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ABSTRACT

Purpose: To examine the tracking and trajectories of active commuting (AC) from childhood to midlife and their association with physical activity (PA) levels over 35 years.

Methods: Self-rated AC and PA data were extracted from the Young Finns Study across six phases (1983−2018) for tracking (n = 2851) and trajectories (n = 1220). Accelerometer-derived PA was quantified in 2018–2020 (n = 1134). AC tracking was analyzed using Spearman's correlation, percentage agreements, and kappa statistics. Latent class analysis was used to identify distinct AC trajectories, and their associations with adult PA were subsequently evaluated.

Results: Tracking correlations of AC over 3−4, 6−7, 15, 18, and 35 years for both sexes were 0.40−0.43, 0.30−0.33, 0.25−0.32, 0.20−0.23, and 0.15−0.22 in summer, and 0.38−0.42, 0.35−0.41, 0.30−0.40, 0.25−0.33, and 0.23−0.31 in winter, respectively. Percentage agreements exceeded 54%, with kappa statistics ranging from slight to fair over time. Based on AC trajectories, four classes were identified for men (M) and five for women (W): stable car commuting (M:58.9%, W:37.4%), decreasing AC (M:16.5%, W:22.2%), increasing AC (M:12.8%, W:17.3%), and stable AC (M:11.8%), stable active walking (W:12.2%), and stable active summer cycling (W:10.8%). Compared to stable car-commuting ones, women who consistently walked or cycled in summer had higher adult moderate-to-vigorous PA and step counts. Men with consistent AC accumulated more steps and higher self-reported PA. Increasing AC in men also reported higher total PA. Stable AC participants were more physically active on weekdays, while men in the increased AC group were more active on weekends.

Conclusions: Tracking of AC from childhood to mid-adulthood was low to moderately high. Stable and increasing AC trajectories predicted higher adult PA levels during weekdays or weekends.

Key Words: WALKING, CYCLING, YOUTH, ADULT, ACCELEROMETER, FOLLOW-UP

INTRODUCTION

Regular active commuting (AC), which involves walking or cycling to school or work twice a day on weekdays, has been shown to significantly increase overall physical activity (PA) both concurrently and prospectively (1). AC, particularly when cycling is the chosen mode of transportation, is associated with improvements in health outcomes (2) and a substantial decrease in all-cause mortality (3). Incorporating PA into children's daily routines through walking and cycling, especially in the context of commuting to school, has been positively reviewed by contemporary literature (4,5). Finland differs from the US and UK in infrastructure and cultural attitudes toward youth AC. Well-maintained routes and high safety standards, especially in urban and suburban areas, make AC feasible, particularly through cycling infrastructure and policies. Cultural factors emphasize outdoor activities and physical exercise, with AC seen as part of Finland's broader societal value of maintaining PA and well-being. A recent systematic review highlighted a consistent and positive association between AC to school or work and PA among children, youth, and adults (6). This positive association has been documented to contribute an additional 5 to 45 minutes of daily PA for individuals engaging in AC. It's important to note that age and sex can act as moderating factors influencing the relationship between AC and PA (1). Despite sufficient supporting data on the relationship between AC and PA among individuals of all age groups, most studies have predominantly utilized a cross-sectional research design.

A few longitudinal studies have explored the impacts of changes in commuting modes on PA and cardiorespiratory fitness in children (7–11), and all except one suggested that children who adopted walking or cycling to school demonstrated increased daily moderate-to-vigorous PA after a 1-year follow-up (9,11), and improved cardiorespiratory fitness (7) and reduced cardiovascular risk factors (8) after 6 years compared to those who did not engage in these modes of commuting at different time points. In contrast, Rosenberg et al. (10) found no significant association between AC and total PA in school children over a 2-year period. Among adults, only two longitudinal studies have reported changes in AC and their association with changes in PA. These studies revealed that an increase in AC corresponded to a concurrent increase in PA, while a decrease in AC was linked to a higher likelihood of reduced PA over 1 year (12) and 4 years (13). Findings from the Cardiovascular Risk in Young Finns Study (YFS) revealed that maintaining AC over 6 years in youth or young adulthood was associated with higher adult PA levels than consistently passive commuting. Additionally, increasing AC was associated with higher PA after a 27-year follow-up (1). This suggests that promotion AC in early life may be beneficial for sustaining high AC levels into adulthood. However, limited research has explored the tracking of transportation modes from childhood to mid-adulthood, which could provide insight into AC stability and predictability. Furthermore, describing AC trajectories identifies subgroups following similar AC patterns throughout the life course, although further understanding is needed to target these trajectory groups effectively. It remains uncertain whether distinct AC trajectories exist between childhood and mid-adulthood in such populations (1), with age-related declines in AC to school possibly (14,15) contributing to sex differences over an extended period (1,16).

While there is a growing interest in PA tracking (17) and its trajectory (18), a notable gap exists in the literature regarding the tracking and trajectory of AC over time. Longitudinal cohort studies that comprehensively assess these associations from childhood to adulthood using a longitudinal design are currently lacking. It’s crucial to acknowledge that AC is significantly influenced by seasonal variation in Finland, with it being less common in winter (November–

March) compared to spring/autumn (April–October) for both children (19) and adults (20). To address this knowledge gap, the aim of this study was to 1) investigate the tracking of AC over 35 years, 2) identify developmental trajectories of AC from 2001 to 2018 during adulthood through four successive phases and evaluate their associations with accelerometer-derived and self-reported PA in mid-adulthood, and 3) explore sex and seasonal differences in these associations.

METHODS

Participants

The YFS is an ongoing longitudinal study that focuses on cardiovascular risk factors from childhood to adulthood (21). Briefly, the baseline study (1980) consisted of children and adolescents aged 3−18 years, born in six cohorts. Participants were randomly selected, with 3596 individuals (83% of those invited) chosen from the five Finnish university cities with medical schools (Helsinki, Kuopio, Oulu, Tampere, and Turku) and their surrounding communities. The survey on travel modes has been conducted six times over 35 years, with intervals ranging from 3 to 15 years. The participants were aged 41 to 56 in 2018. For this study, 1983 was selected as the baseline year because that was when the travel mode was categorized into summer and winter. Participants who had at least one measure of their mode of transport across their lifespan within the five older age groups (n = 2851) were included in the tracking analyses. The participants in all six age groups (n = 1220) were considered to examine transportation patterns over time in the trajectory analyses. Ethical approval was obtained from the local ethics committees. Participants provided informed consent at baseline, and written consent was obtained during follow-up, in accordance with the Helsinki Declaration.

Travel mode

The mode and distance of travel to school or to work during both summer and winter were collected through questionnaires in 1983, 1986, 2001, 2007, 2011, and 2018. In 1983, the questions were asked separately: 'How do you usually commute to school in summer?' and 'How do you usually commute to school in winter?' Between 1986 and 2001, they were slightly modified to: 'How do you usually commute to school/work in summer/winter?' In 2007 and later, the questions changed to: 'How do you usually commute to work in summer/winter?' The response alternatives were then recoded into four scales: 1 = own car or carpool, 2 = public transport (e.g., bus, tram, and train), 3 = walking, and 4 = cycling. Commuters were grouped as active (walking and cycling) and passive (bus and car users). The 1983 questionnaire was administered in October, when weather conditions resembled those of summer. Furthermore, the transportation modes reported in 1983 were consistent with those observed in both summer and winter at follow-up points. The distance walked or cycled from home to school or work was determined by the actual distance traveled, rounded to the nearest 100 meters. The travel mode question has been found to be reliable and valid (1).

