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NEWCASTLE

Mobility in community dwelling older adults: Predicting successful mobility using an instrumented battery of novel measures

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Abbreviated title: Predictors of mobility

STRUCTURED ABSTRACT

Mobility in older adults is associated with better quality of life. However, evidence suggests that older people spend less time out-of-home than younger adults. Traditional methods for assessing mobility have serious limitations. Wearable technologies provide the possibility of objectively assessing mobility over extended periods enabling better estimates of levels of mobility to be made and possible predictors to be explored.

Eighty-six community dwelling older adults (mean age 79.8 years) had their mobility assessed for one week using GPS, accelerometry and self-report. Outcomes were: number of steps, time spent in dynamic outdoor activity, total distance travelled and total number of journeys made over the week. Assessments were also made of personal, cognitive, psychological, physical and social variables.

Four regression models were calculated (one for each outcome). The models predicted 32 to 43% of the variance in levels of mobility. The ability to balance on one leg significantly predicted all four outcomes. In addition, cognitive ability predicted number of journeys made per week and time spent engaged in dynamic outdoor activity, and age significantly predicted total distance travelled. Overall estimates of mobility indicated step counts that were similar to those shown by previous research but distances travelled, measured by GPS, were lower.

These findings suggest that mobility in this sample of older adults is predicted by the ability to balance on one leg. Possible interventions to improve out-of-home mobility could target balance. The fact that participants travelled shorter distances than those reported in previous studies is interesting since this high-functioning subgroup would be expected to demonstrate the highest levels.

Keywords: GPS, mobility, aging, monitoring,

INTRODUCTION

Aging is associated with a reduction in mobility, with people over 70 years making fewer and shorter journeys than younger people (1). Increasing age and lower income levels have been associated with reduced out-of-home mobility, which can have widespread, detrimental effects in older people for example reduced quality of life, independence and well-being (2, 3-5).

Out-of-home mobility has historically been assessed using self-report (e.g. diaries, questionnaires and surveys 6 - 8). The accuracy of such methods is unknown (9) with bias and memory constraints influencing responses. Wearable devices offer new opportunities for researchers to objectively and unobtrusively monitor activity over extended periods.

Accelerometry has been increasingly used to measure mobility in adults across the lifespan (10 -13). Different studies report different accelerometry outcomes (e.g. percentages of sedentary and active behaviour, amount of moderate activity and/ or step counts), which can result in difficulties comparing activity levels between populations. Accelerometry can be a useful tool for assessing mobility, however, because it is based on limb movement it gives no indication of context and whether the person is inside or out-of-home.

Novel technology provides a more ecologically valid tool. Global positioning system (GPS) technology enables the measurement of out-of-home mobility using an unobtrusive, portable device that is readily available and affordable with claims of excellent spatial and temporal accuracy (14). Recently it has been used to track and map older individuals in health and social care settings (15), with dementia (16) and in the community (17-20).

This increasing range of tools to assess out-of-home mobility in older adults provides a range of mobility outcomes to explore and this study is unique in using all three methods to do so.

Of further interest is the identification of predictors that may impact on mobility outcomes. These characteristics are broadly divided into five categories that have been shown to influence mobility, quality of life and/or mortality in older adults: personal (e.g. age) (4), cognitive (21), physical (22), psychological (e.g. fear of falling) (23) and social (19). As such, a broad range of characteristics from these categories were assessed in this study. Each of these has been shown to individually influence mobility, however, the extent to which they interact and, which, if any, makes the largest contribution to levels of mobility have yet to be established.

The first aim of this study was to use a novel battery of measures including GPS to explore mobility in a group of community dwelling, cognitively intact older adults. Secondly, we wished to identify personal, cognitive, psychological, physical and social factors that predict mobility.

