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Residential relocation and travel behavior change: Investigating the effects of changes in the built environment, activity space dispersion, car and bike ownership, and travel attitudes

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ABSTRACT

The influence of residential relocation, as a life event, on travel behavior has become the focus of research on determinants of travel behavior in recent years. Although several studies have investigated the influence of changes in the built environment of the residential environment, the complex relationships between the built environment, travel attitudes and travel behavior has remained controversial. One crucial research gap in this area is the paucity of longitudinal and semi-longitudinal research designs that could capture the influence of changes in the built environment, activity space dispersion, car and bike ownership, latent attitudes towards travel, as well as travel behavior, and the interrelationships between these factors. This study attempts to fill this gap by collecting retrospective travel behavior and attitudinal data in Helsinki Metropolitan Area using an online map-based survey tool. In total, 1321 residents who had relocated to a new residential location between three to eleven months prior to the survey date participated in the study. The study collected data related to common home-based trips during a typical week in September 2017 and September 2018, stated change in the use of different modes of transport after the move, as well as socio-demographic, and attitudinal data before and after the move. Based on residential location and the visited destinations during a typical week, respondents' activity space dispersion was measured. Structural equation modelling was then used to investigate the interrelationships between changes in the built environment, activity space dispersion, car and bike ownership, travel attitudes, and travel behavior. Results indicate the existence of reciprocal influences between changes in car and bike ownership, travel attitudes, and travel behavior. It is also found that the built environment can modify and change travel related attitudes and influence activity space dispersion, which in turn affects travel behavior. The results of this study support the effectiveness of nudging approaches rather than marketing activities in changing travel attitudes and encouraging sustainable travel behavior.

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1. Introduction

After some decades of car-oriented development and sprawl, concerns about impacts on the environment and society have arisen. As a response, the pioneering works of researchers (e.g. Pushkarev and Zupan, 1977; Smith, 1984; Friedman et al., 1994; for reviews see: Anderson et al., 1996; Badoe and Miller, 2000; Crane, 2000; Ewing and Cervero, 2010), who argued for the effect of land use and physical characteristics of urban neighborhoods on travel behavior and trip generation dominated the urban mobility research, especially among urban planners. This opened a wide field of research to come up with urban design and planning solutions that could encourage the use of more sustainable and active means of transportation. However, the complexity of travel behavior was also highlighted in the field by the idea of residential self-selection (RSS). The idea is that people may choose their residential neighborhoods based on their travel mode preferences and attitudes (e.g. Weisbrod et al, 1980; Mokhtarian and Cao, 2008). This brought up the question of whether the studied built environmental factors have a causal effect on travel behavior or there exists an RSS bias. Several research approaches and methodologies have been proposed and utilized in research to better account for the effects of RSS, and to explore the interrelationships between the residential built environment and travel behavior.

However, the importance of adopting a mobility biography approach and considering the influence of residential relocation, as one of the key life events, on travel attitudes and behavior has been highlighted in recent years (e.g. Chatterjee and Scheiner, 2015; De Vos and Ettema, 2020). It is still rather unclear how travel attitudes and travel mode choices evolve after a residential relocation (De Vos et al., 2018). Although there are numerous studies on the effect of the built environment on travel behavior in the literature, studies focusing on the reciprocal influences of changes in built environment, travel behavior, and attitudes on one another are scarce (De Vos and Ettema, 2020). As Lin et al. (2017) put it, for example, not acknowledging the possible effects of the built environment on travel attitudes over time may lead to the overestimation of the influence of RSS on the link between the built environment and travel behavior and the underestimation of the influence of built environment on travel behavior. Although a number of studies have adopted a longitudinal or semi longitudinal (i.e. using retrospective surveys) approach to investigate the influence of changes in the social and/or built environmental characteristics of one's residential environment after relocation (e.g. Lin et al, 2018; De Vos et al, 2018; Wang and Lin, 2019), the complex relationships between changes in the built environment, travel attitudes, and travel behavior require further attention and investigation.

The purpose of the present study is to contribute to the literature by adopting a semi-longitudinal approach that collects retrospective travel behavior, sociodemographic, and attitudinal data from 1321 residents of Helsinki Metropolitan Area (HMA) who have relocated within HMA between three to eleven months prior to the survey date (September 2018), using an online map based survey tool. Based on the literature review, a conceptual framework highlighting the interrelationships between changes in built environment, activity space dispersion, car and bike ownership, travel related attitudes, and travel behavior is hypothesized which is then tested using structural equation modelling (SEM). This study is among the very few studies that use a semi longitudinal approach with a large sample size (+1300) to address the relationships between built environment, car and bike ownership, travel attitude, and travel behavior. In addition, it is the first study to empirically investigate the factors influencing a change in activity space dispersion after a residential relocation and its ultimate effect on travel behavior.

The rest of the paper is organized as follows. Section 2 provides a review of relevant studies and highlights the research gaps. Section 3 presents the conceptual framework, based on literature review, which illustrates the hypotheses of this study. Section 4 presents the methodology including data collection and analysis procedures. Section 5 presents and discusses the results. Finally, in the conclusion section, the key findings and contributions of this study to both research and practice, and future research directions are presented.

2. Literature review

There are numerous studies on the effects of built environment on travel behavior. Although differences exist in the ways that the built environmental factors have been measured and considered in these studies, density, diversity of land uses, and design, or as Cervero and Kockelman (1997) call it, the "three Ds'' of residential environment, have been the most commonly studied factors. Destination accessibility and distance to transit have also been commonly evaluated (Ewing and Cervero, 2001; Ewing et al., 2009). However, controversies in the empirical findings regarding the built environmental factors that influence travel behavior (e.g. Ewing and Cervero, 2010; Böcker et al., 2017) and evidence that the observed association between built environment and travel behavior may be attributable to travel-related attitudes (i.e., RSS), emphasize that the knowledge about the real effect of built environment on travel behavior is far from complete (Wang and Lin, 2019). Several review papers now exist in the literature, which provide a detailed discussion of different approaches and methodologies to account for the effect of RSS as well as the pros and cons of each approach. Providing details of all these different methodologies and approaches is out of the scope of this paper. We rather discuss the research gaps highlighted and the best approaches proposed to examine and account for the effects of built environment versus travel attitudes in the literature.

A number of studies provide a review of the theories, methodologies, and the empirical studies to date to examine the effect of RSS (Mokhtarian and Cao, 2008; Cao et al., 2009; Bohte et al., 2009). They refer to different approaches and methods used to date and come up with the conclusion that longitudinal SEM is the most appropriate as it can examine different causality directions among different dependent and independent variables (e.g. travel behavior, built environment, and attitudes) and therefore account for and examine more complex relationships. Bohte et al. (2009) focus on the methods that explicitly include attitudes in the modelling structures and argue that although several studies state that RSS is accounted for by the inclusion of attitudes, the complexity of the inclusion and the measurement of attitudes often leads to an under- or overestimation of the role of RSS. They especially refer to the direction of causality highlighting the fact that travel behavior could also affect attitudes in time, which is referred to in the literature as reverse causality. They argue for the lack of measurement of attitudes in different points in time in existing studies.

Chatterjee and Scheiner (2015) refer to research gaps that highlight travel behavior complexities too. They argue that destination choice and activity spaces before and after residential moves have been examined less frequently than built environmental factors of the residential environment. The few studies that have accounted for the effect of destination choice typically focus on spatial ties to the former place of residence after the move (e.g. Scheiner, 2007; Bauer et al., 2005) without considering the possibility of changes to one's activity space after the move, its determinants, and the way it may ultimately change travel behavior. For example, it has not been well studied whether those having most of their daily destinations close to home, i.e. having a monocentric activity space as defined by Hasanzadeh (2019), would shape a new monocentric activity space concentrated around the new home or would they change their activity space to a polycentric one (i.e. choosing destinations both close to the new home and in one or more clusters further from home, for example, close to previous home) after the move. Moreover, whether such a change in activity space dispersion would change travel behavior (e.g. less walking and cycling and more transit or car use) is unknown. This is while recent studies have shown that activity space dispersion is influenced by the residential neighborhood and sociodemographic characteristics (Hasanzadeh et al., 2021) and can in turn influence travel behavior (e.g. Hasanzadeh et al., 2021; Ramezani et al., 2019).

Scheiner (2014) discusses the importance of integrating the approach of mobility biographies to RSS studies. He suggests a perspective for widening the scope of research on the built environment-travel link. Besides the effect of changes in one's household composition, and/or employment changes, he argues, attitudes and preferences may also change over time. People are not born with either strong or weak preferences, and even self-selectors may attenuate their preferences when circumstances change or simply do not allow their realization. A study by Chatterjee and Scheiner (2015) focuses on the review of travel behavior studies that have adopted a biographical approach. It highlights the effect of life events on travel behavior, as well as residential relocation and travel behavior interrelationships. It also refers to research gaps such as lack of longitudinal data and reliance on data gathered through retrospective surveys that have asked respondents to recall 5 to 10 years prior to the survey date. Moreover, in both aforementioned studies, the lack of measurement of attitudes and preferences at different points in time has been emphasized. Scheiner (2014) refers to only two studies (Scheiner, 2007; Bauer et al., 2005) that collected a retrospective measure of preferences (measured as residential satisfaction level). However, as discussed by Scheiner (2014), the time span for which the respondents were asked to report their satisfaction levels in those studies has been very long. As Scheiner (2014) puts it, "the difference between the mobility biography and the RSS studies is that the RSS-travel debate focuses on residential choice and travel, while the mobility biographies approach is much wider in scope, acknowledging that the mutually related decisions on residential choice and daily travel are themselves embedded in stability and change in the spatio-temporal and social context in which an individual lives". In other words, travel and neighborhood preferences can emerge in an individual's life course and preferences can also be adapted to context over time. These points open up a wide field of research (Scheiner, 2014). A few studies (e.g. Kamargianni and Polydoropoulou, 2014; De Vos et al., 2020) analyzing the effects of neighborhood characteristics on attitudes, confirm the possible effects of spatial context on attitudes. However, such studies are very rare in the literature. Although many studies have referred to such complexities of travel behavior and suggested that built environment can impact travel attitudes and lifestyles directly or through the travel patterns stimulated by the new built environmental characteristics, very few have tested such hypotheses (e.g. van Acker and Witlox, 2016; De Vos et al., 2018).

However, using the mobility biography approach to understand built environment-Travel behavior relationships has gained more popularity recently. Studies using this approach mainly focus on the way travel behavior, travel attitudes, and travel satisfaction can change due to residential relocation (De Vos and Ettema, 2020). While many longitudinal and semi longitudinal studies still focus solely on the effect of changes in sociodemographic factors and the built environment on changes in travel behavior (e.g. Næss, 2005; Buchanan and Barnett, 2006), a few go a step forward and include the relationship between residential relocation and changes in personal social networks and neighborhood social environments on travel behavior (e.g. Lin et al., 2018). A few studies also look at changes in attitudes after the relocation. For example, using a mobility biography approach, Janke and Handy (2019) examine the ways life course events, such as residential relocation, explain changes in attitudes towards and levels of cycling in Davis (California, US). Wang and Lin (2019) take a longitudinal approach to consider travel-related attitudes before and after residential change. Their results show a significant influence of built environment on travel preferences and that individuals' travel attitudes may change after a home relocation. Taking a semi longitudinal approach, De Vos et al. (2018), found that both travel attitudes and travel mode choice change after a relocation, albeit in different ways depending on the current (urban versus suburban) and previous residential neighborhood (more/equally/less urbanized). They also found that not only changes in the built environment but also changes in travel behavior (e.g. changes in the frequency of walking, cycling, and car use) influence changes in travel attitudes referring to the reverse causality between travel attitudes and travel behavior. In other words, travel attitudes become more in line with travel behavior stimulated by the new residential neighborhood, i.e., moving to urban neighborhoods improves attitudes towards public transport and active travel, while moving to suburban neighborhoods improves car attitudes (De Vos et al., 2018; Wang and Lin, 2019). Although this might be considered the expected relationship, that people will be positive about ways of travel that are supported by the new context after relocation, the influence of changes in the residential environment and travel behavior after relocation on travel attitudes has rarely been empirically tested.

