Practice of Epidemiology

Longitudinal Patterns of Physical Activity Among Older Adults: A Latent Transition Analysis

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Most epidemiologic studies of physical activity measure either total energy expenditure or engagement in a single type of activity, such as walking. These approaches may gloss over important nuances in activity patterns. We performed a latent transition analysis to identify patterns of activity, as well as neighborhood and individual determinants of changes in those activity patterns, over 2 years in a cohort of 2,023 older adult residents of New York, New York, surveyed between 2011 and 2013. We identified 7 latent classes: 1) mostly inactive, 2) walking, 3) exercise, 4) household activities and walking, 5) household activities and exercise, 6) gardening and household activities, and 7) gardening, household activities, and exercise. The majority of subjects retained the same activity patterns between waves (54% unchanged between waves 1 and 2, 66% unchanged between waves 2 and 3). Most latent class transitions were between classes distinguished only by 1 form of activity, and only neighborhood unemployment was consistently associated with changing between activity latent classes. Future latent transition analyses of physical activity would benefit from larger cohorts and longer follow-up periods to assess predictors of and long-term impacts of changes in activity patterns.

aging; latent class analysis; latent transition analysis; older adults; physical activity patterns; walking

Abbreviations: MET, metabolic equivalent of task; PASE, Physical Activity Scale for the Elderly.

Researchers studying influences of the built environment on physical activity, including those operating among older adults, have frequently invoked the need for specificity in both environmental measures and activity measures (1–5). For example, pleasing neighborhood aesthetic characteristics more plausibly influence walking in one's neighborhood than one's occupational physical activity. A study assessing the impact of neighborhood aesthetics on total physical activity would thus have less power to detect a true effect than one using a measure of walking alone (6).

However, it can be problematic to study supports for and barriers to a single form of activity, such as walking, in isolation. Qualitative evidence suggests that older adults show interest in multiple forms of activity, including not only organized sports or exercise classes but also inexpensive, unstructured activities such as walking and gardening (7). Neighborhood support for these various forms of activity varies depending on setting. For example, urban neighborhoods conducive to walking may lack space

for gardening, whereas rural settings may lack access to recreational facilities or walkable destinations (8, 9).

Yet there are also challenges in working with fully disaggregated activity data. For example, analyzing each possible type of activity (e.g., dishwashing, racquetball, carpentry) separately would require impractically large sample sizes to garner adequate statistical power, owing to the small proportion of the population engaging in most types of activity. As a result, physical activity researchers have recently begun to consider patterns of activity with respect to time or activity type rather than, or in addition to, total energy expenditure. These researchers have used several analytical techniques to date, including: analyses of patterns of activity in minute-by-minute high-density accelerometer or fitness tracker data sets (10); latent class growth models of trajectories of energy expenditure through time (11); and latent class analyses of questionnaire data to classify study participants into groups with relatively homogeneous activity patterns (12, 13). These analytical approaches retain

theoretically relevant components of the heterogeneity in the underlying data while also collapsing similar groups to increase statistical power, as compared with what would be available in fully disaggregated data.

Such holistic approaches to physical activity research that identify and analyze patterns of activities may shed light on the contextual supports for and barriers to types of activity above and beyond what could be identified from analyses of energy expenditure alone. In particular, longitudinal mixture modeling techniques such as latent transition analysis may identify characteristic patterns of types of activity (14), wherein subjects may change patterns over time. These changes and the individual and neighborhood variables that predict changes may in turn help to identify influences on activity patterns. However, while mixture models have been applied to types of activities adolescents (15) and younger adults (16) engage in, to the best of our knowledge, no prior study has applied a latent transition analysis to examine patterns of types of activities older adults engage in longitudinally.

We used a latent transition analysis to identify patterns of activity types, individual and neighborhood correlates of patterns, transitions between patterns, and determinants of those transitions over the course of two 1-year waves of follow-up in a cohort of older adult residents of New York City.

METHODS

Subjects and setting

New York City Neighborhood and Mental Health in the Elderly Study II was a longitudinal study of 3,497 residents of New York, New York, aged 65–75 years at baseline (13). Subjects were initially recruited by telephone, starting in May 2011 and continuing through November 2011. We attempted to recontact each subject by phone once in summer or fall 2012 and once in summer or fall 2013. In all, 2,023 subjects (58% of those included at baseline) were contacted in all 3 waves of the study. At each wave, subjects were paid \$10 for participating, in the form of either a CVS Pharmacy gift card (CVS Health, Woonsocket, Rhode Island) or a check.