METHODS

Participants

Participants were recruited from a larger longitudinal study: North East Age Research (NEAR), which is a 29 year study of cognitive aging in healthy, community resident older people in North East England (24). 308 of the 'oldest old' volunteers were invited to participate in the study. One hundred and forty-one individuals accepted (45.7%), of which 100 were contacted to participate and 86 (66 for GPS) of those participated in the study (63 female and 23 male). All participants gave informed written consent before participating. This study was approved by the School of Life Sciences Ethics Committee, Northumbria University.

Procedure

Experimental Protocol

Prior to measurement of mobility a comprehensive battery of standardised tests were administered to assess personal, cognitive, psychological, physical and social variables. Measures included age, gender and health, cognitive function, memory, sleep quality, depression and anxiety, gait speed, balance and social network size (11, 25).

Mobility Measures

Three mobility measurement tools were used:

GPS Location-based Tracking

Participants were visited at their home and fitted with an i-locate GPS tracking device (Trackaphone, UK). The GPS tracking kit used in this study (manufactured by H&G Communications Ltd and supplied by Trackaphone, UK) consisted of: a portable unit (100g, 180*95*13mm) containing a GPS receiver, a charge stand with mains adapter and a material outer sleeve that enables the unit to be worn visibly or discreetly around the arm, shoulders or waist. For a period of seven days, participants were asked to wear the device every time they left their home. One charge lasted for approximately 48-hours and when not being used (i.e. when participants were in their home) the device was stored on its charger. When not charging, location was sampled every two minutes.

For the week that the device was worn the following outcomes were measured:

i. Number of journeys outside home – Data points within a 50m radius of home were defined as "home" anything more than 50m was deemed to be out-of-home. A journey was indicated by home coordinates (coordinates within 50m of home) followed by out-of-home coordinates (coordinates that were >50m from home) followed by home coordinates all on the same day. Due to communication issues with the GPS, there were occasions where home was not recorded at the beginning or end (or both) of a journey. For these occasions, home coordinates were manually inserted, to ensure the journeys could be used in the analysis
ii. Total distance travelled (km) – The distance between successive coordinates was calculated and the summed over the 7-days. All distances were included including those that were within the home radius (50m).
iii. Furthest distance travelled (km) - The coordinates, reached by the participant, that were furthest from their home coordinates.

Accelerometry

Participants also wore an ActivPAL™ activity monitor, which included an accelerometer (PAL Technologies Ltd, Glasgow, UK). This was worn throughout the day and only removed for sleeping, bathing, swimming and showering (11,) Seven variables were extracted from ActivPAL data to represent typical characteristics of active and sedentary behaviour (26, 27).

Diary (self-report)

Activity for each day was recorded using an activity diary, which incorporated a grid divided into 15-minute intervals. There were 30 possible activities for participants to select. Diary data were reduced to 4 types of activity: sedentary indoor (SI), sedentary outdoor (SO), dynamic indoor (DI) and dynamic outdoor (DO). Two diaries were completed, one prior to the study and one during the study week. Comparison of the diaries at the two time points revealed no differences between participants' SO, DI and DO ($F_{(1,77)}$=0.03, 0.13 and 2.28 respectively, all p-values >0.05) showing that their behaviour on these measures was not significantly different when they had the devices compared to when they did not have the devices. However, SI was significantly higher at the first time point (before the devices; $F_{(1,77)} = 9.71$, $p=0.003$). DO was selected as the outcome for this measure.

Data analysis

Preliminary analysis was conducted to identify key mobility outcomes. Pearson product correlation coefficients were calculated for each outcome (three from GPS, four from diary and seven from accelerometer) with all possible predictors (personal, cognitive, psychological, physical and social). Four outcomes emerged: two from GPS: total distance travelled and number of journeys; one from accelerometry (number of steps) and one from diary data ('dynamic outdoors').

Correlational analysis

Pearson product moment correlations were then used to explore associations between the four outcomes (see above) and all potential predictors. For each outcome, the variables with which it significantly correlated ($p<0.05$), were entered into a multiple regression model. Four models were calculated. If a number of predictors all correlated with the DV and the predictors were highly correlated then one predictor variable was selected to represent them. Selection was based on theoretical grounds (e.g. TUG for gait measures) or strength of correlation with the outcome. Consequently, each model contained different predictors which were deemed to be the best fit for the individual outcomes (Table 1).