Numerous studies have looked at the influence of the built environment on car ownership (e.g. Yang, 2006) and the influence of changes in car ownership after relocating on changes in travel mode frequency (e.g. De Vos and Ettema, 2020). Therefore, in addition to testing the direct influence of changes in built environment and neighborhood social environment on changes in travel mode frequency (Lin et al, 2018), and the direct and indirect influences of the changes in the built environment and travel attitudes (De Vos et al, 2018; Wang and Lin, 2019), the intermediate influence of car ownership in this process has been analyzed as well (e.g. Lin et al., 2018; Wang and Lin, 2019). While a few abovementioned studies have looked at the interrelationships between the built environment, the social environment of the neighborhood, travel attitudes, car ownership, and travel behavior, to the authors' knowledge, no study additionally looks at the possible influence of changes in activity space dispersion after the move in this process.

To summarize, some of the existing empirical studies on the relationships between the built environment and travel behavior and reviews of RSS studies highlight gaps in conceptual frameworks (e.g. causality structure) while others refer to data collection methods and analytical approaches. The highlighted gaps and shortcomings include:

- Mostly cross-sectional data is used
- Lack of longitudinal data and reliance on retrospective surveys that have asked respondents to recall their behavior over a very long period (i.e. 5 to 10 years prior to the survey date)
- Lack of measurement and investigation of the effect of changes in one's household composition, employment changes, and attitudes and preferences over time
- Lack of investigation of the influence of changes in car ownership on travel attitudes and vice versa
- Lack of examination of the influence of destination choice, and changes in activity space after residential moves
- Lack of investigation of reciprocal causality directions between different sets of variables (e.g. reciprocal influences between Travel behavior and Attitudes, car ownership and attitudes, car ownership and travel behavior)

The discussions on the research gaps in the literature highlight the complexity of travel behavior and the need for more holistic studies that look at the multitude of factors influencing changes in travel behavior. It is discussed that some of the factors influencing travel behavior may not only be in turn influenced by travel behavior but also have reciprocal influences on one another. Few studies have considered the full set of variables influencing travel behavior at the same time (e.g. Wang and Lin, 2019; De Vos et al., 2020), and the reciprocal influences between these variables are rarely studied. Moreover, it is emphasized that such complex relationships between different sets of factors influencing travel behavior can be best captured if longitudinal or semi longitudinal research designs and Structural equation modeling techniques are adopted (e.g. Cao et al., 2009; and Bohte et al., 2009).

3. Conceptual framework

Given the research gaps and shortcomings highlighted in Section 2, this empirical study builds upon a conceptual framework illustrated in Fig. 1. This study adopts a semi-longitudinal research design that could capture the simultaneous influence of changes in sociodemographic factors, residential built environmental factors, changes in activity space dispersion, car, and bike ownership, and latent attitudes towards travel on travel behavior after residential relocation as well as the reciprocal influences of these factors on one another. The arrows show the causality directions hypothesized in this study which are based on the literature. Although not all these

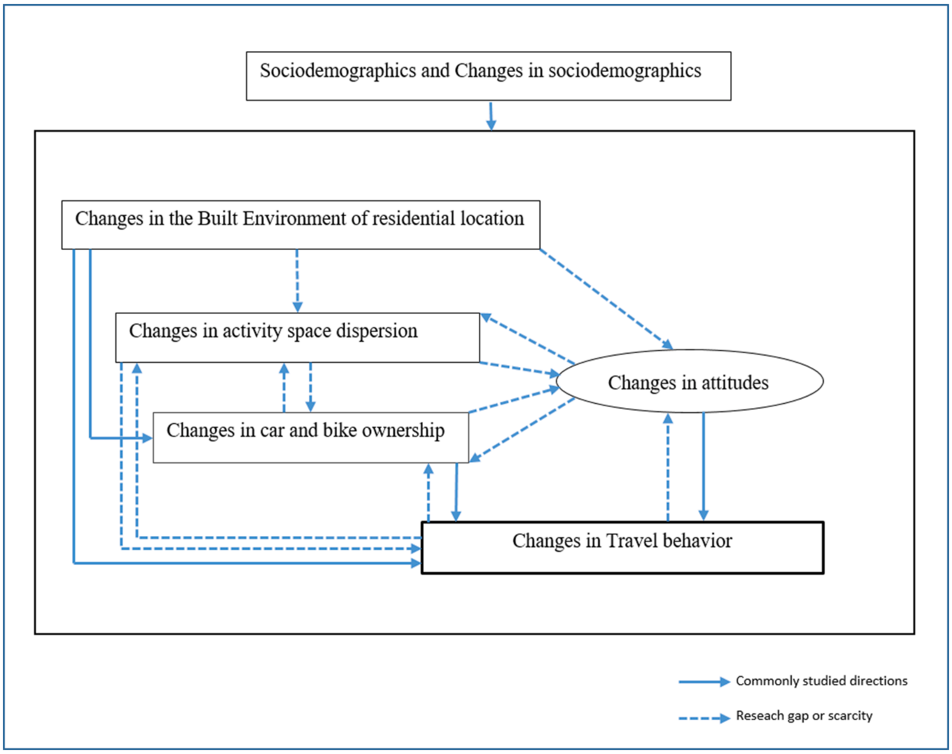

Fig. 1. The conceptual framework of the study illustrating the hypothesized links between variables.

hypothesized causality directions have been empirically investigated, they have been at least theoretically discussed in the literature (see Section 2). The sociodemographics and their changes are hypothesized to influence all the other factors in this conceptual framework. The dashed lines illustrate the directions that have been either very scarcely considered in empirical research or have not been studied at all, to the best of the authors' knowledge. One might argue that changes in travel attitudes, activity space dispersion, car and bike ownership, and travel behavior may also influence residential relocation and therefore changes in the built environmental characteristics of one's residential location. Such causality directions could be studied only through longitudinal studies that could track the respondents over a long period to collect travel behavior and attitudinal data before and after a residential relocation decision is made, which is not the case for this study as will be described in Section 4. As mentioned in the introduction (Section 1), this study focuses on the residents who have already relocated to a new residential location within a year before the survey and collects retrospective travel behavior and attitudinal data immediately before and after the relocation.

4. Methodology

4.1. Study area

The HMA is the largest metropolitan area in Finland with a population of 1,17 million people (OSF, 2018). It consists of the central cities of Helsinki, Vantaa, Espoo, and Kauniainen. Based on statistics, 45% of the households of Helsinki do not own any cars, 42% own one car, and 13% own two or more cars. In Espoo, 27% do not own a car, 48% own one car, and 25% own two or more cars. In Kauniainen, 19% do not own a car, 46% own one car, and 35% own two or more cars. In Vantaa, 27% do not own a car, 47% own one car, and 26% own two or more cars (HSL, 2019). Based on the HSL travel survey in autumn 2018, which collected data related to the trips of HMA residents older than 6 years, the trip rate in HMA is 3,5 trips per person, on an average working day. Of all the trips, 33% are made by car, 26% by public transport, 10% by bike, 30% on foot, and 1% by other modes (HSL, 2019). The public transport system in HMA is efficient especially in the intensive public transport zones where the maximum waiting time is 5 min for busses and 10 min for trains and trams (SYKE, 2015). Moreover, as an incentive to use public transport some employers in the HMA offer their employees free or discounted transit cards (employer-subsidized ticket). Information about the sociodemographic characteristics of HMA population is provided in Table 1 which compares the characteristics of the HMA population with the sociodemographics of the sample used in this study.

4.2. Data collection

The data for this study was collected using an online map-based survey tool. Map-based survey tools allow for the collection of place-based data with geographical coordinates, which can be easily analyzed with geographic information systems (GIS), in addition to the commonly collected survey data such as sociodemographic and attitudinal data (Brown and Kyttä, 2014). This study draws on data collected through a retrospective survey targeting a random sample of 10,000 residents of HMA who aged over 18 and had relocated to a new residential location within HMA between three to eleven months prior to the survey date (i.e. September 2018). The contact information of the sample was acquired from Finland's Population Register Center in 2018. An invitation letter to participate in the online survey was mailed to the sample. Thirty out of the 10,000 invited residents could not be located (due to address changes)

Table 1
The sociodemographic characteristics of respondents (n = 1321) compared to the population of HMA.

	Sample	HMA population*
Gender (%)		
Female	62.3	52.2
Male	37.7	47.8
Age (%)		
18–24	22.14	10.6
25–34	43.68	21.3
35–44	14.96	18.7
45–64	14.21	13.9
above 64	4.98	20
Education (%)		
Basic education	2.9	[a] 24.61
Upper secondary education	21	[a] 33.12
Lowest level of tertiary education	8.46	[a] 8.17
Bachelor's degree	36	[a] 14.58
Master's degree	28.7	[a] 17.41
Doctoral degree	2.13	[a] 2.08
Monthly Income in euro (mean)	1820	1718
Housing type (%)		
Detached/row house	20	32.14
Apartment	80	67.86

* The sample consists of Finnish people living in the capital area, aged 18+, in 2018 (a exception).
[a] The reference sample consists of Finnish people living in the capital area, aged 15+, in 2018.

and only 9970 received the invitation letters. The Minimum of three months of stay in the current neighborhood was considered as one of the criteria for sample selection to make sure the respondents had settled, and their travel behavior and attitudes had been shaped in the new neighborhood. The maximum 11 months of stay in the new neighborhood was considered since the study aimed to ask the respondents to recall not more than one year prior to the survey date. Literature shows that one year is an appropriate time span within which one can recall changes in their behavior (e.g. Cao et al, 2007; Scheiner, 2014). Semi-longitudinal data of travel-related attitudes (with a two-year time span) has been also collected in some recent studies (e.g. De Vos et al. 2018, 2020; Thigpen, 2019a, b). While in retrospective surveys there exists some recall bias, the study by Thigpen (2019b) has shown strong associations between recalled answers (even for abstract, subjective constructs) and prospective answers (based on an existing panel data), providing support for the measurement validity of studies that rely on participants' recollections. Respondents were asked to recall and report changes in their use of different modes of transportation in a typical week in the current neighborhood in September 2018 compared to when living in their previous neighborhood about a year ago in the same season (i.e. September 2017). The changes in the use of different modes of transport were measured on a 5-point Likert-scale from 1 (=a lot less now) to 5 (=a lot more now). Respondents were also asked to map their current and previous home locations as well as all their destinations during a typical week in September 2018 and in the same season in the previous neighborhood (i.e. September 2017). This helped to control for the influence of season on changes in travel behavior. These destinations included workplaces as well as places for recreation, shopping, personal errands, and childcare. Fig. 2 shows the online interface where the respondents mapped their destinations during a typical week. This place mapping helped to measure changes in activity space dispersion details about which is provided in Section 4.3.2. Attitudinal data was collected using 31 Likert scale statements. Respondents were asked to rate the degree to which they agree with those statements on a 5-point Likert scale from 1 (=strongly agree) to 5 (=strongly disagree). They were also asked to rate the same statements based on their attitudes when they lived in their previous neighborhood. Details about these statements are provided in Section 4.3.3. Socio-demographic data and their changes after the move were also collected. Altogether, the survey included 9 sections including current socio-demographic information, current travel attitudes, mapping current home location, changes in the use of different modes, mapping destinations in a typical week in the current neighborhood, mapping previous home location, mapping destinations in a typical week in previous neighborhood, travel attitudes in the previous neighborhood, and changes in sociodemographic characteristics after the move. The survey was available in English, Finnish, and Swedish and took about 30 min to complete.

