Land use mix and physical activity in older adults: a longitudinal study examining changes in land use mix in two Dutch cohorts

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DECLARATIONS

AUTHOR CONTRIBUTIONS

JMN was responsible for conceptualizing the study, conducting the analyses and writing the manuscript. MAB, JOG, and FJvL helped with the conceptualization of the study and provided valuable input on drafts and final manuscripts. MAB, JOG, and EJT contributed substantially to the analyses and provided valuable input on the drafts and final manuscript. EJT, IM, and MH also contributed to the conceptualization of the study and provided valuable feedback on the drafts and final manuscript. All authors approved the final manuscript as submitted.

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COMPETING INTERESTS

None declared.

DATA AVAILABILITY STATEMENT

The datasets generated for the MINDMAP project are not publicly available due to study participant privacy considerations. However, data access can be requested from the individual cohort studies

via the respective data access procedures in place. The BBG exposure data is openly accessible via Statistics Netherlands.

ETHICS APPROVAL

The use of personal data in the GLOBE study follows the Dutch Personal Data Protection Act and the Municipal Database Act and has been registered with the Dutch Data Protection Authority (number 1248943). LASA was approved by the Ethical Review Board of its institution and confirms to the principles embodied in the Declaration of Helsinki.

CONSENT FOR PUBLICATION

All authors approved the final manuscript and approve with submission to the International Journal of Behavioral Nutrition and Physical Activity.

ABSTRACT

BACKGROUND

With urbanization and aging increasing in coming decades, societies face the challenge of keeping aging populations active. Land use mix (LUM) has been associated with cycling and walking, but whether changes in LUM relate to changes in cycling/walking is less known.

OBJECTIVES

Our objective was to study the effect of LUM on cycling/walking in two Dutch aging cohorts using data with 10 years of follow-up.

METHODS

Data from 1,114 respondents from the Longitudinal Aging Study Amsterdam (LASA) and 1,561 respondents from the Health and Living Conditions of the Population of Eindhoven and Surroundings (GLOBE) study were linked to LUM in 1000-meter sausage network buffers at three time-points. Cycling/walking outcomes were harmonized to include average minutes spent cycling/walking per week. Data was pooled and limited to respondents that did not relocate between follow-up waves. Associations between LUM and cycling/walking were estimated using a Random Effects Within-Between (REWB) model that allows for the estimation of both within and between effects. Sensitivity analyses were performed on smaller (500-meter) and larger (1600-meter) buffers.

RESULTS

We found evidence of between-individual associations of LUM in 1000-meter buffers and walking (β: 11.10, 95% CI: 0.08 ; 21.12), but no evidence of within-associations in 1000-meter buffers. Sensitivity analyses using 500-meter buffers showed similar between-associations, but negative within-associations (β: -35.67, 95% CI: -68.85 ; -2.49). We did not find evidence of between-individual associations of LUM in any buffer size and cycling, but did find evidence of negative within-associations between LUM in 1600-meter buffers and cycling (β: -7.49, 95% CI: -14.31 ; -0.66).

DISCUSSION

Our study found evidence of positive associations between LUM and average walking time, but also some evidence of negative associations between a change in LUM and cycling/walking. LUM appears to be related to cycling/walking, but the effect of changes in LUM on cycling/walking is unclear.

Words: 300

INTRODUCTION

Physical inactivity has been identified as the fourth leading risk factor for global mortality [1] and increasing physical activity (PA) has been marked as a top-priority intervention to reduce death rates of non-communicable diseases [2]. Multiple studies have shown positive associations between PA and measures of urban form, such as urban green spaces, public open spaces, residential density, and land use mix [3-5]. Changes in the built environment, such as increased investment in green spaces and pedestrian and cycling infrastructure, as well as transforming cities towards more compact, mixed-used environments can potentially aid in promoting PA [4, 6]. Furthermore, extensive modification of the built environment for health-related purposes could gain more traction in the coming years as a co-benefit of structural urban changes, such as climate control efforts.

One commonly studied physical-environmental exposure with regards to PA is that of land use mix (LUM). Land use mix represents how evenly different types of land use are distributed within a specified area [7]. Mixed-use areas contain a variety of different land uses and are believed to encourage PA because they include a larger number of destinations [8-9]. However, much of the evidence linking varying land uses to PA is cross-sectional, which makes it difficult to establish a causal relationship. Many studies adjust for confounding factors, but it remains unclear which factors should be included. Furthermore, selection bias remains an issue as individuals may choose to live in areas based on lifestyle preferences and socioeconomic factors [10]. A physically active person may deliberately choose to live in a PA friendly area, inflating the possible relation between LUM and PA.

