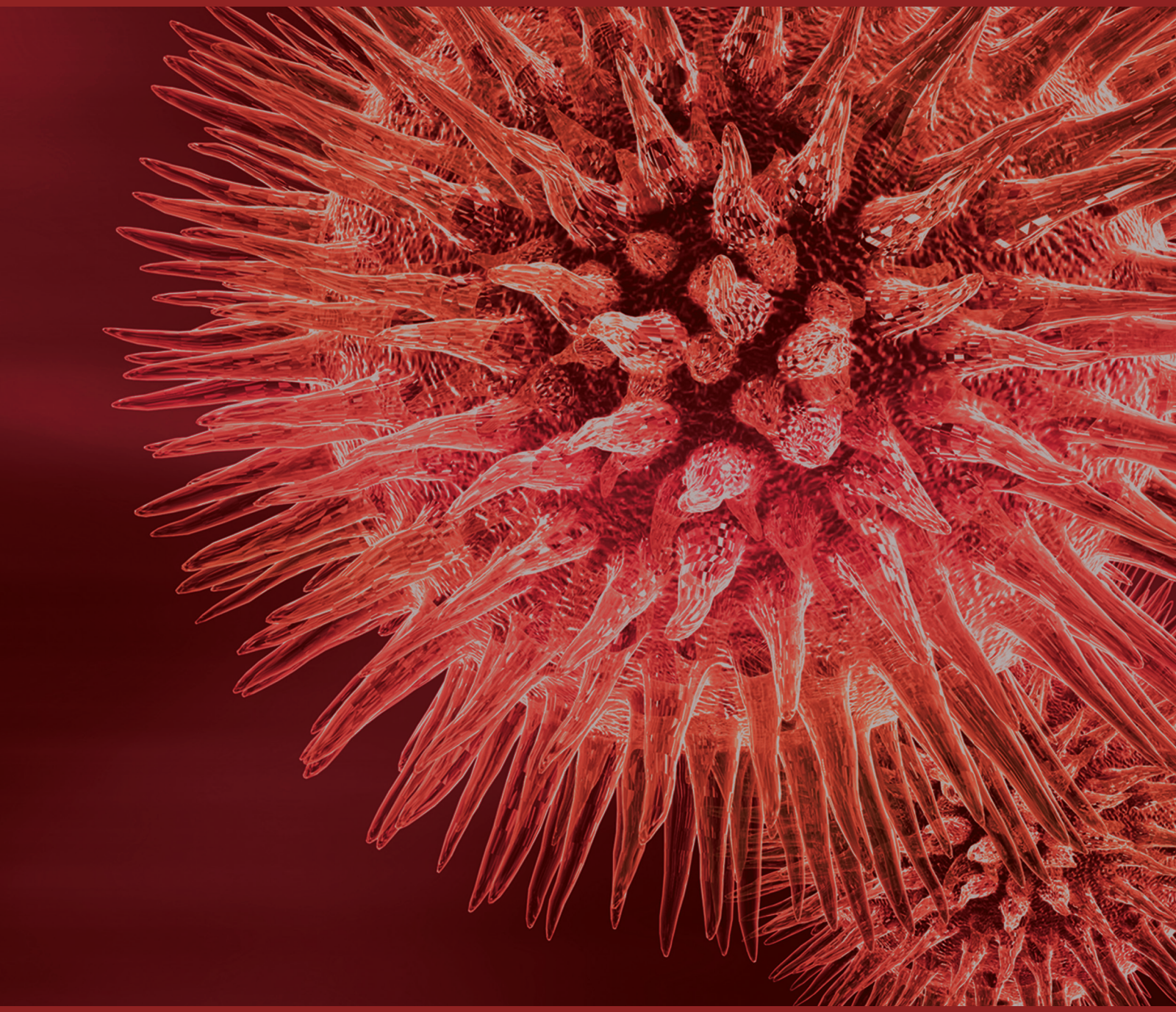
BioMed Research International

Advances in Long Term Physical Behaviour Monitoring

Guest Editors: Jorunn L. Helbostad, Lorenzo Chiari, Sebastien Chastin, and Kamiar Aminian



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Editorial

Advances in Long Term Physical Behaviour Monitoring

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Along with the development of cheap and easily available body-worn and environmental sensors, monitoring of physical behaviour in everyday life situations is now possible and has become increasingly popular in research and for clinical purposes. Availability of such sensors and instruments may move assessment of physical function and activity from controlled laboratory settings to the natural environments and situations where people live their daily lives. It may also shift focus of the assessment from what people are capable of doing, as typically assessed in lab, to what people actually do and how they do it in their daily lives. Availability of a new generation of sensing technologies gives new opportunities for gaining knowledge with regard to health and function, but it also raises several challenges! One of the current challenges is lack of standards for data collection and processing, making comparison and harmonisation of data across studies and systems limited [1].

Body-worn sensors may include accelerometers, gyroscopes, magnetometers, barometers, light sensors, and global positioning systems (GPS) and are used for a range of different purposes like assessing the amount and patterns of physical activity and related energy expenditure, sleep pattern, and movement characteristics of specific activities, for example, gait and rising from a chair or fall detection. Such information may further be used to develop risk assessment tools for diseases, functional decline, and falls and for giving individualised feedback on physical behaviour as part of a preventive intervention. In a home setting, environmental sensors, like cameras, radars, infrared light sensors like the Kinect system, or even optic fibres embedded in the flooring, are available for monitoring behaviours like mobility and movement patterns, falls, sleep, and sedentariness as well as exercise behaviour while playing exergames.

Even if the technology is easily available, the understanding of the signals derived from the monitoring still needs more attention, and algorithms developed for different purposes and settings need more thorough testing for reliability, validity, and sensitivity to change [2]. Furthermore, in order to motivate people to adopt the technology, its utility has to be linked to what people need and want to know about themselves and what is needed in order to prevent or treat diseases [3]. Moreover, the technology must be unobtrusive, and usability has to be in focus when developing the systems [4]. Mobile technology commonly used by people, like smartphones [5] and smartwatches, may increase adherence to the use of the technology also for monitoring purposes.

In this special issue, we have solicited submission of research papers applying monitoring technology that can stimulate the continuing efforts to better understand physical behaviour as part of preventive health care and rehabilitation. The six papers that are included demonstrate usage of a variety of monitoring technologies applied in different populations and for different purposes, including assessment of gait characteristics related to fall risk, heart rate variability in relation to chronic neck pain, differences between physical performance and free-living activity in older people, quantification of outdoor mobility in older people, assessment of cardiometabolic risk and health-related quality of life, and in-home assessment of risk of falling in people with Parkinson's disease. The papers nicely demonstrate the current state of

the research field, by focusing either on development of new features to describe free-living physical behaviour or on applying the technology to understand aspects of behaviour that has not been easily assessable previously.

The European population is ageing and more people live with chronic diseases, while at the same time the number of employees per pensioner is decreasing. Technology and its applications presented in this special issue might be of importance for solving some of these challenges by making people able to monitor and control their own health and function, thereby staying independent longer and reducing health care costs. The field of mobile health technology (mHealth) and telemedicine is moving forward at a high speed, but there is still a gap between development of new methods and what is implemented in clinical practice. Clinical intervention studies with sufficient sample sizes will be needed in the near future to demonstrate feasibility and added value of using the technology with respect to usual standard of care provided in our health care systems.

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Research Article

Mobility in Old Age: Capacity Is Not Performance

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Background. Outcomes of laboratory-based tests for mobility are often used to infer about older adults' performance in real life; however, it is unclear whether such association exists. We hypothesized that mobility capacity, as measured in the laboratory, and mobility performance, as measured in real life, would be poorly linked. *Methods*. The sample consisted of 84 older adults (72.5 ± 5.9 years). Capacity was assessed via the iTUG and standard gait parameters (stride length, stride velocity, and cadence). Performance was assessed in real life over a period of 6.95 ± 1.99 days using smartphone technology to calculate following parameters: active and gait time, number of steps, life-space, mean action-range, and maximum action-range. Correlation analyses and stepwise multiple regression analyses were applied. *Results*. All laboratory measures demonstrated significant associations with the real-life measures (between $r = .229$ and $r = .461$). The multiple regression analyses indicated that the laboratory measures accounted for a significant but very low proportion of variance (between 5% and 21%) in real-life measures. *Conclusion*. In older adults without mobility impairments, capacity-related measures of mobility bear little significance for predicting real-life performance. Hence, other factors play a role in how older people manage their daily-life mobility. This should be considered for diagnosis and treatment of mobility deficits in older people.

1. Introduction

With advancing age, it often becomes increasingly difficult to access community resources like grocery stores, doctor's offices, banks, and other essential services and to participate in sociocultural activities. Diminished independent mobility is a predictor of institutionalization [1], falling [2], and dependence and mortality [3] and is inversely associated with quality of life [4, 5] and health status [6]. Independent mobility is therefore a key to successful aging and is routinely assessed by gerontologists and geriatricians.

Mobility is often assessed with established field tests such as the Timed Up-and-Go test [7, 8], the Performance-Oriented Mobility Assessment [9], and the Elderly Mobility Scale [10]. Other common approaches are assessments based upon gait measures [11] and balance tasks [12]. These assessments are reliable since they are performed in a standardized fashion to control for confounding influences; however, they do not necessarily have high construct validity: it remains unclear how well persons' test scores are correlated with their mobility in daily life. Movements of daily life are typically self-initiated, embedded in a rich behavioral context and ecologically valid, while standardized laboratory-type movements are usually initiated by an external "go" signal, are executed in isolation, and serve no ultimate purpose. It has indeed been documented that performance in the laboratory can be substantially different from this in real life [13, 14] and that seniors' performance deficits are sometimes more pronounced in real life than in the laboratory [15] and sometimes less pronounced in real life [13, 16].

Mobility in daily life depends not only on an intact sensorimotor system but also on intact cognition and psychosocial factors. For example, studies have shown that low cognitive status [17], reduced visual attention [9], self-efficacy beliefs [18], and perceived help availability [19] are all associated with reduced mobility in older adults. Again, however, a person's

scores on standardized cognitive tests are poorly related to their cognitive performance in real life [20].

The International Classification of Functioning, Disability and Health (ICF), introduced by the World Health Organization (WHO), dissociates between assessments in a standardized-environment, measuring *capacity*, which is indicative of the highest possible level of functioning of an individual in a given domain at a certain moment, and real-life assessments measuring *performance* which is what individuals do in their own current environment [21]. Within the ICF framework, the above work indicates that the known age-related decrease in the *capacity* to be mobile may poorly predict actual mobility *performance*.

With the advent of new miniaturized technology such as GPS and accelerometers, installed in mass-market products such as smartphones and fitness "watches," objective assessment of everyday in-home as well as out-of-home mobility becomes feasible [22, 23]. Parameters such as number of steps performed, length of active periods, life-space, defined as the area in which an individual moves in a certain time period [24], and other measures have been used to depict the action-range of older adults [25–29]. The present study applies these methods to find out how well real-life mobility is predicted by standard laboratory measures of mobility or, in other words, how closely capacity and performance are linked. We hypothesized that capacity and performance are poorly linked, which would have important implications for the diagnosis and treatment of mobility deficits.

2. Methods

Data were collected as part of a cohort study aiming to analyze determinants of daily-life mobility in older adults. All participants underwent a laboratory-based test battery divided into two sessions including several physical, cognitive, social, and psychometric tests as well as an ambulatory mobility assessment. The study has been approved by the Ethics Committee of the German Sport University Cologne, confirming that study design is according to the principles expressed in the Declaration of Helsinki.

2.1. Participants. The recruitment strategy included presentations of the project at local senior citizen gatherings, individual invitation letters to persons who expressed interest in participating in studies of the Institute of Movement and Sport Gerontology in the past, and handing out information brochures about the study and individual approach in settings such as local doctor's offices, pharmacies, churches, and senior sport groups. We also contacted assisted-living facilities and if the management showed interest in the project and gave their approval, we presented our project in their facilities and tested persons willing to participate on-site.

In total, 86 persons meeting the criteria for participation in the study were recruited. Inclusion criteria were age older than 65 years, no serious neurological diseases which could interfere with functional mobility, no severe/acute cardiovascular diseases, ability to stand up from a chair independently, a physician's written statement of nonobjection for this person to participate, and an informed consent to the study design.

2.2. Standard Laboratory Measures. Mobility capacity was assessed in the laboratory using the extended, instrumented version of the Timed Up-and-Go test [8] (iTUG) [30]. The iTUG is a mobility test, which requires participants to stand up from a chair, walk 7 m at their preferred speed, turn, walk back towards the chair, and sit down again. It was implemented by attaching six inertial measurement units (Opal, APDM Inc., Portland, OR, USA) to the body, two just proximal to the wrists, two just proximal to the ankles, one on the center of the sternum, and one on the waist, approximately above the fifth lumbar vertebra. Each measurement unit contained a triaxial accelerometer, a triaxial gyroscope, and a triaxial magnetometer, whose signals were transmitted via Bluetooth connection to a computer and were processed later by proprietary software package (Mobility Lab™), to calculate the parameters: total completion time (iTUG) (s), cadence (steps/min), stride length (m), and stride velocity (m/s). The latter two were determined as the mean of the left and right leg over the 7 + 7 m of straight walking. Each participant completed three trials. The first was considered as practice and the best performance value of the other two trials was used for further analyses.

2.3. Real-Life Measures. Mobility performance in real life was assessed using a combination of physical activity and GPS-derived measures via smartphone technology. Participants were given a smartphone (Samsung Galaxy SIII™) in an elastic belt and were instructed to don the belt every morning after waking up; they were asked to put the belt around their waist in such a way that the smartphone was located at their back and their body midline. They were requested to leave the smartphone in place until they went to bed at night and to charge it overnight. Data logging was implemented by two applications (apps), one collecting motion sensor data and the other GPS data. Because the majority of participants had not used a smartphone before, they received a manual and about 15 min of familiarization which covered how to turn the smartphone on and off, charge it, use the touch screen, and start the apps. Each participant was offered the opportunity to contact the instructors in case they had questions or faced complications regarding smartphone use. The real-life data recording was conducted between the first laboratory session, where participants received the smartphone, and the second session, where they returned it. We aimed to record the participants' activities for 7 days. However, it was not always possible to organize the sessions exactly 7 days apart. As a result, the total registration time ranged from 6 to 9 days.

Mobility-related activities were recorded via the "uFall" mobile app recently developed within the FARSEEING European research project [31]. The "uFall" app integrates a real-time fall detector which was not enabled in the present study; the app was only used for the continuous recording of the smartphone's raw accelerometer, gyroscope, and magnetometer signals. Recorded data were processed after

the registration period and were used to categorize participants' postures and mobility-related activities into different types, such as not worn periods, lying time, sedentary time, active time, and gait time, and to calculate the number of steps. Identification of active and sedentary intervals was performed by means of activity counts and metabolic equivalents (METs) defined in agreement with Sasaki et al. [32]: activity counts were calculated over 1 s time windows. A time window was labelled as "active" when estimated METs were above 1.5 [33]; otherwise, the time window was labelled as "sedentary." Within active intervals, gait episodes were identified by means of a step detector which is described in the study of Ryu et al. (2013) [34]. Signal processing and features extraction algorithms were implemented in Matlab (The MathWorks Inc., Natick, MA, Release 2012a). Further analyses focused on the following two variables: the sum of active and gait time (AGT) (h) and number of steps (No. of Steps). Since data collection did not target full 24-hour periods and registration times differed between days and participants, we adjusted the data by excluding data which were collected before 7.00 AM and after 9.00 PM as well as data collected on days with activities shorter than 9 hours; AGT and No. of Steps scores were then scaled to fit a 12-hour day and were subsequently averaged across all registration days of a given participant.

Out-of-home movement was assessed with a self-developed app that collected raw GPS data with a sampling rate of 1 per minute. From these data we calculated the following parameters: life-space (km^2), the area within which the participants moved during the registration period calculated as the convex hull of all GPS coordinates with Matlab® convhull function; mean action-range (AR-mean) (km), the straight-line distance between the participants' home and the most distal point of each journey, averaged across all journeys during the registration period; and maximum action-range (AR-max) (km), the largest straight-line distance during the registration period. Only data within 15 km around the participants' home (comparable to the size of the greater area of Cologne, Germany, where the study took place) were included in the analysis. Figure 1 presents a typical example of GPS data obtained over 7 recording days.

2.4. Statistical Analyses. The variables "life-space" and "AR-mean" were square-root-transformed to achieve normal distribution. Outliers were identified using the Tukey's outlier filter [35] and removed. Missing data (5.1%) were imputed using the k-nearest neighbor algorithm [36]. To make sure that the imputed dataset was not biased, we applied the Little's MCAR test, which showed that data were missing randomly. The hypothesis that laboratory measurements poorly predict daily-life mobility was initially assessed using a correlation approach, looking into the relationships between laboratory and real-life measures. We also conducted a series of stepwise multiple regression analyses in which the five real-life measures (AGT, No. of Steps, life-space, AR-mean, and AR-max) served as dependent variables and the four laboratory measures (iTUG, stride length, stride velocity, and cadence) as predictors. For the stepwise model the limit was 0.10 for entry and 0.05 for removal of variables. For all analyses, the significance level was set at 0.05.

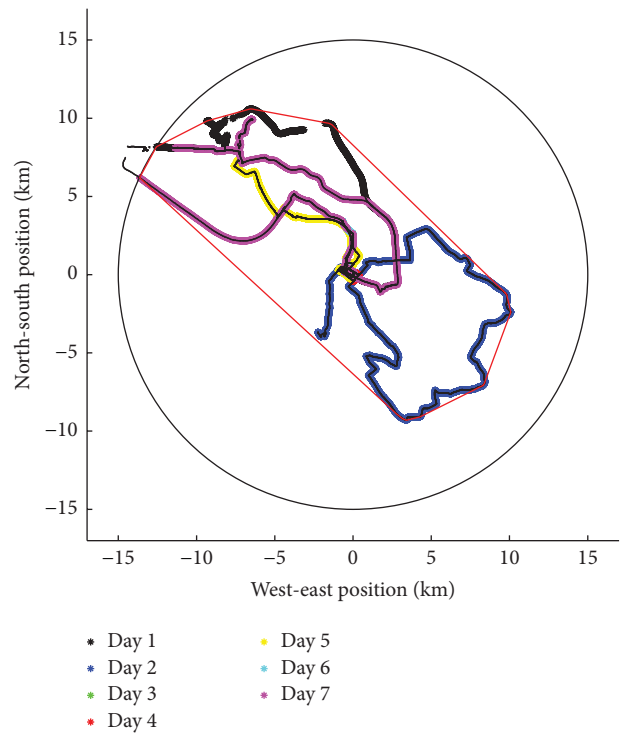

Figure 1: Sample GPS record of one participant demonstrating home location (point (0, 0)) and trajectories for each registration day. The thin red line including all trajectories within the 15 km radius circle represents the parameter "life-space."