Of the 9970 invited residents, 1460 participated in the survey providing a 14.6 percent response rate. 1321 of these respondents had provided complete answers necessary for the current study, which were taken for further analysis. This sample consisted of 823 women (23% aged 18–24, 43% aged 25–34, 13,6% aged 35–44, 15,2% aged 45–64, and 5,2% above 64) and 498 men (20,9% aged 18–24, 44,2% aged 25–34, 17,3% aged 35–44, 12,4% aged 45–64, and 5,2% above 64). Table 1 compares the sociodemographic characteristics of the sample with the HMA population, based on Official Statistics of Finland (OSF, 2018). Residents aged 18–24 and 25–34 are overrepresented and those aged above 64 are underrepresented in the sample. Moreover, those living in apartments are overrepresented. These differences can reflect the age group and housing type of movers. The mean income of the sample is rather similar to the mean income of the HMA population. Females are also overrepresented in the sample which is a common case in surveys. Regarding education, those with basic education are underrepresented and those with a bachelor or master's degree are over-represented which might also reflect the age distribution of the sample. The online PPGIS methodology might have caused some

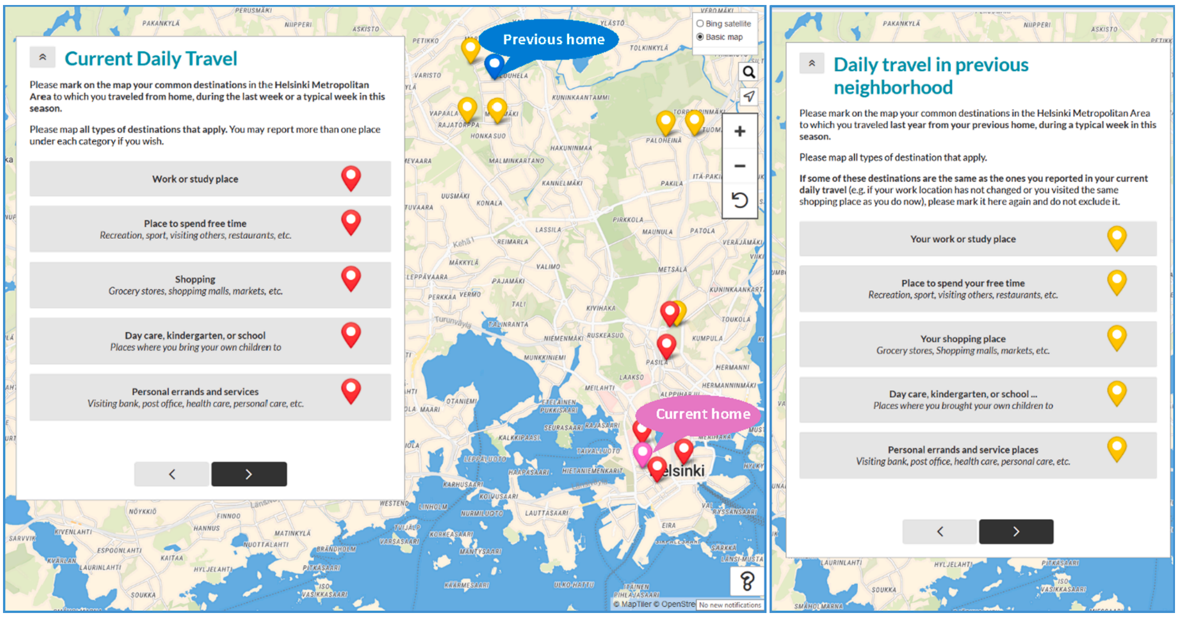

Fig. 2. The online interface of the survey where respondents marked on a map their current and previous home as well as the errand points in a typical week in autumn in the current and previous neighborhood.

limitations, as those with poor computer literacy or no access to the internet might have been excluded from the study. However, Finns are technology-savvy, and public e-services are well used in Finland regardless of age (Taipale, 2013). Moreover, online map-based survey methods have shown to be usable also among older adults, a population group whose Internet skills remain limited compared to those of younger age groups (Gottwald et al., 2016). Table 2 summarizes the self-reported changes in socio-demographic characteristics and travel behavior of the respondents after the move.

4.3. Data analysis

Data analysis was conducted in four stages. First, a 1-km buffer was modeled around current and previous home locations using ArcGIS 10.6. This buffer was used as the spatial unit of analysis to measure the built environmental factors of home location (see Section 4.3.1). Second, to measure the dispersion of activity space, the method proposed by Hasanzadeh (2019) for measurement of centricity of activity spaces was used (see Section 4.3.2). Third, Factor analysis was conducted on the statements measuring attitudes to identify different travel-related attitudes within the sample population (see Section 4.3.3). Finally, the variables measured in the aforementioned stages were used in the structural equation modeling process (see Section 4.3.4) to test the hypotheses of this study presented in Section 3.

4.3.1. Measurement of built environmental factors

The built environmental factors that have commonly been considered in the empirical research on the influence of the built environment on travel behavior (see Section 2) were adopted in this study. These include land use mix, population density, job density, and distance from home to work and non-work places. These measures were calculated in a 1-km buffer around the current and previous home location of the respondents, as the spatial unit of analysis. Changes in the built environment factors of the home location were measured by subtracting the value of each built environmental factor in the previous home buffer from the value of that factor in the current home buffer. All these change values were standardized. Moreover, since previous studies in the Finnish context showed rather high correlations between the urban zone at domicile and travel behavior (e.g. Hasanzadeh, 2019; Hasanzadeh et al, 2018), this classification was used to examine whether moving to zones with more intensive public transport service would lead to changes in travel behavior. This variable is a measure of transit accessibility.

Four different geographical datasets were used to measure the built environmental factors. The information concerning land use was extracted from the CORINE land cover 2018 dataset. **CORINE** is a raster dataset that provides information on Finnish land cover and land use. The data of CORINE has been produced as a part of the European Gioland 2012 project by the Finnish Environment Institute (SYKE). Population data was drawn from the building dataset of SeutuCD 2018. **SeutuCD** is an extensive collection of GIS data, which compiles the most essential register, map, and data for planning of the Helsinki Metropolitan Area. Helsinki Region Environmental Services Authority (HSY) produces and provides SeutuCD data. Job data was measured with Statistics Finland Grid

Table 2
Self-reported Changes in socio-demographics and travel behavior after residential relocation (n = 1321).

Variable name	Mean/%	St. dev
Got job	10%	–
Lost job	6.9%	–
Retired	2.2%	–
Car acquisition	8%	–
Car disposal	15.1%	–
Bike acquisition	8.1%	–
Bike disposal	7.4%	–
Got transit pass	7.5%	–
Lost transit pass	15.6%	–
Change in number of children in household	−0.04	0.59
Change in number of adults in household	−0.23	1.2
Changes in household income	0.2	1.12
Got Physical limitations preventing walking	0.8%	–
Got physical limitations preventing cycling	0.8%	–
Got physical limitations preventing driving	1%	–
Got physical limitations preventing transit use	0.9%	–
Increase in walking after relocation	41%	–
Decrease in walking after relocation	22.9%	–
No change in walking	36.1%	–
Increase in cycling after relocation	36.2%	–
Decrease in cycling after relocation	24.7%	–
No change in cycling	39.1%	–
Increase in transit use after relocation	37.9%	–
Decrease in transit use after relocation	25.3%	–
No change in transit use	36.8%	–
Increase in driving after relocation	18.9%	–
Decrease in driving after relocation	29.6%	–
No change in driving	51.5%	–

Database 2018. **Statistics Finland Grid Database 250*250** contains coordinate based statistical data calculated by map grid. The grid database contains data describing the population's structure, education, the main type of activity and income, households' stage in life and income, as well as buildings and workplaces. The grid size is 250 m × 250 m. Lastly, **urban zone data (YKR)** is a 250 m × 250 m grid-based dataset provided by SYKE in which all city regions in Finland are divided into different zones based on three main criteria: distance to the city center, public transit frequency and walking distance to public transit stops. These criteria are calculated for each YKR grid cell which is then assigned a value indicating if it belongs to a car zone, poor public transport zone, basic public transport zone, or intensive public transport zone.

More details about the built environment measures considered in this study are presented below.

Land Use Mix was defined as an entropy index describing the heterogeneity of different land uses. Since literature has shown controversies regarding the influence of land use mix on travel behavior and as the importance of compatibility of the land uses that are included in the entropy index have been emphasized (e.g. Manaugh and Kreider, 2013), three different land use mix entropy indices were measured to be examined in this study. CORINE 2018 land cover dataset (raster data) was used to measure the percentage of different land uses within the home buffers. The first entropy index included three categories of land uses, namely residential, commercial, and opportunity for leisure. Opportunity for leisure was defined as a mix of leisure, urban green, forest, water, and sea land uses. The second entropy index included only residential and commercial land uses, and the third entropy index included only residential and opportunity for leisure land uses. Each of these land use indices were calculated as follows:

$$LUM = -1\left(\sum_{n}^{i=1} pi^{*}ln(pi)\right) / ln(n)$$

where LUM is the land-use mix score, pi is the proportion of the home buffer covered by the land use i against the summed area for land-use categories of interest, and n is the number of land-use categories of interest.

Population density was calculated by dividing the number of populations in each home buffer by the buffer area in square kilometer.

Job density was calculated by dividing the number of jobs in each home buffer by the buffer area in square kilometer.

Distance to the workplace is the shortest network distance in square kilometer from home to the work location mapped by the respondents, calculated using network analysis in ArcGIS 10.6.

Distance to non-work places was calculated as the average of shortest distances in square kilometer from home to the non-work-related locations mapped by the respondents. The shortest distance was calculated using the network analysis in ArcGIS 10.6.

Move to an Intensive public transport zone is measuring improvement in transit accessibility after the move. For this study we defined one dummy variable, namely "moving to intensive public transport zone", to see if a move from zones with poor or basic transit

Table 3
Current attitudes within the sample population.