Physical activity

In 2018, PA in mid-adulthood was assessed through questions, focusing on the intensity of PA, frequency of vigorous PA, hours spent on vigorous PA, average duration of a PA session, and participation in organized PA. These questions demonstrated acceptable-to-good internal consistency (Cronbach's α=0.73). Responses were based on the average number of hours/times per week. Each item was coded from 1 to 3 and then summed to form an index (5−15), with higher scores representing higher levels of PA (22). The PA index has been established as a reliable and valid measure for assessing PA across the life course (22,23). In 2018-2020, the participants were instructed to wear a triaxial accelerometer (ActiGraph GT3X+ or wGT3X+, FL, USA) on the right hip for seven consecutive days and nights, with removing it only during bathing and water activities. Data were collected at a 60-Hz sample rate using a normal filter and then averaged to 60-s epochs. For data to be considered valid, it had to meet specific criteria, including at least four days of recording with 600 minutes or more per day, with non-wear time defined as 60 minutes of consecutive zero counts (24). In the study, the outcome variables included average daily vector magnitude counts per minute (cpm) as an index of total PA, steps per day, and moderate-to-vigorous PA (MVPA defined as ≥2690 cpm) (25). Details of accelerometer-measured PA in the YFS have been reported elsewhere (22,26).

Covariates

Age was considered as a potential confounder. Residential location was categorized into two groups: urban (urban centers and suburban areas) and rural (rural centers and peripheral areas). The number of children was dichotomized into two categories: having one child or more and having no child. Educational attainment was self-reported and applied as completed school years. Occupation was divided into three categories according to the criteria of the Central Statistical Office of Finland: manual (e.g., builders, metal workers, nannies), lower non-manual (e.g., civil servants, specialized and skilled workers), and upper non-manual (e.g., administrators, managers, academics). Income levels were classified as follows: < €25000, €25000−45000, €45001−70000, and > €70000. Body weight was measured with a Seca scale (Vogel & Halke, Hamburg, Germany) and body height with a Seca anthropometer. Body mass index (BMI) was calculated as weight (kg)/height (m^2). In regression models, accelerometer wear time was fitted as a covariate, particularly when the recorded frequency of specific behaviors might be influenced by the duration of daily measurements.

Statistical analyses

Descriptive characteristics of active commuters were presented as percentages for men and women during summer and winter in six age groups over six consecutive years. Spearman correlation coefficients with 95% confidence intervals were used to track travel modes separately for both sexes in the two seasons. The confidence intervals provide an estimate of where the true value of the correlation is likely to fall in the population. The correlations were categorized as low (< 0.30), moderate (0.30−0.60), and moderately high (> 0.60)(27). Percent agreement and weighted kappa coefficients with 95% confidence intervals were utilized to estimate agreement, stability, and changes in commuting habits. The strength of agreement for the kappa values were interpreted as follows: 0.01–0.20 = slight, 0.21–0.40 = fair, 0.41–0.6 = moderate, 0.61–0.80 = substantial, and > 0.80 almost perfect (28).

Latent class analysis (LCA) was used to identify AC trajectories, with all analyses stratified by participant sex. Indicator variables included a comprehensive set of commuting-related variables: continuous commuting distances and dummy variables representing commuting modes during both summer and winter, across four adult follow-up periods (2001, 2007, 2011, and 2018). Due to the 15-year gap between childhood and adulthood AC measures, it was not feasible to analyze trajectory groups from childhood using LCA. Classification of AC was adjusted for potential covariates (29). Several model fit measures were calculated and evaluated to determine the optimal number of classes, including information-theoretic criteria (AIC, BIC, ABIC), entropy values (> 0.70), and average posterior probabilities describing classification uncertainty (30). Solutions for 2 to 7 latent classes were analyzed. Classification was adjusted for follow-up age, residential location, BMI, having children, education, occupation and income.

The optimal solution, supported by information criteria, was determined through an analysis of the latent class contents. This approach favored a parsimonious and interpretable model, with a minimum relative class size of 10% (31). Once the optimal latent classes were defined, their parameters were fixed. The mean daily PA on all days, weekdays, and weekends for each subgroup was included as auxiliary variables to test for equality of means across latent classes using the BCH method (32). All analyses were conducted using R environment (33) and Mplus Version 7.0 (34) via R software package MplusAutomation (35) in 2024. The Mplus software analysis options included 5000 random starts, 50 initial stage iterations, and 500 final stage optimizations. Inclusion criteria required at least 8 non-missing observations of seasonal commuting modes and distances (out of a possible 16). Additionally, a complete dataset of adjusting factors and device-based measurements of PA was necessary. Missing data in indicator variables were assumed to be missing at random and were treated as a function of observed covariates and outcomes (34). Full information maximum likelihood estimation with robust standard errors was employed to account for the missing at random assumption, reducing potential bias in the parameter estimates and enhancing the ability to detect statistically significant effects. The randomness of missing data was tested using a set of 16 logistic regression models, where each indicator was tested individually to predict participants' inclusion in the final analysis.

RESULTS

Table 1 shows the distribution of active commuters across age-sex groups at baseline and follow-up, with seasonal stratification. During summer, the highest proportion of active commuters was observed among boys (83.6−88.1%) and girls (80.8−83.5%) aged 9-12, gradually declining with age until stabilizing after age 30 for both sexes. By ages 30-56, AC levels decreased by approximately 20% in men and 30% in women. In winter, the highest proportion of active commuters was found in the 9-12 age group, with 74.8−80.1% among boys and 73.8−76.8% among girls. Subsequently, AC declined sharply with age for both sexes. AC levels were consistently lower during winter compared to summer. On average, males traveled longer distances than females over time.

Spearman correlation coefficients for transportation modes categorized by sex, age, and seasons across various time intervals are presented in Table 2. In summer, inter-age correlations over 3- and 4-year periods ranged from 0.23 to 0.71 for men and 0.17 to 0.62 for women. Similarly, correlations over 6- and 7-years intervals were observed between 0.42 to 0.71 for men and 0.26 to 0.67 for women. Over a 15-year follow-up, correlations varied from -0.06 to 0.28 for men and -0.02 to 0.25 for women. In the 35-year follow-up, correlations ranged from -0.02 to 0.07 for men and -0.16 to 0.31 for women. During winter, inter-age correlations across 3- and 4-year periods ranged from 0.31 to 0.62 for men and 0.15 to 0.62 for women. Corresponding correlations over 6- and 7-years intervals were found between 0.27 to 0.63 and 0.30 to 0.63, respectively. Over 15 years, correlations varied from -0.02 to 0.20 for men and -0.05 to 0.27 for women. For the extended 35 years, correlations ranged from -0.02 to 0.08 for men and -0.10 to 0.11 for women. On average, tracking correlations from 3 to 15 years were statistically significant for both sexes, except for the 35-year follow-up, observed in both seasons.