3. Results

3.1. Mobility Registration Time. The mean number of registration days for the whole sample was 6.95 ± 1.99, with a mean registration time of 70.7 ± 15.00 h for the activity-monitoring data and 104.3 ± 58.5 h for the GPS data.

3.2. Descriptive Statistics. From the initial 86 participants two were excluded from the analysis because they did not complete the ambulatory mobility assessment. Table 1 provides a description of some of the sample's demographics and also summarizes their laboratory as well as real-life measures. Participants were primarily women. Men and women were similar in age. Sixteen percent of the participants were living in assisted-living facilities. Fifty-one percent of the subjects were living alone and only 17% had a higher education degree. Only 3 participants were using gait assistance. In total, 74% of the participants reported health problems (42% were multimorbid and another 32% suffered from a sole disease). The main reported health problems were cardiovascular diseases (42% of the subjects), internal/endocrinological diseases (38%), orthopedic problems (38%), neurological/psychiatric diseases (9%), and others (3%). Regarding use of medication, 59% of the participants reported using medication (34% of

Table 1: Participants' descriptive data and laboratory- and real-life measures.

	Mean	SD	Min	Max
Age (total sample)	72.5	5.9	65	88
Men (n = 31)	72.4	5.8	65	88
Women (n = 53)	72.5	5.9	65	88
BMI	24.1	3.2	16.7	33.1
iTUG (s)	16.0	2.6	10.5	27.5
Stride length (m)	1.38	0.13	1.01	1.65
Stride velocity (m/s)	1.34	0.16	0.82	1.76
Cadence (steps/min)	115.9	10.4	87.8	145.2
AGT (h)	4.3	0.9	1.8	6.2
No. of Steps	11042	3474	3903	20890
Life-space (km^2)	52.9	43.8	0.2	178.2
AR-mean (km)	1.4	1.0	0.1	3.8
AR-max (km)	10.4	4.2	0.5	15.0

Mean: average values; SD: standard deviation; Min: minimum values; Max: maximum values; BMI: body mass index; iTUG: instrumented Timed Up-and-Go test; AGT: active and gait time; No. of Steps: number of steps; AR-mean: average action-range; AR-max: maximum action-range.

Table 2: Associations between laboratory and real-life measures (Pearson's correlation coefficients, r ($^{*}p < .05$; $^{**}p < .01$)).

	AGT	No. of Steps	Life-space	AR-mean	AR-max
iTUG	$-.461^{**}$	$-.442^{**}$	$-.295^{**}$	$-.199$	$-.229^{*}$
Stride length	$.266^{*}$	$.369^{**}$	$.331^{**}$	$.232^{*}$	$.234^{*}$
Stride velocity	$.396^{**}$	$.421^{**}$	$.273^{*}$	.213	.130
Cadence	$.261^{*}$	.185	.034	.052	$-.036$

AGT: active and gait time; No. of Steps: number of steps; AR-mean: average action-range; AR-max: maximum action-range; iTUG: instrumented Timed Up-and-Go test.

the participants used more than one kind of medication and 25% only one kind).

3.3. Correlations. Table 2 illustrates that all laboratory measures had significant associations with real-life measures. iTUG, stride length, and stride velocity correlated significantly with at least three of the five real-life measures and also showed the strongest correlations (between $r = .229$ and $r = .461$), while cadence correlated significantly only with AGT. Overall, the correlation coefficients were weak [37].

3.4. Multiple Regression Analysis. To evaluate the predictive ability of the laboratory measures for each of the real-life measures five stepwise multiple regression analyses were conducted. Their results are summarized in Tables 3 and 4.

The best model for all real-life measures had only one significant predictor. Overall, the analyses indicated that laboratory measures accounted for a significant but very low [37] proportion of variance (between 5% and 21%) in real-life measures. The best predictors for real-life measures were stride length, which was retained in three models, and iTUG, which was retained in two. Stride velocity and cadence did not contribute significantly to any of the models.

Table 3: Significant predictors and their standardized regression coefficients for the mobility-related activity measures.

AGT		No. of Steps	
Predictors	Beta	Predictors	Beta
iTUG	$-.461^{***}$	iTUG	$.442^{***}$
$F(1, 82) = 22{,}155$		$F(1, 82) = 19{,}894$	
$R^2 = .213^{***}$		$R^2 = .195^{***}$	

Bottom row: degrees of freedom and coefficients of determination (R^2) for each model.
$^{***}p < .001$.
AGT: active and gait time; No. of Steps: number of steps; iTUG: instrumented Timed Up-and-Go test.

Table 4: Significant predictors and their standardized regression coefficients for the GPS-derived measures.

Life-space		AR-mean		AR-max	
Predictors	Beta	Predictors	Beta	Predictors	Beta
Stride length	$.331^{**}$	Stride length	$.231^{*}$	Stride length	$.233^{*}$
$F(1, 82) = 10{,}094$		$F(1, 82) = 4{,}625$		$F(1, 82) = 4{,}713$	
$R^2 = .110^{**}$		$R^2 = .053^{*}$		$R^2 = .054^{*}$	

Bottom row: degrees of freedom and coefficients of determination (R^2) for each model.
$^{*}p < .05$; $^{**}p < .01$.
AR-mean: average action-range; AR-max: maximum action-range.

4. Discussion

The aim of this study was to examine the predictive ability of standard laboratory measures for real-life mobility and thus also the relationship between capacity and performance measures. The results confirmed our hypothesis that gait measures and mobility tests conducted in the laboratory have very moderate explanatory value for real-life mobility measures and therefore stress the importance of distinguishing between capacity and performance. This evidence highlights the need for real-life mobility-related measures to complement (rather than replace) laboratory measures in geriatric assessments.

As anticipated, the correlation analysis showed significant relationships between the laboratory and the real-life measures. iTUG, stride length, and stride velocity correlated significantly with most of the real-life measures, while cadence correlated significantly only with AGT. Altogether, the measures of real-life mobility-related activities show more and stronger correlations with the laboratory measures than the GPS-derived mobility measures. This can be explained by the fact that the use of assistive devices or other means of transportation like cars, trains, and so forth contribute to the GPS-derived measures, and therefore these measures do not necessarily reflect independent mobility (i.e., walking or bicycling). It is possible that people with lower capacity show larger GPS-derived values due to use of means of transportation other than walking, for example, using car or train rides. If this is the case for some of the participants with low capacity, it would lead to a reduction of the positive correlation between the capacity and the GPS-derived measures of performance. Thus, it is no surprise that laboratory-based

capacity measures are more associated with real-life mobility-related activity measures than GPS-derived measures. This is also confirmed by our regression analyses which show that the laboratory measures used in this study explained almost double the variance for AGT and No. of Steps in comparison to life-space, AR-mean, and AR-max. Apparently, factors other than physical capacity play an important role in real-life mobility performance, and especially for life-space related measures of mobility.

While some previous studies found that life-space measures could be predicted by standard measures of functioning, such as gait velocity [28], ADL difficulty [38], and overall physical functioning [29], our comparable measures (stride velocity and iTUG duration) did not. Instead, stride length was the only variable retained in the "life-space" model. This may have to do with the variables included in the regression model. In our study, all models contained partly similar laboratory measures. Gait speed and step length are known to be directly related [39]. Indeed, also in our dataset, stride length correlated significantly with stride velocity ($r = .653$; $p < .001$) as well as with iTUG ($r = -.538$; $p < .001$). Therefore, our results do not contradict the above work.

Among the four capacity measures, iTUG was the strongest and stride length the most consistent predictor for daily-life mobility. The iTUG is a complex task, since it includes demanding mobility-related tasks, which older adults perform in their everyday lives and often have difficulties with (such as standing up and negotiating an object while turning), compared with simple gait variables. Indeed, AGT is the most physically demanding parameter of the real-life mobility parameters measured here, which may explain iTUG being its best predictor. Stride length was the only variable retained to all three life-space models, explaining, however, only a very low (5–11%) proportion of variance. Cadence and stride velocity were not retained in any of the models. This is somewhat surprising, especially for gait speed, as it is considered the most reliable, valid, and specific gait measure [40, 41] and it has been found to be related to physical activity [42–45]. It therefore seems advisable to assess the iTUG, which in addition to its other components includes two walks over 7 meters, rather than only assessing gait during straight walking trajectories, since the combination of iTUG components seems to be more indicative of the requirements for real-life mobility.

Previous research (e.g., [46, 47]) showed somewhat stronger associations between laboratory and real-life measures than our results. However, these studies were primarily based on subjective methods. Results of studies using objective methods in different target groups (e.g., [48–51]) are similar to our findings; only a small percentage of the variance of daily-life mobility is explained by laboratory-based capacity tests. Moreover, a recent study [52] conducted a factor analysis and found that physical capacity measures, similar to the ones used in our study (Sit-to-Stand test, TUG test, and the short Physical Performance Battery), and objective physical activity measures (total duration, number of periods, and mean duration of mobility-related activities) result in two different factors. All of these findings support the hypothesis that standard field tests measuring mobility in laboratory settings and daily-life mobility measures represent different aspects of mobility, each of which has relevance for different domains. Outcomes of capacity tests like the TUG (or the iTUG) inform about fall risk, balance, and functional mobility [8, 53, 54]; on the other hand, real-life physical activity and life-space measures give insight into the extent to which older persons are actively exploiting their capacity. Even when physical capacity is limited, other factors such as the use of assistive devices and/or public transportation may allow older persons to participate in their social context. On the other hand, persons may be inactive, even when their capacity would allow. Obviously other factors than an individual's capacity influence real-life mobility, for example, cognition, mood [17, 55], self-efficacy [18], and weather [56]. Therefore, decisions about interventions aiming to improve mobility in older persons should consider measures of real-life mobility as well as the outcomes of capacity tests. Future studies should further examine the role of different factors on real-life mobility.

Although the current study has the strength of presenting comprehensive mobility patterns of older adults, including long-term real-life physical activity and out-of-home movement measures, we acknowledge several limitations. In order to achieve a performance spectrum as wide as possible we strived to enlist participants living in assisted-living facilities, whose mobility is typically more restricted than this of independent-living older adults. However, only 13 persons (15.5% of the total sample) living in assisted-living facilities could be recruited. Though our sample does present a considerable range of performance at the laboratory measures, it mostly represents community-dwelling older adults living independently without severe mobility impairments. Hence, care should be taken when interpreting our results as they cannot be extended to other populations or adults with severe mobility impairments. Future research should examine the predictive ability of field tests for real-life mobility also in less active samples and/or samples with mobility impairments such as neurological patients or people with cognitive impairments.

Additionally, the real-life data registration period (6.9 ± 1.9 days) varied between participants within the total study period. One of the most important weather parameters which influence physical activity is maximum temperature [48]. In order to control for seasonal variations, we examined the relationship between the average maximum temperature (AMT) for the registration period of each participant and the real-life variables and found that AMT correlates significantly but very weakly ($r = .184$, $p = .047$) only with life-space. However, future studies should aim for a fixed mobility registration period for all the participants to avoid bias [57] due to seasonal variations and in case there are linear relationships between seasonal and mobility variables, seasonal parameters should be controlled for.

5. Conclusion

The current study presents mobility patterns in a sample of rather active community-dwelling older adults without

severe mobility impairments based on combination of capacity and performance measures and shows that standard laboratory-based tests have limited predictive ability for real-life mobility. This shows that capacity and performance represent different aspects of mobility. Therefore, comprehensive mobility assessments should include capacity measures as well as measures of real-life out-of-home mobility. Additionally, as anticipated, this study confirms that physical activity is better explained by physical functioning, when compared with life-space measures. Finally, this study highlights the utility of the iTUG and, considering its rather simple execution, it suggests that it should be preferred over simple gait measures, as it explains more aspects and higher proportion of real-life mobility.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Research Article

Could In-Home Sensors Surpass Human Observation of People with Parkinson's at High Risk of Falling? An Ethnographic Study

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Self-report underpins our understanding of falls among people with Parkinson's (PwP) as they largely happen unwitnessed at home. In this qualitative study, we used an ethnographic approach to investigate *which* in-home sensors, in *which* locations, could gather useful data about fall risk. Over six weeks, we observed five independently mobile PwP at high risk of falling, at home. We made field notes about falls (prior events and concerns) and recorded movement with video, Kinect, and wearable sensors. The three women and two men (aged 71 to 79 years) having moderate or severe Parkinson's were dependent on others and highly sedentary. We most commonly noted balance protection, loss, and restoration during chair transfers, walks across open spaces and through gaps, turns, steps up and down, and tasks in standing (all evident walking between chair and stairs, e.g.). Our unobtrusive sensors were acceptable to participants: they could detect instability during everyday activity at home and potentially guide intervention. Monitoring the route between chair and stairs is likely to give information without invading the privacy of people at high risk of falling, with very limited mobility, who spend most of the day in their sitting rooms.

1. Background

People at high risk of falling spend most of their time at home, and, like many other manifestations of illness, falls happen predominantly unwitnessed at home. Therefore, our understanding of what happens *before, during, and after* a fall is largely dependent on self-report (predominantly through interviews, diaries, and surveys). As Weis et al. [1] stated, "Unfortunately, self-report is... the gold-standard for characterizing and quantifying fall frequency" but authors discuss the accuracy of patient recall as a limitation of their work across a range of conditions [2–7].

Costing over £2 billion per year, falls are an NHS priority, with 30% of people aged 65 or older falling each year, and 50% of those aged 80 or older [8]. "Unless concerted action is taken," falls are likely to become increasingly prevalent and costly as the population ages [9], despite our current understanding of the risk factors and circumstances in which people tend to fall. We need to understand more about *near-misses* ("occasions on which individuals felt that they were going to fall but did not actually do so" [10]), *falls* ("events that results in a person coming to rest unintentionally on the ground or another lower level, not as the result of a major intrinsic event or overwhelming hazard" [11]), and the *fear of falling* to manage their causes, consequences, and costs [8, 10].

The quality and quantity of self-report depend on the interviewee's and interviewer's motivations and abilities. Transient risk factors (such as dizziness) contribute to falls, fear of falling, morbidity, and dependence [9] but fleeting signs of impending instability are difficult to describe and evaluate (and therefore manage), unlike the obvious signs of landing (injuries and environmental disruption). Someone who has fallen may not know what happened, let alone why, as someone falls, by definition "unintentionally," while their

attention is elsewhere. Even clear insights may fade without immediate reporting or documentation. Some people may not want to report every (or any) event. To summarise, the drawbacks of relying on self-reporting to understand fall-events include

(i) overreliance on a single witness whose attention was elsewhere during an unexpected event,

(ii) vague/transient warning signs that gave insufficient insight at the time to prevent a fall (or soften a landing) probably leaving minimal evidence afterwards,

(iii) the fact that if people want to document and/or report events, they need an opportunity to record or recall the details before insights diminish.

User-friendly, minimally invasive video-based or wearable sensors in the home could tackle many of these issues. They could, for example, record deviations from normal gait that a human observer might not notice, let alone document. Sensors could be "a virtual witness," recording the circumstances that precede, surround, and follow fall-events. By recording a baseline, deviations, and fall-events, sensors could enhance the management and self-management of fall risk and inform clinicians about instability associated with fleeting symptoms that are difficult to recount. Beyond the individual/clinical application, information from sensors (that individuals "control" and are willing to share) could change our current thinking about the evolution of fall risk over time, the circumstances of falling, and behavioural change after falling.

For our understanding of falls to improve, we need to observe many real events. Some fall-detection algorithms probably perform so poorly in the field, for example, 85 false alarms per day [12], because researchers developed them from data collected on simulations. Volunteers throwing themselves to the ground (e.g., as Bourke et al. asked them to do [13]) do not land unexpectedly. It would not require many in-home sensors to capture more "real" falls than researchers have witnessed to date, generating data that could refine detection algorithms. Beyond simply capturing the mechanics of an event, sensors could help us to understand what happens beforehand. Cameras showed, for example, that more falls in care homes occurred from standing and while transferring and fewer during walking than reports suggested [14].

Understanding what happens before balance is lost has a preventive value. Understanding what happens afterwards has value in preventing the deleterious consequences of immobility and fear, such as isolation and dependence. But identifying what people at risk of falling do at home and how to extract useful data under the less-than-ideal conditions of the domestic setting are challenges. Deciding where to position the minimum number of sensors capable of capturing useful data, unobtrusively, in appropriate locations requires consideration. When Feldwieser et al. [15] trialled a fall-detection system in elderly people's homes, 15 falls occurred (over 1000-plus measurement days) but none within range of the Kinect sensor installed; algorithms falsely detected multiple falls every day (4592 in total); and the participants' acceptance of technology they considered "generally useful" before installation decreased with experience. To avoid some of these unwanted outcomes, we proposed a qualitative study to initiate our programme of research.

We planned to investigate the healthcare applications of a sensor platform in the home (predominantly with elderly people, as they make the greatest use of health services). People with Parkinson's (PwP) are a very high-risk group for falling at home; near-misses may herald the onset of significant postural instability and predict future falls [10, 16, 17]. If sensors could alert them to increasingly frequent near-misses at home, individuals with the most potential to benefit from rehabilitation [18] could instigate intervention before injurious falls became likely. We began our programme with an ethnographic study involving a small group of people with significant healthcare needs. "Home-based technologies research with older adults needs to be flexible and paced to fit their lives" [19], so we sought to gain insight into living at high risk of falling, attitudes to in-home sensors, and the practicalities of testing sensors under real-life conditions. We aimed to observe people with moderate or severe Parkinson's in their own homes to identify what types of sensors, and in which locations, were capable of monitoring mobility and balance in a way that would be acceptable to participants and meet the researchers' needs.

Objectives. The objectives were as follows:

(1) To observe people at high risk of falling moving freely at home, noting, and recording (with video, Kinect, and wearable devices):

  (a) movement patterns (e.g., habitual activities),

  (b) behaviours (likely to increase or decrease fall risk),

  (c) locations and actions associated with (historic or observed) falls and near-misses (collectively "fall-events" [10]) and fear of falling.