Attitude	Cronbach's Alpha	Measurement indicator	Factor loading
1. Pro-transit	0.71	I prefer to take public transport than drive whenever possible	0.676
		I like travelling by public transport	0.507
		I like driving	−0.482
		I like to be able to rest or read while travelling	0.421
		We could manage pretty well with one fewer car than we have (or with no car)	0.347
2. Pro-active travel	0.85	I prefer to cycle rather than drive whenever possible	0.946
		I prefer to walk rather than drive whenever possible	0.725
		I like riding a bicycle	0.667
3. Susceptible to peer pressure	0.83	People in my neighborhood have a positive view of people who use public transport	0.934
		People in my neighborhood have a positive view of people who walk or cycle for daily travel	0.815
4. Time sensitive	0.59	I do not like to wait for another travel mode while travelling	0.593
		I like to avoid queues and congestion while travelling	0.588
		I do not like to have variation in my daily travel time	0.584
5. Car safety perception	0.79	Travelling by car is safer overall than walking	0.962
		Travelling by car is safer overall than riding a bicycle	0.670
		Travelling by car is safer overall than taking public transport	0.582
6. Confident in transit schedule awareness	0.58	The bus and/or train schedule is sometimes hard to understand	0.607
		Using text message (SMS) to get real time information about bus and train schedule could be easier than using internet for me	0.537
		I use the Internet easily to find out about the bus or train schedule	−0.534
7. Cost sensitive	0.43	Fuel price and/or price of parking affects my choice of daily travel by car	0.666
		Transit fare affects my choice of daily travel by public transport	0.368
8. Environmentally aware	0.66	Changing how people travel is a great way to improve the environment	0.644
		Using electric vehicles can significantly reduce air pollution	0.579
		Vehicles should be taxed on the basis of the amount of pollution they produce	0.468
		I try to limit my driving to help improve air quality	0.363

Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.806. Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

coverage to more intensive transit service would show a change in travel behavior. The value of this dummy variable is 1 if the respondent was living in either a car zone, poor transit zone, or basic transit zone previously and moved to an intensive transit zone, and 0 otherwise.

4.3.2. Measurement of dispersion of activity space

To measure the dispersion of activity space, the method proposed by Hasanzadeh (2019) for measurement of centricity of activity spaces was used. Accordingly, centricity was calculated as an ordinal variable of activity space measuring the number of activity centers in an individual's activity space. We identified the activity clusters using a customized spatial clustering approach taking into account the number and frequency of the activity places (Hasanzadeh, 2019). These activity places are the common weekly locations mapped by the respondents including both work and non-work destinations. Consequently, activity spaces were classified into two groups: *Monocentric*– activity spaces that consist of a single cluster of activity places located in the home surrounding, *and Polycentric*– activity spaces that in addition to the cluster of activities around the home, have at least one center of activities somewhere further from home. In the original study by Hasanzadeh (2019), there is an extra group for bicentric activity spaces (i.e. activity spaces that in addition to the cluster of activities around the home, have another center of activities further from home). As described in the definition of polycentric activity space used in this study, we have merged bicentric activity space into the polycentric group. This measure was calculated separately for the current and previous activity places. Finally, two dummy variables were defined to measure whether a respondent's activity space dispersion has changed after the move. The value of "Change to monocentric activity space" is 1 if the respondent had a polycentric activity space previously while having a monocentric activity space currently, and 0 otherwise. Similarly, the value of "Change to polycentric activity space" is 1 if the respondent had a monocentric activity space previously while having polycentric activity space currently, and 0 otherwise.

4.3.3. Travel related attitudes within the sample population

Two separate principal axis factor (PAF) analyses were conducted in SPSS 25 to retrieve latent attitudinal factors from 31 Likert-scale statements related to previous and current attitudes. To account for correlations between factors, direct Oblimin rotation with Kaiser Normalization was applied. In all analyses, only statements with factor loadings over 0.32 were retrieved (Tabachnick and Fidell, 2013). Seven statements that did not show correlations with any of the extracted factors were excluded from further analysis.

Table 4
Previous attitudes within the sample population.

Attitude	Cronbach's Alpha	Measurement indicator	Factor loading
1. Pro-transit	0.65	When living in my previous neighborhood I preferred to take public transport than drive whenever possible	0.847
		When living in my previous neighborhood I liked travelling by public transport	0.485
		When living in my previous neighborhood I liked driving	−0.407
2. Pro-active travel	0.78	When living in my previous neighborhood I preferred to cycle rather than drive whenever possible	0.883
		When living in my previous neighborhood I liked riding a bicycle	0.741
		I preferred to walk rather than drive whenever possible	0.386
3. Susceptible to peer pressure	0.87	People in my neighborhood had a positive view of people who walk or cycle for daily travel	0.893
		People in my neighborhood had a positive view of people who use public transport	0.871
4. Time sensitive	0.59	I did not like to wait for another travel mode while travelling	0.679
		I did not like to have variation in my daily travel time	0.579
		I liked to avoid queues and congestion while travelling	0.439
5. Car safety perception	0.84	I believed travelling by car was safer overall than walking	0.935
		I believed travelling by car was safer overall than taking public transport	0.783
		I believed travelling by car was safer overall than riding a bike	0.660
6. Confident in transit schedule awareness	0.59	Using text message (SMS) to get real time information about bus and train schedule could be easier than using internet for me	−0.568
		The bus and/or train schedule was sometimes hard to understand	−0.560
		I used the Internet easily to find out about the bus or train schedule	0.556
7. Cost sensitive	0.57	When living in my previous neighborhood Fuel price and/or price of parking used to affect my choice of daily travel by car	0.670
		When living in my previous neighborhood Transit fare used to affect my choice of daily travel by public transport	0.561
8. Environmentally aware	0.66	I believed changing how people travel is a great way to improve the environment	0.846
		I believed using electric vehicles can significantly reduce air pollution	0.591
		I believed that vehicles should be taxed on the basis of the amount of pollution they produce	0.417
		When living in my previous neighborhood I was trying to limit my driving to help improve air quality	0.333
9. Anti-travel	0.39	I preferred to organize my errands so that I make as few trips as possible	0.542
		When I needed to buy something, I usually prefered to get it at the closest store possible	0.464

Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.753. Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

Final solutions were retrieved based on the assessment of the scree-plot and component eigenvalues larger than 1.0. The suitability of the data for PAF analyses was confirmed with Bartlett's test of sphericity, which was significant ($p < 0.001$) for all analyses. Each analysis had an overall Kaiser-Meyer-Olkin measure exceeding 0.75. In the first analysis, eight latent factors for the current attitudes (Table 3) and nine latent factors for the previous attitudes (Table 4) were identified. The 8-factor solution for current attitudes explained altogether 63.5% of the total variance. The 9-factor solution for previous attitudes explained altogether 67.7% of the total variance. Most of the factors and their indicators were the same for both current and previous attitudes towards travel (see Tables 3 and 4). However, there was one extra factor identified for the previous attitudes (i.e. Anti-travel) and the pro-transit factor for the current attitudes had more indicators than the similar one in previous attitudes (see Tables 3 and 4). Since this study investigates the influence of changes in attitudes after relocation, similar attitudes had to be taken for further analysis. Therefore, the indicators of the extra factor for previous attitudes, as well as the indicators that were not similar in both current and previous attitudinal factors (i.e. two indicators in current pro-transit attitude), were removed. The analysis was conducted again on the remaining statements to make sure the extracted factors will remain the same after removing those statements. Since no change was observed, only those factors and indicators that were the same in both factor analyses of current and previous attitudes were taken for further analysis. To measure changes in each of these attitudes after residential relocation, the ranking values of each statement after the move was subtracted from the ranking value of that statement before the move, and these change values were used as indicators of changes in each latent attitudinal factor in SEM. The objective of factor analysis was to identify the underlying constructs (i.e., latent factors measuring changes in attitudes) and the indicators (i.e., statements) for each of these constructs to be used in the SEM. Table 8 in Section 5.4 will present the results of the measurement model in the SEM indicating the changes in attitudes that showed significance and their indicators. This is worth noting that the method used in this study to measure a change in latent attitudinal factors is based on the literature (e.g. Lin et al., 2018). However, factor analysis was added in this study so that the statements to be compared before and after the move, as indicators of changes in latent attitude factors, are not arbitrarily chosen. Nevertheless, it is acknowledged that this method is not void of limitations either, as the factor loadings for the indicators of the latent attitudinal factors before and after the move are not equal.

4.3.4. *Structural equation modelling*

To test the hypotheses of this study illustrated in Fig. 1, Structural Equation Modelling was used. In such an approach, a variable can be an explanatory variable in one equation (e.g., changes in car ownership influencing changes in travel behavior) but an outcome variable in another equation (e.g., changes in car ownership influenced by changes in activity space dispersion or the built environment). Therefore, the concepts 'endogenous' and 'exogenous' variables are used (Van Acker et al., 2011). Variables that are not influenced by any variable in the model are called exogenous. Variables that can be influenced by some variables and at the same time influence other variables are called endogenous. The relationships between exogenous and endogenous variables are represented by the structural model (Van Acker et al., 2011). Since this study explores reciprocal causal influence between endogenous variables (bi-directional paths between endogenous variables) a non-recursive reciprocal causation SEM model is estimated. Although this study used a semi longitudinal approach to collect travel behavior and attitudinal data retrospectively, the endogenous variables (e.g. changes in the built environment, changes in attitudes, changes in travel behavior) are cross-sectional in nature (i.e. the change variables are measured at one point in time - after residential relocation). Non-recursive Structural Equation Models (which use cross-sectional data) are used for an approximation of the cross-lagged reciprocal effects between endogenous variables (Wong and Law, 1999).

As Wong and Law (1999) put it, there are pros and cons of using recursive longitudinal and non-recursive cross-sectional data in analyzing reciprocal relationships in structural equation analyses. They argue that the non-recursive model is a good representation of reality for synchronous reciprocal effects. For example, in this study, travel attitudes and travel behavior can change synchronously after the relocation. Furthermore, it is clear that although the true effects may be longitudinal between some endogenous variable (e.g. changes in travel mode, car ownership, and activity space in this study), it is not always possible for researchers to identify, and have access to data that match, the exact time duration of the cross-lagged effects (Wong and Law, 1999). For example, mode choice could change quite quickly after relocation if the move is to a place with substantially different travel choices than in the previous location whereas changes in vehicle ownership might take a bit longer. In these cases, using the non-recursive model as a proxy is a viable alternative for studying reciprocal relations (Wong and Law (1999).

It is worth noting that reciprocal feedback loops between endogenous variables in SEM do not imply a correlation between the endogenous variables. An endogenous variable is an outcome variable - it has some predictors (exogenous or endogenous predictors), which explain some of its variances. A correlation (or covariance) implies that two variables share some of their variances. If endogenous variables Y1 and Y2 are correlated, that might be because they have a common cause (X) that is the cause of their correlation. In SEM, that correlation is accounted for - that is, some of the variances of Y1 and Y2 can be thought of as belonging to X. That is the reason that instrumental variables (variables that influence Y1 but not Y2 and vice versa) are needed in the model to be able to identify a non-recursive reciprocal SEM. Moreover, the residual of Y1 and Y2 can be correlated (i.e. the variables that might influence Y1 and Y2, which we have not included in the model, can be correlated as well). Allowing the residuals of endogenous variables to correlate has been mentioned in the literature as another requirement for the identification of non-recursive reciprocal SEM (e.g. Wong and Law, 1999). In other words, the correlation among endogenous variables in SEM is a function of (a) the correlations among the exogenous variables which determine the endogenous variables, (b) the estimated effects of endogenous variables on each other (if any), and (c) the correlations among the error terms or residuals (if any). The point is that correlations among the endogenous variables whether directly observed or latent, are a function of other parameters in the model and are not estimable parameters themselves.