Regression analysis

Four forced entry, linear regression models were calculated (one each for outcome: steps, distance, journeys and DO). Collinearity diagnostics (VIF and tolerance) were examined to check for multicollinearity and Durbin-Watson statistic was used to test for autocorrelation. All data met the assumptions for regression analysis. The alpha level was set to 0.05. IBM SPSS Statistics for Windows (V 22) was used to analyse the data.

RESULTS

Sample characteristics

Table 2 shows that participants were aged 70-91 years (mean age 79.8) and were cognitively intact (Mini Mental State Exam (MMSE) mean = 27.78). Observed daily step counts were 5775.46. Diaries showed just over two hours per day of dynamic outdoor activity (with a maximum of 5.45 hours per day). The GPS data showed that, over the week, participants travelled 49.6Km (30.8 miles) and they made 6.3 separate journeys.

Linear Regression Analysis: prediction of mobility

Balance (single leg stance), MMSE and age significantly predicted the four mobility outcomes, explaining between 32% (GPS: journeys made) and 43 % (accelerometry: number of steps and diary data: amount of time spent in dynamic outdoor activity) of variance in outcome (Table 3). Balance emerged as a significant predictor of all four outcomes.

DISCUSSION

This study used a novel combination of mobility measures to evaluate mobility in community-dwelling, older adults. The keys findings are that the ability to balance on one leg significantly predicts how mobile older adults are; this includes all movement within and outside the home. Moreover, in terms of out-of-home mobility (as measured by GPS and Diary) MMSE (a measure of cognitive ability) is also a significant predictor.

The mobility profile of the group showed lower step counts (5775.46 steps per day) than previous findings of 6000-8500 per day for healthy elderly adults (13, 28) but within an observed range (18) and higher than that found for residents in continuing care (12). In terms of the diary assessment participants reported spending an average of two hours per day engaging in dynamic outdoor activity (with a maximum of 5.45 hours per day). The GPS data showed that on average, participants travelled 49.6 km (30.8 miles) over the week (average daily distance is 7.09km - 4.4 miles) and they made 6.3 separate journeys per week. These distances are considerably lower than those reported for healthy elderly in Israel (approximately 33km/day for 66-72 year olds and around 23km/day for 77-90 year olds) (21) but greater than the average distance travelled from home (0.71 miles/1.14 km) in New York (19) . These discrepancies may be due to cultural, climate or location differences.

In this study we sought to determine the factors that can predict mobility in the older age-group. Physical characteristics, specifically the ability to balance on one leg, predicted all four mobility outcomes. Number of journeys and dynamic outdoor activity were both predicted by cognitive ability and balance. Total distance travelled was predicted by age and balance; and steps were predicted by balance only.

The fact that balance influences mobility is not surprising given that balance impairment increases the risk of falls in high-functioning older adults (29). In addition, balance improvement interventions have successfully reduced falls in some groups of older adults (30). However, fear of falling did not predict mobility, which is surprising given the relationship between balance and falls. Moreover, fear of falling did not correlate with either of the GPS outcomes. This may be due to the fact that these participants are a high functioning group with none of them scoring at the higher end of the FES-I scale (the maximum score achieved in this study was 49 out of a possible 64).

Better cognitive ability was associated with increased dynamic outdoor activity and increased number of journeys. There was also a trend for better cognitive ability to be associated with increased distance travelled. Completion of diaries probably relies on aspects of cognitive function so this relationship is not surprising. However, given that cognitive ability also predicted an objective measure of mobility suggests that cognitive ability is directly associated with mobility rather than artefact of diary completion. In addition, this is consistent with previous findings (31) whereby cognitively impaired participants (MCI or dementia) tended to remain closer to home and spent less time out-of-home than healthy participants.