(2) To observe participants repeatedly demonstrating one habitual activity they associate with a particularly high fall risk (e.g., descending steps), recording from multiple camera positions.

2. Methods

With Ethics Committee approval, we distributed information packs to people with Parkinson's (via presentations to support groups), aiming to recruit the first five volunteers who could

(1) walk at home without the assistance of another person,

(2) describe multiple recent fall-events that caused them to fear falling (or falling again).

We visited potential participants to secure their written informed consent and the consent of anyone else likely to be video-recorded (e.g., a spouse at home while we were recording).

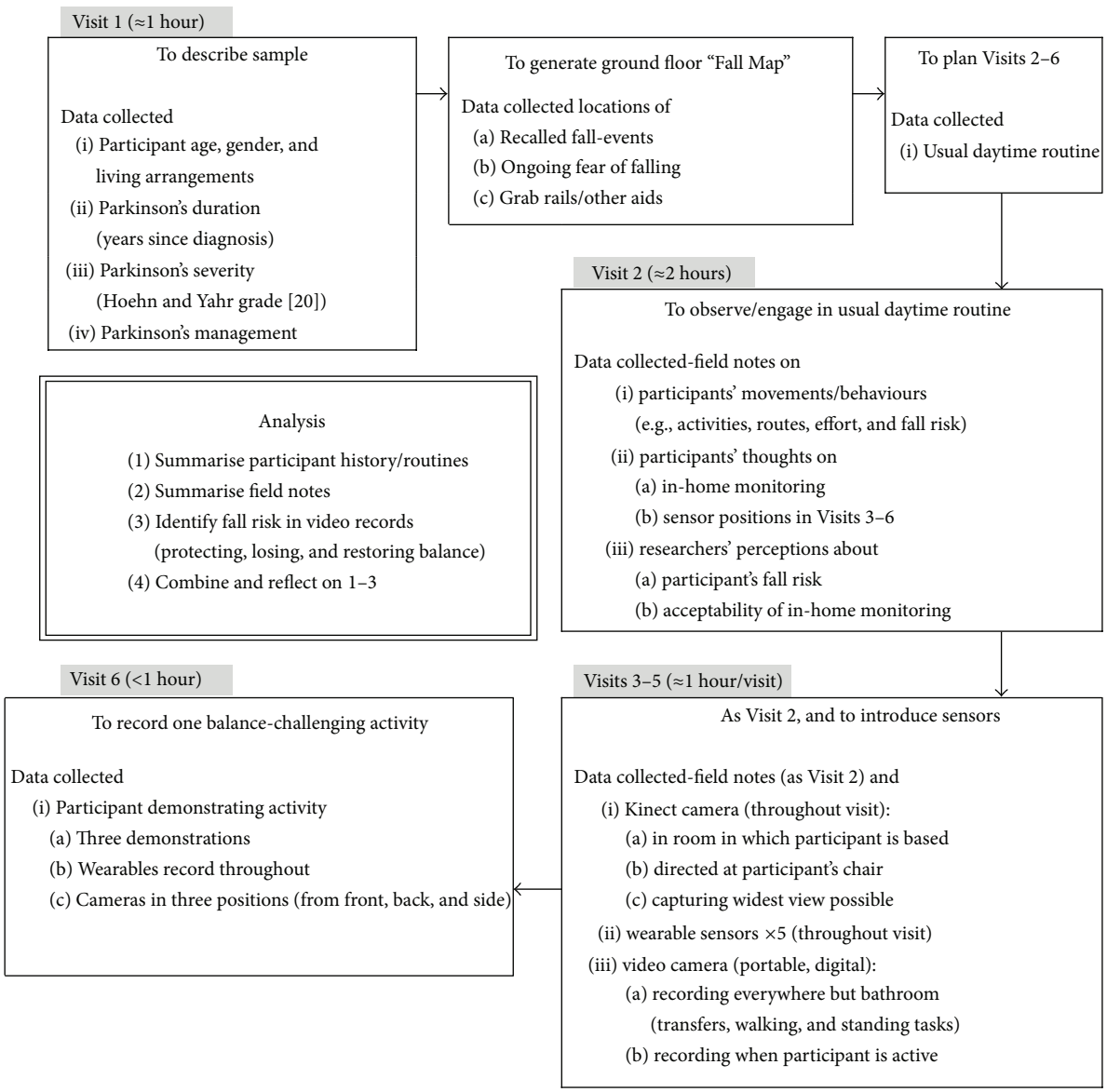

Figure 1: Summary of the data collection and analysis process.

2.1. Data Collection and Analysis. Between September 2014 and February 2015, we saw participants six times (approximately weekly), engaging in their usual morning and afternoon routines at home (see Figure 1). From Visit 3, we supplemented real-time observation with video/audio recording while we were present.

Although we explored the use of Kinect and wearable sensors with each participant, this paper reports on only the qualitative data (derived from field notes and video review). Participants wore five self-contained watch-sized devices that were under development for a larger research collaboration (of which this study forms part) and not commercially available (see Figure 2). Each contained a triaxial accelerometer and triaxial gyroscope to measure accelerations and angular velocities. The devices ran on battery power throughout data collection and logged data that we downloaded to a computer for later analysis. We charged them fully before use and secured them around the wrists and ankles and over the lumbar spine using Velcro straps.

Figure 2: Prototype inertial measurements logger (as worn (×5) by participants).

Visit 6 focused on an activity frequently challenging participants' balance (identified from their history and our observations). A physiotherapist annotated the videos, identifying when and how participants (1) protected, (2) lost, and (3) restored their balance (e.g., used support, swayed or stumbled, and made saving reactions).

3. Results

3.1. Sample. One participant withdrew after consenting, concerned about fitting data collection into a busy family and working life. Five completed the study, including two falling at least monthly and one with an implanted deep brain stimulator. Our participants were all retired, living alone or with a spouse, and largely housebound without assistance. We summarise their characteristics in Table 1. Three had significant healthcare needs besides Parkinson's, including neurological conditions, recurrent infections, skeletal deformities, and chronic pain and one had a spouse with significant needs. All five participants

(i) were under the care of Parkinson's specialists and multidisciplinary teams and followed their regular regime of "anti-Parkinson" medication throughout the study, so we observed them at peak dose (moving most freely) and as the effects wore off,

(ii) typically spent the day in a favourite chair in their reception rooms (watching television or using a computer, e.g.) and/or sitting in the kitchen,

(iii) described frequent near-misses and a fear of falling, at best making them "*cautious*," at worst "*inhibitory*."

Although in most falls at home the participants had not sustained serious injuries and had recovered to their feet without anyone's assistance, there were traumatic exceptions: one had fallen backwards from the top to the bottom of their staircase; another had fractured a femur and waited an hour, alone on the ground, for assistance. We highlight the locations associated with one participant's fall-events and fear of falling on a Fall Map in Figure 3.

3.2. Observation in the Home: Field Notes

3.2.1. Participant's Behaviour. We spent approximately seven hours with each participant, during which time they were all largely sedentary (staying downstairs throughout the day, mostly in one favourite chair). We positioned the Kinect in the sitting room, facing the participants' favourite chairs, except once when we focused on the computer station in the dining room. They predominantly used the furniture or walls for support (rather than mobility aids or purposely fitted rails, see Figure 4) as they showed us around their homes and gardens and demonstrated the following activities:

(i) Walking between rooms (e.g., to collect something or to relocate).

(ii) Preparing drinks or cooking.

(iii) Sorting, washing, and hanging out clothes.

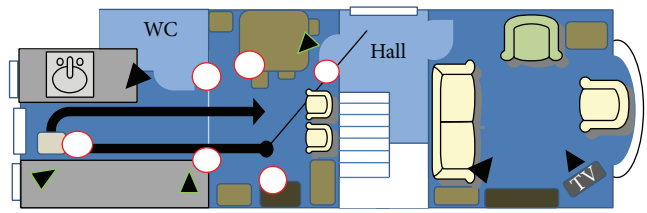

Figure 3: Example of Fall Map. Solid arrow shows a route through the kitchen-dining room that frequently challenges one participant; circles mark significant previous fall-events. A step between what were previously two rooms is less hazardous since the addition of grab rails on both sides. However, the participant relies on a heavy chair to provide additional support. Triangles mark camera positions.

Figure 4: Examples of people at high risk of falling "furniture creeping." With or without walking aids, participants relied on the support of furniture to move safely across rooms and often appeared vulnerable in open space.

(iv) Ascending and descending stairs.

(v) Negotiating steps between rooms.

(vi) Crossing open spaces in large rooms.

3.2.2. Participant's Thoughts. Every participant agreed to wear five sensors throughout every session; no one said they were cumbersome; some remarked they had forgotten that they were wearing them. Participants asked about the sensors' functions and potential uses. One, who had always detested "being watched" (e.g., by a supervisor at work), felt some people might not welcome long-term video-surveillance at home. Another felt that, as carers rarely went out, sending them alerts about every fall might make them feel they had to hurry back, when that was rarely what the faller needed or wanted (as fallers keep some falls to themselves).

3.2.3. Researcher's Perceptions. We felt intrusive staying "too long," aware that people had saved tasks for when we were present, giving us "something to film." We restricted most visits to 90 minutes, aware that participants and other residents might feel uncomfortable saying they were tired or needed privacy. Every participant was at high risk of falling (one spouse had documented approximately 30 falls over 18 months) and we *felt* anxious when they lost their balance (e.g., "*oops, nearly!*") or mentioned previous events (e.g., "*this is where I had my last really bad fall*"). No one fell when we were

Table 1: Characteristics of the participants, their fall histories, and video records.

	ID-1	ID-2	ID-4	ID-5	ID-6
Age (years), gender	72, male	79, male	71, female	76, female	73, female
Parkinson's					
Years diagnosed	11	5	13	7	8
Severity (Hoehn and Yahr [20])	IV, severe	IV, severe	IV, severe	III, moderate	III, moderate
Living arrangements	With wife Needs help to leave (semidetached) house Uses mobility scooter	With wife Needs help to leave (semidetached) house Uses mobility scooter	With husband Usually only leaves (detached) house with help	With husband Usually only leaves (detached) house with help	Alone, family nearby Needs help to leave (single storey) house
Mobility	Uses stick, grab rails, and perching stool Limited stair climbing	Marked fluctuation and freezing; using riser chair; limited stair climbing (having stairlift)	Marked fluctuation Little use of aids	Little use of aids	Uses perching stool and trolley No stairs at home
Recent fall history					
Falls	>12/year	>12/year	>1/year	>1/year	0
Fractures	Yes	No	Yes	Yes	n/a
High-risk activity	Walk through kitchen-diner, negotiating step	Walk from armchair, across hall to toilet	Negotiating stairs	Negotiating stairs	Walk across open space in sitting-dining room
Video review					
Instability noted (walking/standing/transfers)	38 times in 36 min, 1.1/min (13/14/11)	86 times in 62 min, 1.4/min (66/1/19)	33 times in 19 min, 1.7/min (13/1/19)	49 times in 71 min, 0.7/min (22/12/15)	21 times in 58 min, 0.4/min (9/5/7)

min = minutes.

Table 2: Summary of key observations from all participants' video records, frequency observed by activity.

	Walking	Standing	Sitting to standing	Standing to sitting
Fall prevention				
Used arms			×58	×33
Held/cruised furniture	×25	×21	×2	
Held banisters/rails	×25			
Held kitchen counter	×3	×14	×1	
Held wall with free hand(s)	×13	×4		
Used stick	*1 × throughout*	×2 (leaned on)	×6	
Pause/adjust midway	×14 (turns, in space, steps)		×13	×8
Aborted attempt		×1 (to reach)	×6	
Observed instability				
"Sway" or "wobble" (e.g.)	×51 (turns, steps)	×21 (pointing, reaching)	×20 (walked straight away)	
No control/heavy (no hands)				×23/×12
Stepped/swayed backward		×6 (step(s) back)	×11 (toes off floor)	
Fell backward			×5 (into chair)	×11 (feet off floor)
Shuffled feet	×25			
Stumbled or caught foot	×13	×1		
Froze	×13			
Feet crossed	×8			
Balance recovery				
Staggered	×15	×1	×2	
Grabbed furniture	×5	×3	×2	
Grabbed wall	×2			
Grabbed banister/rail	×2			
Sat quickly	×1	*×1 with help*		*×1 with help*
Caught by researcher	*×1*		*×1*	
Quickly given stick			*×1*	

present but we observed near-misses and remained vigilant throughout. Participants frequently recounted falls with a sense of humour and told us we were being *overcautious*. Two avoided using any support despite severe instability, even when demonstrating an activity associated with previous fall-events (which appeared the only physically demanding aspect of the study, though every participant was willing to do it). Participants also seemed comfortable with how we applied sensors. The wearables did not appear to hinder or distract them but some participants appeared unstable during (or fatigued by) the repeated sitting to standing actions necessary for the application of wearables. Our greatest concern about the wearables and the Kinect was that our uncertainty about whether they were recording diverted our attention from the participants.

3.3. Video Analysis: Observed Risk of Falling. We reviewed 246 minutes of participant activity. Although occasionally they moved out of camera view or something/someone obscured our view (see Figure 5), we counted 227 occasions when a participant appeared at imminent risk of falling (see Table 2).

All participants used support (mostly furniture) to preserve their balance; particularly when turning or rising, participants paused and either repositioned their hands or feet or aborted the action. They flexed or rotated their trunks markedly to use every available support on the stairs (see Figure 6).

Figure 5: Examples of furniture obscuring the camera and challenging balance. Monitoring transfer into chairs and manoeuvring through gaps between furniture pieces would be informative as these activities frequently challenge balance. The obscured camera view highlights the importance of wearable devices as part of a sensor array.

Participants appeared particularly unsteady during turns and on steps, if they started to walk immediately on rising, and if they did not use support when standing or sitting

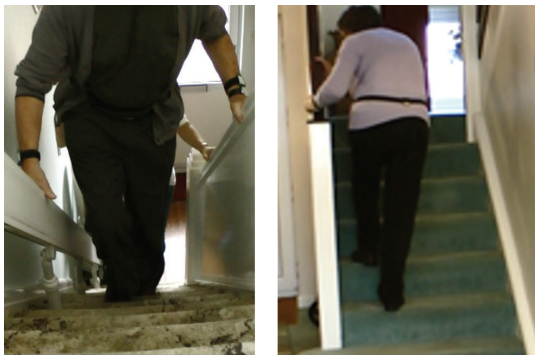

Figure 6: Reliance on banisters and rails. Participants utilised every available support when tackling the stairs. In the absence of a banister on both sides of the stair case, one participant kept a hand on the stairlift track and one placed both hands on the one available rail.

down. Balance was often lost backwards, but, in walking, participants tended to stumble forwards or sideways when their feet did not clear the floor or crossed, or they tripped or froze. Unsteady transfers were characterised by swaying backwards (so that the toes lifted on standing) or by actually falling backwards into the chair (either on rising, or so violently during sitting that both feet lifted off the floor: twice a participant nearly missed the chair).

Participants unsteady walking or in standing mostly took recovery steps, grabbed something, or sat down quickly to restore their balance. When participants were unsteady transferring, the chair broke the potential fall, though on five occasions (three during transfers) another person assisted/caught the participant.

3.4. Reflections on the Combined Data. The participant's histories, behaviour, and thoughts, alongside the researchers' observations, suggested that monitoring five activities could identify balance protection, loss, and recovery:

(1) Chair transfers.

(2) Walking (through open spaces and around furniture).

(3) Turning (in standing and walking).

(4) Stepping onto, off, or over obstacles/steps.

(5) Performing tasks in standing (e.g., conversing, cooking).

3.5. Missing Data. We attempted to record sensor data on eighteen visits (as we reduced data collection to reduce the burden on one participant). We collected video data every time, Kinect data 17 times (94%) as a connection between sensor and lap top failed once, and wearable data 12 times (67%) after four equipment failures and two operator errors.

4. Discussion

Following the principles of ethnographic research, we sought to keep the situation as natural as possible before introducing sensors and continued to engage as visitors while the sensors recorded and we noted what the participants were doing. We *experienced* the reality of living with a high risk of falling, rather than simply "observed" it and support the assertion that a subjective perspective in research is valuable and increases "the knowledge yield" [21]: we gained more insight than we could have through observing, evaluating, or questioning the participants anywhere other than at home. As in previous studies [15] we had some technical issues (with equipment failure and obscured sensors) and participants disclosed some concerns about surveillance but every insight gained at this stage will inform a programme of research that is now based on experience rather than supposition.

Some people might find researchers repeatedly observing them at home difficult to accommodate to and overly intrusive but our participants allowed us to record wherever (and whatever) we wanted: none dropped out during the study. Participants may have felt that sitting the whole time we were observing them was not what we wanted to see: it is widely accepted that being part of a study can cause people to change their behaviour ("the observer effect"). Rather than a limitation, "staging a performance" can be a strength in ethnography, wherein the findings are not the raw data but the interpretation of data in context [22]. In the current study, participants may have saved activities to demonstrate while we were recording but we still found them to be sedentary (and thus surmise that they were even more sedentary when we were absent). Furthermore, our focus on fall risk meant that we were observing unintentional balance loss, rather than anything "staged."

4.1. The Challenges of Using Sensors. The residential environment poses many more challenges to movement research than does the laboratory: working in a real home brought theoretical challenges into focus. The needs of residents and researchers can seem contradictory, when, for example, environmental features that assisted the residents obscured the camera's view. Some people at risk of falling rely on "furniture creeping" to negotiate safely a route around their homes, so it would be inappropriate for researchers to manipulate "obstructions" (like carefully placed chairs). However, environmental features (like doorways and gaps between furniture pieces) also *challenge* residents. We therefore suggest that when residents are largely sedentary, perhaps restricting their opportunities to fall, cameras should focus on the few challenges they still have to tackle habitually. In the current study, the need to change direction (or level) often put people at imminent risk of falling.