In this study, current household and personal sociodemographic characteristics, as well as changes in sociodemographic characteristics after relocation, were included as exogenous variables. Although several sociodemographic variables were tested in the process of model development, only those that showed consistent significance in all models are reported in this paper. These included 9 variables; namely income, education, gender, having walking limitations, living in a house (versus an apartment), changes in the number of adults in the household, changes in the number of children in the household, losing transit pass, and obtaining transit pass. Losing transit pass is a dummy variable getting a value of 1 if the respondent had a transit pass in the previous neighborhood but not in the current neighborhood, and getting a value of 0, if otherwise. On the contrary, obtaining a transit pass is a dummy variable getting a value of 1 if the respondent did not have a transit pass when living in the previous neighborhood but obtained one in the current neighborhood, and getting a value of 0, if otherwise. Transit pass ownership was included in this study as an exogenous variable since some employers offer their employees free or subsidized transit pass in the study area and losing or gaining a transit pass in Finland could be due to changes in jobs or employers' policies for commuting. However, like car and bike ownership, transit pass ownership could also be influenced by residential relocation and the built environment of the new neighborhood and future studies should include it as an endogenous variable in models. In addition, we did not collect exact information about the type of transit pass owned by the respondents. Future studies should ask about the type of transit pass (e.g. completely free versus subsidized cards).

23 endogenous variables were tested in the process of model development, 19 of which showed statistical significance and remained in the final model. Of these 23 endogenous variables, six were related to Changes in the built environmental factors (i.e. change in Land use mix, change in population density, change in job density, change in distance to the workplace, change in distance to non-work places, and moving to intensive public transport zone). Two were related to changes in the dispersion of activity spaces (i.e. change to monocentric activity space and change to polycentric activity space), four to changes in car and bike ownership (i.e. car acquisition, car disposal, bike acquisition, and bike disposal), eight to changes in attitudes (i.e. changes in pro-transit, pro-active travel, susceptible to peer pressure, time-sensitive, car safety perception, confidence in transit schedule awareness, cost-sensitive, and environmentally aware attitudes), and the last three to changes in travel behavior (i.e. self-reported changes in walking, cycling, and transit use after relocation). This study focuses on changes in sustainable travel behavior and therefore change in car use is excluded from the model. Moreover, changes in car use showed a very high negative correlation with changes in walking, cycling, and transit use and its inclusion in the model could cause multicollinearity issues in equations where travel behavior changes were included as predictors of changes in other endogenous variables such as attitudes. Changes in attitudes were included as latent factors in models and their indicators (as described in Section 4.3.3) are exogenous.

The maximum likelihood (ML) approach, which is the most commonly used estimator, was used to estimate the structural equation models using AMOS (version 26.0). Our data slightly violated the multivariate normality assumption, like in many other studies (e.g. Cao et al., 2007; van den Berg et al., 2013, and Lin et al., 2018). Therefore, we used a bootstrapping procedure to address the non-normal data (Byrne, 2010). SEM is a confirmatory analysis method and involves testing a theoretical model. Unlike many other statistical methods, the entire theoretical model can be tested in one analysis. As part of the analysis, the researcher can test both the specific hypothesized relationships among his or her variables and the plausibility of the overall model (i.e., the fit of the model). SEM has several benefits for studying relatively complex theoretical models (Martens and Hasse, 2006, p.879). The conceptual framework

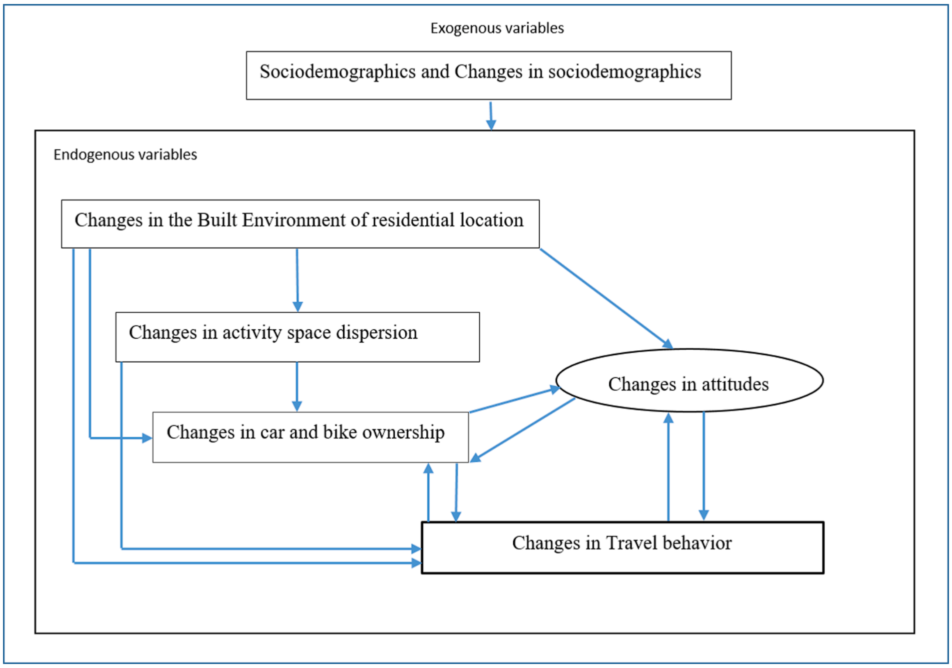

Fig. 3. The relationships between different variables based on SEM results. SEM model fit measures: X2/df = 2.180, CFI = 0.908, IFI = 0.910, RMSEA = 0.03.

in Fig. 1 was tested in this study using a non-recursive reciprocal causation SEM. For a non-recursive reciprocal causation model to be accepted the fit of the model should be acceptable and all the paths between endogenous variables included in the model (including the bidirectional paths) should be significantly different from 0 (Martens and Haase, 2006). To estimate non-recursive reciprocal causation SEM a number of conditions should be met providing the details of which is out of the scope of this paper. The readers can refer to Martens and Haase (2006), Schaubroeck (1990), and Maruyama (1997) for more details. However, one common solution to deal with problems in the identification of reciprocal causation SEM is the use of instrumental variables. Exogenous variables were used as instrumental variables in this study. As Martens and Haase (2006, p.897) put it "even making judicious choices of instrumental variables in advance may not be completely satisfactory, and some trial and error may well be necessary (Berry, 1984; Schaubroeck, 1990)". Therefore, although these exogenous variables have been chosen based on the literature and the conceptual framework of this study, several models with different paths between exogenous and endogenous variables were tested. Variables and paths that consistently showed no significance were excluded from the model. The model with the best fit to the data, in which all included paths were significantly different from 0, was selected as the final model. Widely used indexes were used to assess the goodness-of-fit of the models, including the Chi-square value, the ratio of X2 over degrees of freedom, the Comparative Fit Index (CFI), the Incremental Fit Index (IFI), and the Root Mean Square Error of Approximation (RMSEA) (Byrne, 2010). As suggested, for a model with a good fit, the ratio of $\chi2$ over degrees of freedom must be smaller than 5.0, CIF and IFI must be larger than 0.9, and RMSEA must be smaller than 0.08. The results of the final model are presented in the results and discussion section (Section 5).

5. Results and discussion

The result of the final SEM is illustrated in Fig. 3. This figure shows only the paths between endogenous variables that showed statistical significance. The hypothesized paths in Fig. 1 that did not show significance are removed. The final model fit statistics include $X^2/df = 2.180$, $CFI = 0.908$, $IFI = 0.910$, $RMSEA = 0.03$. As presented in Section 4.3.4, according to Byrne (2010), these values show an adequate fit of the model to the data. Factors influencing each of the five sets of endogenous variables are presented separately in six different tables (Tables 5–10) to make the results more readable.

As illustrated in Fig. 3, some of the exogenous sociodemographic factors showed a significant influence on the endogenous factors. Among the hypothesized reciprocal influences between endogenous variables only the ones between changes in travel behavior and changes in attitudes, between changes in travel behavior and changes in car and bike ownership, and between changes in the travel-related attitudes and car ownership hold. The results of SEM rejected some of the hypothesized paths between the endogenous variables. It was found that changes in travel behavior do not influence changes in activity space dispersion while the opposite direction is statistically significant. Similarly, changes in car and bike ownership do not show any influences on changes in activity space dispersion while the opposite direction is significant. Neither of the paths between changes in activity space dispersion and changes in attitudes showed statistical significance. Changes in the Built Environment of residential location influence all the other endogenous variables directly and/or indirectly through intermediate factors. The results indicate that changes in attitudes have a more significant effect on changes in travel behavior than changes in the built environment. However, changes in the Built Environmental factors show a very highly significant direct influence on changes in attitudes, which ultimately affect travel behavior. The following sub-sections

Table 5
Factors influencing changes in the built environment of residential location.

		Changes in distance to non-work related places	*Changes in distance to work place*	*Changes in land use mix*	*Changes in population density*	*Changes in Job density*	*Move to intensive public transit zone*
Household and personal socio-demographics (after move)	**Income**	0.00 (0.00)	0.00 (0.00)	**−0.035[c]** **(−0.035[c])**	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Education	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Gender (Female)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Living in a house	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Walking limitation	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Changes in socio-demographics	**Changes in number of adults in HH**	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Changes in number of children in HH	0.00 (0.00)	**0.109[a]** **(0.109[a])**	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Lost transit pass	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Obtained transit pass	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

Notes: (1) [a]Significantly different from zero at $p < 0.01$; [b]Significantly different from zero at $p < 0.05$; [c]Significantly different from zero at $p < 0.10$. (2) Both direct and total effects are listed, and total effects are in parentheses. All effects are standardized.

Table 6
Factors influencing changes in dispersion of activity space.