Age predicted walking pattern in this group of participants (22) and this is consistent with earlier work (32). The fact that age influences mobility (i.e. total distance travelled) is consistent with previous work (21) which demonstrated that healthy older adults travel shorter daily distances than younger elderly adults. Possible reasons for this have been suggested (17, 19)

Limitations of this study include the low response rate and small sample size along with a broad age range.. The low response rate may mean there is participant bias within the volunteer sample so the findings may not generalise to other subgroups of older adults. Data collection issues and missing data reduced the sample size from 100 to 86 (66 for the GPS study). This is larger than other samples reported in the literature (31) but may have resulted in under-powered analysis, as could the broad age range for the sample size. The post hoc power of the models ranged from 0.49 to 0.85 with the lowest power from the GPS models. The self-report diary methods may be viewed as out-of-date due to the advancement and availability of technology such as smartphones to assess mobility. However, ownership by older adults is still low compared to younger populations (33) so mobility metrics used must be available, feasible and acceptable for the population.

Overall this study demonstrates the importance of a few factors in predicting mobility in this group of successfully aging adults. However, there is a need to further explore the contribution of balance to overall mobility in a larger, more diverse sample. In addition the potential benefit of simple balance interventions to increase mobility are considerable and they should be examined further. A Cochrane review (34) concluded that there was a need for randomised controlled trials to examine the efficacy of balance interventions to reduce falls in older adults. The current research suggests that future research should also examine the long-term effects of balance interventions to improve mobility and consequently improve quality of life and wellbeing of older adults.

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GRAPHICS

Table 1. Variables entered into each regression model based on univariate analysis

Domain	Steps	Distance	Journeys	DO
Personal	Age (-0.41**)	Age (-0.33**)	Age (-0.31*)	Age (-0.47***)
	Medications (-0.38**)		Illness (-0.32*)	Medications (-0.34**)
Cognitive		MMSE (0.29*)	MMSE (0.39**)	MMSE (0.36***)
		Spatial memory % (-0.26*)	Spatial memory span (0.25*)	NART IQ (0.23*)
				Planning (errors) (-0.25*)
Psychological	STAI trait (0.25*)			STAI trait (0.27*)
	Fear of falling (-0.34**)			Fear of falling (-0.33**)
Physical	TUG (-0.36**)	Stride time mean (-0.30*)	TUG (-0.32*)	TUG (-0.39**)
	Balance (0.60**)		Balance (0.37**)	Balance (0.48***)
		Balance (0.30*)		
Social	People in network (0.32**)			Perceived social network (0.32**)

Abbreviations: MMSE=Mini Mental State Exam, NART=National Adult Reading Test, STAI=State-Trait Anxiety Inventory, TUG=Timed Up and Go

(correlation coefficient of variable and outcome. Significant at *p<0.05, **p<0.01, ***p<0.005)

Table 2. Descriptive statistics for the four outcome measures and all predictors used in the models

	N	Mean	Std. Deviation	Median	IQR	Skew	Kurtosis
Personal characteristics							
Age (years)	85	79.77	5.01	80	76, 84	0.18	-0.61
Number of illnesses	72	1.99	1.74	2	1, 3	1.14	2.36
Number of medications	72	3.99	3.01	4	2, 5	1.19	1.70
Cognitive function							
MMSE (range 0-30)	76	27.78	2.16	29	26, 29	-1.04	0.28
NART IQ	76	120	5.01	121	119, 124	-1.62	3.28
Spatial memory %	74	79.66	9.34	80	75, 85	-0.15	0.37
Spatial memory span	74	4.46	1.06	5	4, 5	-0.17	-0.68
Planning (errors)	73	29.30	28.38	19	12, 43	3.20	13.21
Psychological characteristics							
Trait anxiety	82	31.11	8.06	30.5	25, 36	1.30	3.19
Fear of falling (range 16-64)	84	24.10	8.28	21	18, 28	1.46	1.44
Physical characteristics							
Balance (secs)	70	9.49	9.12	6.21	3, 16	1.12	-0.11
Stride time mean (secs)	74	0.05	0.09	0..03	.02, .05	7.29	58.28
TUG mean (secs)	73	12.60	9.21	9.91	9, 10	5.19	32.69
Social characteristics							
Perceived social network	84	3.62	2.56	3	2, 4	2.31	8.05
People in network	82	7.99	4.25	8	5, 10	1.86	9.41
Mobility outcomes							
Accelerometer: number of steps per day	70	5775.46	2890.51	5740.72	3796, 7237	0.74	1.22
Diary: dynamic outdoors (mins/ day)	78	126.92	75.01	124.29	64, 176	0.46	-0.16
GPS: total distance travelled (km per week)	66	49.57	48.21	31.40	10, 89	1.05	0.42
GPS: total number of journeys per week	66	6.33	3.55	7	4, 9	-0.01	-0.86