When exploring the potential of in-home sensors to impact health and healthcare in future, we must consider whether we need track participants 100% of the time throughout 100% of their homes. Could we answer carefully defined questions with a few appropriate sensors operating at relevant moments in high yield locations? Our findings suggest that a wearable device coupled with cameras in the sitting room and hall could meet the requirements and be acceptable to residents. For clinicians to adopt such technology, however, it would need to be more user-friendly and less distracting than the iterations we utilised: we lost data before we modified the

user-interfaces on the wearables and Kinect. As a combined array however, extended human observation coupled with sensors could be an effective way of understanding how people at risk of falling negotiate or avoid high-risk locations and activities at home. We suggest clinicians working with people at high risk of falling take a detailed fall history [10] and then follow up with a period of in-home monitoring, targeting the areas of most concern on an individual basis. Even having sensors in the home for one week might yield richer data than is obtainable through self-report. In the current study, we asked participants to identify an activity that they felt carried a particularly high fall risk for them and we observed this activity repeatedly (at the end of data collection when we were familiar with the participant). In a research context, this approach is an alternative to basing sensor placement on a complete fall history.

Without witnessing an event or having video to review, clinicians (such as physiotherapists) can only glean what happened before, during, and after the event from someone's recollection. Continuously recording from multiple cameras within the home is impractical but there is the potential to keep a record of *incidents* for later scrutiny. It may be possible, for example, to record for one minute and continuously delete that recording unless there is something to report. This would revolutionise the data on which clinicians base decisions. There is growing interest in using sensors to log simple gait parameters (e.g., in people walking 20 m trials in a laboratory [23]) but the current study suggests that clinicians managing fall risk need to know more than someone's stride length and velocity. Sensors could, for example, reveal fluctuations in performance under different conditions and the availability and success of saving reactions when required.

4.2. The Potential of Sensors to Surpass Human Observers in Monitoring Fall Risk. People recognise an individual is at risk of falling in many ways, from how they look or move to what they say. However, an individual may *feel* that they are going to fall whilst giving no obvious indications to an observer; sensors may surpass humans in being sensitive enough to detect very subtle deviations in motor behaviour. Further research is necessary but evidence suggests that triaxial accelerometers worn on the pelvis may distinguish near falls from other gait patterns observed in healthy subjects on a treadmill in a gait laboratory [1].

Extended in-home observation has multiple advantages over the one-off "home visits" used in clinical practice. With no agenda, the observer sees how the resident uses their space, how they pace activities, and how they manage tasks when their attention is on a goal, not on the task itself. Ticking off a checklist of theoretical challenges and hazards within a single session is likely to be unrepresentative: "assessing" someone descending the steps into their kitchen is unlikely to reflect how they do it when hurrying towards a saucepan that is boiling over. Over an extended period, a human observer would be costly and intrusive; sensors would be more realistic, and monitoring by sensors *alone* would remove any need to "perform" for a *human* observer. A mixed array of sensors is likely to outdo any single type in identifying balance protection, loss, or restoration, though a single sensor has advantages in ease of application.

Without intruding in parts of the home people might prefer to keep private, sensors could monitor the risks of falling, and the associated risks of inactivity and isolation. With reasonable reservations, our participants accepted the technology. They appeared at greatest risk of falling transferring, crossing spaces without handholds, manoeuvring around obstacles, turning through doorways, and negotiating steps. These challenges are amenable to recording and most, if not all, arise along the short route between favourite chair and stair, negating the need for pervasive sensors throughout the home, with no possibility of "escape." Having identified key activities during which experienced observers noted "instability," our next step will be to examine the data recorded by the Kinect and wearable sensors that the participants allowed us to trial. Researchers need to establish that sensors can identify instability during simple isolated actions and then to validate the sensor-based identification of fall risk during complex free-living activities.

4.3. Wider Applications. Our research focusses on monitoring fall risk among people with balance and mobility disorders that restrict their function and participation in society. But our recommendation for focused (nonpervasive) monitoring applies to anyone whose health limits their activity towards a single favoured location, with everything they need close to hand. Though we studied only people with Parkinson's in the current project, the indications of fall risk that we have suggested sensors could identify and monitor are generic (with the probable exception of freezing). Although our participants were sedentary, they were still mobile: we believe that focussing sensors on a defined, frequently occupied, daytime location in the home should be as informative about how and when less sedentary (even active or impulsive) individuals move. However, unobtrusive sensors capable of identifying instability could have even wider applications. For example, alcohol intoxication may alter behaviour and fall risk. It might be possible to monitor remotely indicators of instability, if it is intrusive to monitor an individual or impossible to monitor a crowd.

5. Conclusions

Immersed in the reality of living with the experience, fear and risk of falling, we gained insights we would not have gained any other way. Participants enhanced their safety using banisters and grab rails but more frequently additional support in the form of strategically placed furniture. Researchers cannot remove such "obstacles" but must take their cue from them: these are where people are likely to appear unstable. Because physical obstructions, including other people, frequently obscured the cameras' views, comprehensive monitoring would necessitate multiple cameras plus at least one wearable device. However, the extent to which participants restricted their activity suggests that, by identifying an individual's high-use locations and focussing only on them, researchers and clinicians could leave the remainder of people's homes sensor-free.

We most frequently noted a high risk of falling when people transferred between sitting and standing, walked, turned, negotiated steps, and tackled tasks in standing. We noted that someone was protecting, losing, or restoring their balance largely through visual clues, so we believe that appropriately positioned sensors would also be able to detect indications of instability. Whether sensors can equal, or even surpass, human observers requires further research. People may be less likely to alter their behaviour for a sensor than for a human observer, and sensors might be able to detect changes in stability too subtle for human observers to notice in real time or from video. There is considerable scope for sensors to usefully monitor changing fall risk (rather than merely detect falls) unobtrusively. We suggest that researchers explore the value of monitoring a habitual route (such as between chair and stair, or for people living in homes without stairs, the daytime route between chair and toilet door) when evaluating fall risk over time.

Ethical Approval

The Ethics Committee of the Faculty of Health Sciences, University of Southampton, granted approval to conduct this study in May 2014 (Observing Frequent Fallers at Home: Ethics ID 9766).

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Research Article

Behavioral Periodicity Detection from 24 h Wrist Accelerometry and Associations with Cardiometabolic Risk and Health-Related Quality of Life

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Periodicities (repeating patterns) are observed in many human behaviors. Their strength may capture untapped patterns that incorporate sleep, sedentary, and active behaviors into a single metric indicative of better health. We present a framework to detect periodicities from longitudinal wrist-worn accelerometry data. GENEActiv accelerometer data were collected from 20 participants (17 men, 3 women, aged 35–65) continuously for 64.4 ± 26.2 (range: 13.9 to 102.0) consecutive days. Cardiometabolic risk biomarkers and health-related quality of life metrics were assessed at baseline. Periodograms were constructed to determine patterns emergent from the accelerometer data. Periodicity strength was calculated using circular autocorrelations for time-lagged windows. The most notable periodicity was at 24 h, indicating a circadian rest-activity cycle; however, its strength varied significantly across participants. Periodicity strength was most consistently associated with LDL-cholesterol (r's = 0.40–0.79, P's < 0.05) and triglycerides (r's = 0.68–0.86, P's < 0.05) but also associated with hs-CRP and health-related quality of life, even after adjusting for demographics and self-rated physical activity and insomnia symptoms. Our framework demonstrates a new method for characterizing behavior patterns longitudinally which captures relationships between 24 h accelerometry data and health outcomes.

1. Introduction

Human behaviors that are measured by accelerometer—sleep, sedentary behavior, and more active behaviors—are consistently associated with cardiometabolic risk biomarkers and health-related quality of life [1–4]. Recently, substitution-based and compositional models have been used to better characterize the combined or joint impact these behaviors may have on health [5–8]. Accelerometers can also capture the patterns in which sleep, sedentary, and active behaviors are accumulated. For example, physical activity accumulated in bouts of ≥10 min have stronger relationships with health outcomes than total physical activity [9]. Discontinuous sedentary time is less detrimental for health than sedentary time accumulated in continuous bouts [10]. Finally, in sleep, accelerometers can quantify measures of sleep quality (e.g., sleep efficiency, wake after sleep onset) which typically provide greater predictive value of health outcomes than sleep duration alone [11].

Despite the ability of accelerometers to measure behaviors across the 24 h spectrum, less is known about metrics that encapsulate the full 24 h that could be derived from accelerometer data. These metrics may identify unique patterns of behavior that could further explain relationships with health outcomes. One such known metric that is ascertained from accelerometry is the rest-activity cycle that can represent the human circadian system. Disruptions in the circadian system consistently show profound and detrimental impacts on health [12] and studies using accelerometry have shown relationships with health-related quality of life and better

survival following metastatic colorectal cancer chemotherapy treatments [13, 14].

Recently, with the growth of more "wearable" accelerometers that accommodate larger storage capacities, waterproofing, and more unobtrusive wear locations, long-term monitoring of behaviors (i.e., >1 week) throughout the 24 h spectrum has become more feasible. Indeed, consumer-based accelerometers (e.g., Fitbit, Jawbone) are already achieving long-term population-level data collection of these health behaviors. With the collection of long-term data, it may now be possible to characterize weekly, seasonal, and even annual patterns of behaviors that encapsulate the full 24 h spectrum that extend beyond traditional methods (e.g. accelerometry thresholds, sleep/wake rhythms). Periodicities (i.e., repeating patterns) are observed in many human behaviors and may be derived from various forms of lifelog data [15]. However, such methods have not been applied to long-term monitoring of accelerometry data. Therefore, our primary purpose of the work reported in this paper was to develop a framework for identifying meaningful periodicities (i.e., repeating patterns) from longitudinal wrist-worn accelerometer data. Secondarily, we sought to establish whether these periodicities were independently associated with key cardiometabolic biomarkers and health-related quality of life. We applied five different methods to calculate intensity of the rest-activity cycle and show how each method performed in terms of correlation with biomarkers and health-related quality of life and to see if there was a consistent, or any kind of, pattern across the five methods.

2. Materials and Methods

2.1. Participants. Participants were drawn from a smartphone-based, multicomponent behavioral intervention targeting changes in sleep, sedentary behavior, and more active behaviors. The target population was US Veterans currently receiving clinical care at a regional Veterans Health Administration (VHA) hospital in the Southwestern United States, aged 35–65 years, measured overweight/obese (BMI $\geq 25\,\text{kg/m}^2$), with a fasting glucose of ≥100 mg/dL. Eligibility criteria also included reporting of (a) insufficient physical activity (defined as endorsing activity ranking categories ≤4 on the Stanford Brief Activity Survey [16], which closely aligns with national physical activity guidelines), excessive sitting (defined as ≥8 hours of sitting from the International Physical Activity Questionnaire (IPAQ) [17]), and short sleep duration (<7 hours/night) or mild/moderate sleep complaint (modified version of the Insomnia Severity Index (ISI) [18]). All participants completed telephone screening to determine eligibility. Institutional review boards governing the local VHA hospital and the university to which some of the researchers were affiliated approved all study procedures. All participants provided written informed consent.

2.2. Procedures. Participants were initially screened by telephone and this was followed by an in-person visit to confirm eligibility and complete informed consent procedures. At this visit, participants were given a wrist-worn accelerometer for three consecutive weeks. This period constituted the "run-in" period of the behavioral intervention and baseline data collection period. Participants were instructed to wear the monitor continuously during both sleep and wake. Participants were able to remove the accelerometer but were encouraged to wear the monitor as continuously as possible. As part of the run-in period, participants were asked to self-monitor their sleep, sedentary, and active behaviors using a customized smartphone application designed for this purpose. After two weeks, participants were mailed a second accelerometer and asked to return the first accelerometer in a prepaid envelope. At three weeks, participants returned for a second in-person visit where the second accelerometer was returned and all other study measures including questionnaires, blood draws, and clinical measurements were completed. Participants received $25 USD for completing study measures at this visit. Following this visit, participants were randomized to receive active elements of the behavioral intervention. A full description of the intervention is beyond the scope of this investigation and is discussed elsewhere [19], but briefly, participants were randomized into a full-factorial $2 \times 2 \times 2$ screening experiment where smartphone-based interventions targeting sleep, sedentary behavior, and physical activity were delivered for 8 weeks. All participants maintained self-monitoring of their behaviors using the custom application during the intervention phase. Participants also attended two additional visits during the eight weeks to complete study-related assessments and to return/exchange accelerometers to maintain continuous wear. To take advantage of the continuous and longitudinal nature of the data, the full accelerometer data for the run-in and intervention periods were leveraged for this analysis and the effect of the intervention was statistically controlled for in all analyses.

2.3. Measures

2.3.1. Lifelog Accelerometry. Movements during sleep and wake were monitored objectively and continuously throughout the study period using the GENEactiv accelerometer (Activinsights, Kimbolton, UK). The GENEActiv is an open source, wave-form wrist-worn accelerometer that is fully waterproof, allowing the monitor to be worn continuously, 24 h a day, without the need to be removed during water activities or be shifted from hip to wrist for daytime and nighttime measurement. Since the GENEactiv provides continuous forms of data recordings for periods of at least 1 month, it can be considered a valid form of lifelogging. Data captured on board the device were initially sampled at 40 hz and summarized to 60 s epochs using a gravity-subtracted sum of vector magnitudes provided through the Activinsights software package [20]. Periods of nonwear were screened for and removed based upon variability in the monitor temperature outputs (i.e., low variability indicates lack of normal fluctuation in temperatures indicated of human wear) and visual inspection. Additional removal occurred for overlapping wear periods that occurred when the monitors were in transit by post.

2.3.2. Cardiometabolic Outcomes. Clinical assessments of waist circumference and blood pressure were taken. Waist circumference was measured at the end of normal expiration at the level of the iliac crest by wrapping a flexible measuring tape snugly around the waist with the tape parallel to the floor. Blood pressure was measured twice (five minutes apart) in the seated position after 10 minutes of rest with a single, regularly calibrated, automated blood pressure machine (Casmed 740). Laboratory-based biomarkers were measured following a >9 h fast. A full lipid profile with total cholesterol, high-density lipoprotein (HDL), and low-density lipoprotein (LDL) as well as high-sensitivity C-reactive protein (hsCRP), triglycerides, plasma glucose, and insulin levels was measured. All assays were processed in the VHA clinical laboratory.

2.3.3. Health-Related Quality of Life. A single "general health" quality of life metric was derived from the RAND-36 measure [21], which is similar to those of the Medical Outcomes Study SF-36 [22].

2.3.4. Study Covariates. Sociodemographic and health behavior/status variables considered as potential confounders induced age, gender, race/ethnicity (Caucasian, African-American, Hispanic, and Asian American), leisure-time physical activity (assessed with a metabolic equivalent score from the walking, moderate, and vigorous leisure activities items from the IPAQ [17]), and insomnia symptoms (assessed with a total score from the ISI [18]). Intervention effects were also adjusted for in all models based upon the $2 \times 2 \times 2$ factorial experiment.

2.3.5. Power Spectral Density (PSD) Estimation. PSD estimation can be used to detect significant periodicity or repeating cycles in any kind of signal, including lifelog data. Our previous work showed detected periodicities in several lifelog datasets using various PSD estimation methods [15]. When it is applied to any form of lifelogging, the periodogram can be used to detect the natural cycles that occur in lifestyle, behavior, and activities. Periodicity can be observed in many natural phenomena, such as circadian rhythms associated with our sleep, for example. Intuitively, we think of our routine daily lives as composed of various forms of recurring events with obvious periodicities around daily, weekly, monthly, seasonal, and annual cycles. In any kind of spectral analysis of a lifelog, we expect to see periodicity around these frequencies. However, without the help of lifelogging devices and the resulting lifelog of data, analyzing the periodicity of human life is not a practical proposition.

(1) Periodogram. A periodogram is a visualization of the PSD for a continuous spectrum of frequencies calculated from a stream of data values. Periodogram is widely used to estimate spectrum of both discrete and continuous signals in engineering, astronomy, biology, and physics [23]. When periodograms are applied to lifelogs, they can reveal the cycles which form a natural part of human behavior. Periodograms work best when the lifelog data is sampled at a regular frequency and is continuous, without missing values [24]. Missing data was minimal in this application.

Suppose our complete input data sequence is formalized as $x(n), n = 0, 1, \ldots, N-1$. The normalized Discrete Fourier Transform (DFT) of the sequence is defined as

$$X\left(f_{k/N}\right) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n)\, e^{-j2\pi kn/N}, \tag{1}$$

where the subscript k/N denotes the frequency that each coefficient captures. Suppose that X is the DFT of a sequence $x(n)$. The periodogram P is provided by the squared length of each Fourier coefficient:

$$P\left(f_{k/N}\right) = \left\|X\left(f_{k/N}\right)\right\|^2 \quad k = 0, 1, \ldots, \left\lceil \frac{N-1}{2} \right\rceil. \tag{2}$$

Notice here that k ranges from 0 to $(N-1)/2$. In order to find the k dominant periods, we need to pick the k largest values of the periodogram. This works well for short to medium length periods but, for long periods with low frequencies, performance is worse because each value in the periodogram N indicates the power at frequency interval $[N/k, N/(k-1)]$ which is too wide to capture large periodicity. Thus, the accuracy of periodicity detection at low frequency will be lower than at higher frequency. For lifelogging, this means there is difficulty in detecting patterns measured in years. Another difficulty when using periodograms is spectrum leakage [25], which causes frequencies that are not integer multiples of the DFT bin width to disperse over the entire spectrum which could result in false alarms being detected in the periodogram. Despite this, the periodogram is still an acceptable way to guarantee the accuracy of detected periods with short to medium frequency.

(2) Least-Squares Spectral Analysis. Past work [23] has shown that the Lomb-Scargle periodogram that handles missing data values can be successfully applied to generate periodograms from noncontinuous lifelog data.

Least-squares spectral analysis or LS periodogram is a very different method developed by Lomb and Scargle based on work by Barning and Vanicek to handle continuous data with missing parts [26, 27]. To formalize the problem, suppose we have a data sequence with N data points: $X_n = X_{t_n}, n = 0, 1, \ldots, N-1$. The mean and variance of the data sequence need to be calculated first.