Measures

Individual measures. Subjects reported their demographic characteristics, including sex, age (65–68, 69–71, or 72–75 years), educational attainment (less than high school graduation, high school graduation, some college, or college graduation), race/ethnicity (non-Hispanic black, non-Hispanic white, Hispanic, or other), health status (excellent, good, fair, or poor), and annual household income ($\leq$ \$20,000, \$20,001–\$40,000, \$40,001–\$80,000, or $>$ \$80,000). At each wave, subjects were asked about past-year stressful life events, including retirement, whether their spouse had fallen ill or died, and whether another family member had fallen ill or died.

Neighborhood measures. At each wave, each subject reported his or her home address. Sixty subjects (2.9%) changed addresses between waves 1 and 2, and 24 (1.2%) moved between waves 2 and 3. We used Geosupport (New York City Department of City Planning, New York, New York) and DCP-LION (New York City Department of City Planning) to geocode all 2107

unique addresses. Of these, we geocoded 2,059 (98%) to a rooftop; from the remaining 48 reported addresses, we extracted the zip code and assigned the age 65–74-population-weighted centroid of that zip code as the participant's home location. For each residential address, we computed a 0.25-km network buffer around the address (17–19) and spatially merged measures of the proportion of adults aged 16 years or over in the labor force, neighborhood physical disorder (20, 21), and walkability (22). We selected these neighborhood characteristics because of their prior associations with walking and total physical activity (23–25).

Physical activity. All subjects who were followed up successfully were asked at each wave about past-week physical activity using 16 items derived from the Physical Activity Scale for the Elderly (PASE) (26–28) and detailed in Web Table 1 (available at <https://academic.oup.com/aje>). The item in the PASE instrument assessing job-related activity was not used in this cohort, which comprised mostly retired persons (12% were employed at baseline).

We recoded the 16 ordinal item responses to 12 dichotomous indicators as follows: For the 5 physical activity domains where PASE assesses both number of days and average duration of time in which the subject engaged in the activity (walking, light recreational activity, moderate recreational activity, strenuous recreational activity, and muscle-strengthening exercises), we computed average duration per week for each subject. Because each level of recreational activity intensity was relatively rare on its own and because the energy expenditure from many recreational activities varies greatly depending on how the activity is performed (e.g., cycling can range from 3.5 metabolic equivalent of task (MET) units to 16.0 MET units, depending on how vigorously the cyclist pedals) (29) and hence is subject to misclassification, we did not expect distinguishing recreational activity by vigor to produce interpretable classes. We therefore summed the measures of recreational activity at 3 intensity levels into 1 measure reflecting participation in any sport or recreational activity. Finally, for the resulting 3 domains for which we computed duration per week (walking, sports and recreation, and muscle strengthening), we computed 2 indicators: an “ever” indicator set to true if the subject reported more than 0 minutes/week of the given activity and an “often” indicator set to true if the subject reported more than 30 minutes/week of activity.

The resulting indicators, their prevalence at each wave, and the maximal MET unit value of any activity associated with that indicator are shown in Table 1. This recoding of PASE items to identify interpretable activity subtypes has been used in a previous analysis (13); several alternate recoding options that were tested in that analysis resulted in less substantively interpretable latent classes.

Statistical analysis

We used the “depmixS4” package in R software (R Foundation for Statistical Computing, Vienna, Austria) to identify latent classes and assign probabilities of transitioning between classes. For each identified class, we computed the median PASE score within the class and the maximal MET unit score associated with any activity implied by the class to provide an interpretive bridge from these identified classes to more traditional physical activity measures. To increase model interpretability,

Table 1. Categories of Reported Past-Week Physical Activity Among 2,023 Adults Aged 65–75 Years, New York City Neighborhood and Mental Health in the Elderly Study II, 2011–2013