		Change to monocentric activity space	Change to polycentric activity space
Household and personal socio-demographics (after move)	**Income**	0.00 (0.00)	0.00 (0.00)
	Education	0.00 (0.00)	0.00 (0.00)
	Gender (Female)	0.00 (0.00)	0.00 (0.00)
	Living in a house	0.00 (0.00)	0.00 (0.00)
	Walking limitation	**0.1[a] (0.1[a])**	0.00 (0.00)
Changes in socio-demographics	**Changes in number of adults in HH**	0.00 (0.00)	0.00 (0.00)
	Changes in number of children in HH	**0.00 (−0.023[a])**	**0.00 (0.025[a])**
	Lost transit pass	**0.122[a] (0.122[a])**	0.00 (0.00)
	Obtained transit pass	0.00 (0.00)	**0.172[a] (0.172[a])**
Changes in built environment	**Changes in distance to non-work related places**	**−0.178[a] (−0.178[a])**	**0.150a (0.150[a])**
	Changes in distance to work	**−0.210[a] (−0.210[a])**	**0.231[a] (0.231[a])**
	Changes in land use mix	0.00 (0.00)	0.00 (0.00)
	Changes in population density	0.00 (0.00)	0.00 (0.00)
	Changes in Job density	**0.134[a] (0.134[a])**	**−0.119[a] (−0.119[a])**
	Move to intensive public transit or pedestrian zone	0.00 (0.00)	0.00 (0.00)
Changes in car ownership	**Car acquisition**	0.00 (0.00)	0.00 (0.00)
	Car disposal	0.00 (0.00)	0.00 (0.00)
Changes in bike ownership	**Bike acquisition**	0.00 (0.00)	0.00 (0.00)
Changes in attitudes	**Changes in pro-active transport attitude**	0.00 (0.00)	0.00 (0.00)
	Changes in pro-transit attitude	0.00 (0.00)	0.00 (0.00)
	Changes in environmental accountability	0.00 (0.00)	0.00 (0.00)
	Changes in susceptibility to peer pressure regarding positive role of active transport	0.00 (0.00)	0.00 (0.00)
	Changes in time sensitivity	0.00 (0.00)	0.00 (0.00)
Changes in travel behavior	**Changes in walking**	0.00 (0.00)	0.00 (0.00)
	changes in cycling	0.00 (0.00)	0.00 (0.00)
	changes in transit use	0.00 (0.00)	0.00 (0.00)

Notes: (1) [a] Significantly different from zero at $p < 0.01$; [b] Significantly different from zero at $p < 0.05$; [c] Significantly different from zero at $p < 0.10$. (2) Both direct and total effects are listed and total effects are in parentheses. All effects are standardized.

present and discuss the factors influencing each of the endogenous variables in more detail. Among the land use mix indices (see Section 4.3.1) the index which included only residential and commercial land uses showed significance and improved the fit of the model. Therefore, this index was used in the final model and the land use mix in this section refers to a mix of residential and commercial land uses.

5.1. Factors influencing changes in the built environment of residential location

The only factors that were included in models to examine their influence on changes in the built environment of the residential location were sociodemographics and changes in sociodemographics.

As presented in Table 5, income and changes in the number of children in the household show an influence on changes in the built environment of residential location. More specifically, the higher the income the lower the possibility that one would move to a mixed-use neighborhood in HMA. This can be because the higher-income residents are more car-dependent and prefer more spacious housing that is not usually available in mixed-use neighborhoods. The results of this study regarding the influence of changes in income on changes in car ownership confirm this conclusion (see Section 5.3). This result is also consistent with the previous studies showing the influence of income on car dependency and less active lifestyles (e.g. Haybatollahi et al., 2015). An increase in the number of children in the household showed a very highly significant positive influence on an increase in distance to the workplace after moving. This result can be due to changes in car ownership and therefore less concern about living close to one's workplace. This is confirmed with the results of this study regarding the influence of an increase in the number of children on car acquisition (see Section 5.3). It can be also due to the priority of proximity to childcare places for parents with more than one child or with a newborn.

5.2. Factors influencing changes in activity space dispersion

As reported in Table 6, the results of this study show that among the sociodemographic factors, walking limitation, an increase in the number of children in the household, and changes in transit pass ownership can influence changes in activity space dispersion. Not surprisingly, those reporting to have a walking limitation after moving, have changed their polycentric activity space to a monocentric activity space (i.e. all their common weekly activity places are located close to home). An increase in the number of children in the household does not show a direct influence but an indirect negative influence on the change to monocentric activity space and a positive indirect influence on the change to polycentric activity space. The latter result is also intuitive as the indirect influence is through the effect of this factor on an increase in distance to work location after the move (as reported in Tables 5 and 6) which can create at least one activity cluster further from home and close to work location. Having more children may require a visit to different

Table 7
Factors influencing changes in car and bike ownership.

		Car acquisition	*Car disposal*	*Bike acquisition*
Household and personal socio-demographics (after move)	Income	0.00 (0.002[c])	0.00 (−0.002[c])	0.00 (0.002[c])
	Education	0.00 (0.00)	−0.068[a] (−0.068[a])	0.00 (0.00)
	Gender (Female)	0.114[a] (0.115[a])	0.00 (0.00)	0.00 (0.00)
	Living in a house	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Walking limitation	0.00 (0.00)	0.00 (0.00)	0.00 (−0.001[c])
Changes in socio-demographics	Changes in number of adults in HH	0.00 (0.00)	0.00 (0.00)	0.089[a] (0.089[a])
	Changes in number of children in HH	0.00 (0.012[a])	0.00 (−0.007[b])	0.00 (0.013[a])
	Lost transit pass	0.00 (0.00)	0.00 (−0.13[a])	0.00 (0.001[c])
	Obtained transit pass	0.00 (−0.024[b])	0.00 (0.046[b])	0.00 (−0.031[c])
Changes in built environment	Changes in distance to non-work related places	0.00 (0.007[c])	−0.144a (−0.144[a])	0.00 (0.00)
	Changes in distance to work	0.057[a] (0.109[a])	0.00 (−0.062 [a])	0.00 (0.00)
	Changes in land use mix	0.00 (−0.046[b])	0.00 (0.67[a])	0.00 (−0.062[b])
	Changes in population density	0.00 (−0.036[b])	0.00 (0.053[b])	0.00 (−0.061[b])
	Changes in Job density	0.00 (−0.005[c])	0.00 (0.00)	0.00 (−0.001[c])
	Move to intensive public transit or pedestrian zone	0.00 (−0.002[c])	0.125a (0.128[a])	0.00 (0.00)
Changes in centricity of activity space	Change to monocentric activity space	0.00 (0.00)	0.00 (0.00)	0.00 (−0.006[c])
	Change to polycentric activity space	0.045[c] (0.044[c])	0.00 (0.00)	0.00 (0.00)
Changes in attitudes	Changes in pro-active transport attitude	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Changes in pro-transit attitude	−0.194[a] (−0.202[a])	0.282[a] (0.293[a])	−0.271[a] (−0.272[a])
	Changes in environmental accountability	0.00 (0.00)	0.00 (0.00)	0.329[a] (0.304[a])
	Changes in susceptibility to peer pressure regarding positive role of active transport	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Changes in time sensitivity	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Changes in travel behavior	Changes in walking	0.00 (0.00)	0.00 (0.00)	−0.079[b] (−0.079[b])
	Changes in cycling	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Changes in transit use	0.00 (−0.041[b])	0.00 (0.060[b])	0.00 (−0.006[c])

Notes: (1) [a] Significantly different from zero at $p < 0.01$; [b] Significantly different from zero at $p < 0.05$; [c] Significantly different from zero at $p < 0.10$. (2) Both direct and total effects are listed and total effects are in parentheses. All effects are standardized.

Table 8
Results of the measurement models of SEM (Change in the attitudinal factors and their indicators).

Change in Attitude	Coefficient value	Measurement indicator (i.e. Change in values of the following statements after relocation)
1. Change in Pro-transit attitude	1.00	I prefer to take public transport than drive whenever possible
	1.2[a]	I like travelling by public transport
	−0.139[a]	I like driving
2. Change in Pro-active travel attitude	1.00	I prefer to cycle rather than drive whenever possible
	0.689[a]	I prefer to walk rather than drive whenever possible
	0.587[a]	I like riding a bicycle
3. Change in Susceptibility to peer pressure	1.141[a]	People in my neighborhood have a positive view of people who use public transport
	1.00	People in my neighborhood have a positive view of people who walk or cycle for daily travel
4. Change in Time sensitivity	5.351 [a]	I do not like to wait for another travel mode while travelling
	1.00	I like to avoid queues and congestion while travelling
	4.142 [a]	I do not like to have variation in my daily travel time
5. Change in Environmental awareness	1.183 [a]	Changing how people travel is a great way to improve the environment
	1.12 [a]	Using electric vehicles can significantly reduce air pollution
	1.00	Vehicles should be taxed on the basis of the amount of pollution they produce
	4.662 [a]	I try to limit my driving to help improve air quality

Note: [a] significantly different from zero at $p < 0.01$.

places for childcare or where leisure time activities for parents with more than one child, or at least one new-born, are available, which is probably more important than proximity to work for such parents.

The results also indicate that changes in transit pass ownership can influence the dispersion of activity space with those losing their transit pass after the move modifying their activity space from a polycentric to a monocentric activity space (i.e. limiting their activities to the area close to home). Conversely, those acquiring a transit pass after the move tend to visit places further from home as well and therefore changing their activity space from a monocentric activity space to a polycentric one.

Among the built environmental factors, an increase in distance to work or non-work related places after the move had a negative

Table 9
Factors influencing changes in attitudes.

		Changes in pro-active transport attitude	Changes in pro-transit attitude	Changes in environmental accountability	Changes in susceptibility to peer pressure regarding positive role of active transport	Changes in time sensitivity
Household and personal socio-demographics (after move)	Income	0.00 (0.00)	0.00 (−0.008[b])	0.00 (0.00)	0.00 (−0.004[b])	0.00 (0.008[b])
	Education	0.107a (0.107[a])	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Gender (Female)	0.00 (0.00)	0.00 (−0.001[c])	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Living in a house	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.1[a] (−0.1[a])	0.00 (0.00)
	Walking limitation	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Changes in socio-demographics	Changes in number of adults in HH	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Changes in number of children in HH	0.00 (−0.022[a])	0.00 (−0.024[a])	0.00 (−0.022[b])	0.00 (0.00)	0.00 (0.014[b])
	Lost transit pass	0.00 (0.00)	0.00 (−0.045[b])	0.00 (−0.036[b])	0.00 (0.00)	0.00 (0.00)
	Obtained transit pass	0.00 (0.00)	0.108[a] (0.163[a])	0.00 (0.44[a])	0.00 (0.00)	0.00 (−0.001[c])
Changes in built environment	Changes in distance to non-work related places	−0.108[a] (−0.108[a])	0.00 (0.001[c])	0.00 (0.00)	0.00 (0.00)	0.00 (0.001[c])
	Changes in distance to work	−0.2[a] (−0.2[a])	−0.243[a] (−0.218[a])	−0.219[a] (−0.199[a])	0.00 (0.00)	0.121[b] (0.129[b])
	Changes in land use mix	0.00 (0.00)	0.229[a] (0.238[a])	0.00 (0.007[c])	0.109[a](0.109[a])	−0.239[b](−0.239[b])
	Changes in population density	0.00 (0.00)	0.181[a] (0.188[a])	0.00 (0.006[c])	0.159[a](0.159[a])	0.00 (−0.015[c])
	Changes in Job density	0.00 (0.00)	0.00 (−0.001[c])	0.00 (−0.001[c])	0.00 (0.00)	0.00 (−0.001[c])
	Move to intensive public transit or pedestrian zone	0.00 (0.00)	0.00 (0.011[b])	0.00 (0.008[c])	0.00 (0.00)	0.00 (0.00)
Changes in centricity of activity space	Change to monocentric activity space	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (−0.007[c])
	Change to polycentric activity space	0.00 (0.00)	0.00 (0.008[c])	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Changes in car and bike ownership	Car acquisition	0.00 (0.00)	0.00 (−0.005[c])	0.00 (−0.004[c])	0.00 (0.00)	0.00 (0.00)
	Car disposal	0.00 (0.00)	0.00 (0.005[c])	0.00 (0.004[c])	0.00 (0.00)	0.00 (0.00)
	Bike acquisition	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Changes in travel behavior	Changes in walking	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.1c (−0.1[c])
	changes in cycling	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	changes in transit use	0.00 (0.00)	0.203[a] (0.211[a])	0.160[a] (0.167[a])	0.00 (0.00)	0.00 (−0.005[c])

Notes: (1) [a] Significantly different from zero at $p < 0.01$; [b] Significantly different from zero at $p < 0.05$; [c] Significantly different from zero at $p < 0.10$. (2) Both direct and total effects are listed and total effects are in parentheses. All effects are standardized.

influence on the change to a monocentric activity space and a positive influence on the change to a polycentric activity space. Moreover, an increase in job density of the residential environment seems to have a positive influence on a change to a monocentric activity space and a negative influence on a change to a polycentric activity space. Although based on the literature maintaining social contacts with old neighbors at the former residence may require arranging meetings or joint leisure activities that might be further from current home (e.g. Lin et al., 2018), it seems that those moving to neighborhoods that have higher job density tend to limit their activities to a monocentric activity space. This indicates that the built environmental characteristics of the new place of residence can compete with the geographies of social networks, as claimed by Lin et al. (2018), in determining where social activities would take place.