The Lomb-Scargle periodogram has the following expression:

$$P_X(\omega) = C \left\{ \frac{\left[\sum_{n=1}^{N} y(t_n) \cos\left(\omega\left(t_n - \tau\right)\right)\right]^2}{\sum_{n=1}^{N} \cos^2\left(\omega\left(t_n - \tau\right)\right)} + \frac{\left[\sum_{n=1}^{N} y(t_n) \sin\left(\omega\left(t_n - \tau\right)\right)\right]^2}{\sum_{n=1}^{N} \sin^2\left(\omega\left(t_n - \tau\right)\right)} \right\}, \tag{3}$$

where C could be $1/2$ or $1/2\sigma^2$ and τ is defined as

$$\tan(2\omega\tau) = \frac{\sum_{n=1}^{N} \sin\left(2\omega t_n\right)}{\sum_{n=1}^{N} \cos\left(2\omega t_n\right)}. \tag{4}$$

(3) Periodogram of Autocorrelation Function. In statistics, correlation is basically used to measure how similar two sequences are. This quantitative measurement of similarity of signal 1 and signal 2 can be defined as

$$r_{12} = \frac{1}{N}\sum_{n=1}^{N-1} x_1[n]\, x_2[n]. \tag{5}$$

A cross-correlation between time shifted sequences can be defined as

$$r_{12}(k) = \frac{1}{N}\sum_{n=1}^{N-1} x_1[n]\, x_2[n+k]. \tag{6}$$

All possible k-shifted time series could generate another sequence of numbers only changing with k, which is called full cross-correlation. The correlation between a signal and the time shifted version of itself is called an autocorrelation. A lag operator is used to generate the time shifted signal and "0 lag" equals to mean-square signal power. Autocorrelation can be defined as

$$r_{11}(k) = \frac{1}{N}\sum_{n=1}^{N-1} x_1[n]\, x_1[n+k]. \tag{7}$$

We can observe that if the signal is periodic, the normalized autocorrelation is also periodic. Based on this, it is interesting to use the periodogram of the autocorrelation as a PSD estimator. The following equation is used to calculate the periodogram of autocorrelation function:

$$R\left(f_{k/N}\right) = \frac{1}{N}\left\|\sum_{i=0}^{N-1} r_{11}(i)\, e^{-j2\pi ki/N}\right\|^2. \tag{8}$$

Periodicity Strength. Since 24 h/circadian periodicity is observed and significant in almost all lifelog data generated by human subjects, we would like to use the lifelog to compute the strength of the circadian periodicity for each participant at different points in time. Based on the PSD calculated from the input data, we try to estimate the periodicity strength at given times using different methods and thereafter compare those strengths with markers of cardiometabolic risk and health-related quality of life.

We use the following denotation to explain how we calculate the strength of periodicity.

$\mathscr{F}$ denotes the DFT of signal $x(n)$, $n = 0, 1, \ldots, N-1$, and $\mathscr{F}'$ denotes the inverse transformation. S stands for the strength of periodicity. The autocorrelation was calculated using five different approaches, described as follows:

$$\begin{aligned} \mathscr{A}_1(k) &= \frac{1}{k}\sum_{n=1}^{N-1} x[n]\, x[n+k], \\ \mathscr{A}_2(k) &= \sum_{n=1}^{N-1} x[n]\, x[n+k]. \end{aligned} \tag{9}$$

Method 1:

$$\begin{aligned} S &= P(f) \quad \text{where } f = \frac{1}{\text{day}}, \\ P(f) &= \frac{1}{N}\mathscr{F}(x_n)^2. \end{aligned} \tag{10}$$

Method 2:

$$\begin{aligned} S &= P(f) \quad \text{where } f = \frac{1}{\text{day}}, \\ P(f) &= \frac{1}{N}\mathscr{F}(\mathscr{A}_1(x_n))^2. \end{aligned} \tag{11}$$

Method 3:

$$\begin{aligned} S &= P(f) \quad \text{where } f = \frac{1}{\text{day}}, \\ P(f) &= \frac{1}{N}\mathscr{F}(\mathscr{A}_2(x_n))^2. \end{aligned} \tag{12}$$

Method 4:

$$\begin{aligned} S &= \max(P(f)), \\ P(f) &= \frac{1}{N}\mathscr{F}(x_n)^2. \end{aligned} \tag{13}$$

Method 5:

$$\begin{aligned} S &= \frac{1}{2}\sqrt{\sum_n (x_n - x_n')^2}, \\ x_n' &= \mathscr{F}'(P(f)) \quad \text{if } f \neq \frac{1}{\text{day}},\ P(f) = 0, \\ P(f) &= \mathscr{F}(x_n). \end{aligned} \tag{14}$$

Method 1 uses power carried by 1/day frequency as the strength of circadian periodicity, namely, the correlation between signal and sinusoid with daily periodicity. Methods 2 and 3 use $\mathscr{A}_1$ and $\mathscr{A}_2$ to calculate autocorrelation, respectively. Using the result of autocorrelation as input to compute periodogram, we thereafter use power of daily periodicity as strength of the circadian periodicity. It should be noted that $\mathscr{A}_1$ is normalized autocorrelation. Method 4 uses the maximum power in the periodogram to represent strength of periodicity, though in this case it is not assured that daily periodicity will carry maximum power all the time. Finally, Method 5 calculates a sinusoid with daily periodicity that is correlated to the data most and then computes root-mean-square error (RMSE) between the signal and the most-fit sinusoid with daily period.

If we consider the informal formulation of spectrum estimation as estimating how the total power is distributed over the frequency, the definition of intensity of periodicity can be thought of as the power corresponding to a certain periodicity or several periodicities. Method 1 comes directly from the definition of power spectral density, which uses DTFT to calculate how power is distributed over frequency directly and here in method 1 we only take the power carries

by 24-hour periodicity. Methods 2 and 3 derive from another definition of power spectrum which shows that spectrum can be achieved as the DTFT of the autocorrelation. Method 3 is normally used to calculate autocorrelation in signal processing. The reason we also use Method 2 is because when we lag signal to calculate autocorrelation, the bigger the lag is, the less number of points is involved in the calculation. Method 2 is trying to eliminate this effect by using averaged value. Both of Methods 2 and 3 use power of circadian periodicity as the intensity. Method 4 is using power of frequency with maximum power as intensity. The reason we are using this method is that we are trying to see how the frequency with maximum power would be correlated with biomarkers. In particular, it is interesting to see the result between Methods 1 and 4. Method 5 uses a different way to calculate how the signal is different from the 24-hour periodicity. The rest of the methods use correlation as a metric to quantify the difference while Method 5 uses summed error as the metric to quantify the deviation.

An intensity graph is generated by using a sliding window with selected window and overlapping sizes to visualize the intensity/strength of the periodicity [28]. Within each window, we calculate the strength of the circadian periodicity using Method 1; thus we can see the intensity/strength of periodicity over time.

Descriptive Analyses and Relationships with Cardiometabolic and Health-Related Quality of Life Outcomes. We calculated descriptive statistics to represent the sample including means, SDs, frequencies, and percentages. Multiple linear regression analysis was used to identify which periodicity strength metrics were associated with the cardiometabolic and quality of life outcomes. Partial correlation coefficients, after adjustment for age, gender, race/ethnicity, leisure-time physical activity, insomnia symptoms, and intervention assignment, were used to characterize this relationship. Analyses were conducted using SAS Enterprise Guide 6.1 (SAS Institute, Inc.). Inferential testing was conducted at a $P < 0.05$ significant level; however, due to the relatively small sample size and exploratory nature of the study, moderate effect size correlations and P's < 0.10 were also considered. We considered an r effect size of >0.25 to be "moderate" in strength [29].

3. Results

3.1. Participants. Table 1 provides demographic information regarding the final sample of participants. In total, 24 participants were enrolled for this analysis; however, four were excluded due to not presenting for the study measure completion following the initial three weeks of accelerometer wear. The final sample ($N = 20$) were middle-aged, primarily men and Caucasian, inactive, and with moderate levels of insomnia symptoms. Continuous accelerometer wear time varied from 13.9 (minimum) to 102.0 (maximum) days (mean wear: 64.4 ± 26.2 days). Nonwear time was minimal across the 24 h period in the sample (0.03 ± 0.07 percent of days). Of the 24 participants, 15 had complete data (58.8 ± 26.4 days). The remaining nine participants had 73.6 ± 23.1 days of data collection and 9.2% ± 9.0% days of missing data. Overall missing data across the full data collection period was 3.5% ± 7.1%.

Table 1: Participant demographics ($N = 20$).

Age, M ± SD	49.7 ± 9.1
Men, N (%)	17 (85.0)
Race/ethnicity, N (%)	
Caucasian	14 (70.0)
African-American	3 (15.0)
Hispanic	2 (10.0)
Asian American	1 (5.0)
Leisure-time physical activity (MET-min/week), M ± SD	878.6 ± 1680.9
Insomnia symptoms (ISI), M ± SD	14.8 ± 6.4

ISI = Insomnia Severity Index (range: 0–28).

3.2. Identification of Periodicities. Figure 1 outlines the methodological steps for identifying periodicities and visualizing periodicity strength. Panel (a) provides visualization of the sum of vector magnitudes (1 min epochs) along the y-axis and time along the x-axis over the course of the monitoring period. Sleep and wake periods are evident visually from these data. Panel (b) displays a periodogram calculated from 1 m epochs. The x-axis is frequency and y-axis is energy of the frequency, namely, how strong the corresponding frequency is. In Figure 1, we observe strong circadian periodicity followed by a 12 h periodicity which is the harmonic of the circadian. No within-day or weekly patterns were observed. Panel (c) plots time (x-axis) by the strongest periodicity observed over the 3-day time lagged window. y-axis of Panel (c) is the frequency that carries maximum power within a window. In this example, the 24 h periodicity held consistently for the majority of 3-day windows with small breaks at the beginning of the monitoring period. Panel (d) describes the strength of the periodicity using Method 1 (y-axis) over time (x-axis). The strength/intensity of the 24 h circadian periodicity changes throughout the lifelogged observation period, showing, for example, a weaker period of regular circadian cycle from day 0 to day 14 and again from day 32 to day 44.

3.3. Periodicity Strength Metrics. Table 2 presents descriptive statistics and intercorrelations among the five methods for calculating periodicity. Methods 1–4 displayed very high correlations among methods. In particular, Method 1 was strongly correlated with Method 4 and Method 2 was strongly correlated with Method 3. Method 5 was not strongly correlated (r's < 0.40) with any of the other methods. Normalized versions of these metrics were calculated and similar pattern of results was observed (not pictured).

3.4. Associations with Cardiometabolic and Quality of Life Outcomes. Table 3 presents descriptive data for cardiometabolic and quality of life outcomes and partial correlation

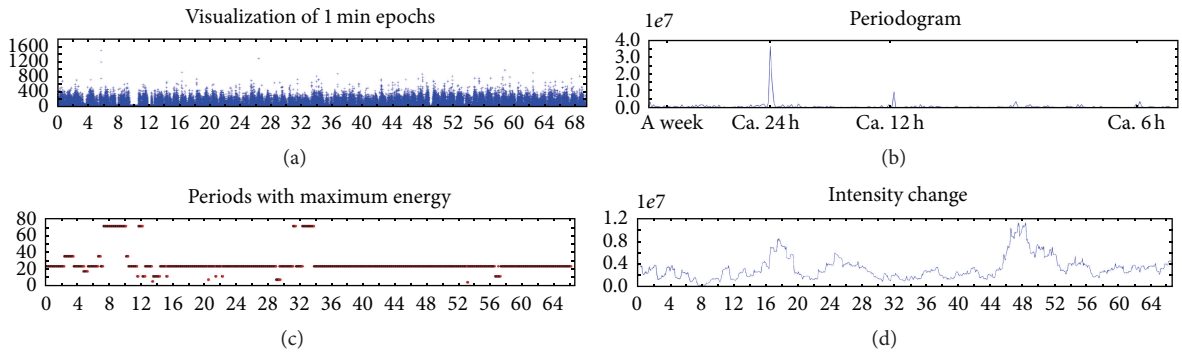

Figure 1: Exemplar data of 24 h behavioral periodicities over 70 consecutive days of wrist-worn accelerometry. 1 min = 1 minute; for more details, see text.

Table 2: Means, standard deviations, and Pearson correlations among five periodicity strength metrics ($N = 20$).

	Method 1	Method 2	Method 3	Method 4	Method 5
Mean	0.20	0.10	0.10	0.23	0.45
SD	0.24	0.22	0.21	0.24	0.15
Method 1					
Method 2	0.93				
Method 3	0.93	0.99			
Method 4	0.98	0.90	0.92		
Method 5	0.29	0.14	0.19	0.38	

coefficients for each of the periodicity strength metrics and cardiometabolic and quality of life outcomes. The profile of participants' descriptive data suggests that the sample was at moderate to high risk for cardiometabolic risk diseases. The strongest and most consistent correlations were observed between the periodicity strength metrics and LDL-cholesterol and triglycerides outcomes. Consistent—yet only moderate in strength—relationships were observed for hs-CRP and health-related quality of life. HDL-cholesterol, plasma glucose, and insulin were not consistently associated with the periodicity strength metrics. As expected (due to high intercorrelations), Methods 1–4 displayed very similar pattern of results. In contrast to Methods 1–4, Method 5 displayed a moderately strong relationship with systolic BP and HDL-cholesterol and no relationship with hs-CRP or triglycerides.

4. Discussion

The purpose of this study was to develop a framework for identifying periodicities (i.e., repeating patterns) from longitudinal wrist-worn accelerometer data and to establish whether these periodicities were independently associated with key markers of cardiometabolic health and health-related quality of life. The resultant periodograms demonstrated a consistent 24 h pattern representing a typical rest-activity cycle; however, the strength of this 24 h rest-activity pattern varied within and between individuals. Using varying methods of quantifying periodicity strength, we found preliminary evidence that the strength of the rest-activity cycle was associated with key cardiometabolic risk biomarkers and health-related quality of life independent of self-rated physical activity and insomnia symptoms.

Despite different methodologies in characterizing the rest-activity cycle and health outcomes, this study is consistent with other studies. Mormont et al. [13] examined the rest-activity cycle in metastatic colorectal cancer patients using an autocorrelation coefficient at 24 h and a dichotomy index that compared activity in bed and out of bed. These metrics were positively correlated with improved quality of life, response to treatment, and survival. In a follow-up to this study, Innominato et al. [14] further clarified the importance of the rest-activity cycle, as measured via accelerometry, by demonstrating the stronger correlations observed between the rest-activity cycle metrics compared to mean counts of physical activity for health-related quality of life and survival outcomes in metastatic colorectal cancer patients. Our study extends these findings in some important ways. First, these studies sampled behavior over 3-4 consecutive days. Therefore, our investigation substantially lengthens the monitoring period and therefore provides a clearer picture of habitual 24 h rest-activity cycles. Second, we have explored these relationships and found associations with a broader set of health outcomes in a group at elevated cardiometabolic risk. Finally, our framework for the development of periodograms and metrics to characterize periodicity strength represents a more sophisticated and nuanced approach that may provide a more precise determination of the 24 h rest-activity cycle.

One of the most interesting findings from the current investigation was the differences and similarities in correlation of the various periodicity strength metrics and health outcomes. Methods 1–4 yielded very similar results due to high intercorrelations among these related methods for quantifying periodicity strength. Methods 1–4 computed correlation as the sum of products ($s * r$) over all points, s_i, in the pattern against corresponding points r_i, in the original signal. This tells us how close the shape is between the original signal and the detected pattern. These metrics were consistently and strongly correlated with cardiovascular physiology outcomes such as LDL-cholesterol, triglycerides,

Table 3: Partial correlation coefficients, between cardiometabolic biomarkers and health-related quality of life indices, and periodicity strength metrics ($N = 20$).

	M ± SD	Periodicity strength metrics				
		Method 1	Method 2	Method 3	Method 4	Method 5
Waist circumference, in	66.82 ± 35.10	0.28	0.27	0.25	0.30	‡
Systolic BP, mm Hg	138.6 ± 17.13	‡	‡	‡	‡	0.57^{*}
Diastolic BP, mm Hg	89 ± 16.32	‡	‡	‡	‡	‡
Total cholesterol, mg/dL	177.4 ± 50.51	$0.52^{\dagger}$	0.68^{**}	0.57^{*}	$0.46^{\dagger}$	$0.47^{\dagger}$
HDL cholesterol, mg/dL	33.9 ± 11.76	‡	‡	‡	‡	$0.51^{\dagger}$
LDL cholesterol, mg/dL	109.7 ± 37.64	$0.45^{\dagger}$	0.57^{*}	$0.46^{\dagger}$	0.40	0.42
hs-CRP, mg/dL	7.76 ± 5.60	$0.47^{\dagger}$	0.38	0.30	$0.53^{\dagger}$	‡
Triglycerides, mg/dL	168.7 ± 74.06	0.77^{**}	0.86^{***}	0.81^{***}	0.75^{**}	‡
Plasma glucose, mg/dL	117.2 ± 50.69	‡	‡	‡	‡	‡
Insulin, pmol/L	44.58 ± 73.01	‡	‡	‡	‡	‡
Health-related quality of life	47.25 ± 13.03	0.37	0.54^{*}	0.55^{*}	0.37	$0.52^{\dagger}$

$^{***}P < 0.001$; $^{**}P < 0.01$; $^{*}P < 0.05$; $^{\dagger}P < 0.10$; $^{\ddagger}r < 0.25$ and $P > 0.0$.
All models are adjusted for age, gender, race/ethnicity, leisure-time physical activity, insomnia symptoms, and intervention assignment.

and inflammation (hs-CRP). In contrast, Method 5 produced a different profile of correlation with health outcomes. Method 5 computed correlation as the root-mean-square error of the difference ($s - r$) between corresponding points in the original data and the pattern. This tells us the sum of absolute differences between the pattern and the original signal. This metric was associated with HDL-cholesterol and systolic blood pressure, while Methods 1–4 were not. While it is not directly clear why these unique correlates were identified for the various periodicity strength metrics, it does suggest that nuances in the rest-activity cycle may uniquely contribute to cardiometabolic disease risk.

4.1. Strengths and Limitations. An important strength of this study was the long-term, longitudinal nature of the collection of accelerometry data. Typically, accelerometer data are collected for seven or fewer consecutive days. These analyses demonstrate a novel methodology for harnessing longitudinal accelerometry data with demonstrated additional explanatory power for health outcomes beyond what has typically been reported in reports of accelerometry data and health outcomes. An additional strength was the minimal missing accelerometer data. While the methods employed here were relatively robust to missing data, the trivial missing data demonstrates the feasibility of collecting long-term monitoring data. A final strength of this study was the reliance on a completely open-source, raw data collection methodology with no proprietary algorithms. An important limitation of this preliminary study was the relatively small sample size and limited duration of the monitoring period. While there was substantial within- and between-person variability in periodicity strength observed, a larger sample may have yielded stronger and more definitive patterns in the rest-activity cycle. Relatedly, the sample was exclusively those with elevated cardiometabolic risk and the results may not generalize to a healthy population. Furthermore, while the length of the monitoring was indeed longer than typically what is reported, longer monitoring periods may have yielded more interesting month, seasonal, or annual patterns of data as have been observed in other forms of lifelog data [15]. Additionally, while the periodicity strength metrics were calculated based on longitudinal data, the cardiometabolic and health-related quality of life metrics were measured concurrently, and therefore the relationships reported represent cross-sectional associations. Finally, these data were collected in the context of a behavioral intervention. While the effect of this intervention was statistically adjusted for, residual confounding may exist.