Activity Category	Study Wave and Prevalence, %			Examples ^a	Approximate MET Range
	Wave 1	Wave 2	Wave 3		
Ever engaging in sports	55.2	54.8	55.2	Golf, dancing, basketball, hiking, jogging	3–14
Often engaging in sports	27.9	26.6	25.3	Sports for more than 30 minutes/day	
Ever engaging in exercise	37.6	36.8	38.4	Calisthenics, sit-ups, weight lifting	2–14
Often engaging in exercise	5.9	5.2	5.5	Exercise for more than 30 minutes/day	
Ever walking	91.5	90.6	90.2		
Often walking	52.6	50.0	50.0	Walking for more than 30 minutes/day	2–5 ^b
Caring for others	31.1	30.4	31.2	Caring for a person who requires assistance with daily living tasks such as showering	2–4
Outdoor gardening	21.1	18.7	20.5	Planting plants, pruning, weeding	2–4
Heavy housework	54.5	54.3	53.0	Vacuuming, sweeping, moving furniture	3–7
Home repairs	10.7	9.8	10.5	Painting, plumbing, carpentry	2–6
Light housework	92.0	92.1	92.2	Washing dishes, ironing, laundry	2
Lawn work or yard care	17.5	16.4	16.7	Shoveling snow, lawn mowing	3–6

Abbreviation: MET, metabolic equivalent of task.

^a Listed activity types are taken from the Physical Activity Scale for the Elderly (PASE) instrument.

^b Assuming walking no faster than a “very brisk” pace.

we imposed measurement invariance, such that the model classifying subjects into a latent class was consistent across waves. After fitting the latent class model, we used proportional assignment to assign each subject a latent class (30, 31).

The underlying logic of the proportional assignment approach is that latent class assignment is subject to 2 distinct sources of error: indicator measurement error (e.g., whether a subject accurately reports whether she or he gardened, walked, etc.) and class assignment error (e.g., whether it is most appropriate to consider the subject in class A or class B). To account for the second source of uncertainty, the proportional assignment approach uses weighted observations to treat each subject at each wave as belonging to each latent class in proportion to the estimated probability that his or her true latent class is that class (30–32). Procedurally, for each subject at each wave and in each latent class, we created a record with a weight proportional to the probability that that latent class best defined that subject’s activity pattern at that wave. For example, for a 7-class model, each subject at each wave is represented in the data by 7 observations, each with a weight. These 7 weights sum to 1, resulting in a weighted pseudocohort that better recapitulates the model-estimated class prevalences at the cost of greater subject misclassification (33). Proportional assignment does not account for bias that results from class assignment error in standard regression models, though bias-correction techniques have recently been developed to address such errors (30, 31, 33, 34).

Furthermore, we were concerned about selection bias, due to loss to follow-up of 42% of the subjects contacted at baseline. Unfortunately, lack of software support for weighted latent transition analyses precluded use of inverse-probability-of-censoring weights in identifying latent classes and transitions. However, we

used sex, race/ethnicity, educational attainment, borough of residence, neighborhood disorder, neighborhood pedestrian injury rate, and self-reported health status to compute inverse-probability-of-observation weights for subsequent analyses, which we multiplied by baseline sampling weights. Class prevalences from the weighted cohort thus represent estimates for the population of noninstitutionalized New York City residents aged 65–75 years according to the 2010 US Census ($n = 571,323$), assuming observation is fully explained by the sampling probabilities and the baseline covariates included in the model used to compute the weights. We used the R “survey” package for subsequent analyses of class prevalence, class transitions, and predictors of class membership and class transitions in this weighted pseudocohort.

Relatively few survey data were missing (16.2% of participants did not report income; no other covariate was unreported by more than 10% of participants, while no activity indicator was unreported by more than 2% of the cohort). Nevertheless, we multiply imputed missing data using IVEware (35), such that all available survey responses were used for imputation. Because, to the best of our knowledge, no latent transition model software works with imputed data sets, we selected 1 imputation at random with which to develop the latent transition model; all subsequent analyses accounted for missing covariates by combining results across 5 multiply imputed data sets using Rubin’s rules (36).

After identifying latent classes, we explored individual and neighborhood predictors of class membership and of transition between classes. We selected individual age, race/ethnicity, sex, income, education, health status, change in health status, neighborhood disorder, neighborhood walkability, and neighborhood unemployment rate as potential predictors. We selected these

neighborhood variables to cover distinct theoretically relevant domains of neighborhood context frequently studied as drivers of physical activity. Because our initial explorations identified relatively stable latent classes, we focused our analyses on predictors of any latent class transitions. Because, in this exploratory analysis, we did not have a causal theory to inform a multi-variable model and did not have software support to apply bias-correcting weights, we considered only bivariate relationships between predictors and any latent class transition.