Various methods have been applied to account for these methodological shortcomings, such as adjustments for proxy indicators of preferences, as well as applying fixed effects (FE) models that control for time-invariant characteristics, assuming that they remain stable over time. While the FE model provides a valuable tool for assessing the effects of temporal changes, it disregards between-individual variability. As the method solely relies on within-individual changes, it might not be the best fit for LUM measures, as it is debatable how much LUM in an urban context changes over time. The primary alternative – the random effects (RE) model – makes use of between-

individual variability, but in turn does not remove the effects of time-invariant causes, and assumes that the unmeasured causes are uncorrelated with measured causes. The latter is often a difficult assumption to make and, if violated, will result in omitted-variable bias [11]. Methods exist that combine elements of both RE and FE models and take “the best of both worlds.” These models go by different names, such as random effects between-within models (REWB), Mundlak models, or simply hybrid models, and make use of centering of all individual units around their means [12-13]. Such models can be of great value for research considering the impact of LUM on PA as they not only explore the differences between individuals, but also how a change in LUM might influence a change in PA. However, these models have only been scarcely applied within the public health domain [13].

Further complicating the evidence in the field of environment-PA research is a lack of consistency in both the geographic units and scale used to define the individual’s residential environment [14-15]. To quantify environmental exposures, researchers traditionally relied on neighborhood-level data, such as pre-existing administrative units. A more refined method that is especially relevant for PA comes with the use of network buffers that define buffers as areas accessible via a street network. The “sausage” or “line-based” buffering method selects roads within a certain distance of the individual and creates a buffer around these roads by a set distance (e.g. 25 meters). This ensures that only those features that are directly accessible from the street network are selected. This method has several key advantages as it is based directly on the road network where people travel [15-16]. Sausage buffers therefore offer an attractive alternative to more traditional Euclidian buffers – especially when PA is concerned – as these buffers represent areas that are actually accessible via the road network.

Our study uses sausage buffers to define LUM within the individual’s residential environment and links this data to cycling and walking outcomes. We linked data from two Dutch cohorts with 10 years of follow-up to a harmonized land use dataset, and explored both within-person and between-person associations of LUM on cycling/walking.

METHODS

STUDY POPULATION

Data were obtained from two longitudinal cohort studies on ageing in the Netherlands that are participating in the MINDMAP project [17]: the Health and Living Conditions of the Population of Eindhoven and Surroundings (GLOBE) study, and the Longitudinal Aging Study Amsterdam (LASA). The GLOBE study is a prospective cohort study on the role of living conditions for health in the Netherlands [18]. The 2004 sample of GLOBE participants who resided in the city of Eindhoven and surrounding areas was selected for the analyses (N=4,775) with follow-up data collected for the years 2011 and 2014. The LASA study is a longitudinal population-based study of the predictors and consequences of aging in the Netherlands [19]. The 2005/2006 LASA sample of participants who resided in the cities of Amsterdam, Zwolle, and Oss and their surrounding areas was selected for the analyses (N=2,165) with follow-up data collected for the years 2008/2009 and 2011/2012. The residential addresses of these respondents were geocoded using geographical software package QGIS [20] and a geocoding plug-in developed by the Dutch National Spatial Data Infrastructure (PDOK) [21]. To maintain respondent privacy, addresses were extracted and geocoded using a process previously described [17, 22]. Respondents whose addresses could not be geocoded, who did not participate in all three data collection waves, or who moved outside of the study area for the respective cohorts were excluded. The sample was limited to respondents that did not relocate during follow-up waves, resulting in a final sample of 1,561 respondents for GLOBE and 1,114 respondents for LASA. Sensitivity analyses were performed on the total sample including respondents that moved between follow-up waves. The use of personal data in the GLOBE study follows the Dutch Personal Data Protection Act and the Municipal Database Act and has been registered with the Dutch Data Protection Authority (number 1248943).

LAND USE EXPOSURE MEASURES

Exposure measures were obtained using the dataset ‘Bestand Bodemgebruik’ (BBG) which is maintained by Statistics Netherlands [23]. The BBG database is a harmonized dataset based on ‘Top10NL’ digital 1:10,000 topographic maps provided by the Dutch mapping agency Kadaster [24].

