also measured our models using the ADF approach but found that these models were inferior to the models using MLE. We therefore chose the MLE approach for our final models.

[8] Paths with the highest p-values were removed one by one (i.e. backward elimination) until all p-values of paths from socio-demographics to endogenous variables were lower than 0.1.

Table 3 Measures of fit for the SEMs; recommended values shown in brackets (for a description of the measures, see e.g. Mokhtarian and Ory 2009)

	Commute models (N = 1430)				Leisure models (N = 1650)			
	Car	PT	Cycling	Walking	Car	PT	Cycling	Walking
χ^2/degrees of freedom (< 5)	2.423	1.118	1.204	2.246	2.126	2.311	2.235	2.753
GFI; Goodness-of-fit index (> 0.9)	0.994	0.997	0.997	0.995	0.996	0.995	0.995	0.993
AGFI; Adjusted goodness-of-fit index (> 0.9)	0.982	0.991	0.991	0.983	0.986	0.984	0.985	0.981
NFI; Normed fit index (> 0.9)	0.948	0.972	0.979	0.961	0.963	0.955	0.966	0.962
RFI; Relative fit index (> 0.95)	0.870	0.929	0.943	0.898	0.907	0.889	0.915	0.915
IFI; Incremental fit index (> 0.9)	0.969	0.997	0.996	0.978	0.980	0.974	0.981	0.976
CFI; Comparative fit index (> 0.9)	0.968	0.997	0.996	0.977	0.979	0.973	0.980	0.975
RMSEA; Root mean square error of approximation (<0.08)	0.032	0.009	0.012	0.030	0.026	0.028	0.027	0.033

endogenous variables (which can be considered as conceptually less important).[9] Doing so resulted in goodness-of-fit measures which can be considered as very good (Table 3), indicating that the (adjusted) models fit the data well.

Estimation results

The direct effects estimated for the eight models are shown in Tables 4, 5, 6, 7, 8, 9, 10 and 11, and an overview of the direct and total effects between changes in neighborhood, mode frequency and attitudes is provided in Fig. 3. Results indicate that a change in the level of urbanization can affect mode-specific attitudes. We found that moving to a more urban neighborhood significantly improves attitudes towards public transport use, cycling, and especially walking. For commute trips, the effect of changes in neighborhood on attitudes is mainly direct, while rather strong indirect effects through mode frequency changes exist for leisure trips. This indicates that a residential relocation has a stronger effect on changes in mode frequency for leisure trips compared to commute trips, possibly because job locations are mostly located outside the residential neighborhood,[10] while people often perform leisure activities within the residential neighborhood. As a result, leisure trips might be more affected by changes in the residential environment. For public transport and cycling, for instance, we did not find significant effects of changes in neighborhood on changes in commute mode frequency. An increased frequency of public transport and active travel significantly improves the attitude towards that particular mode. For car use, however, this effect is non-significant or weak (for commute trips and leisure trips, respectively). Due to the weak effects from changes in the built environment and car frequency on changes in car attitude, changes in car attitude are poorly explained by the models (Squared multiple

[9] Although a SEM approach is often considered as confirmatory, it is often a combination of confirmatory and exploratory purposes. Studies often apply a SEM, find it to be inadequate, and then test an alternative model based on the output of the original model. Since we cannot be certain of relationships before testing them, we still need considerable exploration to identify the relationships that best fit the data (Garson 2015).
[10] The average one-way commute distance of respondents is 21.9 km.