We performed all analyses in 64-bit R for Windows (R Foundation for Statistical Computing), version 3.3.1.

RESULTS

As compared with the full cohort, the 2,023 subjects who completed 3 waves of data collection and accordingly were included in the latent transition analysis were somewhat more likely to be non-Hispanic white, well-educated, and high-income (Table 2).

Model fit statistics best supported a 7-latent-class model (Web Table 2). The 7-class model also had acceptable substantive interpretability and a good balance of class prevalence (no class contained less than 10% of the overall cohort). After examining the activity patterns by class, we named the classes “mostly inactive,” “walking,” “exercise,” “household activities and walking,” “household activities and exercise,” “gardening and household activities,” and “gardening, household activities, and exercise,” respectively. Table 3 describes the latent classes statistically, showing the probability of endorsing each item within each latent class and the prevalence of each latent class at each wave.

Class membership at baseline was strongly associated with individual and neighborhood characteristics (Table 4). On average, men reported participating in more diverse forms of activity, particularly more yard work and gardening, and so were more represented in the more active latent classes. Membership in the two least active classes, “mostly inactive” and “walking,” was associated with indicators of social disadvantage, such as lower income (39% of those with annual household incomes at or below \$20,000 were in the “mostly inactive” or “walking” class as compared with 19% of those with household incomes over \$80,000) and living in neighborhoods with more disorder (32% of those in neighborhoods above the median disorder level were in the “mostly inactive” or “walking” class, as compared with 25% of those living in neighborhoods at or below the median disorder level; Wald test $P < 0.01$).

Class membership was fairly stable across waves, with about half of subjects in each class remaining within their prior latent class between waves 1 and 2 and about 2 of every 3 remaining in the same class between waves 2 and 3. Figure 1 depicts the most common transitions between latent classes, including the types of activities defining the differences between classes. Notably, transitions between latent classes were most common between latent classes sharing more types of activity (e.g., people in the “gardening,” “household activities and walking,” and “exercise” classes transitioned most often into the “gardening” and “household activities and walking” class, and vice versa) (Web Figure 1). The patterns of transition occurring between waves 1 and 2 were consistent with those seen between waves 2 and 3 (Table 5).

In bivariate models, most measured covariates were not consistently associated with the probability of transitioning between

Table 2. Selected Characteristics (%) of the Entire Study Population (Adults Aged 65–75 Years) and the Subset Who Completed All 3 Waves of Data Collection, New York City Neighborhood and Mental Health in the Elderly Study II, 2011–2013

Characteristic	Study Population		χ^2 Test P Value
	All Participants (n = 3,497)	Completed All 3 Waves (n = 2,023)	
Age at baseline, years			0.70
65–68	33	34	
69–71	21	21	
72–75	46	45	
Sex			0.14
Female	60	61	
Male	40	39	
Race/ethnicity			<0.01
Non-Hispanic white	52	55	
Non-Hispanic black	31	30	
Hispanic	11	9	
Other	7	6	
Educational attainment			<0.01
Less than high school	19	16	
Completion of high school	27	26	
Some college	18	17	
Completion of college	36	41	
Annual household income			<0.01
≤\$20,000	36	33	
\$20,001–\$40,000	25	24	
\$40,001–\$80,000	21	22	
>\$80,000	18	21	

classes. The sole exception was living in a neighborhood with an unemployment rate above the median (versus at or below the median), which was positively associated with transitioning between classes both between waves 1 and 2 and between waves 2 and 3 (Table 6). However, the differences in the proportions of participants transitioning between classes (48% vs. 45% between waves 1 and 2; 35% vs. 33% between waves 2 and 3) were modest. A change in self-reported health status was not significantly associated with a change in latent class.