Table 3 presents kappa coefficients and percent agreement for active mode patterns across different time intervals. In summer, kappa coefficients for active mode patterns ranged from 0.38 to 0.52 in men and 0.43 to 0.53 in women. In winter, these coefficients ranged from 0.40 to 0.47 in men and 0.45 to 0.62 in women at 3-year intervals. The overall percent agreement exceeded 70% at these intervals, with only two exceptions. However, both the correlations and percent agreement tended to decrease over time for both sexes in both seasons. They ranged from -0.01 to 0.10 and 41.2 to 86.8 at the 18-year follow-up intervals, from -0.03 to 0.06 and 40.3 to 84.8 at the 24-year follow-up intervals, from -0.02 to 0.09 and 43.3 to 85.2 at the 28-year follow-up intervals, and from -0.03 to 0.06 and 36.9 to 84.5 at the 35-year follow-up intervals, respectively.

Inclusion criteria for the LCA were met by 1220 participants (491 males and 729 females). Among the included participants, commuting modes and distances were observed at rates of 80% or higher across seasons and follow-ups. None of the indicator variables were statistically significantly associated with inclusion in the LCA, supporting the assumption of missingness at random. For men, the AIC, BIC, and ABIC all reached local minima at the 4-class solution in the LCA model (Table 4). The entropy level for this solution exceeded 98%, and all class sizes were greater than 10% for the 2–4 class solutions. Consequently, the 4-class solution was selected due to its interpretability. The identified latent classes were as follows: stable car commuting (58.9%) subjects who neither walked nor cycled throughout the study period; decreasing AC (16.5%) subjects who walked or cycled during early adulthood but reduced these activities by midlife, shifting to more passive commuting; increasing AC (12.8%) subjects who transitioned from passive commuting to active commuting during adulthood; and stable AC (11.8%) subjects who consistently accumulated the longest active commuting distances, mainly by cycling or walking throughout adulthood (Figure 1).

For women, the three information criteria reached a minimum at the 6-class solution in the LCA model. The entropy levels were high, over 94%, and class sizes were greater than 10% for all solutions with 2–6 classes. However, the 6-class solution included two latent classes with somewhat similar interpretations: mixed commuting modes with decreasing percentages of AC and actively commuted distances. Therefore, the best-fitting, well-interpretable model was the 5-class solution, where the decreasing commuting classes were unified into one latent class. The chosen 5-class solution included the following latent classes: stable car commuting (37.4%), decreasing AC (22.2%), increasing AC (17.3%), stable active walking (12.2%) subjects who consistently walked or commuted by public transport to work during both seasons throughout adulthood, and stable active summer cycling (10.8%) subjects who consistently cycled to work daily during the summer and either cycled, walked or commuted by public transport during the winter throughout the study period (Figure 2).

Men who were persistently active commuters accumulated more steps ($p = 0.002$) and reported higher levels of self-reported PA ($p = 0.033$) in mid-adulthood than those who were persistently car commuters (Table 5). Men in the increasing AC group reported higher levels of total PA ($p = 0.037$) compared to those who persistently drove. Among women, those in the stable active walking group had higher levels of adult MVPA ($p = 0.025$) and accumulated more steps (p

= 0.001) compared to those in the stable car commuting group. Similarly, women in the stable active summer cycling group had higher adult MVPA ($p = 0.029$) and more step counts ($p = 0.008$). These associations were independent of covariates.

Women who consistently walked in both seasons accumulated higher adult MVPA ($p = 0.004$) and more steps ($p < 0.001$) on weekdays compared to those who consistently commuted by car, even after adjusting for potential covariates (Table 6). Similarly, women who consistently engaged in summer cycling had higher levels of MVPA ($p = 0.013$) and more steps ($p = 0.004$) on weekdays than those who consistently drove. On weekends, no significant differences in both objective and subjective PA levels were observed among women across the AC trajectory groups. For men, only the stable AC group was significantly associated with higher step counts ($p = 0.001$) on weekdays. On weekends, men in the increasing AC group had higher total PA ($p = 0.003$), MVPA ($p = 0.017$), and more steps ($p = 0.014$) compared to those who consistently commuted by car.

DISCUSSION

This study is the first to investigate AC tracking from childhood to mid-adulthood and to identify distinct AC trajectories that predict self-reported and accelerometer-derived PA patterns in mid-adulthood. Four AC trajectory classes were identified for men: stable car commuting, decreasing AC, increasing AC, and stable AC. For women, the five classes were: stable car commuting, decreasing AC, increasing AC, stable active walking, and stable active summer cycling. The results revealed that AC tracking coefficients tended to be lower over longer time intervals for both sexes across 35 years periods. The AC trajectory classes were differentially linked to PA levels prospectively. This study not only expands our understanding of AC across the adult life course but also highlights the importance of maintain PA levels into mid-adulthood.

The decline in AC among youngsters over time indeed reflects broader societal developments and changes in PA culture. As more communities become car-dependent, and as daily routines prioritize convenience and efficiency over movement, passive commuting becomes more common, especially from childhood through adulthood. Our findings showing that over half of men and one-third of women continue passive commuting behaviors throughout adulthood align with observations made in various populations, including children (19) and adults (20) in Finland. Generally, the persistence of passive commuting behavior into adulthood reflects deeply ingrained habits and societal norms. This suggests that passive commuting is not merely a childhood issue but rather a behavior that endures over time. Factors such as infrastructure limitations, safety concerns, and cultural norms contribute to the dominance of passive commuting. These trends are evident across both sexes, although men exhibit higher rates of passive commuting. A key challenge in addressing this issue is the lack of effective interventions aimed at reducing passive commuting behavior from childhood through mid-adulthood. This gap indicates the need for more comprehensive, life-course approaches that address commuting habits throughout different life stages. For instance, long-term educational campaigns can promote the benefits of AC (e.g., environmental, health, and well-being benefits) and provide practical guidance for incorporating it into daily routines. This approach recognizes that an individual's ability and motivation to commute actively changes over time, so policies must be adaptable to remain effective. Such interventions should be long-term and adaptable to the evolving needs of individuals as they age, helping to reshape deeply embedded behaviors.

This study expands our understanding of how AC levels track from childhood to mid-adulthood in both summer and winter. Unlike previous research, which did not provide seasonal stability coefficients for AC over time, this study offers valuable insights. After accounting for measurement error, stability coefficients from 1983 to 2018 ranged from 0.30 to 0.55 in men and 0.28 to 0.52 in women during summer, and from 0.23 to 0.49 in men and 0.26 to 0.52 in women during winter. The observed differences in tracking correlations between summer and winter suggest the direction and magnitude of seasonal variation in AC tracking. Regarding direction, some periods show stronger positive correlations between AC tracking in summer than winter, while others indicate weaker or negative correlations in either season. This suggests that seasonal trends in AC tracking are inconsistent. For example, stronger correlations in shorter follow-up periods may indicate a closer link between measurement years and age-sex groups. In terms of magnitude, summer tracking is more sensitive to heat, rain and wind, while winter tracking is affected by snow, cold, and darkness. These variations likely reflect how individuals adapt to weather conditions based on seasonal needs. Moreover, AC tracking correlations were generally lower over longer follow-up periods compared to shorter ones. These results highlight childhood AC as a predictor of AC in young and mid-adulthood, emphasizing the importance of promoting childhood AC for lifelong benefits. It's essential to continue efforts to increase AC at all life stages. Further research is needed to explore childhood interventions for establishing positive AC trajectories across the life course. The observed differences may be due to declining AC levels over time, particularly in men during winter.