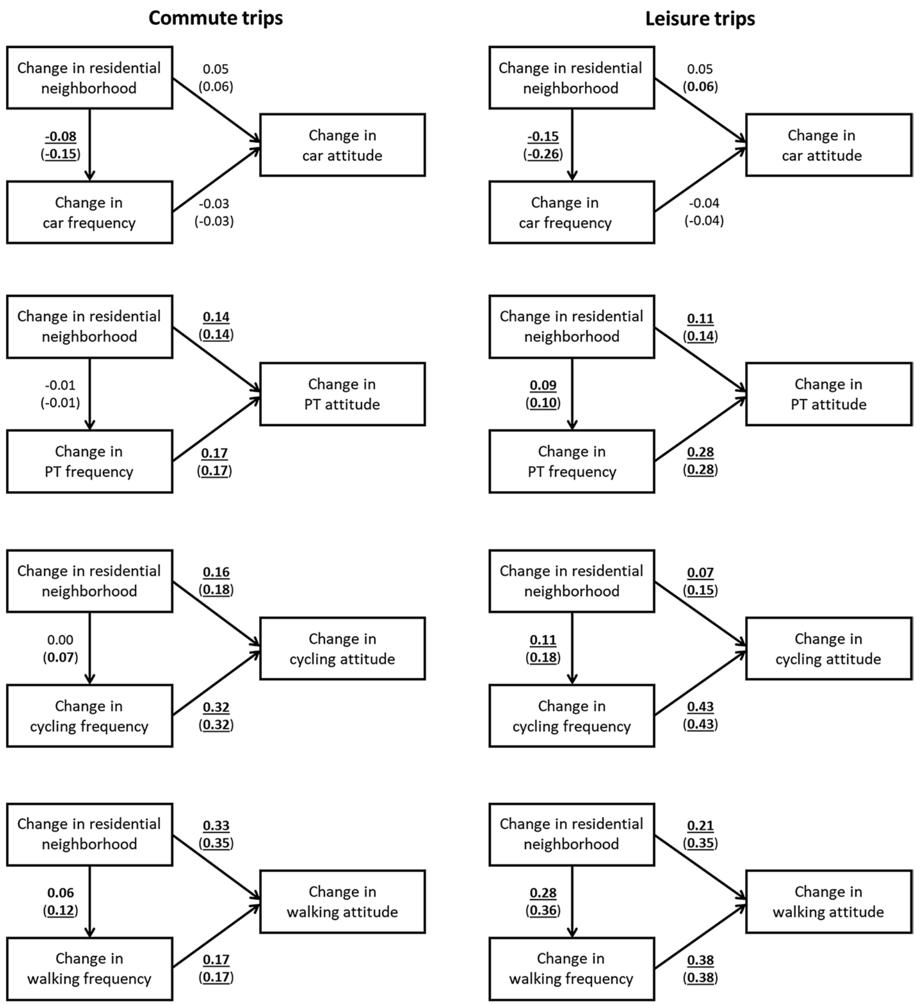

Fig. 3 Overview of direct effects and total effects (in brackets) of relationships between changes in residential location, mode frequency and mode-specific attitudes (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

correlations (R^2s) are only 0.01 for both car models). The models clearly explain changes in public transport attitudes, and especially cycling and walking attitudes a lot better (R^2s for changes in attitudes towards public transport, cycling and walking are respectively 0.06, 0.14 and 0.16 for commute trips, and 0.12, 0.21 and 0.25 for leisure trips).

Changes in distance and car ownership are important mediating variables explaining the effect of changes in neighborhood on changes in mode frequency (Tables 4, 5, 6, 7, 8, 9, 10 and 11, Fig. 3). Moving to a less urban neighborhood has a positive effect on household car ownership and travel distance for commute trips and especially leisure trips. Owning more cars and travelling longer distances, in turn, increases the frequency of car use and decreases walking and cycling frequency. Increased public transport use results from

Table 4 Standardized direct effects for the model on car use and commuting (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in commute distance	Change in car frequency	Change in car attitude
Age	<u>**– 0.09**</u>	–	–	<u>**– 0.14**</u>	<u>**0.08**</u>
Gender	–	–	**– 0.06**	–	–
Income	<u>**– 0.10**</u>	<u>**0.08**</u>	**0.05**	0.05	–
Education	<u>**0.08**</u>	–	–	–	–
Children	<u>**-0.14**</u>	–	–	–	–
Change in neighborhood	–	<u>**– 0.16**</u>	<u>**– 0.21**</u>	<u>**– 0.08**</u>	0.05
Change in car ownership	–	–	–	<u>**0.17**</u>	–
Change in commute distance	–	–	–	<u>**0.24**</u>	–
Change in car frequency	–	–	–	–	– 0.03