DISCUSSION

We used latent transition analysis to identify 7 patterns of physical activity performed by a cohort of older adults aged 65–75 years in New York City. Based on the types of activities subjects engaged in, we labeled the patterns 1) mostly inactive, 2) walking, 3) exercise, 4) household activities and walking, 5) household activities and exercise, 6) gardening and household activities, and 7) gardening, household activities, and exercise. Most subjects stayed within the same activity class between waves. Subjects who changed classes most often changed between classes that

Table 3. Distribution (%) of Past-Week Physical Activities by Latent Class Among Adults Aged 65–75 Years at Baseline, New York City Neighborhood and Mental Health in the Elderly Study II, 2011–2013

Activity	Latent Class						
	Exercise	Walking	Household Activities and Walking	Mostly Inactive	Gardening and Household Activities	Gardening, Household Activities, and Exercise	Household Activities and Exercise
Sports, minutes/week							
0	14	77	59	87	54	5	9
>0–29.9	33	21	34	11	30	24	28
≥30	53	2	7	2	16	71	62
Walking, minutes/week							
0	1	18	4	52	2	1	1
>0–29.9	31	57	43	40	49	25	14
≥30	68	24	52	7	49	74	84
Strengthening exercises, minutes/week							
0	35	81	82	78	81	26	36
>0–29.9	55	17	18	17	17	52	54
≥30	10	2	0	5	2	22	10
Outdoor gardening	5	1	3	1	78	88	5
Lawn work or yard care	1	0	1	0	68	78	3
Light housework	85	97	100	29	96	95	98
Heavy housework	11	23	83	1	75	77	82
Home repairs	2	2	6	1	27	32	13
Caring for others	19	20	39	8	39	45	39
Proportion of cohort							
Wave 1	13	21	21	6	13	10	16
Wave 2	13	22	21	6	12	9	16
Wave 3	13	22	21	6	13	9	16

incorporated more similar activities. Neighborhood unemployment was associated with a higher probability of transitioning between classes; however, this association was modest and not consistent with any broader pattern of neighborhood or individual characteristics. Taken together, these findings indicate that although there were between-individual differences in the patterns of activity engaged in by these older adults, study participants in general maintained habitual patterns of activity over the course of the study period.

Our analysis adds to the literature regarding the changing patterns of activity as adults age. One 2012 study of patterns of physical activity over 12 years among older adult women aged 70 years or more at baseline identified 4 patterns of total activity (11). Three of the patterns identified in that study, which together accounted for 80% of the women, were defined by roughly constant levels of activity over time, consistent with our finding that

activity patterns among older adults, once set, are resistant to change. This finding is further supported by several studies assessing trajectories of total physical activity or leisure-time physical activity in other age groups that have also found activity to be constant over time for the majority of subjects (37–39). The degree to which this consistency is due to consistent behavioral habits among the subjects as opposed to consistent environmental influences applied to the subjects is an area for future research among older adults who change residences. More broadly, the relative stability of behavior patterns over time supports the notion that childhood or young adulthood may act as a critical period for establishing an active lifestyle (40).

Our analysis focused on patterns of activity and determinants of patterns and changes in those patterns. However, activity patterns identified by latent transition analyses may be salient in studying the effects of activity as well. For example, if 2 people

Table 4. Prevalence (%) of Latent Classes of Past-Week Physical Activity at Baseline According to Selected Individual and Neighborhood Characteristics Among Adults Aged 65–75 Years, New York City Neighborhood and Mental Health in the Elderly Study II, 2011

Characteristic	Latent Class						
	Exercise	Walking	Household Activities and Walking	Mostly Inactive	Gardening and Household Activities	Gardening, Household Activities, and Exercise	Household Activities and Exercise
<i>Individual Measures</i>							
Age at baseline, years							
65–68	14	20	20	6	12	11	17
69–71	14	21	21	6	13	9	16
72–75	12	24	21	7	13	8	15
Sex							
Female	11	24	24	6	12	8	15
Male	15	18	17	7	14	11	17
Race/ethnicity							
Non-Hispanic white	14	19	19	5	15	11	16
Non-Hispanic black	11	26	24	6	11	7	14
Hispanic	10	25	23	13	5	5	20
Other	14	19	22	8	13	11	13
Educational attainment							
Less than high school	10	28	23	13	9	4	13
Completion of high school	9	25	26	6	13	7	14
Some college	12	22	21	4	14	11	17
Completion of college	16	16	17	4	14	13	18
Annual household income							
≤\$20,000	11	28	25	11	8	4	14
\$20,001–\$40,000	9	20	24	4	14	11	18
\$40,001–\$80,000	13	19	19	4	16	12	17
>\$80,000	19	16	14	3	17	15	15
<i>Neighborhood Measures^a</i>							
Disorder ^b							
Above median	11	25	23	7	10	7	16
At or below median	14	19	19	6	16	12	15
Unemployment ^c							
Above median	10	24	23	7	11	7	16
At or below median	15	19	19	5	15	11	16
Walkability ^d							
Above median	13	22	22	7	11	8	17
At or below median	12	22	21	6	15	11	15