While previous studies have explored PA trajectories using data from different cohorts (18,22,36), the current study represents the first attempt to identify AC trajectories across the life course through repeated measurement in multiple cohorts. Specifically, trajectories of commuting categories were identified, providing the most comprehensive assessment of overall commuting activities. The identified trajectories reveal the stability of AC levels across the adult life course. These trajectories not only confirm the tracking of AC from childhood through mid-adulthood but also underscore the pivotal role of early adulthood AC levels in shaping later AC trajectories. The findings indicate that participants predominantly maintained stable AC, particularly walking and summer cycling in women, experienced increasing AC, decreasing AC levels, or engaged in persistently passive commuting throughout adulthood. These results emphasize the importance of promoting AC in children, regardless of their initial AC levels, to optimize the likelihood of them following favorable AC trajectories into adulthood.

Stable passive commuting can be a risk factor for future health outcomes, although its immediate impact may be limited. Higher levels of AC during childhood, adolescence, and young adulthood are associated with increased MVPA (1,6) and reduced cardiovascular risk (8). Our trajectory analyses suggest that childhood AC can be a valuable indicator for identifying individuals to maintain AC into adulthood, which may lead to physical health outcomes (7). It is essential to consider both environmental and genetic factors that influence PA, including AC, when planning strategies to boost AC and encourage favorable AC patterns (37,38). Genetic factors can influence AC trajectories and its levels over time. Furthermore, over 75% of 13–18-year-olds in Finland did not meet the recommended 60 minutes of daily MVPA (19). Stable passive commuting may hinder the development of AC behavior across the life course. To promote favorable AC trajectories, future research is needed to understand why AC levels tend to persist over time, including the role of genetics and the examination of barriers and facilitators to participation.

Our results revealed age and sex disparities in AC. Specifically, the prevalence of AC was approximately 15% higher in women than in men aged 21 to 45. This difference may be due to the common occurrence of single-car ownership in Finnish families, with men typically driving the car. Significant variations in the association between stable AC and adult PA levels were observed in both sexes, particularly in women. The results also indicated that consistent active walking and cycling were linked to significant increases in PA patterns among women during weekdays, while increased AC was associated with higher PA levels in men on weekends. These findings contrast with those of a previous study (39), which suggested that individuals who are more physically active during both worksite and leisure time on weekdays tend to maintain higher activity levels on weekends. This suggests that maintaining or increasing AC throughout life is associated with higher levels of certain adult PA patterns, either on weekdays or weekends, and plays a crucial role in sex differences. Additionally, men may be more likely to report longer commute distances, a greater variety of transportation options, or more positive attitudes toward commuting than women, which could more accurately reflect commuting behaviors and preferences in Finland. Further research is needed to explore the impact of long-term AC, including leisure-time AC patterns, on weekday and weekend PA patterns in adulthood.

The study utilized the LCA approach to categorize commuters into homogeneous classes based on their responses across four adulthood phases, as the current LCA does not account for the life course from childhood. While many commuters engaged in some levels of AC during specific phases, their overall AC levels consistently remained low. This finding may explain why the 4- or 5-class solution predominantly identified individuals as stable passive commuters. To address these issues, further research is necessary to explore more effective methods for integrating data from multiple AC phases. The inclusion of objective measures, such as global positioning system (GPS) and geographic information system (GIS)-based distances between home and school or workplace, could provide a more accurate assessment of changes in AC behavior over time. The study underscores the importance of the chosen analytical approach when examining long-term AC patterns, highlighting the need for methodological adaptations or alternative approaches to effectively capture behavioral changes over extended periods.

The study had several strengths, including its comprehensive, longitudinal, population-based design, which spanned six age cohorts, six consecutive measurements, two seasons (summer and winter), and a 35-year follow-up. However, there were potential limitations. First, the reliance on self-reported transportation modes at six time intervals could introduce social desirability bias and underestimate AC trends, limiting the accuracy in capturing nuanced changes in AC behavior. To overcome these challenges, utilizing accelerometers combined with GPS or GIS could provide a practical solution for improving the accuracy of travel patterns in the population. Second, the YFS focused on transportation modes during summer and winter with single questionnaire responses, which may lead to information bias and often fail to fully capture behavioral variations over time. Further research is needed for validation, especially for season-based comparisons. Third, this study considered common transportation modes (public transportation, car, walking, and cycling) but excluded others such as skateboarding, kick-scooting, cross-country skiing, roller-skating, and jogging/running. It also did not account for potential changes in travel modes with seasons and life stages, potentially underestimating overall AC levels. Fourth, AC mainly included both walking and cycling, but for participants whose AC primarily involved cycling, there was a potential measurement limitation. Hip-worn accelerometers were not particularly effective at capturing cycling activity, as cycling did not produce significant acceleration at the hip. Even though cycling was generally considered MVPA, the accelerometer might underestimate its intensity and mistakenly categorize it as light intensity PA due to the minimal hip movement involved in cycling. Fifth, while the study considered the residential environment as a covariate, it did not measure other environmental factors such as the home, neighborhood, school, community, and workplace. Future research should address these factors when studying AC trends. Sixth, some participants were excluded due to missing accelerometer data, which could introduce bias and underestimate trajectory groups. However, a sensitivity analysis confirmed similar results. Lastly, Finland's strong infrastructure, cultural attitudes toward outdoor activity, and safety standards make AC more prevalent. These factors might limit the generalizability of the findings to populations with different infrastructures, cultures, or socioeconomic conditions.

Lifelong AC trends are influenced by various factors, including motives, parental and peer influence, distance, changes in living location, types of PA, life transitions, lifestyle behaviors, and weather conditions (e.g., wind, rain, darkness, snow, and cold), particularly in Finland (1). Moreover, ongoing changes such as shared mobility and autonomous vehicles present new challenges that complicate the connection between the built environment and travel behavior (40). In Finland, micro-mobility has already transformed commuting patterns, with many cities increasingly investing in bike and pedestrian lanes to promote AC. On the other hand, changes in travel modes, such as transitioning from motorized transport to non-motorized options like walking or cycling should be considered. From a health promotion perspective, recognizing the fundamental role of increasing and maintaining AC is vital for a healthy lifestyle. Different forms of AC should be integrated to major health promotion strategies, fostering a more active lifestyle in later years. Notably, cycling to school or work may maximize health benefit. Our results suggest that persistent AC during adulthood independently associates with increases overall PA in mid-adulthood.

CONCLUSIONS

In conclusion, the ongoing 35-year study from the YFS reveals a substantial decline in AC prevalence with age. AC tracking correlations were moderate to high for 4- to 9-year periods but declined for 15- and 35-year periods in adults across age groups. Stability in active commuters exceeded passive ones, regardless of the season. Different AC patterns from early adulthood to mid-adulthood in both sexes and seasons were identified. Stable and increasing AC could foster a physically active lifestyle in mid-adulthood, whether on weekdays or weekends. This highlights the importance of promoting AC from childhood or young adulthood to establish and sustain lifelong PA habits throughout the week. The implication is that stakeholders, including parents, teachers, PA organizers, health professionals, and policymakers should enhance children's daily AC experience and strategically optimize environmental factors to encourage adult AC engagement. Further attention is warranted to explore whether interventions targeting increased AC in childhood could establish favorable AC trajectories across the life course, leading to better future health.