The harmonization of the BBG data ensures that observed changes are representative of actual changes in the environment and not related to changes in GIS processing or methodology. The total land use data was grouped into 11 land use categories (supplementary file 2, table 13). LUM was calculated using network buffers of 1000 meters as the main exposure with additional buffers of 500 and 1600 meters for sensitivity analyses. The Dutch 'Nationaal Wegenbestand' (NWB) database [25] was used for the calculation of the network buffers. The NWB is an open source database with all publicly available roads in the Netherlands with either a street name or a road number. Roads that are not available to pedestrians and cyclists, such as highways, were excluded to provide an accurate estimation of reachable destinations. Sausage buffers were created using line buffers with a radius of 25 meters [16, 26]. Land use mix was calculated for all buffer sizes using the following entropy formula:

$$LUM = -\frac{\left[\sum_{j=1}^{N} p^j \ln\left(p^j\right)\right]}{\ln(N)}$$

whereby LUM is an entropy score with a value between 0 and 1, p^j the percentage of each land use class j of the total buffer area, and N the total amount of land use classes. The calculated entropy value represents a measure of heterogeneity, whereby 1 represents a perfect mix of land use classes and 0 no mix of classes [27]. N was set to 11 LUM classes to avoid measurement bias and to improve comparability of the changes in LUM over time [28]. The LUM entropy score was scaled in the analyses to represent a 10% change in LUM to improve interpretation. Cohort data from each wave was linked to both NWB and BBG data from a preceding year, keeping in line with an appropriate chronology of exposure preceding outcome. LUM exposure data was calculated for all respondents in the final sample.

OUTCOME MEASURES OF WALKING AND CYCLING

Walking and cycling outcomes were assessed using self-reported time spent walking and cycling and defined as average minutes spent walking and cycling per week. GLOBE uses the Short Questionnaire to Assess Health enhancing physical activity (SQUASH) tool, which was created by

the Dutch National Institute of Public Health and the Environment to measure habitual physical activity levels in an adult population [29]. In accordance with the SQUASH guidelines, it was assumed that participants who filled-in hours or minutes per week, but omitted 'days per week,' had been active for at least one day. If the number of days was provided without a corresponding time frequency, the median minutes per day of all respondents was substituted. LASA uses the LASA Physical Activity Questionnaire (LAPAQ), which asks respondent how often and for how long they engaged in various activities, including walking and cycling in the last two weeks. LAPAQ has been validated against 7-day physical activity diaries and 7-day pedometer counts in a subsample of LASA participants [30]. A final measure of average minutes per week was computed for both cohorts.

COVARIATES

Time-invariant characteristics (as measured at baseline) that were included in the analyses include age, sex (male, female) and education as measured using the International Standard Classification of Education (lowest=ISCED 0-1, low=ISCED 2, middle=ISCED 3-4, high=ISCED 5-7) [31]. Education was considered to be time-invariant because of the relatively old age of the cohorts. Marital status (married/partnership, not married, divorced, widowed), household income (monthly; <€1200, €1200-1800, €1800-2600, >€2600), and employment status (employed, non-employed) were included as relevant time-varying confounders. All time-varying covariates for both studies were measured at all three time points, capturing changes that occurred during follow-up. Missing data on covariates were handled via multiple imputation using the covariates listed above as well as self-rated health (excellent, very good, good, fair, poor), smoking (yes, no), and BMI. Only the covariates education, income, and employment (GLOBE), and income and employment (LASA) had missing values, ranging from 2% - 11% for GLOBE and 5% - 12% for LASA.

STATISTICAL ANALYSES

The imputed data of both cohorts was pooled and limited to respondents with three measurements on the outcomes. Pooling the data enabled us to observe more changes in the environment as well

as increasing variation in environmental exposure, therefore strengthening both the between- and within-analyses. The analysis was restricted to non-movers to limit selection effects. Sensitivity analyses were performed on data from the separate cohorts as well as on the total sample including those who had moved between data collection waves.