Table 10
Factors influencing changes in travel behavior.

		Change in walking	*Change in cycling*	*Change in transit use*
Household and personal socio-demographics (after move)	**Income**	0.00 (0.00)	**0.00 (0.001[c])**	**0.00 (−0.002[b])**
	Education	0.00 (0.00)	**0.00 (0.055[a])**	**0.00 (−0.002[b])**
	Gender (Female)	0.00 (0.00)	0.00 (0.00)	**0.00 (−0.003[b])**
	Living in a house	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Walking limitation	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Changes in socio-demographics	**Changes in number of adults in HH**	0.00 (0.00)	**0.00 (0.009[a])**	0.00 (0.00)
	Changes in number of children in HH	**0.00 (−0.009[b])**	**0.00 (−0.011[b])**	**0.00 (0.013[a])**
	Lost transit pass	**0.00 (−0.003[b])**	**0.00 (0.008[c])**	**−0.216a (−0.204[a])**
	Obtained transit pass	**0.00 (0.014[c])**	**0.00 (−0.003[c])**	**0.234a (0.271[a])**
Changes in built environment	**Changes in distance to non-work related places**	**0.00 (−0.013[c])**	**0.00 (−0.067[c])**	**0.00 (0.003[c])**
	Changes in distance to work	**0.00 (−0.081[c])**	**0.00 (−0.104[b])**	**0.155a (0.122[a])**
	Changes in land use mix	**0.00 (0.002[c])**	**0.00 (−0.031[c])**	**0.00 (0.045[a])**
	Changes in population density	**0.147[a] (0.149[a])**	**0.00 (−0.008[c])**	**0.00 (0.035[a])**
	Changes in Job density	**0.00 (0.010[b])**	**0.00 (0.009[c])**	**0.00 (−0.005[c])**
	Move to intensive transit zone	**0.00 (0.003[c])**	0.00 (0.00)	**0.045[a] (0.050[a])**
Changes in centricity of activity space	**Change to monocentric activity space**	**0.073[b] (0.073[b])**	**0.065[c] (0.064[c])**	0.00 (0.00)
	Change to polycentric activity space	0.00 (0.00)	0.00 (0.00)	**0.041[c] (0.042[c])**
Changes in car and bike ownership	**Car acquisition**	**0.00 (−0.001c)**	0.00 (0.00)	**−0.026[b] (−0.027[b])**
	Car disposal	**0.00 (0.001[c])**	0.00 (0.00)	**0.023[b] (0.024[b])**
	Bike acquisition	0.00 (0.00)	**0.101[a] (0.101[a])**	0.00 (0.00)
Changes in attitudes	**Changes in pro-active transport attitude**	0.00 (0.00)	**0.518[a] (0.518[a])**	0.00 (0.00)
	Changes in pro-transit attitude	**0.00 (0.010[b])**	**0.00 (−0.028[b])**	**0.177a (0.196[a])**
	Changes in environmental accountability	**0.323a (0.323[a])**	**0.00 (0.027[b])**	0.00 (0.00)
	Changes in susceptibility to peer pressure regarding positive role of active transport	**0.073[b] (0.073[b])**	0.00 (0.00)	0.00 (0.00)
	Changes in time sensitivity	0.00 (0. 00)	**0.105[b] (0.105[b])**	0.00 (0.00)

Notes: (1) [a] Significantly different from zero at $p < 0.01$; [b] Significantly different from zero at $p < 0.05$; [c] Significantly different from zero at $p < 0.10$. (2) Both direct and total effects are listed and total effects are in parentheses. All effects are standardized.

5.3. Factors influencing changes in car and bike ownership

Table 7 presents the factors that showed an influence on changes in car and bike ownership. Among the sociodemographic factors, income shows an indirect positive influence on car and bike acquisition and an indirect negative influence on car disposal. Education has a negative influence on car disposal as well. Being a female has a positive influence on car ownership after the move and having walking limitations has an indirect negative effect on bike acquisition. An increase in the number of adults in the household has a positive influence on bike acquisition. An increase in the number of children in the household has an indirect positive influence on both car and bike acquisition and an indirect negative influence on car disposal. Losing a transit pass has an indirect positive influence on bike acquisition and an indirect negative influence on car disposal. Conversely, acquiring a transit pass has an indirect positive influence on car disposal and an indirect negative influence on car acquisition. It also shows an indirect negative influence on bike acquisition. These results concerning the influence of sociodemographics on car ownership have been emphasized by a number of studies in the literature (e.g., Bagley and Mokhtarian, 2002).

Among the built environmental factors, an increase in distance to work and/or non-work places leads to car acquisition and has a negative influence on car disposal. An increase in land use mix measure, as well as the density measures, have a negative influence on both car and bike ownership and a positive influence on car disposal. Rather similarly, moving to an intensive transit zone has a negative influence on car acquisition and a positive influence on car disposal. These results are consistent with the literature referring to the impact of relocating home and changes in the built environmental factors on mobility adjustments (Lin et al., 2018) such as car ownership (e.g. Yang, 2006; Buchanan and Barnett, 2006; Wang and Lin, 2019).

As for the influence of changes in activity space dispersion, changing to a polycentric activity space after relocation has a positive influence on car acquisition. On the other hand, change to a monocentric activity space has an indirect negative influence on bike acquisition which might be due to the location of activity places most of which are located within walking distance from home.

Changes in attitudes also showed to influence changes in car and bike ownership. An increase in pro-transit attitude shows to have a very significant negative influence on car and bike acquisition and a very positive influence on car disposal. Moreover, an increase in environmental accountability has a very positive influence on bike acquisition. Although Wang and Lin (2019) had found that car ownership after the move can influence travel attitudes, they had not considered the reverse causality from changes in attitudes to changes in car ownership. This study which tested both causality directions between changes in car ownership and changes in travel attitudes found that the reverse causality direction holds as well and is more significant than the influence of changes in car ownership on changes in attitudes.

This study considered the reverse causality between travel behavior and car and bike ownership as well. The results revealed that an increase in walking has a direct negative influence on bike acquisition. Moreover, an increase in transit use after relocation negatively influences car and bike acquisition and positively influences car disposal although this influence is indirect. This indicates that in the long run changes in travel behavior can influence changes in car and bike ownership as well.

5.4. Factors influencing changes in attitudes

Among the eight latent factors tested in models measuring a change in attitudes (see Section 4.3.3) only five showed significance and increased the fit of the model to the data. Therefore, only these five factors are retained in the final SEM. In this section, the factors that showed to influence these latent factors are reported. Table 8 presents the measurement model in SEM that shows these five latent factors and their measurement indicators. Table 9 will then present factors influencing changes in these attitudes after residential relocation.

Among the different sets of factors included in this study, changes in the built environmental factors showed to have the most significant effects on changes in attitudes, followed by changes in travel behavior, sociodemographics, activity space dispersion, and car ownership, respectively.

Among the built environmental factors, an increase in distance to workplace decreased pro-transit and pro-active transport attitudes as well as environmental accountability. Conversely, it increased time sensitivity. An increase in distance to non-work places decreased pro-active transport attitude and very slightly and indirectly increased pro-transit attitude and time sensitivity. An increase in land use mix and population density increased pro-transit attitude, environmental accountability, as well as susceptibility to peer pressure regarding the advantages of using active transport while decreasing time sensitivity. An increase in job density showed a slight indirect and negative effect on pro-transit attitude, environmental accountability, and time sensitivity. Moving to an intensive transit zone showed an indirect positive influence on pro-transit attitude and environmental accountability. This result confirms the discussions in the literature regarding the influence of built environment on travel attitudes and that individuals adjust their travel attitudes after residential relocation (Bohte et al., 2009; Cao et al., 2009; Mokhtarian and Cao, 2008; Chatman, 2009; Næss, 2014; De Vos et al., 2018; Wang and Lin, 2019). It is consistent with the few empirical studies testing the reverse causality between attitudes and the built environment (e.g., Ewing et al., 2016; Van Acker et al., 2014).

Among the travel behavior factors, an increase in transit use showed to increase pro-transit attitude and environmental accountability very significantly and decreased time-sensitivity slightly and indirectly. An increase in walking decreased time-sensitivity significantly. This reverse causality between travel behavior and attitudes is consistent with the theory of cognitive dissonance (Festinger, 1957), which argues that after a choice, stated attitudes will be aligned to this choice although most studies that investigate attitude-behavior-relationships in the transport sector refer to the theory of planned behavior (Haustein, 2012). Evidence regarding the influence of mobility behavior on attitudes has been found in a few earlier studies (e.g. Dobson et al., 1978; Golob, 2001; De Vos et al., 2018; Kroesen, 2019), although it is not commonly considered in the built environment-travel behavior and RSS studies. For example, Bagley and Mokhtarian (2002) used SEM to test the influence of behavior on attitudes. They concluded that the number of vehicle miles driven influences pro-driving attitude.

Among the sociodemographic factors, an increase in income decreased pro-transit attitude and susceptibility to peer pressure regarding the advantage of active transport. On the contrary, it increased time sensitivity. Education increased pro-active transport attitude. Being a female decreased pro-transit attitude indirectly. Living in a house rather than an apartment decreased susceptibility to peer pressure regarding the advantage of active transport. An increase in the number of children had an indirect negative influence on pro-transit attitude, pro-active transport attitude, and environmental accountability, and a positive indirect influence on time sensitivity. Losing one's transit pass influenced pro-transit attitude and environmental accountability negatively. Obtaining a transit pass, on the other hand, increased pro- transit attitude and environmental accountability and decreased time sensitivity.

As for the influence of activity space dispersion on attitudes, a change to a monocentric activity space decreased time sensitivity, and a change to polycentric activity space increased pro-transit attitude.

Car acquisition decreased pro-transit attitude as well as environmental accountability. Conversely, car disposal increased these two attitudes. This result regarding the influence of car ownership on attitudes is consistent with the recent empirical studies in the literature (e.g. Wang and Lin, 2019).

5.5. Factors influencing changes in travel behavior

As presented in Table 10, among the different sets of factors examined in this study, changes in attitudes showed to have the strongest influence on changes in travel behavior, followed by changes in the built environment and sociodemographics as the second most important sets of factors, and changes in activity space dispersion and car and bike acquisition as the third sets of influencing factors.