Table 5 Standardized direct effects for the model on public transport use and commuting (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in commute distance	Change in PT frequency	Change in PT attitude
Age	<u>**– 0.09**</u>	–	–	0.05	<u>**0.12**</u>
Gender	–	–	**– 0.06**	–	–
Income	<u>**– 0.10**</u>	<u>**0.08**</u>	**0.05**	–	–
Education	<u>**0.08**</u>	–	–	–	<u>**– 0.07**</u>
Children	<u>**– 0.14**</u>	–	–	–	–
Change in neighborhood	–	<u>**– 0.16**</u>	<u>**– 0.21**</u>	– 0.01	<u>**0.14**</u>
Change in car ownership	–	–	–	**-0.06**	–
Change in commute distance	–	–	–	**0.06**	–
Change in PT frequency	–	–	–	–	<u>**0.17**</u>

longer distances (for commute trips) and lower car ownership. Changes in distance and car ownership even have modest indirect effects on attitudes towards cycling and walking, through changes in cycling and walking frequency.

The effects of socio-demographics on changes in neighborhood, mode frequency, travel distance, car ownership and attitudes are rather limited, and standardized direct effects are

Table 6 Standardized direct effects for the model on cycling and commuting (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in commute distance	Change in cycling frequency	Change in cycling attitude
Age	**– 0.09**	–	–	**0.06**	**0.06**
Gender	–	–	**-0.06**	–	–
Income	**– 0.10**	**0.08**	**0.05**	–	–
Education	**0.08**	–	–	**0.11**	–
Children	**– 0.14**	–	–	–	**0.06**
Change in neighborhood	–	**– 0.16**	**– 0.21**	0.00	**0.16**
Change in car ownership	–	–	–	**– 0.13**	–
Change in commute distance	–	–	–	**– 0.23**	–
Change in cycling frequency	–	–	–	–	**0.32**

Table 7 Standardized direct effects for the model on walking and commuting (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in commute distance	Change in walking frequency	Change in walking attitude
Age	**– 0.09**	–	–	**0.05**	–
Gender	–	–	**– 0.06**	–	0.04
Income	**– 0.10**	**0.08**	**0.05**	–	**– 0.06**
Education	**0.08**	–	–	**0.07**	–
Children	**– 0.14**	–	–	–	–
Change in neighborhood	–	**– 0.16**	**– 0.21**	**0.06**	**0.33**
Change in car ownership	–	–	–	**– 0.11**	–
Change in commute distance	–	–	–	**– 0.20**	–
Change in walking frequency	–	–	–	–	**0.17**

mostly below 0.1 (Tables 4, 5, 6, 7, 8, 9, 10 and 11). A change in neighborhood seems most affected by socio-demographics. Older respondents living in a high-income household with children tend to move to more suburban-style neighborhoods, while highly educated respondents often move to more urban-style neighborhoods. Changes in car ownership and travel distance, commute distance in particular, mainly seem affected by income.

Table 8 Standardized direct effects for the model on car use and leisure trips (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in leisure distance	Change in car frequency	Change in car attitude
Age	<u>**– 0.07**</u>	–	–	<u>**– 0.18**</u>	0.05
Gender	–	–	– 0.04	–	–
Income	<u>**– 0.08**</u>	<u>**0.07**</u>	–	<u>**0.06**</u>	–
Education	<u>**0.07**</u>	–	–	**0.05**	–
Children	<u>**– 0.15**</u>	–	–	–	–
Change in neighborhood	–	<u>**– 0.17**</u>	<u>**– 0.35**</u>	<u>**– 0.15**</u>	0.05
Change in car ownership	–	–	–	<u>**0.22**</u>	–
Change in leisure distance	–	–	–	<u>**0.20**</u>	–
Change in car frequency	–	–	–	–	-0.04

Table 9 Standardized direct effects for the model on public transport use and leisure trips (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in leisure distance	Change in PT frequency	Change in PT attitude
Age	<u>**– 0.07**</u>	–	–	<u>**0.11**</u>	<u>**0.13**</u>
Gender	–	–	– 0.04	–	–
Income	<u>**– 0.08**</u>	<u>**0.07**</u>	–	–	–
Education	<u>**0.07**</u>	–	–	<u>**– 0.06**</u>	**– 0.05**
Children	<u>**-0.15**</u>	–	–	–	–
Change in neighborhood	–	<u>**– 0.17**</u>	<u>**– 0.35**</u>	<u>**0.09**</u>	<u>**0.11**</u>
Change in car ownership	–	–	–	<u>**– 0.08**</u>	–
Change in leisure distance	–	–	–	0.02	–
Change in PT frequency	–	–	–	–	<u>**0.28**</u>