We constructed a random effects within-between (REWB) model to conduct the analyses [11, 13]. This model decomposes the time-varying LUM variable into deviations from the individual-specific means (within-individual estimates) and individual-specific means (between-individual estimates). The estimated between-individual regression coefficient represents how the exposure across all participant-observations is related to the outcome, and the within-individual coefficient represents how variation in exposure around the individual's mean level is related to the outcomes. In addition, the model can include both time-varying and time-invariant covariates. A random intercept is added to account for the dependence of multiple measurements for each participant. The following model was used for the analyses:

$$PA_{it} = \beta_0 + \beta_{1W}(x_{it} - \bar{x}_i) + \beta_{2B}\bar{x}_i + \beta_3 Z_i + \beta_4 \gamma_i + (v_i + \epsilon_{it})$$

whereby PA_{it} indicates the PA outcome for individual *i* at time *t*, and x_{it} is the time-varying land use mix variable. The relationship between x_{it} and PA_{it} is decomposed into two parts with β_{1W} representing the average within effect and β_{2B} the between effect. β_3 represents the effects of time-invariant measures Z_i, and β_4 represents the effects of time-varying measures γ_i. v_i is the model's random effect for individuals I, and ϵ_{it} are the model's level-1 residuals. All analyses were performed using R [32].

RESULTS

Both cohorts consist of middle-aged and older adults with the mean age ranging from 53 (GLOBE) to 69 years (LASA) (Table 1). The respondents had an average LUM entropy score of 0.26 (GLOBE) or 0.24 (LASA) on a scale from 0 – 1. Both the average cycling and walking time was

higher for GLOBE with 171 minutes spent cycling per week and 173 minutes walking compared to 72 minutes of cycling and 167 minutes of walking for LASA.

Table 1: Description of the baseline study samples for GLOBE and LASA

	GLOBE N = 1,561	**LASA** N = 1,114
EXPOSURE	**Mean (SD)**	**Mean (SD)**
Land use mix in 1000-meter buffers, entropy score	0.26 (0.07)	0.24 (0.09)
OUTCOMES		
Average cycling time per week, minutes	171 (231)	72 (111)
Average walking time per week, minutes	173 (247)	167 (221)
INDIVIDUAL CHARACTERISTICS		
Time-invariant characteristics		
Male, %	47%	44%
Education, %		
Lower secondary or less (ISCED 0-2)	22%	45%
Upper secondary (ISCED 3)	16%	15%
Post-secondary non-tertiary education or short-cycle tertiary education (ISCED 4,5)	25%	19%
Bachelor, master, doctoral, or equivalent (ISCED 6,7,8)	37%	21%
Time-varying characteristics		
Age, mean (SD)	53 (13)	69 (8)
Employment status, %		
Currently in paid employment	53%	20%
Currently not in paid employment	47%	80%
Income, %		
< €1200	9%	18%

€1200 - €1800	24%	32%
€1800 - €2600	31%	50%
> €2600	36%	n.a.*
Marital status, %		
Married or registered partnership	76%	68%
Never married	13%	5%
Divorced	7%	7%
Widowed	4%	20%

***** The highest income class for LASA consists of respondents with an income of > €2270.

Within-individual changes in LUM were observed for approximately 44% of all person-observations (Table 2). The observed changes consisted of both decreases and increases in the LUM which corresponded to an average 5% decrease and an average 3% increase. Within-individual changes were also observed for both outcomes with approximately 18% (cycling) and 14% (walking) reporting no change in the average amount of minutes spent walking/cycling per week.

Table 2: Within-individual changes in land use mix in 1000-meter buffers and average cycling and walking time per week between 2004 and 2014 using pooled data from respondents that did not relocate during follow-up

	Decrease		**No Change**		**Increase**	
N = 6,303 person-observations	Mean	N	Mean	N	Mean	N
Exposure						
Land use mix in 1000-meter buffers	-0.05	942	0	3513	0.03	1848
Outcomes						
Average cycling time per week (minutes)	-120	2974	0	1157	159	2172
Average walking time per week (minutes)	-182	2635	0	905	180	2763

REWB models provided no evidence of within or between associations between LUM in 1000-meter buffers and the average time spent cycling (Table 3). Sensitivity analyses conducted on 1600-meter buffers provided no evidence of between-associations, but did provide evidence of a

negative association between a within-individual change in LUM and average time spent cycling (β: -7.49, 95% CI: -14.31 ; -0.66) (supplementary file 1, table 5). REWB models modelling the average time walking showed evidence of positive between-individual associations between average LUM in 1000-meter buffers and the average walking time (β: 11.10, 95% CI: 0.08 ; 21.12). Sensitivity analyses conducted using 500-meter buffers showed similar between-individual associations, but also negative within-individual associations (β: -35.67, 95% CI: -68.85 ; -2.49) (supplementary file 1, table 9).