Among the attitudinal factors changes in pro-active transport attitude showed to be the most influencing factor which increases cycling with high statistical significance. An increase in environmental accountability increased walking significantly and showed a moderate influence on an increase in cycling. An increase in pro-transit attitude had a highly significant and positive influence on transit use, an indirect moderate and positive influence on walking, and an indirect moderate and negative influence on cycling. An increase in susceptibility to peer pressure regarding the advantage of active transport had a moderate positive influence on an increase in walking. An increase in time sensitivity had a moderate positive influence on cycling. The results of this study regarding the strong influence of attitudes on travel behavior are consistent with the first study on residential self-selection that used SEM by Bagley and Mokhtarian (2002) who had also found that travel attitudes had the highest direct and indirect influences on travel behavior. However, this study showed that an individual's attitudes are not static and do change after residential relocation. This study provided empirical evidence for the claims by some earlier studies which had referred to the possibility that changes in travel behavior after a home relocation are also induced by changes in travel preferences (e.g. Cao et al., 2007; Krizek, 2003).

Almost all the built environmental factors were found to influence travel behavior indirectly through their intermediate effect on other factors such as attitudes. However, an increase in population density (which increased walking), distance to work (which increased transit use), and moving to an intensive transit zone (which increased transit use) showed to have a direct influence on travel behavior. This result is consistent with previous studies which referred to better access to public transport (i.e. Aditjandra et al., 2012) and commute distance (Bagley and Mokhtarian, 2002) as important factors influencing travel behavior. However, all the other built environmental factors that did not show direct influence on travel behavior had an indirect influence on travel behavior as presented in Table 10. For example, land use mix, which did not show a direct influence on travel behavior, had a positive indirect influence on walking and transit use and a negative indirect influence on cycling. Changes in the distance to work and non-work places showed a negative indirect influence on walking and cycling and a positive influence on transit use. An increase in job density showed a positive indirect influence on walking and cycling and a negative indirect influence on transit use.

Among the sociodemographic factors, changes in transit card ownership were the most influencing factor. Obtaining a transit card had a very highly significant positive influence on transit use and an indirect positive influence on walking. Losing a transit card showed a very negative influence. This is consistent with the results of previous studies emphasizing the influence of transit pass ownership on transit use and even walking (e.g. Ramezani et al., 2018a,b; Ramezani et al., 2015). An increase in the number of children in the household had a negative indirect influence on walking and cycling and a positive indirect influence on transit use. An increase in the number of adults in the household increased cycling. Income and education both showed a negative indirect influence on transit use and a positive indirect influence on cycling. Being a female had a negative indirect influence on transit use as well.

Changes in activity space dispersion also showed to have a significant influence on travel behavior. A change from a polycentric activity space to a monocentric activity space after residential relocation increased walking and cycling while a change from monocentric to polycentric activity space increased transit use. This result regarding the influence of a polycentric activity space on more transit use is consistent with the results of a recent study on the shopping trip mode choice of older adults in HMA (Ramezani et al., 2019).

Bike acquisition showed a very significant direct and positive influence on biking. Car acquisition had a negative influence on transit use and walking. Conversely, car disposal showed a positive influence on transit use and walking. These results are consistent with the literature referring to the influence of car ownership on travel behavior (e.g. Wang and Lin, 2019).

6. Conclusion

This paper adopted a semi longitudinal approach to study the interrelationships between changes in the built environment, activity space dispersion, car and bike ownership, travel-related attitudes, and travel behavior after residential relocation in the Helsinki Metropolitan Area. It sought to gain a better understanding of the complex relationships between the built environment, travel attitudes, and travel behavior, which is more complex than what has been revealed in the existing literature. It provided empirical evidence for the reverse causality direction from the changes in the built environment to changes in travel attitudes as well as the reciprocal relationships between travel attitudes, car and bike ownership, and travel behavior. It also found that changes in the built environment can lead to changes in the dispersion of an individual's activity space which eventually influences their travel behavior.

The study found that although some of the built environmental factors of residential location may not show a direct influence on travel behavior, they do have an intermediate effect through their influence on travel attitudes, dispersion of activity space of the individuals, and car and bike ownership. This emphasizes that the influence of residential self-selection might have been overestimated and the influence of the built environment might have been underestimated in some previous studies that use a cross-sectional approach in understanding travel behavior and the ones that do not consider the reciprocal relationships investigated in this study. Although changes in attitudes were found to have the highest contribution to changes in travel behavior (as expected) and were more important than changes in the built environment, it was very interesting to find out that the influence of changes in the built environment of the residential environment on travel attitudes was higher than that of other sets of factors such as changes in socio-demographics. It shows that behavioral orientations (e.g., values, attitudes, preferences) can be modified and made more sustainable. Lifestyles and attitudes must therefore be considered dynamic rather than static and given (van Acker and Witlox, 2016). Moreover, the results of this study found that the built environmental characteristics of an individual's home location influence their activity space, which in turn determines the mode of transport they use more frequently. Although, based on the literature, maintaining social contacts with old neighbors at the former residence may require arranging meetings or joint leisure activities that might be further from current home (e.g. Lin et al., 2018), leading to polycentric activity spaces, and therefore more use of motorized modes of transport (e.g. transit) rather than walking and cycling, those individuals moving to neighborhoods that have higher job density tend to limit their activities to a monocentric activity space.

In addition to contributing to the literature on built environment-travel behavior, the information gained through this study provides some insights for policymakers. For example, this study found that both changes to the built environment and the use of more sustainable modes of travel lead to more sustainable travel attitudes. Although this study did not use a truly experimental approach to investigate the influence of interventions in the built environment on changes in sustainable travel attitudes the obtained results provide empirical evidence for the notion that travel attitudes (which lead to sustainable travel behavior) can be modified and made more sustainable by changes in the environment (e.g. through sustainable spatial planning and transportation policies). The results of this study therefore support the effectiveness of nudging approaches rather than marketing activities in changing travel attitudes and encouraging sustainable travel behavior. The principles of nudging have been claimed to serve as a strategy to increase physical activity (Thaler and Sunstein, 2008). Nudging, giving a soft push to direct people towards healthier choices, is an approach to change people's behavior to improve their health and wellbeing (Vallgårda, 2012). While nudging, formally known as libertarian paternalist agenda proposed by Thaler and Sunstein (2008), has been shown having some ethical and conceptual inconsistencies (Vallgårda, 2012; Hausman and Welch, 2010), the general idea behind the term could serve as an additional way to promote the use of the more active and sustainable mode of transportation especially for the urban and transportation planning professionals making decisions on land use and transportation policies. As Mont et al. (2014) put it, nudging tools (in this case changes in the physical environment) are facilitators of behavior. Residents can make choices, but the choice architecture is designed to promote the desired behavior. Changes in the built environment in this study do not interfere with or limit freedom of transport mode choice. Movers still have the option to choose other modes, but changes in the environment, such as increased land use mix and more frequent public transport, ease the choice of more sustainable modes for them. Mont et al. (2014) refer to such changes in the built environment as one of the nudging tools for changing travel behavior by citing the work of Pucher and Ralph (2008) who tried to understand the most significant factors behind an increase in cycling as means of transport in Denmark, Germany and the Netherlands. They found that the most important policies to increase the share of cycling in total transport is related to changes to the physical environment (e.g. the provision of separate cycling facilities along heavily travelled roads and intersections) and more generally– urban planning that focuses on density and the prevention of city sprawling. Although nudges have been sometimes defined as "small changes to the environment" as Mont et al. (2014) put it, interventions need to be proportionate to the gravity of the behavior and its impacts they are trying to change. They argue that governments have been nudging people's behavior change in different areas, without defining or framing policy instruments as nudges. Today, however, nudges are being explored by governments in several countries as a promising policy tool in the policy package for behavior change management.

Moreover, the significant and rather strong influence of changes in some socio-economic factors on travel behavior can provide some insights about the influence of incentives for the use of sustainable transportation modes. For example, employers could provide their employees with free transit cards as an incentive to increase the use of public transport for commute trips, as transit card ownership showed a very significant positive influence on transit use.

Although this study provided some new insights and empirical evidence regarding the complexity of the relationship between the built environment and travel behavior, it is not void of limitations and some directions for future research can be identified. First, the influence of some of the variables tested in this study on travel behavior and the reciprocal relationships between travel behavior, car and bike ownership, and travel attitudes have been rarely empirically examined. Any generalizations regarding the direction of causality between these factors could only be made after it is tested in other contexts and with different datasets. For example, determinants of changes in activity space dispersion and its interrelationships with travel behavior should be tested in other contexts. Moreover, as discussed in Section 4.3.4, transit pass ownership was included in this study as an exogenous variable. Future studies should collect data about the type of transit pass and include it as an endogenous variable in models to test if other endogenous variables such as changes in the built environment and activity space can have a causal influence on transit pass ownership. Second, although this study adapted a semi longitudinal approach and collected retrospective travel behavior and attitudinal data before and after residential relocation, due to data limits it could not examine how changes in attitudes, activity space, car and bike ownership, and travel behavior over time could influence the decision to relocate to a new neighborhood with specific built environmental characteristics. In other words, the reverse causality direction from changes in these factors to the changes in the built environment could not be examined and therefore no conclusion regarding the degree of influence of RSS could be made. Moreover, one must be mindful of the fact that the data analyzed in this study is cross-sectional in nature (change variables are measured only at one point after relocation), and consequently, it is not possible to determine the order of the loop for reciprocal influences. The analysis suggests only that some of the causal influences are bidirectional and reciprocal. Future studies with true longitudinal nature could collect similar data over a longer period. Data should be collected at several points in time before and after the decision to relocate is made, as well as before and after the move to a new residential neighborhood has taken place. Such data would make it possible to test the hypothesis that the RSS is less important than the changes in travel behavior and travel attitudes induced by changes in the built environment. It would also allow determining the order of the reciprocal influences. Moreover, there can be always a recall bias in retrospective surveys and the priority of true longitudinal data collection over retrospective surveys should not be underestimated. This is especially true for the measurement of attitudes over time. As Thigpen (2019b) put it, concrete characteristics are more readily recalled than more abstract attributes. Although the use of an online map-based survey tool proved to be very useful for collecting retrospective attitudinal and travel behavior data as its visual component could help the respondents remember their past behavior, difficulties in more detailed longitudinal data collection through retrospective surveys could be resolved using a combination of emerging data collection technologies such as map-based survey tools and travel tracking applications.

However, it should be also noted that as Wong and Law (1999) put it, from a pragmatic point of view, although causes should precede effects, the exact time lag between them is difficult to identify. Without knowing the exact duration of this time lag, using longitudinal data may not be preferable to cross-sectional data. For example, if it takes 1 month for the causal variables to affect the outcome variables, a longitudinal design with 3 months between phases of data collection would not be meaningful because the causal variables that lead to the outcome variables may have changed largely. Future studies might still be able to identify the time lag by combining qualitative and quantitative research approaches. Experimental (or semi-experimental) research designs that would focus on the influence of new interventions in the physical environment on changes in travel behavior could also provide a better understanding of the effectiveness of nudging sustainable travel behavior through changes in the physical environment.

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CRediT authorship contribution statement

Samira Ramezani: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization. **Kamyar Hasanzadeh:** Data curation, Formal analysis. **Tiina Rinne:** Formal analysis. **Anna Kajosaari:** Formal analysis. **Marketta Kyttä:** Supervision.

Declaration of Competing Interest

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

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