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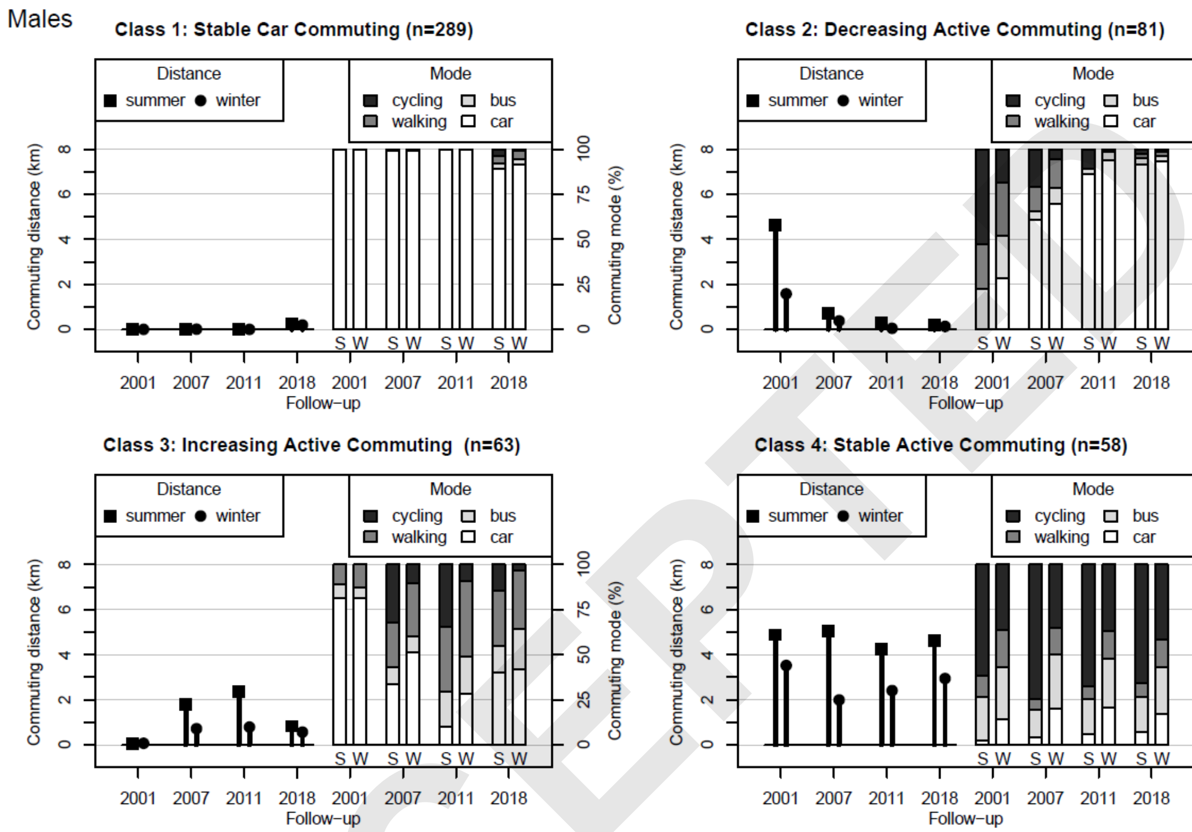
FIGURE LEGEND

Figure 1. Latent commuting classes for men (4 classes, n = 491), showing commuting distances and modes for summer and winter. The x-axis represents follow-up years, the left y-axis displays average commuting distances, and the right y-axis illustrates proportions of commuting modes. Seasons are indicated by S (summer) and W (winter).

Figure 2. Latent commuting classes for women (5 classes, n = 729), showing commuting distances and modes for summer and winter. The x-axis represents follow-up years, the left y-axis displays average commuting distances, and the right y-axis illustrates proportions of commuting modes. Seasons are indicated by S (summer) and W (winter).

Figure 1



Males
Class 1: Stable Car Commuting (n=289)
Class 2: Decreasing Active Commuting (n=81)
Class 3: Increasing Active Commuting (n=63)
Class 4: Stable Active Commuting (n=58)
Distance
summer
winter
Mode
cycling
bus
walking
car
Commuting distance (km)
Commuting mode (%)
Follow−up
2001
2007
2011
2018
S W

Figure 2

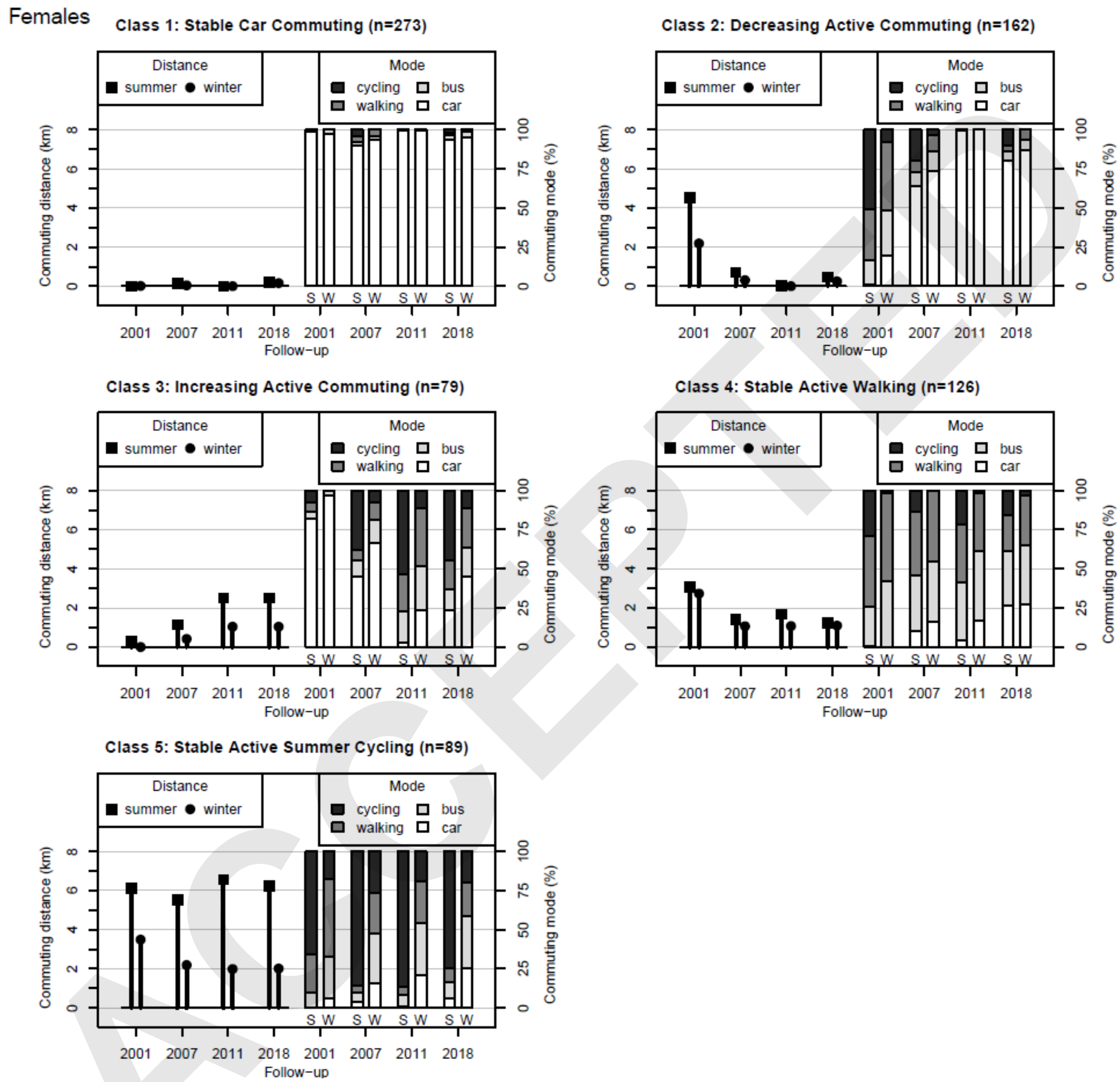

Females
Class 1: Stable Car Commuting (n=273)
Class 2: Decreasing Active Commuting (n=162)
Class 3: Increasing Active Commuting (n=79)
Class 4: Stable Active Walking (n=126)
Class 5: Stable Active Summer Cycling (n=89)
Distance
summer
winter
Mode
cycling
bus
walking
car
Commuting distance (km)
Commuting mode (%)
S W
2001 2007 2011 2018 2001 2007 2011 2018
Follow−up