High-income household members often witness an increase in car ownership and commute distance after relocating. Effects of socio-demographics on changes in mode frequency are rather diverse. Older respondents, for instance, tend to increase their frequency of active travel and public transport use, and decrease their car use frequency. People living in a high-income household tend to travel more by car after they moved, while highly educated respondents mainly seem to cycle more often. Finally, we found that income negatively affects walking attitudes, having children positively influences cycling attitudes, and that being highly educated negatively affects public transport attitudes. Age seems to positively affect improvements in car and especially public transport attitudes.

Table 10 Standardized direct effects for the model on cycling and leisure trips (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in leisure distance	Change in cycling frequency	Change in cycling attitude
Age	<u>**– 0.07**</u>	–	–	– 0.05	–
Gender	–	–	– 0.04	–	–
Income	<u>**– 0.08**</u>	<u>**0.07**</u>	–	–	–
Education	<u>**0.07**</u>	–	–	<u>**0.09**</u>	–
Children	<u>**– 0.15**</u>	–	–	<u>**0.10**</u>	**0.05**
Change in neighborhood	–	<u>**– 0.17**</u>	<u>**– 0.35**</u>	<u>**0.11**</u>	<u>**0.07**</u>
Change in car ownership	–	–	–	<u>**– 0.10**</u>	–
Change in leisure distance	–	–	–	<u>**– 0.14**</u>	–
Change in cycling frequency	–	–	–	–	<u>**0.43**</u>

Table 11 Standardized direct effects for the model on walking and leisure trips (bold = significant at $0.01 < p < 0.05$; bold and underlined = significant at $p < 0.01$)

Explanatory variables	Endogenous variables				
	Change in neighborhood	Change in car ownership	Change in leisure distance	Change in walking frequency	Change in walking attitude
Age	<u>**– 0.07**</u>	–	–	<u>**0.06**</u>	–
Gender	–	–	– 0.04	–	–
Income	<u>**– 0.08**</u>	<u>**0.07**</u>	–	–	-0.04
Education	<u>**0.07**</u>	–	–	–	–
Children	<u>**– 0.15**</u>	–	–	–	–
Change in neighborhood	–	<u>**– 0.17**</u>	<u>**– 0.35**</u>	<u>**0.28**</u>	<u>**0.21**</u>
Change in car ownership	–	–	–	<u>**– 0.10**</u>	–
Change in leisure distance	–	–	–	<u>**– 0.18**</u>	–
Change in walking frequency	–	–	–	–	<u>**0.38**</u>

Re-evaluating the links between the built environment, travel behavior and attitudes

Although we found that the built environment can affect travel attitudes, both directly and indirectly through travel behavior, this does not mean that reverse effects from attitudes to the built environment and travel behavior do not exist. In fact, multiple studies have demonstrated that these effects are likely. In the parallel study using the same data (De Vos et al. 2020), we also found significant effects from attitudes towards public transport, cycling and walking on the use of the respective modes. In sum, this suggests that five relationships are at play between the built environment, travel behavior and attitudes; one from the built environment to travel behavior, and four relations created by the interrelationships between the built environment and travel attitudes, and travel behavior and travel attitudes. These five links can explain certain behavior, i.e. the residential location choice and travel behavior (e.g. travel mode choice), but also changes in attitudes caused by the built environment and travel behavior. Travel behavior is affected by travel attitudes both directly and indirectly, through the residential location choice, while the built environment exerts both a direct and indirect effect (through travel behavior) on travel attitudes.