Table 3: Within and between associations of land use mix in 1000-meter buffers and average minutes cycling and walking per week using pooled data on respondents that did not relocate during follow-up

N = 6,303 person observations	**WITHIN EFFECTS**		
REWB model*	β	95% CI	p-value
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	-5.55	-17.17 ; 6.07	0.349
Average walking time per week (minutes)	0.75	-14.31 ; 15.80	0.922
	BETWEEN EFFECTS		
REWB model*	β	95% CI	p-value
Land use mix in 1000-meter buffers			
Average cycling time per week (minutes)	5.06	-4.91 ; 15.04	0.320
Average walking time per week (minutes)	11.10	0.08 ; 22.12	0.048

*adjusted for study, time-invariant individual characteristics sex and education, and time-varying characteristics age, employment, income, and marital status.

DISCUSSION

In the present study, we found evidence of between-individual associations of land use mix in 1000-meter buffers and the average amount of walking per week. We did not find evidence of within-associations between LUM in 1000-meter buffers and walking nor did we find evidence of within- or between-associations between LUM in 1000-meter buffers and cycling. We did find evidence of

a negative within-effect on cycling in larger 1600-meter buffers, and evidence of a positive between- and negative within-effect on walking in 500-meter buffers.

The 1000-meter network buffer is a commonly used exposure measure in PA research as it is believed to be a reasonable distance that people can walk [8]. The associations that we found for this buffer are in line with other studies on this subject. For example, a recent study using the GLOBE data found no evidence of within-associations of green spaces in 1000-meter buffers on cycling and walking outcomes [33]. Our study also found no evidence of within-associations between a change in LUM in the residential environment and cycling/walking. A study conducted in Brisbane, Australia found that results of estimates from random effects models indicated positive associations between any walking for transport and an increase in LUM of 10%, which is in line with the between-associations that we observed for walking [8]. This Australian study also found positive, if less pronounced, within-individual associations. While our study did not observe within-associations for our main exposure buffers, we did observe within-associations for the smaller 500-meter buffers, but these were the inverse of the between associations.

Little consensus exists about what buffer sizes to use when analyzing how LUM and cycling/walking relate, with other studies reporting both smaller and larger buffers [34]. As both the GLOBE and LASA cohorts include a large proportion of older adults, we included a smaller buffer of 500 meters in our sensitivity analyses to test whether LUM in this smaller buffer was associated with walking. We also included a larger 1600-meter (approximately 1 mile) buffer in our analyses specifically for the cycling outcome. The 1600-meter buffer is another commonly used buffer and can be especially relevant for cycling as larger distances can be covered compared to walking. The results for the larger and smaller buffer sizes were contrary to what we expected based on the existing literature. For example, a study conducted in Perth, Australia found that an increase in access to destinations in the residential environment was associated with taking-up cycling, providing evidence that changes in the built environment may support the uptake of cycling among formerly non-cycling adults [35]. Our study did not find evidence that a change in LUM in the residential environment is associated with time spent cycling in our main exposure buffers of 1000 meters and some evidence of negative associations between LUM and cycling in larger 1600-meter buffers (supplementary file 1, table 5). Explanations for these results may be found in cultural

differences between cycling in The Netherlands and Australia, but also in the definition of the exposure and the mechanisms between LUM and cycling outcomes. Whereas the study in Perth included respondents that moved to a new residential neighborhood, our study specifically only included respondents that did not relocate during follow-up. The within-changes are therefore indicative of changes in the residential environment and not the result of moving to a different residential environment. Different mechanisms may therefore be at play when compared to the effect that moving to a different neighborhood can have. As our study provides mixed results, more research is needed that explores how changes in the residential environment relate to cycling/walking. This is not only an important question from a scientific point of view, but also from a policy perspective as it provides policy makers with more insights how a change in the environment might relate to a change in cycling/walking.

These findings have several implications for research on the effects of LUM on cycling/walking outcomes. Firstly, this study provides evidence that associations between environmental exposures and health outcomes can vary greatly based on the size and type of the buffers used ("crow-fly" Euclidian buffers or network buffers). This is not a new phenomenon and has been described extensively in the health and environment literature [15, 36]. A study comparing different buffer types for PA research concluded that the sausage buffer method remains the most defensible method for creating network buffers as it increases both comparability and repeatability [15]. By including multiple individual-specific network buffers and by excluding roads that are not accessible to pedestrians and cyclists, we aimed to provide an accurate exposure measure that accounts for these issues as much as possible. Secondly, the between-individual and within-individual effects of LUM on cycling/walking appear to be substantially different. Our study found robust positive between-associations of LUM and walking, but unexpected negative within-associations for our 500-meter buffers. These results therefore strongly advocate the use of both between- and within-individual analyses when the effect of (built-)environmental exposures on cycling/walking outcomes is considered. More longitudinal research on this topic is therefore urgently needed; a call that has been echoed by other authors in the field in recent years [37].