Table 1. Proportion of active commuters (walking and cycling combined) and actively commuted distance by gender, age, and measurement year in summer and

	Males							Females						
	1983	1986	2001	2007	2011	2018		1983	1986	2001	2007	2011	2018	
Age (1983)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n*[†]	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n*[†]
Summer														
6	-	203 (84.2)	60 (34.5)	39 (25.5)	29 (22.0)	27 (19.6)	269	-	201 (83.4)	112 (60.9)	57 (35.6)	41 (27.7)	38 (26.2)	269
9	209 (83.6)	199 (88.1)	51 (31.3)	30 (21.4)	24 (18.3)	21 (16.8)	272	215 (80.8)	202 (83.5)	100 (48.1)	74 (36.5)	37 (21.0)	37 (22.7)	295
12	250 (84.5)	117 (49.0)	44 (21.4)	32 (18.9)	27 (17.5)	27 (18.8)	315	230 (82.4)	154 (66.1)	81 (38.6)	57 (31.1)	55 (30.4)	47 (28.3)	312
15	139 (61.8)	76 (43.2)	42 (21.9)	35 (20.8)	22 (15.0)	22 (16.5)	290	170 (59.6)	112 (50.5)	89 (37.9)	81 (36.2)	55 (28.6)	58 (29.4)	321
18	96 (53.0)	55 (36.4)	43 (21.7)	31 (18.1)	29 (19.2)	22 (16.3)	265	131 (58.0)	100 (54.6)	91 (40.1)	81 (39.1)	71 (37.2)	66 (35.1)	299
21	61 (44.9)	49 (39.2)	30 (18.1)	36 (24.0)	28 (19.0)	26 (22.2)	225	101 (65.6)	92 (56.8)	67 (36.4)	63 (33.9)	51 (27.6)	38 (25.0)	257
Mean (SD)	2.1 ± 4.5	2.0 ± 2.3	7.6 ± 6.5	7.3 ± 7.8	7.7 ± 9.3	6.4 ± 6.5	1636	1.9 ± 3.1	2.2 ± 1.9	6.6 ± 5.8	6.4 ± 6.9	5.8 ± 6.0	6.7 ± 6.1	1753
Winter														
6	-	184 (78.0)	44 (25.1)	22 (14.0)	20 (15.0)	21 (15.2)	268	-	182 (76.8)	83 (43.0)	32 (19.4)	22 (14.8)	22 (15.5)	269
9	184 (74.8)	173 (80.1)	32 (19.8)	27 (18.6)	20 (15.2)	15 (12.0)	271	192 (73.8)	169 (73.2)	62 (28.8)	51 (24.9)	22 (12.4)	19 (11.7)	295
12	213 (76.6)	106 (44.5)	26 (12.8)	20 (11.7)	14 (9.1)	17 (11.8)	313	196 (74.5)	124 (52.3)	55 (25.3)	32 (17.0)	35 (19.4)	33 (19.9)	311
15	127 (53.4)	53 (30.3)	30 (15.6)	26 (15.2)	14 (9.5)	15 (11.3)	291	138 (47.9)	84 (38.0)	58 (24.6)	45 (19.9)	37 (19.2)	34 (17.3)	320
18	77 (42.8)	43 (28.5)	31 (15.7)	24 (13.3)	21 (13.9)	16 (11.9)	266	92 (41.6)	76 (41.5)	65 (27.8)	55 (25.2)	42 (21.9)	42 (22.3)	301
21	43 (33.9)	38 (30.9)	21 (12.4)	24 (15.5)	19 (12.8)	21 (17.9)	224	68 (44.7)	64 (39.5)	52 (27.4)	42 (21.9)	29 (15.6)	24 (15.7)	257
Mean (SD)	1.7 ± 4.3	1.5 ± 1.0	5.2 ± 3.9	4.5 ± 4.8	4.2 ± 4.5	4.2 ± 4.9	1633	1.3 ± 2.6	1.6 ± 1.1	4.6 ± 3.7	3.8 ± 4.1	3.3 ± 3.2	4.1 ± 4.2	1753

[†]Total sample size included at least one valid observation across study occasion and used in a trajectory model. Age in bold font is used in tracking analysis.

Table 2. Spearman correlations and 95% confidence intervals of tracking of active commuting by gender, age, and measurement year in summer and winter