^a For each residential address, a 0.25-km network buffer around the address was computed (17–19) and measures of the proportion of adults aged 16 years or over in the labor force, neighborhood physical disorder (20, 21), and walkability (22) were spatially merged.

^b Neighborhood disorder was measured using a scale derived from systematically audited Google Street View imagery (Google LLC, Mountain View, California).

^c Unemployment was measured as the proportion of adults aged 16 years or over not in the labor force.

^d Walkability was measured using a validated walkability scale incorporating land use, population density, urban design, and public transit access.

expend the same amount of energy in a week but the first expends the energy through daily gardening tasks and the second attends an intensive biweekly exercise class, a study assessing only energy

expenditure would gloss over the different effects these different types of activity might have on the individuals' physical and mental health (12, 41, 42). Future latent transition analyses of activity

Figure 1. Latent classes of physical activity patterns identified in an analysis of 2,023 New York City residents aged 65–75 years, including arrows noting the common transitions between classes and dotted lines noting the type of activity defining that transition, New York City Neighborhood and Mental Health in the Elderly Study II, 2011–2013.

types in larger cohorts with longer-term follow-up may help to optimize behavior change interventions to maximize health-promoting activities among older adults.

This analysis had several notable strengths. Though several prior studies applied latent class growth models or repeated-measures latent class analyses to assess trajectories of total activity among adult populations (11, 37, 38), to the best of our knowledge, this was the first analysis to identify longitudinal patterns of activity *types* among older adults. Understanding such patterns is vital not only for understanding the contextual determinants of overall activity but also for targeting interventions that increase activity most effectively (13, 43). Additionally, although we could not incorporate sampling weights in computing latent classes, our remaining analyses were weighted to allow an estimate of the population prevalence of the latent classes we did identify.

However, our findings should be considered in light of the following limitations. First, because we were unable to conduct the latent transition analysis in the full sample, the identified patterns are representative of activity patterns among the generally healthier and more privileged groups that were followed up for 3 waves and thus may not represent patterns of activity among older adults more broadly. Our concerns on this front are somewhat mitigated by the similarity between the latent classes identified here and those previously identified in the full cohort at baseline only (13) and by our use of inverse-probability-of-censoring weights in analyses of transitions between classes. Second, because New York City Neighborhood and Mental Health in the Elderly Study II had a low response rate, even the full sample may not have represented the older adult population of New York City. However, our use of a population-based sample and incorporation of analyses that accounted for the sampling

Table 5. Percentage of Adults Aged 65–75 Years Transitioning Between Specific Latent Classes of Past-Week Physical Activity Across Study Waves, New York City Neighborhood and Mental Health in the Elderly Study II, 2011–2013

Original Study Wave and Latent Class	Subsequent Study Wave and Latent Class						
	Exercise	Walking	Household Activities and Walking	Mostly Inactive	Gardening and Household Activities	Gardening, Household Activities, and Exercise	Household Activities and Exercise
Wave 1				Wave 2			
Exercise	43	17	10	5	3	3	17
Walking	8	58	19	8	3	0	3
Household activities and walking	5	22	51	1	6	1	13
Mostly inactive	6	27	3	64	1	0	0
Gardening and household activities	5	7	14	2	56	11	5
Gardening, household activities, and exercise	6	1	3	0	21	54	14
Household activities and exercise	13	6	20	1	4	6	51
Wave 2				Wave 3			
Exercise	57	12	7	5	4	4	11
Walking	6	70	14	5	4	0	1
Household activities and walking	3	17	62	1	6	0	11
Mostly inactive	4	18	1	75	2	0	0
Gardening and household activities	4	5	8	1	70	8	3
Gardening, household activities, and exercise	4	1	1	1	13	68	12
Household activities and exercise	9	3	15	1	3	5	65