4.2. Future Directions. Logical next steps for this work are threefold. First, replication of these methods in larger and more diverse samples is warranted. This may include the use of existing cohorts where raw data collection protocols of 24 h accelerometry are in place (even protocols that only include seven days of wear) with health-related outcomes measured in a cross-sectional or longitudinal fashion (e.g., US National Nutrition and Health Examination Survey, UK Biobank). Second, if these metrics are further shown to be related to health outcomes, it becomes critical to understand whether these metrics may be amenable to behavioral intervention and by what means this may be possible. It is not known whether this metric may be more sensitive to changes in sleep, sedentary behavior, physical activity, some combination of these behaviors, or some alternative strategy not currently being considered. Given this metric's independence from physical activity and sleep, it may require novel intervention strategies. Further clarification is needed for why these metrics were associated with certain biomarkers and not others, as well as why there was such variability in the strength of these associations with various biomarkers. Carefully laboratory-based studies that seek to experimentally manipulate the rest-activity cycle (and consequently change periodicity strength) may be useful in understanding the physiological mechanisms underlying these relationships. Finally, because of the cross-sectional nature of the current study, causality cannot be established, and therefore it is

imperative that these relationships be followed longitudinally where periodicity strength is experimentally manipulated in a manner to invoke changes in cardiometabolic risk biomarkers. This would provide greater clarity regarding the overall direction of the mechanistic effects.

5. Conclusion

The use of periodograms and periodicity strength represents a novel methodology for understanding long-term monitoring of 24 h accelerometry data. This analytical framework can be used with minimally processed accelerometer data and, in this sample, demonstrated moderate to strong independent associations with key cardiometabolic and health-related quality of life outcomes. This framework and preliminary work may be useful as long-term monitoring of accelerometer data across the 24 h becomes more commonplace in epidemiological and intervention research.

Disclaimer

The contents of this paper do not represent the views of the Department of Veterans Affairs or the United States Government.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Research Article

Quantification of Outdoor Mobility by Use of Accelerometer-Measured Physical Behaviour

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Hip fractures in older persons are associated with both low levels of daily physical activity and loss of outdoor mobility. The aim was to investigate if accelerometer-based measures of physical behaviour can be used to determine if people undertake outdoor walking and to provide reference values for physical behaviour outcomes related to outdoor mobility. Older persons ($n = 245$), ≥70 years, one year after hip fracture, participated. Six objective measures of physical behaviour collected by an activity monitor were compared with self-reported outdoor mobility assessed with the Nottingham Extended ADL scale. All measures of time and length in upright periods were significantly lower in participants who reported not walking outdoors ($p < 0.001$). A set of cut-off points for the different physical behaviour variables was generated. Maximum length of upright events discriminated best between groups, with 31 minutes as a threshold to determine if a person is more likely to report that they walk outdoors (sensitivity: 0.805, specificity: 0.704, and AUC: 0.871) or 41 minutes or more to determine if a person is more likely to report outdoor walking on their own (AUC: 0.891). Physical behaviour variables from activity monitoring can provide information about patterns of physical behaviour related to outdoor activity performance.

1. Introduction

The ultimate aim for many older people is to preserve mobility and stay independent and particularly maintain the ability to walk outdoors. Mobility limitations are however common and have often serious consequences for daily life. Activities of daily living (ADL) instruments often assess if people feel capable of performing activities, for example, outdoor walking [1]. However, for prevention of mobility decline early detection of changes in amount and patterns of actually performed physical activities during daily life is essential.

Low levels of physical activity are common following hip fracture [2, 3] and affect mobility in the short and long run [4]. Few older people return to their prefracture mobility levels after a hip fracture, and many will not be able to walk independently or go out of the house alone [5]. To regain walking ability after hip fracture sufficient mobilisation and physical activity is needed [6].

Activity monitoring using small, body-worn accelerometers enables continuous recording of physical behaviour and can inform on what people actually do during daily life. Thus, such instruments and methods have become important supplements to measures of health and function. Several variables derived from activity monitoring could potentially provide details also on outdoor mobility.

There is little known about the relationship between the monitored free-living physical behaviour and self-reported outdoor mobility. We hypothesised that measures of time and length of upright periods could be used to determine if people walk outdoors. If contextual information about outdoor versus not outdoor walking could be derived directly from the activity monitoring data, this could contribute to early detection of changes in daily life that could be important for prevention of mobility decline in older people in general and hip fracture patients in particular. The aim of this study was therefore twofold: to investigate if accelerometer-based

measures of physical behaviour can be used to determine if people undertake outdoor walking and to determine reference values for measures of physical behaviour related to outdoor mobility in this population.

2. Methods

2.1. Study Design and Recruitment. This was a cross-sectional study using data from the Trondheim Hip Fracture Trial which included 397 community-dwelling subjects with hip fracture aged 70+ years with the ability to walk 10 meters prior to the fracture. In total 245 participants completed the activity monitoring recordings one year after the hip fracture. The study protocol, the intervention, and the main results have been published previously [3, 7–9]. For this paper all participants with a minimum of three complete continuous days of activity monitoring (range 3–7 days) one year following the hip fracture were included. The Trondheim Hip Fracture Trial was approved by the Regional Committee of Ethics in Medical Research (REK 4.2008.335), the Norwegian Social Service Data Services (NSD19109), and the Norwegian Directorate of Health (08/5814). ClinicalTrials.gov registry number was NCT00667914.

2.2. Measures. Prefracture function was assessed retrospectively using the Nottingham Extended Activities of Daily Living scale (NADL, 0–66) [10] and the Barthel Index (BI, 0–20) [11]. Other demographic variables included age, sex, and fracture type (intracapsular or extracapsular). Background information one year following the fracture included NADL, BI, cognitive function by the Mini Mental State Examination (MMSE, 0–30) [12], mobility by the Timed Up-and-Go (TUG) (sec) [13] and the Short Physical Performance Battery (SPPB) (0–12) [14], Gait Speed over 4 meters assessed as part of SPPB (m/s), depression by the geriatric depression scale (GDS) (0–15) [15], Grip Strength using a Jamar Hydraulic Hand Dynamometer (kg), and self-reported Fear of Falling by the 7-item Fall Efficacy Scale International (FES-I) (7–28) [16].

Physical behaviour was assessed using thigh-worn, single-axis accelerometer-based activPAL monitors (PAL Technologies Ltd., Glasgow, United Kingdom). The monitor is 7 mm (depth) × 53 mm (length) × 35 mm (width) and weighs 20 grams, sampling at 10 Hz, and the battery capacity allows monitoring for more than 7 days. The inertial sensor produces a signal related to thigh inclination and can thus identify posture (sitting/lying from standing) from the position of the thigh [17]. The activity monitors were attached to the front of the participants' nonaffected lower thigh with waterproof tape and worn continuously during the recording period. From the software output of the activPAL information on all upright (standing plus walking) events can be derived for the entire recording period. For this study individual number of upright events and the duration of each of these upright events were used in the analysis. Classification of number of upright events and duration of upright events has previously been shown to be 100% accurate in hip fracture patients [18]. In this study we derived outcomes over each participant's recording period, which varied from three to seven recording days. The six physical behaviour outcomes of interest were mean upright time per day, mean number of upright events per day, mean and median length of upright events, maximum length of all upright events, and variability in upright event lengths (the interquartile range (IQR) measured in minutes).

Outdoor mobility 12 months after the fracture was assessed by use of one of the NADL items, where participants, or their next of kin, were asked if they had been walking outdoors during the past 14 days. The possible responses to this item were as follows: not walking outdoors, walked outdoors with personal assistance, walked outdoors alone with difficulty, or did walk outdoors alone.

From the sample, 81 participants reported that they had not been outdoors, 33 did go outdoors with personal assistance, 36 did go outdoors alone with difficulty, and 95 did go outdoors alone. Those reporting not to have walked outdoors ($n = 81$) during the past 14 days were classified as "not outdoors," and those who reported that they had walked outdoors either alone, alone with difficulty, or with assistance ($n = 164$) were classified as "outdoors." We also divided the sample into "not outdoors alone," those reporting that they had not been walking outdoors or had been walking outdoors with assistance ($n = 114$), and "outdoors alone" if reporting walking outdoors alone or alone with difficulty ($n = 131$).

2.3. Statistical Analysis. Data were checked for normality by visual inspection of Q-Q plots and the Kolmogorov-Smirnov test. Results are reported as means and standard deviations (SD). The association between physical behaviour and outdoor mobility was assessed by Spearman's correlation coefficients. Differences in physical behaviour between groups were analysed using independent samples t-tests and Mann-Whitney U tests, and p values <0.05 were considered statistically significant.

The Receiver Operating Characteristic (ROC) curves for all six measures of physical behaviour were plotted to discriminate both "outdoors" from "not outdoors" and "outdoors alone" from "not outdoors alone." Sensitivity was defined as the probability of correctly classifying "outdoors" and "outdoors alone" and specificity was defined as the probability of correctly classifying "not outdoors" and "not outdoors alone." The area under the ROC curves (AUC) is the product of sensitivity and specificity, where 1.0 represents perfect classification of the outdoor mobility question, and values of ≥0.90 are considered excellent, 0.80–0.89 good, 0.70–0.79 fair, and <0.70 poor [19]. The AUC was used to evaluate overall performance of each physical behaviour outcome measure. For each measure a cut-off point with sensitivity as close to 80% as possible was selected and used as the optimal cut-off point for that measure. All analyses were performed using IBM SPPS statistics 19.0.

3. Results

The 245 participants had a mean age of 83.1 years (SD 5.9) and 76% were women. Femoral neck fractures occurred in 153/245

Table 1: Sample characteristics 12 months after hip fracture surgery.

	Number of subjects *N*	Value Mean (SD)	Spread (Range)
Physical behaviour:			
Mean upright time per day (min)	245	215.5 (133.6)	(0.3–553.2)
Mean number of upright events per day	245	43.8 (19.9)	(0.5–107.7)
Mean length of upright events (min)	245	4.8 (2.8)	(0.6–16.5)
Median length of upright events (min)	245	2.4 (1.3)	(0.52–7.95)
Maximum length of upright events (min)	245	48.9 (35.2)	(0.84–179.6)
Upright event variability (IQR, min)	245	4.8 (3.4)	(0.2–25.6)
Mobility:			
TUG 12 months (sec)	225	22.3 (15.8)	(7.8–126.9)
SPPB (0–12)	241	5.3 (3.3)	(0–12)
Gait Speed (m/s)	231	0.63 (0.25)	(0.07–1.42)
ADL function:			
BI (0–20)	245	16.9 (3.8)	(4–20)
NADL (0–66)	245	34.4 (19.3)	(1–66)
Cognitive function, MMSE (0–30)	243	24.0 (5.0)	(5–30)
Depression, GDS (0–15)	235	4.1 (3.2)	(0–13)
Grip Strength (kg)	234	21.6 (8.0)	(4–54)
Fear of Falling, FES-I (7–28)	231	11.1 (4.1)	(7–28)

*Mean upright time per day (min): total minutes of all upright events/number of recording days; mean number of upright events per day: average number of upright events per day; mean length of upright events: average length in minutes based on all upright events during the recording period; maximum length of upright events: maximum length in minutes for the longest upright event during the recording period; median length of upright events: median length in minutes based on all upright events during the recording period; upright event variability: the interquartile range (IQR) of upright events lengths in minutes during the recording period; TUG: Timed Up-and-Go; SPPB: Short Physical Performance Battery; Gait Speed: based on the 4-meter gait test from SPPB; BI: Barthel Index; NADL: Nottingham Extended Activities of Daily Living scale; MMSE: Mini Mental State Examination; GDS: geriatric depression scale; Grip Strength: measured by the JAMAR dynamometer in kg; FES-I: the 7-item Fall Efficacy Scale International FES-I.

(62.4%). Their prefracture BADL score was 18.6 (SD 2.2) and NADL score was 45.7 (SD 16.9). Detailed information about participants' physical behaviour and characteristics 12 months after surgery are presented in Table 1.

The results for the six measures of physical behaviour for the four subgroups based on level of self-reported outdoor mobility are shown in Figure 1. Scores on the outdoor mobility scale and outcome measures of physical behaviour showed positive correlation: mean upright time ($r = 0.61$, $p < 0.001$), number of upright events ($r = 0.36$, $p < 0.001$), mean length of upright events ($r = 0.58$, $p < 0.001$), median length of upright events ($r = 0.37$, $p < 0.001$), maximum length of upright events ($r = 0.67$, $p < 0.001$), and upright event variability ($r = 0.52$, $p < 0.001$).

Furthermore, the six measures of physical behaviour were all significantly different between groups regardless of the classification used, "outdoors" versus "not outdoors" and "outdoors alone" versus "not outdoors alone" ($p < 0.001$); for details see Table 2(a). Figure 2 shows the distribution of the length of upright events in the total sample and in the "outdoors" versus "not outdoors" and the "outdoors alone" versus "not outdoors alone."

Cut-off points of outdoors mobility for mean upright time per day, mean number of upright events per day, mean length of upright events, median length of upright events, maximum length of upright events, and upright event variability are reported in Table 2(b). Maximum length of upright events provided the best cut-off points for both "outdoors" and "outdoors alone" (AUC = 0.87 and 0.89, resp.). If the maximum length of upright events was above 31 minutes it was more likely that subjects reported that they walked outdoors, with a sensitivity of 80.5% and specificity of 70.4%. For those with independence in outdoor walking, levels above 41 minutes for maximum length of upright events showed a sensitivity of 80.2% and specificity of 83.3%. Good classification accuracy was also shown for mean upright time per day, mean length of upright events, and upright event variability, with sensitivity of >0.80 and specificity of >0.60 for correct classification of outdoor mobility. Number of upright events per day and median length of upright events showed fair classification accuracy (AUC > 0.70, 95% CI from 0.62).

4. Discussion

This study investigated the relation between self-reported outdoor mobility and monitored physical behaviour in older people one year after hip fracture in order to see how well physical activity monitoring can be used to estimate outdoor walking.

Hip fractures in older persons are associated with low levels of daily physical behaviour and a loss of outdoor mobility. Participants in this study had a mean upright time of 3 hours and 36 minutes, an average of 44 transitions to

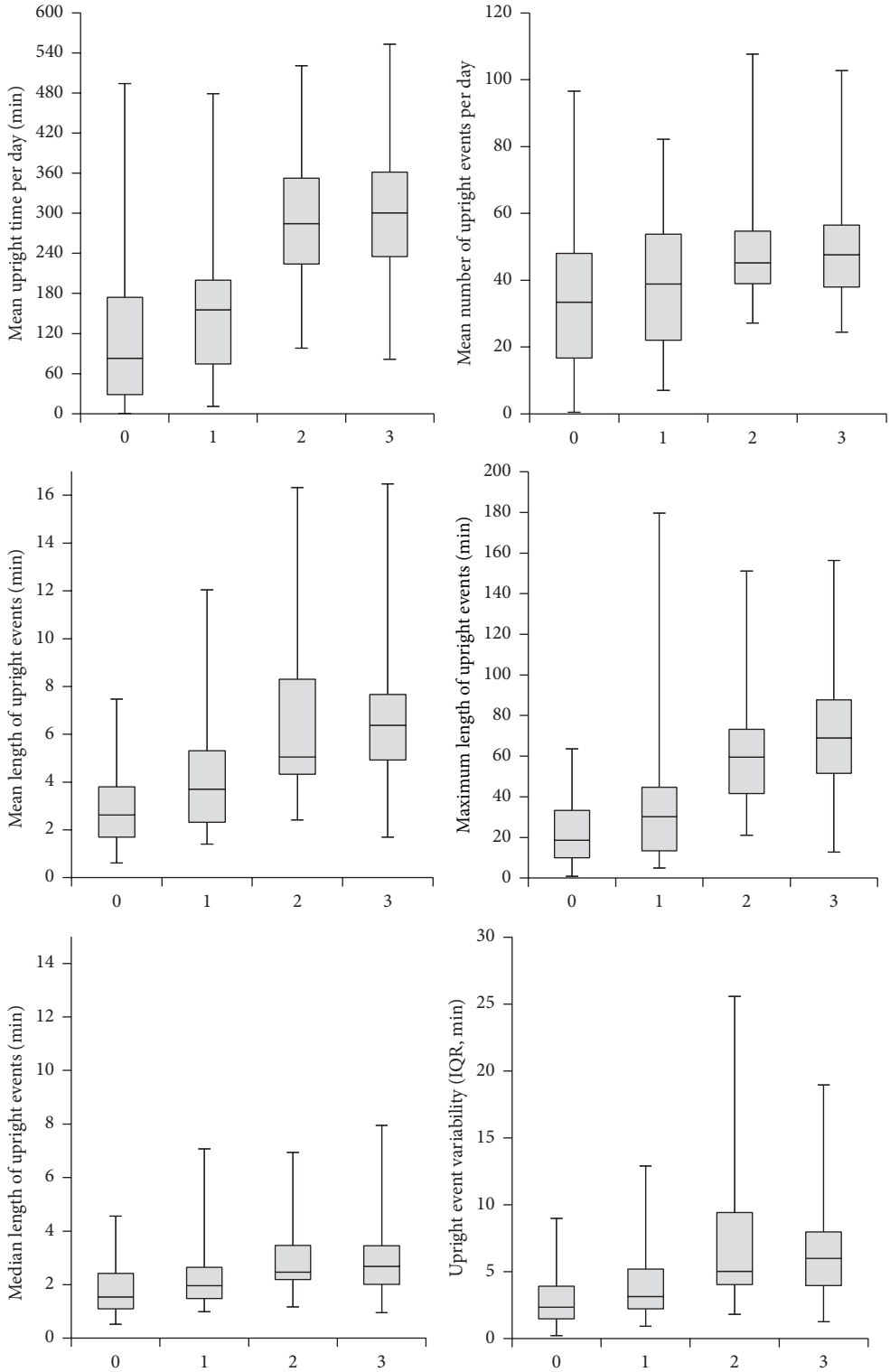

Figure 1: Physical behaviour in the four groups based on the single question from NADL. The boxplots show the lower quartiles, median, and upper quartiles, and the whiskers show the minimum and maximum values, for the six outcomes of physical behaviour. *0: not walking outdoors; 1: did go walking outdoors with personal assistance; 2: did go walking outdoors alone with difficulty; 3: did go walking outdoors alone. Those reporting 0 were classified as "not outdoors" versus 1, 2, and 3 as "outdoors"; those reporting 0 and 1 were classified as "not outdoors alone" versus 2 and 3 as "outdoors alone."