	Follow-up period (years)					
Age (1983)	1983–1986 (3)	1986–2001 (15)	2001–2007 (6)	2007–2011(4)	2011–2018 (7)	1983–2018 (35)
Summer	Males					
9	0.46 (0.34, 0.56)**	-0.06 (-0.22, 0.11)	0.46 (0.30, 0.59)**	0.69 (0.58, 0.78)**	0.42 (0.24, 0.57)**	0.06 (-0.12, 0.25)
12	0.37 (0.25, 0.47)**	0.07 (-0.08, 0.22)	0.42 (0.28, 0.55)**	0.66 (0.55, 0.75)**	0.50 (0.35, 0.62)**	-0.02 (-0.19, 0.15)
15	0.42 (0.28, 0.55)**	0.28 (0.11, 0.43)**	0.71 (0.62, 0.79)**	0.71 (0.61, 0.79)**	0.56 (0.41, 0.68)**	0.07 (-0.12, 0.26)
18	0.35 (0.18, 0.50)**	0.12 (-0.06, 0.30)	0.57 (0.45, 0.67)**	0.53 (0.39, 0.64)**	0.58 (0.44, 0.69)**	0.05 (-0.15, 0.25)
21	0.23 (0.03, 0.42)*	0.26 (0.07, 0.43)**	0.44 (0.28, 0.57)**	0.74 (0.64, 0.81)**	0.48 (0.31, 0.62)**	-0.03 (-0.26, 0.20)
All cohorts	0.40 (0.34, 0.46)**	0.15 (0.09, 0.22)**	0.49 (0.44, 0.54)**	0.62 (0.58, 0.67)**	0.50 (0.43, 0.55)**	0.01 (-0.08, 0.09)
n	801	810	789	725	621	529
Winter						
9	0.47 (0.35, 0.57)**	-0.02 (-0.19, 0.15)	0.39 (0.22, 0.53)**	0.62 (0.49, 0.72)**	0.27 (0.07, 0.44)**	0.08 (-0.10, 0.27)
12	0.41 (0.29, 0.51)**	0.13 (-0.02, 0.28)	0.45 (0.31, 0.57)**	0.47 (0.32, 0.59)**	0.60 (0.47, 0.70)**	0.01 (-0.16, 0.19)
15	0.38 (0.23, 0.50)**	0.09 (-0.09, 0.26)	0.57 (0.45, 0.67)**	0.62 (0.50, 0.72)**	0.59 (0.45, 0.71)**	0.08 (-0.11, 0.26)
18	0.31 (0.14, 0.47)**	0.20 (0.03, 0.37)*	0.63 (0.52, 0.71)**	0.44 (0.30, 0.57)**	0.56 (0.42, 0.68)**	-0.02 (-0.22, 0.18)
21	0.31 (0.10, 0.50)**	0.19 (-0.00, 0.37)	0.41 (0.26, 0.54)**	0.51 (0.36, 0.62)**	0.58 (0.43, 0.69)**	0.06 (-0.18, 0.29)
All cohorts	0.43 (0.37, 0.48)**	0.13 (0.06, 0.20)**	0.44 (0.38, 0.49)**	0.52 (0.46, 0.57)**	0.49 (0.42, 0.54)**	0.02 (-0.07, 0.10)
n	776	798	806	741	623	514
Summer	Females					
9	0.62 (0.53, 0.69)**	-0.02 (-0.17, 0.13)	0.31 (0.16, 0.45)**	0.59 (0.48, 0.69)**	0.43 (0.28, 0.56)**	-0.07 (-0.23, 0.09)
12	0.36 (0.24, 0.47)**	-0.03 (-0.18, 0.12)	0.26 (0.10, 0.41)**	0.57 (0.45, 0.67)**	0.58 (0.45, 0.68)**	-0.16 (-0.31, 0.00)
15	0.48 (0.37, 0.58)**	0.19 (0.04, 0.34)*	0.57 (0.46, 0.66)**	0.48 (0.35, 0.59)**	0.61 (0.50, 0.70)**	-0.01 (-0.15, 0.14)
18	0.35 (0.20, 0.48)**	0.05 (-0.12, 0.22)	0.35 (0.22, 0.48)**	0.45 (0.33, 0.57)**	0.66 (0.56, 0.74)**	0.01 (-0.15, 0.18)
21	0.17 (-0.01, 0.35)	0.25 (0.08, 0.41)**	0.57 (0.45, 0.67)**	0.58 (0.46, 0.67)**	0.67 (0.57, 0.75)**	0.31 (0.12, 0.48)**
All cohorts	0.43 (0.38, 0.49)**	0.12 (0.06, 0.18)**	0.39 (0.33, 0.44)**	0.50 (0.45, 0.54)**	0.58 (0.54, 0.63)**	-0.01 (-0.08, 0.07)
n	923	924	928	907	827	717
Winter						
9	0.62 (0.53, 0.70)**	-0.05 (-0.20, 0.10)	0.34 (0.20, 0.47)**	0.53 (0.40, 0.63)**	0.36 (0.21, 0.50)**	-0.06 (-0.22, 0.10)
12	0.36 (0.23, 0.47)**	0.13 (-0.02, 0.27)	0.30 (0.15, 0.44)**	0.49 (0.35, 0.60)**	0.51 (0.37, 0.62)**	-0.03 (-0.20, 0.14)
15	0.50 (0.39, 0.60)**	0.27 (0.12, 0.40)**	0.56 (0.45, 0.65)**	0.45 (0.32, 0.56)**	0.49 (0.37, 0.61)**	-0.01 (-0.16, 0.14)
18	0.38 (0.23, 0.51)**	0.02 (-0.14, 0.18)	0.36 (0.23, 0.48)**	0.48 (0.36, 0.59)**	0.50 (0.37, 0.61)**	-0.10 (-0.26, 0.07)
21	0.15 (-0.04, 0.32)	0.16 (-0.01, 0.33)	0.53 (0.40, 0.63)**	0.52 (0.40, 0.63)**	0.63 (0.51, 0.72)**	0.11 (-0.09, 0.30)
All cohorts	0.45 (0.40, 0.50)**	0.10 (0.04, 0.17)**	0.39 (0.34, 0.45)**	0.48 (0.42, 0.52)**	0.50 (0.44, 0.55)**	-0.04 (-0.11, 0.03)
n	897	942	978	929	826	704

**P* < 0.05 and ***P* < 0.01 (two-tailed).

Tables 3. Stability of active commuting patterns by gender across different time intervals in summer and winter

	Summer				Winter			
	Males		Females		Males		Females	
Follow-up year	Kappa (95% CI)	Agreement (%)	Kappa (95% CI)	Agreement (%)	Kappa (95% CI)	Agreement (%)	Kappa (95% CI)	Agreement (%)
1983–1986								
Active modes	0.38 (0.31, 0.44)**	70.5	0.43 (0.36, 0.49)**	75.1	0.40 (0.34, -0.46)*	69.7	0.45 (0.39, 0.50)**	72.4
Walking	0.52 (0.42, 0.61)**	77.0	0.53 (0.44, 0.61)**	76.5	0.45 (0.38, 0.52)**	71.8	0.45 (0.39, 0.51)**	72.4
Cycling	0.40 (0.33, 0.47)**	69.3	0.49 (0.42, 0.56)**	74.7	0.47 (0.37, 0.58)**	81.2	0.62 (0.47, 0.77)**	93.4
1983–2001								
Active modes	0.02 (-0.03, 0.07)	41.2	0.04 (-0.02, 0.09)	48.2	0.00 (-0.05, 0.04)	42.8	0.03 (-0.02, 0.09)	47.5
Walking	-0.01 (-0.08, 0.05)	53.6	0.00 (-0.08, 0.08)	49.6	0.00 (-0.05, 0.05)	47.7	0.03 (-0.02, 0.08)	47.9
Cycling	0.01 (-0.05, 0.07)	45.2	0.08 (0.01, 0.15)*	51.3	0.01 (-0.07, 0.09)	67.5	0.10 (0.04, 0.24)*	86.8
1983–2007								
Active modes	0.03 (-0.02, 0.07)	40.3	0.04 (-0.02, 0.09)	46.2	0.02 (-0.03, 0.06)	44.0	0.02 (-0.03, 0.07)	46.6
Walking	-0.03 (-0.09, 0.03)	51.4	0.04 (-0.03, 0.12)	52.2	-0.02 (-0.07, 0.03)	47.7	0.02 (-0.03, 0.07)	47.5
Cycling	0.02 (-0.04, 0.08)	45.8	0.04 (-0.03, 0.11)	48.0	0.00 (-0.07, 0.08)	70.3	0.06 (-0.06, 0.19)	84.8
1983–2011								
Active modes	0.02 (-0.02, 0.07)	38.7	0.03 (-0.02, 0.08)	42.6	0.01 (-0.04, 0.05)	43.1	-0.01 (-0.06, 0.03)	43.3
Walking	0.02 (-0.03, 0.08)	54.9	-0.02 (-0.08, 0.04)	47.1	-0.02 (-0.06, 0.03)	47.2	0.00 (-0.05, 0.04)	44.7
Cycling	0.00 (-0.06, 0.06)	44.1	0.09 (0.02, 0.15)*	50.9	0.00 (-0.07, 0.08)	72.4	0.01 (-0.10, 0.13)	85.2
1983–2018								
Active modes	0.00 (-0.04, 0.05)	36.9	0.00 (-0.05, 0.05)	40.3	0.01 (-0.04, 0.06)	42.0	-0.03 (-0.08, 0.02)	42.9
Walking	0.03 (-0.05, 0.10)	51.8	-0.01 (-0.08, 0.05)	47.0	0.01 (-0.04, 0.06)	46.3	-0.02 (-0.07, 0.03)	44.1
Cycling	0.01 (-0.04, 0.07)	42.8	0.06 (-0.01, 0.13)	48.6	0.04 (-0.05, 0.13)	71.3	0.01 (-0.10, 0.12)	84.5