Abbreviations: GPS=Global Positioning System, Km= kilometres, mins=minutes, MMSE=Mini Mental State Exam, NART=National Adult Reading Test, secs=seconds, TUG=Timed Up and Go, IQR=Inter-Quartile Range

Table 3. Regression models

	B	SE B	β	t	p	R^2	Adjusted R^2
Diary: Dynamic outdoor activity (n=62)							
Constant	-196.56	276.67		-0.71	.48	0.52	0.43 (p<0.005)
Age	-0.91	1.91	-0.06	-0.48	.64		
MMSE	9.56	3.73	0.28*	2.56	.01		
NART IQ	1.00	1.61	0.07	0.62	.54		
Planning errors	-0.27	0.27	-0.10	-1.01	.32		
Medications	-1.64	2.75	-0.07	-0.60	.55		
Balance	2.69	1.03	0.33*	2.61	.01		
Trait anxiety	0.70	1.04	0.08	0.67	.51		
Fear of falling	-1.36	1.00	-0.15	-1.36	.18		
Perceived social network	6.02	3.04	0.21	1.98	.05		
TUG mean	-0.83	0.97	-0.10	-0.85	.40		
Accelerometer: Number of steps (n =62)							
Constant	8694.2	5600.59		1.55	.13	0.49	0.43 (p<0.005)
Age	-40.48	70.60	-0.07	-0.57	.57		
Medications	-147.46	103.36	-0.15	-1.43	.16		
Balance	133.78	38.77	0.42**	3.45	.00		
Trait anxiety	9.26	40.51	0.03	0.23	.82		
Fear of falling	-66.79	38.62	-0.19	-1.73	.09		
Total people in network	140.01	69.90	0.21	2.00	.05		
TUG mean	-13.38	37.17	-0.04	-0.36	.72		
GPS : Total distance travelled (n = 59)							
Constant	236.05	157.59		1.50	.14	0.43	0.37 (p<0.005)
Age	-3.41	1.30	-0.35*	-2.62	.01		
MMSE	4.85	2.47	0.22	1.96	.06		
Spatial memory %	-0.77	0.57	-0.15	-1.34	.19		
Balance	1.56	0.63	0.30*	2.48	.02		
Stride time mean	-56.02	60.23	-0.11	-0.93	.36		
GPS: Number of journeys (n = 59)							
Constant	-16.09	10.62		-1.52	.14	0.39	0.32 (p<0.005)
Age	0.05	0.10	0.07	0.51	.61		
MMSE	0.62	0.20	0.38***	3.17	.00		
Spatial memory span	0.34	0.38	0.10	0.89	.38		

Balance	0.13	0.05	0.32*	2.62	.01
Illnesses	-0.39	0.23	-0.19	-1.69	.10
TUG mean	-0.06	0.05	-0.16	-1.30	.20

Abbreviations: MMSE= Mini Mental State Exam, NART= National Adult Reading Test, TUG=Timed Up and Go

*p<0.05, **p<0.01, ***p<0.005

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CONFLICT OF INTEREST

The authors have nothing to disclose.

ETHCIAL STANDARDS

This study was approved by the School of Life Sciences Ethics committee, Northumbria University.