Table 6. Percentage of Adults Aged 65–75 Years Transitioning Between Any Latent Classes of Past-Week Physical Activity Across Study Waves, According to Selected Covariates, New York City Neighborhood and Mental Health in the Elderly Study II, 2011–2013

Characteristic	Transition Period					
	Wave 1 to Wave 2			Wave 2 to Wave 3		
	Changed Class, %	Did Not Change, %	χ^2 Test P Value	Changed Class, %	Did Not Change, %	χ^2 Test P Value
<i>Individual Measures</i>						
Age, years			0.99			0.49
65–68	46	54		33	67	
69–71	46	54		35	65	
72–75	46	54		34	66	
Sex			0.45			0.19
Female	47	53		35	65	
Male	46	54		33	67	
Race/ethnicity			0.31			0.12
Non-Hispanic white	45	55		33	67	
Non-Hispanic black	48	52		36	64	
Hispanic	48	52		33	67	
Other	49	51		34	66	
Educational attainment			0.88			0.95
Less than high school	47	53		35	65	
Completion of high school	46	54		34	66	
Some college	48	52		34	66	
Completion of college	46	54		34	66	
Annual household income			1.00			0.10
≤\$20,000	47	53		34	66	
\$20,001–\$40,000	46	54		34	66	
\$40,001–\$80,000	47	53		37	63	
>\$80,000	46	54		31	69	
Change in health status			0.14			0.59
Yes	48	52		33	67	
No	46	54		34	66	
<i>Neighborhood Measures^a</i>						
Disorder ^b			1.00			0.99
Above median	46	54		34	66	
At or below median	46	54		34	66	
Unemployment ^c			<0.01			0.04
Above median	48	52		35	65	
At or below median	45	55		33	67	
Walkability ^d			0.80			0.99
Above median	47	53		34	66	
At or below median	46	54		34	66	

^a For each residential address, a 0.25-km network buffer around the address was computed (17–19) and measures of the proportion of adults aged 16 years or over in the labor force, neighborhood physical disorder (20, 21), and walkability (22) were spatially merged.

^b Neighborhood disorder was measured using a scale derived from systematically audited Google Street View imagery (Google LLC, Mountain View, California).

^c Unemployment was measured as the proportion of adults aged 16 years or over not in the labor force.

^d Walkability was measured using a validated walkability scale incorporating land use, population density, urban design, and public transit access.

weights partially mitigates our concerns, as does a prior analysis indicating that the subjects included in this analysis were demographically representative of the overall older adult population of New York City (12). Third, because our only measure of activity types was a survey of past-week activity, there may have been substantial misclassification in our activity measure. We note, however, that the relative stability of latent classes between waves would require the misclassification to be consistent within people over time, and prior studies have generally found PASE to be reliable and valid (27, 28, 44, 45). One caveat to this interpretation is that the greater latent class stability we observed between waves 2 and 3 as compared with waves 1 and 2 was not anticipated; this raises the possibility of a response bias wherein participants recalled their prior response rather than their true past-week activity, which would have resulted in overstating class stability.

Fourth, we were unable to fully account for the tendency of people with a choice of places to live to choose the places that best support their behavioral preferences (46). However, we did adjust statistically for common determinants of residential location, including household income and subject race/ethnicity (47). Fifth, the 3-step latent class assignment procedure results in biased estimates of associations between exposures and latent classes (30, 33), and though bias-correction techniques have recently been developed (31, 34), these techniques were not available in the software we used to estimate predictors of class transitions. We therefore limited our exploration of predictors of transitioning to bivariate comparisons, which do not require estimating coefficients that would be biased in the absence of bias-correction techniques. A final but important limitation of this analysis is that, as in all latent classification analyses, class labels were selected by researchers rather than derived from data, and thus were intrinsically value-laden (48). As a result, caution must be taken when interpreting classes by name.

In conclusion, this latent transition analysis identified 7 patterns of activity types observed over the course of 2 years in older adult residents of New York City. Patterns of activity types were generally stable, with the notable exception of engagement in exercise. These patterns of activity suggest that barriers to both starting and stopping exercise may be more transient, whereas barriers to other daily life activities may be more constant over time.

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