**P* < 0.05, ***P* < 0.01 (two-tailed)

Table 4. The estimation results of latent class model fit for active commuting levels in males and females

Interpretation classes	AIC	BIC	ABIC	Entropy	Class proportions†‡§
Males (*n* = 491)					
2	11997	12333	12079	0.976	76.0%, 24.0%
3	10959	11462	11081	0.983	65.4%, 18.3%, 16.3%
4	**10174**	**10846**	**10338**	**0.981**	**58.9%, 16.5%, 12.8%, 11.8%**
5	9688	10527	9892	0.971	53.2%, 15.7%, 11.0%, 10.4%, 9.8%
6	9254	10261	9500	0.980	53%, 15.3%, 14.3%, 6.7%, 6.1%, 4.7%
7	9059	10234	9346	0.977	55.8%, 9.0%, 7.9%, 7.7%, 7.1%, 7.1%, 5.3%
Females (*n* = 729)					
2	21700	22067	21813	0.967	63.2%, 36.8%
3	20179	20730	20349	0.945	42.4%, 31.0%, 26.6%
4	19353	20087	19579	0.951	37.3%, 25.9%, 25.1%, 11.7%
5	**18661**	**19579**	**18944**	**0.956**	**37.4%, 22.2%, 17.3%, 12.2%, 10.8%**
6	18197	19299	18537	0.962	37.4%, 22.1%, 14.3%, 10.3%, 8.2%, 7.7%
7	17638	18924	18035	0.959	36.5%, 15.1%, 15.0%, 10.4%, 8.6%, 8.1%, 6.3%

†Final class proportions for the latent classes were based on participants' most likely latent class membership.
Active commuting levels were converted to commuting modes and average distances commuted actively in both summer and winter.
‡The proportion in bold font represents the model chosen through contextual analysis, supported by information criteria.
§The models were adjusted for participants' adult age, residential place, BMI, having children, education, occupation, and income.
Abbreviations: AIC, Akaike's Information Criterion; BIC, Bayesian Information Criterion; ABIC, Adjusted Bayesian Information Criterion.

Table 5. Equality tests of means of accelerometer-derived and self-reported physical activity in mid-adulthood across active commuting classes using the BCH procedure.

	Accelerometer-derived PA						Self-reported PA	
Latent commuting classes[†‡]	Total PA (cpm)		MVPA (min/day)		Daily steps (step/day)		Score	
Males (n=491)	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p
Stable Car Commuting (n=289)	1060 (25)	(ref.)	62.1 (2.1)	(ref.)	8318 (172)	(ref.)	8.89 (0.12)	(ref.)
Decreasing Active Commuting (n=81)	1097 (44)	0.471	62.2 (3.6)	0.988	8726 (345)	0.293	9.18 (0.23)	0.270
Increasing Active Commuting (n=63)	1211 (68)	0.037	72.5 (5.5)	0.078	9146 (398)	0.057	8.95 (0.26)	0.846
Stable Active Commuting (n=58)	1093 (49)	0.557	64.3 (4.4)	0.654	9652 (402)	0.002	9.47 (0.24)	0.033
Females (n=729)	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p
Stable Car Commuting (n=273)	992 (22)	(ref.)	47.5 (1.7)	(ref.)	8186 (168)	(ref.)	9.04 (0.12)	(ref.)
Decreasing Active Commuting (n=162)	988 (26)	0.908	46.1 (2.1)	0.609	8307 (226)	0.675	9.35 (0.15)	0.117
Increasing Active Commuting (n=79)	1032 (36)	0.344	47.8 (2.7)	0.918	8509 (282)	0.326	8.81 (0.22)	0.362
Stable Active Walking (n=126)	1057 (42)	0.164	55.2 (3.0)	0.025	9343 (307)	0.001	9.03 (0.17)	0.974
Stable Active Summer Cycling (n=89)	1048 (36)	0.182	54.6 (2.8)	0.029	9208 (349)	0.008	9.45 (0.20)	0.074

[†]Stable car commuting serves as the reference group for each test for both males and females. P-value of testing the equivalence of mean.

[‡]Classification is adjusted for participants' adult age, residential place, BMI, having children, education, occupation, and income.

Abbreviations: M, mean; SE, standard error; PA, physical activity; MVPA, moderate-to-vigorous PA; cpm, counts per minute.

Table 6. Equality tests of means of accelerometer-derived physical activity at weekdays and weekends in mid-adulthood across active commuting classes using the BCH procedure.												
	Weekdays						Weekends					
Latent commuting classes‡	Total PA (cpm)		MVPA (min/day)		Daily steps (step/day)		Total PA (cpm)		MVPA (min/day)		Daily steps (step/day)	
Males (n = 491)	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p
Stable Car Commuting (n=289)	1176 (30)	(ref.)	62.6 (2.3)	(ref.)	8475 (193)	(ref.)	771 (22)	(ref.)	60.8 (2.5)	(ref.)	7947 (205)	(ref.)
Decreasing Active Commuting (n=81)	1222 (56)	0.472	61.6 (3.9)	0.835	8791 (384)	0.465	776 (48)	0.915	63.2 (5.2)	0.681	8548 (438)	0.216
Increasing Active Commuting (n=63)	1289 (71)	0.141	70.7 (5.8)	0.195	9083 (429)	0.197	1019 (81)	0.003	78.5 (6.9)	0.017	9413 (556)	0.014
Stable Active Commuting (n=58)	1227 (57)	0.427	65.8 (4.6)	0.536	9954 (420)	0.001	758 (45)	0.804	60.6 (5.3)	0.962	8937 (561)	0.098
Females (n = 729)	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p	M (SE)	p
Stable Car Commuting (n=273)	1075 (24)	(ref.)	46.1 (1.8)	(ref.)	8229 (180)	(ref.)	783 (24)	(ref.)	50.9 (2.2)	(ref.)	8095 (205)	(ref.)
Decreasing Active Commuting (n=162)	1087 (29)	0.742	45.0 (2.1)	0.688	8345 (231)	0.695	742 (29)	0.298	49.0 (2.7)	0.607	8247 (294)	0.677
Increasing Active Commuting (n=79)	1107 (42)	0.502	46.8 (2.7)	0.830	8643 (293)	0.229	836 (43)	0.286	50.4 (3.7)	0.911	8174 (399)	0.860
Stable Active Walking (n=126)	1169 (47)	0.074	56.4 (3.2)	0.004	9655 (325)	0.000	787 (40)	0.935	52.2 (3.3)	0.732	8592 (357)	0.227
Stable Active Summer Cycling (n=89)	1170 (44)	0.055	54.7 (3.0)	0.013	9434 (372)	0.004	749 (34)	0.425	54.7 (3.4)	0.346	8701 (389)	0.168

† Stable car commuting (*n* = 258 males/252 females) serves as the reference group for each test for both males and females.

‡Classification is adjusted for participants' adult age, residential place, BMI, having children, education, occupation, and income.

Abbreviations: M, mean; SE, standard error; PA, physical activity; MVPA, moderate-to-vigorous PA; cpm, counts per minute.