Table 2: (a) Group differences in physical behavior. (b) Results of receiver operating characteristic curve between measures of physical behaviour and reports on outdoor mobility (n = 245).

(a)

	"Not outdoors" versus "outdoors"					"Not outdoors alone" versus "outdoors alone"				
	Group 0, Figure 1 (n = 81)		Groups 1, 2, and 3, Figure 1 (n = 164)		Independent t-test	Groups 0 and 1, Figure 1 (n = 114)		Groups 2 and 3, Figure 1 (n = 131)		Independent t-test
	Mean	(SD)	Mean	(SD)	p =	Mean	(SD)	Mean	(SD)	p =
Mean upright time per day (min)	114.8	(100.3)	265.2	(119.4)	<0.001	127.9	(104.1)	291.7	(107.2)	<0.001
Mean number of upright events per day	35.0	(21.9)	48.2	(17.3)	<0.001	36.2	(21.3)	50.4	(15.9)	<0.001
Mean length of upright events (min)	2.9	(1.5)	5.8	(2.8)	<0.001	3.3	(1.9)	6.2	(2.7)	<0.001
Maximum length of upright events (min)	21.7	(14.7)	62.3	(34.7)	<0.001	26.3	(23.7)	68.5	(31.8)	<0.001
Median length of upright events (min)	1.8	(0.9)	2.7	(1.3)	<0.001	2.0	(1.1)	2.8	(1.3)	<0.001
Upright event variability (min)	2.8	(1.7)	5.8	(3.5)	<0.001	3.2	(2.2)	6.3	(3.5)	<0.001

*The NADL question used was if the participants had been walking outdoors the past 14 days. "Not outdoors": participants who had not walked outdoors; "outdoors": participants who had walked outdoors either alone, alone with difficulty, or with assistance; "not outdoors alone": participants who had not walked outdoors or walked outdoors with assistance; "outdoors alone": participants who reported walking outdoors alone or alone with difficulty. Mean upright time per day (min): total minutes of all upright events/number of recording days; mean number of upright events per day: average number of upright events per day; mean length of upright events: average length in minutes based on all upright events during the recording period; maximum length of upright events: maximum length in minutes for the longest upright event during the recording period; median length of upright events: median length in minutes based on all upright events during the recording period; upright event variability: the interquartile range (IQR) of upright events lengths in minutes during the recording period.

(b)

Measure of PB	Outdoor mobility					Independent outdoor mobility				
	AUC	95% CI	SENS	SPEC	CP	AUC	95% CI	SENS	SPEC	CP
Mean upright time per day	0.836	0.78–0.89	0.805	0.716	157.7	0.865	0.82–0.91	0.802	0.754	198.9
Mean number of upright events per day	0.697	0.62–0.77	0.805	0.531	34.8	0.707	0.64–0.77	0.802	0.526	36.8
Mean length of upright events	0.834	0.78–0.89	0.811	0.679	3.4	0.838	0.79–0.89	0.802	0.719	4.0
Maximum length of upright events	0.871	0.83–0.91	0.805	0.704	30.8	0.891	0.85–0.93	0.802	0.833	41.2
Median length of upright events	0.732	0.66–0.80	0.805	0.519	1.7	0.719	0.66–0.78	0.802	0.535	1.8
Upright event variability	0.804	0.75–0.86	0.805	0.605	3.2	0.810	0.76–0.86	0.802	0.640	3.5

*AUC: area under receiver operating characteristic curve; CP: cut-off point for predictors above which subject is more likely to report that they are outdoor walking; n: sample; SENS: sensitivity; SPEC: specificity; PB: physical behaviour; mean upright time per day: total minutes of all upright events/number of recording days; mean number of upright events per day: average number of upright events per day; mean length of upright events: average length in minutes based on all upright events during the recording period; maximum length of upright events: maximum length in minutes for the longest upright event during the recording period; median length of upright events: median length in minutes based on all upright events during the recording period; upright event variability: the interquartile range (IQR) of upright events lengths in minutes during the recording period.

upright per day, and only half of them reporting that they had been outdoors alone (53%) one year following the hip fracture. On average participants' longest upright event was almost 50 minutes. However, the mean length of upright events was just below five minutes with a variability of almost 5 minutes. For this relatively inactive sample the ability to walk outdoors would represent an important function in their daily life of great importance for independence in activities of daily living.

To our knowledge, this study is the first study to evaluate if we can derive context from activity monitoring data. In this study, all the six chosen outcome measures of physical behaviour could discriminate if a participant reported to have walked outdoors and cut-off points for all measures were therefore determined. Maximum length of upright events provided the best cut-off for outdoor mobility, with a specificity of 80-81% and a sensitivity of 70–80%. The high classification accuracy could be because a person's maximum

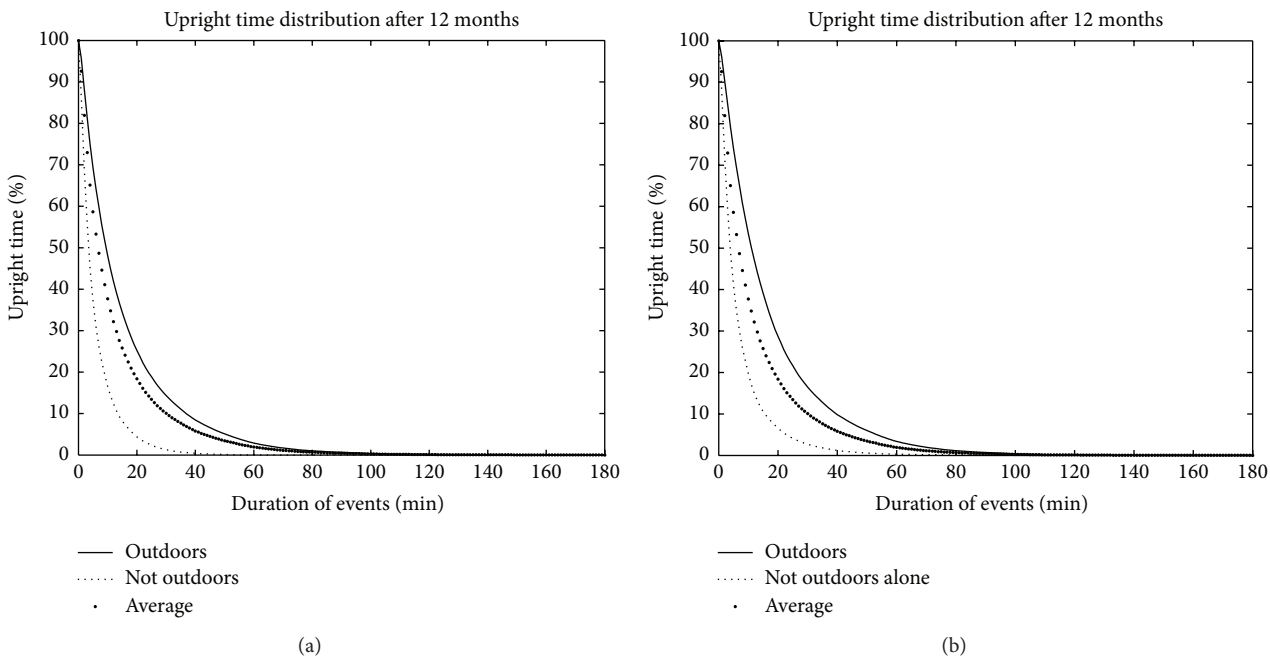

Figure 2: Plot of distributions of time according to lengths of upright event, where outdoors versus not outdoors (a) and outdoors alone versus not outdoors alone (b) are shown. The distribution for the average participant is shown in both figures (black dots in the middle). The percentage of upright time (y-axis) by lengths of upright events from shortest to longest (x-axis) shows that more of the total upright time was spent in longer upright events for the outdoors/outdoors alone versus not outdoors/not outdoors alone.

length of an upright event might be more closely related to outdoor walking episodes as compared to the other measures of physical behaviour included in this study.

Walking time was not included as a separate outcome in this study, because the monitor's ability to detect steps for older persons walking at very slow gait speeds has been shown to be inaccurate [18]. We therefore used upright time, including both standing and walking. Upright time is a commonly used measure of physical behaviour reported in studies of older persons [3, 20], and results from this study showed that this outcome was a good discriminant of self-reported outdoor mobility in this population. Walking related outcomes from activity monitoring could possibly be even more relevant measures, especially when outdoor walking is of interest.

This study has several limitations. First, we did not consider use of walking aids in the analyses. The single question from NADL only included three answers for those walking outdoors, distinguishing walking alone from walking with difficulty from walking with assistance [10]. In groups 2 and 3 (Figure 1), it would have been interesting to identify those using walking aids, knowing that walking aids could be marker for impairment in older persons who report no difficulty when walking [21]. We also only used six measures of physical behaviour all related to upright periods and therefore consider this paper as an initial first step. Furthermore, we assessed outdoor walking as self-report, which may be affected with recall bias when assessed over a period of 14 days in this old and relatively frail population.

Further work should look into the different measures of physical behaviour and how levels and patterns of these measures are associated with physical function. This will allow clinicians to quantify patterns of physical behaviour important for prevention of functional decline in older populations.

This study confirmed that self-reported outdoor mobility and monitored physical behaviour are related. This study is however the first step in demonstrating that activity monitoring can be used to indicate if a person walks outdoors or not. Based on the data we cannot detect the exact periods of outdoor activity and cannot thus quantify the amount and pattern of the outdoor activity.

Activity monitoring provides information that is valuable because it is different from what can be obtained using assessment of physical function by self-report. Future studies should explore measures of physical behaviour more in detail, especially related to amount or level of activity needed to maintain outdoor mobility in older age.

5. Conclusion

Objective accelerometer-measured physical behaviour can provide important information related to outdoor mobility. The suggested cut-off points for the six physical behaviour measures in this study can be used to distinguish persons who usually walk outdoors from persons who do not walk outdoors, particularly for those who walk outdoors independently from those who do not walk outdoors independently. If a person spends long periods above 41 minutes upright, he or she is likely to be undertaking independent outdoor mobility (specificity of 80% and sensitivity of 83%). Furthermore, the six cut-off points can be used as reference values, providing quantitative information about physical behaviour

related to outdoor mobility that may be useful for clinicians aiming at maintaining outdoor mobility in older people.

Conflict of Interests

Malcolm H. Granat is a coinventor of the activPAL physical activity monitor and a Director of PAL Technologies Ltd.

Authors' Contribution

Kristin Taraldsen, Malcolm H. Granat, and Jorunn L. Helbostad were responsible for the design, interpretation of results, writing the paper, and approving of the final paper.

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Research Article

Long-Term Monitoring of Physical Behavior Reveals Different Cardiac Responses to Physical Activity among Subjects with and without Chronic Neck Pain

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Background. We determined the extent to which heart rate variability (HRV) responses to daily physical activity differ between subjects with and without chronic neck pain. *Method*. Twenty-nine subjects (13 women) with chronic neck pain and 27 age- and gender-matched healthy controls participated. Physical activity (accelerometry), HRV (heart rate monitor), and spatial location (Global Positioning System (GPS)) were recorded for 74 hours. GPS data were combined with a diary to identify periods of work and of leisure at home and elsewhere. Time- and frequency-domain HRV indices were calculated and stratified by period and activity type (lying/sitting, standing, or walking). ANCOVAs with multiple adjustments were used to disclose possible group differences in HRV. *Results*. The pain group showed a reduced HRV response to physical activity compared with controls ($p = .001$), according to the sympathetic-baroreceptor HRV index (LF/HF, ratio between low- and high-frequency power), even after adjustment for leisure time physical activity, work stress, sleep quality, mental health, and aerobic capacity ($p = .02$). The parasympathetic response to physical activity did not differ between groups. *Conclusions*. Relying on long-term monitoring of physical behavior and heart rate variability, we found an aberrant sympathetic-baroreceptor response to daily physical activity among subjects with chronic neck pain.

1. Introduction

Chronic pain in the neck region is a common condition [1], particularly in the working population [2]. Long-term, continuous monitoring of behavioral and physiological responses in daily living opens new opportunities for gaining knowledge on the pathophysiology, prevention, and treatment of these pain conditions.

Research suggests that the autonomic nervous system (ANS) is involved in the development and persistence of chronic muscle pain at both central and peripheral levels [3–5], as well as in adaptive responses to acute experimental pain [6].

Heart rate variability (HRV) is a valid and reliable biomarker of autonomic regulation, including parasympathetic and sympathetic-baroreceptor influences on cardiac modulation [7–10]. Autonomic activity, as assessed through HRV indices in time and frequency domains, differs between subjects with and without chronic neck pain during controlled laboratory rest [11] and during sleep [12, 13]. This reflects a reduced basal parasympathetic activity in subjects with pain, corroborating studies using heart rate and blood pressure as measures of ANS activity at rest [14, 15].

Even the HRV response to physical work appears to be affected in pain conditions. In a recent study [11], chronic neck pain was associated with attenuated low-frequency (LF) spectral power during submaximal isometric handgrip, while high-frequency (HF) spectral power was similar for the pain and control groups. Similarly, Shiro et al. [16] found the LF/HF ratio to be increased in healthy subjects during maximal isometric contractions of the trapezius muscles, while no change in LF/HF was found in subjects with neck pain, suggesting an aberrant sympathetic-baroreceptor response to

isometric exercise in pain, and parasympathetic withdrawal is normal. The latter was confirmed by Elcadi et al. during sustained shoulder elevation [17]. These autonomic responses are clinically important as they may contribute to altered pain processing [4, 18], decreased tolerance to physical loads [19], and poor cardiovascular prognosis [20, 21]. Thus, maladaptive autonomic responses to physical work may be involved in maintaining chronic neck pain.

While pain and control groups differ in HRV response to controlled physical work, no study has, to our knowledge, investigated the extent to which HRV is altered in response to naturally occurring physical activity in people with chronic neck pain, with due consideration to essential confounders, such as mental and physical health [22], sleep quality [23], and work stress [24]. Notably, chronic pain is often associated with reduced levels of physical activity [25], which is, in turn, associated with reduced HRV [26–28].

Studies of physical activity require accurate and precise measurement methods, preferably based on objective devices such as accelerometers, as self-reported measures of physical activity are less reliable, prone to bias [29], and operate at a level of resolution which may not be sufficient to disclose associations between, for instance, the temporal structure of physical activity and health outcomes. In this context, it is important to discriminate between physical activity practiced at work and during leisure, which may differ markedly in both structure and effects. For instance, studies have found that leisure time physical activity is beneficial for cardiovascular health [30], including an enhanced autonomic function [27], while occupational physical activity may be even detrimental [31, 32]. Work and leisure periods can be separated by means of self-reports, which may, however, be both time-consuming and disturbing for the participant, while providing less precise data compared to objective methods [33]. Using information from the Global Positioning System (GPS) is an established tool for objective assessment of time series of geographical data [34, 35], and it does allow for a detailed separation of periods of work and leisure. The present study aimed at determining the extent to which HRV responses to different types of physical activity differ between subjects with chronic neck pain and healthy controls and at investigating whether these HRV responses differ between work and leisure, as identified by GPS complimented with diaries. We hypothesize that chronic neck pain will be associated with an aberrant HRV response to daily physical activity, as compared with no pain.

2. Methods

2.1. Subjects. Twenty-nine workers (13 women, 16 men; mean age 41 (SD = 10) years) with chronic neck pain and 27 age- and gender-matched healthy workers without a recent history of pain participated. Subjects were recruited through advertisement at a large industrial plant in Sweden (>5000 employees at site) belonging to a global steel manufacturing company, in cooperation with ergonomists and health care specialists working at the company.

First, eligibility was evaluated using interviews and questionnaires followed by a physical examination. Inclusion in the pain group required nontraumatic chronic pain (>6 months) localized to the neck-shoulder region (i.e., primarily the neck and/or the regions corresponding to the trapezius muscles according to a pain drawing). Controls were included only if they were reported to be healthy and asymptomatic. Both pain and control subjects had to be between 20 and 59 years of age and to work at least 75% of full-time work. Both males and females were allowed into the study. Exclusion criteria included regular use of medication that could affect cardiovascular function or pain perception (e.g., antidepressants, beta-blockers, and anti-inflammatory drugs). Individuals were also excluded if they reported comorbidity with other disorders known to affect physical activity, autonomic regulation, or pain processing (e.g., diabetes, depression, and cardiovascular diseases), drug abuse, pain of traumatic origin (e.g., whiplash associated disorders), or neuropathic pain conditions. Workers were also excluded if reporting sick leave more than 2 weeks within the past three months.

Eligible subjects with and without pain were examined by a specialized physiotherapist [36]. Subjects were classified as having chronic neck pain, corresponding to the International Classification of Diseases (ICD-10) code M 79.1, if they reported chronic pain from the neck-shoulder region, muscle stiffness, and tenderness at palpation without restricted range of motion of the neck during the examination [36–38]. All subjects were given information about the study prior to participation and provided written informed consent. The study was approved by the regional ethical review board in Uppsala, Sweden, and was conducted according to the Declaration of Helsinki.

2.2. Procedure. Data were collected from May 2011 to June 2012, although no data were collected from November to April to minimize seasonal effects on physical activity. Shortly after being recruited for the study, subjects filled in a battery of questionnaires (below) and went through a long-term recording of objectively measured physical activity, HRV, location by GPS, and self-reported symptoms [12]. With few exceptions, the ambulatory measurement period started at the beginning of a regular week and lasted for up to seven days. An accelerometer for assessment of physical activity was worn for seven days, while a heart rate monitor and a smartphone, containing an electronic diary and GPS software, were worn by the subjects for approximately 72 hours (i.e., the first three days of the seven-day recording), typically representing three full workdays of daytime work. For all of these measures, only data from the first 72 hours were analyzed in the present study. Subjects were equipped with the assessment devices at their work place. The devices were only removed during a shower or a bath and replaced shortly after that. Subjects were instructed to wear the smartphone during all waking hours and to rate their perceived stress level when prompted by an auditory signal (see below). They were instructed to perform their regular activities and were advised to contact the examiner if they had any complaints caused by the data collection.