The question now is: Which effects are in force in which situations? It can be assumed that the effects from attitudes to behavior are not gradually, but intermittently; they mainly occur when a choice has to be made. For instance, travel attitudes will only affect the built environment in case of a residential relocation. These attitudes will also mainly affect travel behavior when people have to make travel-related choices (e.g. travel mode choice). When no choices have to be made, e.g. when a person is not looking for a new place to live, or when a person takes the same travel mode for every trip (i.e. habitual mode choice), attitudes will mostly not affect behavior. The effects from the built environment and travel behavior on attitudes seem more gradually. People will steadily change their attitudes, so they become better in line with the chosen residential neighborhood and ways of traveling stimulated by this neighborhood. Of course, when attitudes keep changing in line with the neighborhood people live in, attitudes will become consistent with the neighborhood (and its related travel), and will not change anymore. It can be argued that an inconsistency between the built environment and travel behavior on the one hand and travel attitudes on the other hand, is only a temporary situation, which diminishes once attitudes become in line with the residential neighborhood and the travel patterns it stimulates (De Vos et al. 2018). As a result, the models measured in this study will probably display less strong effects on changes in attitudes when a random sample is used, and not recently relocated residents (as is the case in our sample). It should be noted that people might not always be able to change their travel attitudes, since they might not find positive elements supporting their behavior (Festinger 1957). For instance, an environmentally aware cycling enthusiast ending up in a rural neighborhood and being forced to frequently travel by car might not see an improvement of his/her car attitudes as this person's forced behavior is not compatible with his/her ideology.

In sum, the relationships between the built environment, travel behavior and attitudes might be more complex than commonly assumed, possibly making it difficult for future studies to disentangle these relationships in a clear way. A potential method that could provide researchers with additional insights could contain of panel surveys including pre-relocation surveys, surveys directly following a relocation and (multiple) post-relocation surveys (Guan et al. 2020). Cross-lagged SEMs could then be applied to measure changes in travel behavior and attitudes. Due to the difficulty of getting in touch with people before relocating (since it is almost impossible to know when households are planning to relocate), targeting future residents of new large-sized housing projects could be an option.

Conclusion

In this paper—using quasi-longitudinal data—we have analyzed direct and indirect effects of changes in the residential neighborhood on changes in travel attitudes. Using a SEM approach on 1650 recently relocated residents, we found that changes in mode-specific attitudes are affected by changes in people's residential location, albeit differently according to travel purpose and travel mode. Attitudes towards public transport and active travel improve after people move to more urban neighborhoods. Changes in the residential neighborhood do not seem to have a strong impact on car attitudes. Due to strong effects of changes in the built environments on changes in mode frequency for leisure trips, changes in the built environment have an important indirect effect on changes in mode-specific attitudes for leisure trips. For commute trips, the effects of neighborhood changes on changes in mode frequency are limited, and as a result indirect effects of neighborhood changes on attitude changes are also limited. In sum, we have indicated that the built environment can affect travel attitudes, both directly and—for leisure trips—indirectly through travel mode choice. To the best of our knowledge, this is the first study exploring this mediating effect of travel mode choice in the effect of the built environment on travel attitudes. This study consequently suggests that besides the well-known effects from attitudes to the built environment and travel mode choice, opposite effects are also likely to occur.

Results from this study indicate that moving to more urban neighborhoods does not only stimulate active travel and public transport use, but can also improve attitudes towards these travel modes (partly indirect through increased use of these modes). Since previous studies have indicated that travel attitudes can influence both travel behavior and the residential location choice, improved attitudes towards active travel and public transport can increase the use of these modes, both directly and indirectly through the residential location choice. As a result, moving to urban neighborhoods can create a positive reinforcement effect between attitudes and usage of active travel and public transport. This can be regarded as an extra motivation for urban planners and policy makers to stimulate people to live/relocate to urban areas, or to create more urban-style neighborhoods (by creating new compact, mixed-use neighborhoods, or by densification and land use mixing in existing neighborhoods). Furthermore, improving public transport services (e.g. increasing frequency and comfort) and infrastructure for active travel (e.g. separated bike lanes, wide and well-lit sidewalks) in urban neighborhoods—making the use of these travel modes more convenient—might further improve attitudes towards public transport and active travel (partly because these interventions might result in more walking/cycling and public transport ridership). Since we found the strongest effects among (changes in) residential neighborhood, travel behavior, and travel attitudes for leisure trips, it can be expected that policy measures aiming to increase the use of—and improving attitudes towards—public transport and active travel will be more effective for leisure travel than for commute travel. Of course, improved attitudes towards public transport and active travel due to an increased use of these modes for leisure trips, might also stimulate their use for other trip purposes, such as commuting.

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Author contributions JDV: Study conception and design, data collection, literature search and review, analysis and interpretation of results, manuscript writing; LC: Analysis and interpretation of results, manuscript editing; FW: Manuscript editing.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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