STRENGTHS & LIMITATIONS

The present study adds to the literature on how the residential environment relates to cycling and walking by using data from two Dutch cohorts with 10 years of follow-up and linking this data to harmonized LUM exposures. It fills an important methodological gap by exploring both between-individual and within-individual effects of LUM on cycling/walking. By applying the REWB framework to longitudinal data of respondents that did not relocate during follow-up, we gain more insight into how different levels of LUM affect cycling/walking and how a change in LUM can potentially change the average cycling and walking time. The REWB model retains the advantages of the standard FE model, but also incorporates between-individual variation, while allowing to control for measured time-invariant confounders. By retaining the virtues of the standard FE approach, it helps to infer potential causal relationships between changes in LUM and cycling/walking that have more potential for evidence-based action [13]. It also helps to answer a relevant (policy) question: is a change in LUM in the residential environment associated with a change in cycling/walking? As most of the research on LUM and cycling/walking is cross-sectional, answering this question can broaden the understanding of potential causal pathways between LUM and PA.

The use of sausage network buffers offers numerous improvements over traditional buffering methods. By excluding roads that are not accessible to cars, we ensured that the resulting network buffers were representable of the areas that can be reached while cycling or walking. This has the limitation that specific land use destinations that can easily be accessed by cars, but less easily by bike or on foot, are excluded. However, we estimate that the impact of this methodological choice is limited as our study was conducted in urban areas with a high density of roads accessible to cyclists and pedestrians and the buffer areas were limited to the residential environment. Network buffers offer improvements in this regard compared to more traditional Euclidian or “crow-fly” buffers that do not consider if the street network allows or prevents access to specific locations. The sausage buffering technique also offers improvements in the repeatability and consistency of network buffer measures compared to other methods, such as ESRI’s ArcGIS Network Analyst. The sausage buffer method results in a representative area for area-based measures regardless of street network connectivity, and ensures that only those features that are accessible from the

road network are included. By applying the buffers to a harmonized land use dataset, we ensured that changes observed in the data are representative of actual changes in the environment and not the result of changes in data processing of GIS methodology.

Finally, the present study also adds to the existing literature by considering the effects of changes in LUM on cycling/walking in a Dutch socio-spatial context where cycling is a big part of everyday life, and for cities that are already very compact compared to those in other countries such as Australia or the United States. Evidence from such countries suggest that a move towards more compact cities with a mixed-use environment can have a positive effect on cycling and walking, but there is little evidence from cities that are already very compact and dense such as the ones in this study [9]. By pooling data from two Dutch cohorts, we were able to both increase variation in environmental exposures as well as increase the statistical power of our analyses.

Our study also has some limitations to consider. First, while individual-level network buffers offer great improvements in measuring exposure compared to more traditional neighborhoods, we were not able to control for other urban-environmental and social-urban factors, such as residential density, safety, or neighborhood socio-economic status. A study conducted in Amsterdam, The Netherlands found evidence that neighborhood safety was associated with cycling [38]. As we used individual-specific network buffers, we were not able to control for such effects in our analyses. Secondly, we were also not able to control for time spent away from the residential environment. However, it has been theorized that older adults may be particularly susceptible to environmental factors in the residential environment as they are likely to spend more time closer to home than younger adults [39]. Finally, in order to pool the data from both cohorts, variables had to be retrospectively harmonized, which means that study variables are harmonized after they have been collected. While retrospective harmonization is a good way to make comparisons between cohorts possible, it does inherently come with the limitation that some detail is lost in the process. For example, income classes in both cohorts did not match well and therefore had to be generalized in order to be comparable. Harmonization choices like these inevitably lead to a loss in sensitivity and specificity of the data. More prospective harmonization would alleviate these limitations and therefore make better comparisons between cohorts possible.

CONCLUSIONS

The present study found evidence of between-individual associations of land use mix in the residential environment and the average walking time per week, as well as some evidence of negative within-associations between land use mix and the average cycling/walking time in respondents that did not move to a different residential address during follow-up. These findings advocate the use of research methods that combine both between- and within-individual analyses in order to gain more understanding of how land use mix in the residential environment can relate to cycling/walking. More longitudinal research is needed to explore how changes in land use mix over time can influence cycling and walking outcomes.

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