2.3. Assessment of Work and Leisure Periods. GPS coordinates were sampled at 0.2 Hz using the freely available software

Map WM (http://www.mapwm.com/) installed on a Smartphone (HTC *HD2*) with a Windows operative system. The GPS coordinates combined with self-reported periods of work, leisure, and sleep, were used to identify periods of work and leisure time, the latter classified as either "at home" or "elsewhere." Working hours were identified solely from the diary reports, and leisure time, whether "at home" or "elsewhere," was recognized only if the diary indicated leisure time. The "at home" location was identified as the spatial region within 50 meters from the median GPS position during sleep and "elsewhere" was defined as anywhere outside this "at home" region. Sleep periods were not considered in the present study. Thus, all temporal data (i.e., physical activity, HRV, and stress ratings) were partitioned according to whether it occurred during "work," leisure "at home," or leisure "elsewhere."

2.4. Objectively Measured Physical Activity. Physical activity was objectively measured using a single triaxial accelerometer (ActivPAL; PAL Technologies Ltd., Glasgow, UK) attached to the thigh using self-adhesive tape, producing data at 20 Hz. The device has shown good validity and reliability in detecting different types and intensities of physical activity in daily life [39–41]. Time spent walking, standing, and sitting/lying, number of steps, and cadence (steps/minute) were calculated offline using the commercial software accompanying the accelerometers. For each of these activities, the average metabolic equivalent (MET/hour) was estimated [42] as a measure of energy expenditure (i.e., *sitting/lying* = 1.25 METs; *standing* = 1.4 METs; *stepping* 120 steps/minute = 4 METs; the increase in walking energy expenditure was estimated to be 0.22 METs for every increment of 10 steps/minute from standing, i.e., 0 steps/minute).

2.5. Heart Rate Variability. Interbeat electrocardiogram intervals (IBIs) were collected using a heart rate monitor (Firstbeat Bodyguard; Firstbeat Technologies Ltd., Jyväskylä, Finland) attached using preglued Ag/AgC1 electrodes (Biopac Systems Inc., USA) on cleansed skin. IBI time series were first processed and analysed using Firstbeat HEALTH (version 3.1.1.0, Firstbeat Technologies Ltd., Jyväskylä, Finland), using procedures for automatic data editing and short-term Fourier transform filtering described by Saalasti [43]. Only periods free from artefacts due to, for example, noise, ectopic beats, or nonwear time, were analysed. On average, one recording included 97.4% (SD 3.7%) acceptable data. HRV was analysed according to Task Force [44] in the time domain (i.e., IBI and the square root of the mean squared successive differences of IBIs RMSSD) and the frequency domain (i.e., the ratio between low-frequency (LF 0.04–0.15 Hz) and high-frequency (HF 0.15–0.4 Hz) spectral power (ms^2), LF/HF). RMSSD was used as a measure of parasympathetic (vagal) activity [7, 9], while LF/HF was used as a measure of sympathetic-baroreceptor activity [44, 45].

2.6. Self-Reported Neck Pain. Pain localization was assessed using a modified pain drawing [46]. The average perceived pain intensity in the neck region during the previous "six months" and "seven days" was rated using the Borg CR10 scale [47]. The response scale ranges from 0 ("nothing at all") to 10 ("extremely strong").

2.7. Assessment of Potential Confounders. Gender, age, weight, height, and type of work (office or production) were assessed by self-reports.

The short form health survey (SF-36) was used to assess health-related functions and quality of life [48]. The mental health component (one out of eight dimensions in SF-36) rated on a 0–100 scale was used in the present study, whereby a higher score reflects better health.

The Karolinska Sleep Questionnaire (KSQ) [49] was used to assess sleep quality based on four items: difficulty falling asleep, repeated awakenings, premature awakening, and disturbed sleep. Subjects rated their experiences over the past six months using a response scale from 1 (always) to 6 (never). The four sleep quality items were added up to create a sleep quality index ranging from 0 to 24, whereby higher values indicated better sleep.

The intensity of current symptoms (pain, stress, and fatigue) was assessed in a custom-made electronic diary, installed on the smartphone. Thus, the intensity of "current" stress was assessed using the CR10 scale [47] 30 minutes after waking up in the morning, every second hour from 09:00 to 17:00, at 20:00, and just before going to bed. An auditory reminder was repeated three times at ten-minute intervals in case a rating was missed.

Aerobic capacity, VO_{2max}, was assessed using a submaximal cycle ergometer test according to Åstrand and Rhyming [50].

2.8. Further Processing of Heart Rate Variability (HRV). All data obtained from the 72-hour recording, including the objective measurements (GPS coordinates, IBI, frequency HRV values (see below), physical activity types, and METs) and the stress ratings were imported to the Spike2 software (version, 7.03, Cambridge Electronic Design) for visual data inspection and further data processing.

Each HRV index was assessed for periods classified as sitting/lying, standing, and walking, respectively, for each of the three locations of work, leisure at home, and leisure elsewhere. Series of IBIs and successive differences of IBIs were concatenated within each activity category (periods containing less than 3 IBIs were excluded). For each activity type, we calculated the average IBIs, RMSSD (average of 5 min RMSSD epochs), and LF/HF (averages of 1 min LF/HF epochs).

In total, 49 subjects (pain, $n = 25$; control, $n = 24$) with acceptable data on GPS, physical activity, and HRV were included in the statistical analyses. The analysis of LF/HF included only 42 subjects (pain, $n = 20$; control $n = 22$), mainly due to a lack of standing periods exceeding 1 min in leisure "elsewhere" for some subjects.

2.9. Statistical Analyses. Descriptive data are presented as frequencies or as mean with standard deviation (SD) between subjects. Chi^2 tests were used to test for differences between

pain and control groups in the distribution of gender and work type (office versus production). t-tests for independent samples were used to test for group differences (pain versus control) in age, BMI, pain intensity, energy expenditure (METs), work stress, mental health, and sleep quality, as well as the duration of work and leisure periods.

Repeated measures ANOVA models were constructed to analyze HRV indices using *activity type* (3 levels: sit/lie, stand, and walk) and *location* (3 levels: work, leisure "at home," and leisure "elsewhere") as within-subject factors and *group* (2 levels: pain, control) and *work type* (2 levels: office, production) as between-subjects factors. In a second step, we included METs in leisure time "elsewhere" as a covariate to investigate the potential association between the extent of physical activity during leisure time, HRV, and pain.

In addition, the same mixed ANOVAs were expanded with a step-wise inclusion of covariates (ANCOVA) in the following order: age, gender, BMI, METs (leisure "elsewhere"), work stress, mental health, sleep quality, and VO_{2max}, all of which were selected based on previous reports of their relationship with autonomic function and pain. Covariates were excluded from the model if they showed p values larger than .10 for either their main effect on HRV or their interaction with *activity type*. All statistical analyses were performed using SPSS, version 22. p values less than .05 were considered to indicate significant effects.

3. Results

Table 1 shows descriptive variables in the pain and control groups. No group differences were observed for age, gender, work type, body mass index (BMI), or aerobic capacity (VO_{2max}). In the pain group, the self-reported duration of neck pain was, on average, 10.1 (SD 8.5) years, and the intensity of neck pain corresponded to "somewhat strong" according to the CR10 scale, for both the past six months and the past seven days. The average number of work days with acceptable recordings of GPS, HRV, and accelerometry was similar for the two groups. Also, there were no significant differences between the groups in total measured time at work or leisure "at home" and "elsewhere" (all $p > .45$). The pain group reported significantly higher perceived stress at work than the controls, although stress levels were overall quite low. Perceived mental health and sleep quality were reduced in the pain group compared with controls, although without reaching significance ($p > .05$).

For physical activity in terms of estimated accelerometry-based MET values, the pain group had significantly lower METs during leisure "elsewhere" than the controls, while no difference was found at work or leisure "at home." Figure 1 shows the proportion of time spent in different physical activities across locations in both groups. In comparison with work, leisure time "elsewhere" was characterized by an increased proportion of time spent in walking and reduced time in sitting/lying in the control group, while this increase in physical activity during leisure did not occur to the same extent in the pain group.

Table 1: Descriptive statistics for subjects with and without chronic neck pain and p values for tests of differences between the two groups.

	Group pain	Control	p
Males, n	13	14	.78
Females, n	12	11	
Office work, n	17	19	.53
Production work, n	8	6	
BMI, mean (SD) $kg{\cdot}m^{-2}$	24.5 (3.8)	23.8 (3.3)	.66
Age, mean (SD) years	42.2 (9.8)	41.2 (9.3)	.71
Pain intensity[a] (six months), mean (SD)	4.2 (1.4)	0.4 (0.8)	**<.0001**
Pain intensity[a] (seven days), mean (SD)	4.0 (1.3)	0.2 (0.4)	**<.0001**
Work stress[b] (CR10, 0–10), mean (SD)	2.1 (1.0)	1.0 (0.8)	**<.0001**
Mental health (SF-36, 0–100), mean (SD)	75.2 (13.9)	81.6 (11.3)	.08
Sleep quality (KSQ, 0–24), mean (SD)	16.8 (3.9)	18.3 (2.1)	.10
VO_{2max} (O_2 mL/kg/min), mean (SD)	44.5 (12.1)	42.0 (10.2)	.45
Measurement duration, mean (SD) work days	3.0 (0.7)	3.0 (0.5)	.96
Time at work, mean (SD) hours	26.5 (6.5)	25.5 (5.0)	.53
Time at home, mean (SD) hours	15.6 (5.1)	15.1 (4.8)	.70
Time elsewhere, mean (SD) hours	7.2 (5.1)	7.8 (4.5)	.65
Self-reported sleep, mean (SD) hours/day	6.5 (0.6)	6.4 (0.3)	.44
Energy expenditure, mean (SD) MET/hour			
MET work	1.6 (0.1)	1.6 (0.2)	.78
MET home	1.6 (0.2)	1.7 (0.3)	.36
MET elsewhere	1.8 (0.3)	2.1 (0.4)	**.02**

[a]Pain intensity was reported using the CR10 scale (range 0–10). [b]Stress ratings from the electronic diary were averaged across all work periods. Continuous variables were tested using independent samples t-tests; distributions of gender and work type were tested by chi^2 tests; significant p-values, <.05, are bold faced. BMI: body mass index; MET: metabolic equivalent.

3.1. Effect of Activity Type and Location on HRV. Significant effects of *activity type* were found for HRV (Tables 2 and 3). IBI and RMSSD decreased with increasing physical activity (i.e., sit/lie, stand, and walk), while LF/HF increased from sit/lie to stand. IBI and RMSSD differed depending on *location* (Table 3, Figure 2); both were reduced for leisure "elsewhere" compared to work and leisure "at home." There was no significant effect of *location* on LF/HF, and there were no significant interactions between *activity type* and *location* for any of the HRV indices.

3.2. Differences in HRV between Pain and Control Groups. Main effects of *group* (pain versus control) were found on

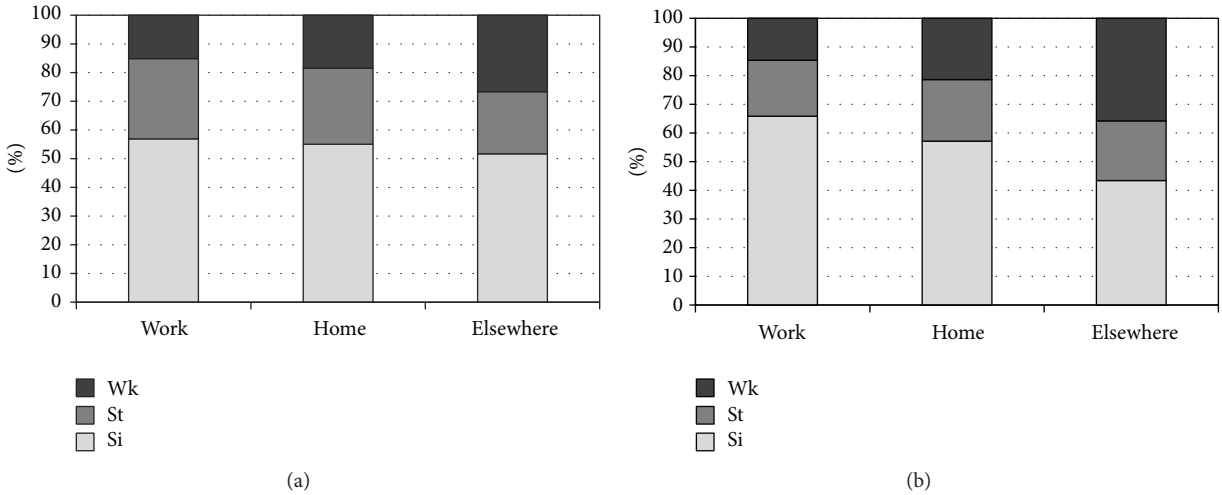

Figure 1: Time spent in physical activity (Si, sit/lie; St, stand; Wk, walk) in pain (a) and control (b) groups. Percentage of analyzed time is shown on the y-axis, and the spatial locations are shown on the x-axis.

Table 2: Mean and standard deviation (SD between subjects) of heart rate variability during different physical activity types (sitting/lying, standing, and walking), averaged across work and leisure periods for the pain ($n = 25$) and control groups ($n = 24$).

HRV index	Group	Sitting/lying Mean (SD)	Standing Mean (SD)	Walking Mean (SD)
IBI (ms)	Pain	814 (104)	727 (93)	646 (63)
	Control	865 (100)	762 (90)	665 (72)
RMSSD (ms)	Pain	34 (17)	26 (12)	21 (9)
	Control	40 (19)	30 (12)	23 (8)
LF/HF (ratio)	Pain	3.9 (2.4)	5.3 (2.9)	4.5 (2.0)
	Control	3.1 (1.3)	4.0 (1.8)	4.6 (2.1)

HRV, heart rate variability; IBIs, interbeat intervals; RMSSD, root mean square of successive differences between interbeat intervals; LF/HF, ratio between low- and high-frequency spectral power of heart rate variability.

HRV (Table 3), with reduced IBI and RMSSD, and increased LF/HF in the pain group compared with controls. However, only the IBI difference reached significance. We found a significant interaction (*activity type* × *group*) for LF/HF (Table 3), with an attenuated LF/HF response to walking (i.e., compared to sitting/lying or standing) in the pain group compared with controls (Figure 2). Post hoc tests showed that this interaction was significant for work ($F(2, 90) = 7.6$; $p = .001$) and leisure "at home" ($F(2, 90) = 5.1$; $p = .03$), while it did not reach significance for leisure "elsewhere" ($F(2, 76) = 2.3$; $p = .11$). The three-way interaction (*activity type* × *location* × *group*) was not significant for any HRV index.

Additional ANCOVA models (Table 4) for LF/HF with step-wise adjustments for multiple covariates showed that the interaction effect (*activity type* × *group*) remained significant after adjustments; only age and gender came out as significant covariates in the model. We also accounted for a possible influence of IBI on LF/HF by regressing IBI against LF/HF for each activity type and by rerunning the ANOVA using the residuals from the regression models as dependent variables. The interaction between *activity type* and *group* was still significant ($F(2, 90) = 6.2$; $p = .003$).

3.3. Association between Leisure Time Physical Activity and HRV. The difference between *activity types* in IBI ($F(2, 88) = 4.3$; $p = .03$) and RMSSD ($F(2, 88) = 9.7$; $p = .002$) depended on the level of leisure time physical activity (METs "elsewhere"), with a larger decline in HRV in response to walking among those subjects having a larger estimated MET value. For RMSSD, this interaction was also significant for work ($F(2, 88) = 8.2$; $p = .004$). Also, the difference between *locations* in RMSSD ($F(2, 88) = 3.6$; $p = .03$), but not in IBI ($p = .39$) or LF/HF ($p = .81$), depended on the metabolic level of leisure time physical activity, with a higher leisure MET being associated with enhanced HRV for work, but not for leisure.

When adjusting for METs in leisure "elsewhere" as a covariate in the ANCOVA, the differences in HRV between the three activity types and locations turned substantially less conclusive than what appeared in the ANOVA without adjustment for METs (Table 3), that is, *activity* main effect: IBI, $F(2, 88) = 2.64$; $p = .08$; RMSSD, $F(2, 88) = 3.29$; $p = .07$; LF/HF, $F(2, 74) = 2.27$; $p = .11$; *location* main effect: IBI, $F(2, 88) = 0.42$; $p = .66$; RMSSD, $F(2, 88) = 2.61$; $p = .08$; LF/HF, $F(2, 74) = 0.24$; $p = .78$.

Also, with inclusion of MET "elsewhere" in the model, the group differences (pain versus control) in HRV were reduced, and for IBI it did no longer reach significance (IBI, $F(1,44) = 2.91$; $p = .10$; RMSSD; $F(1,44) = 0.79$; $p = .38$; LF/HF, $F(1,37) = 2.07$; $p = .20$). The interaction between *activity type* and *group* remained significant for LF/HF even after adjustment for physical activity (MET) in leisure time "elsewhere" (Table 4). This means that group difference in the LF/HF response to physical activity was not explained by a reduced level of leisure time physical activity in the pain group.

Table 3: Results from the repeated measures ANOVAs of heart rate variability indices. F-values and p values are shown for the effects of activity type, location and group, and their interactions.

Variable	n	Main effects						Interaction effects					
		Activity		Location		Group		Activity × group		Location × group		Activity × location × group	
		F	p	F	p	F	p	F	p	F	p	F	p
IBI (ms)	49	**213.6**	**<.0001**	**9.2**	**<.0001**	**5.1**	**.03**	3.2	.07	1.4	.26	0.7	NS
RMSSD (ms)	49	**37.0**	**<.0001**	**4.8**	**.01**	3.8	.06	1.9	.16	0.9	NS	0.3	NS
LF/HF (ms)	42	**18.4**	**<.001**	0.1	NS	2.6	.11	**7.6**	**.001**	2.2	.12	0.2	NS

Note: nonsignificant, NS, $p > .30$; all models are adjusted for type of work.
IBIs, interbeat intervals; RMSSD, root mean square of successive differences between interbeat intervals; LF/HF, ratio between low- and high-frequency spectral power of heart rate variability.

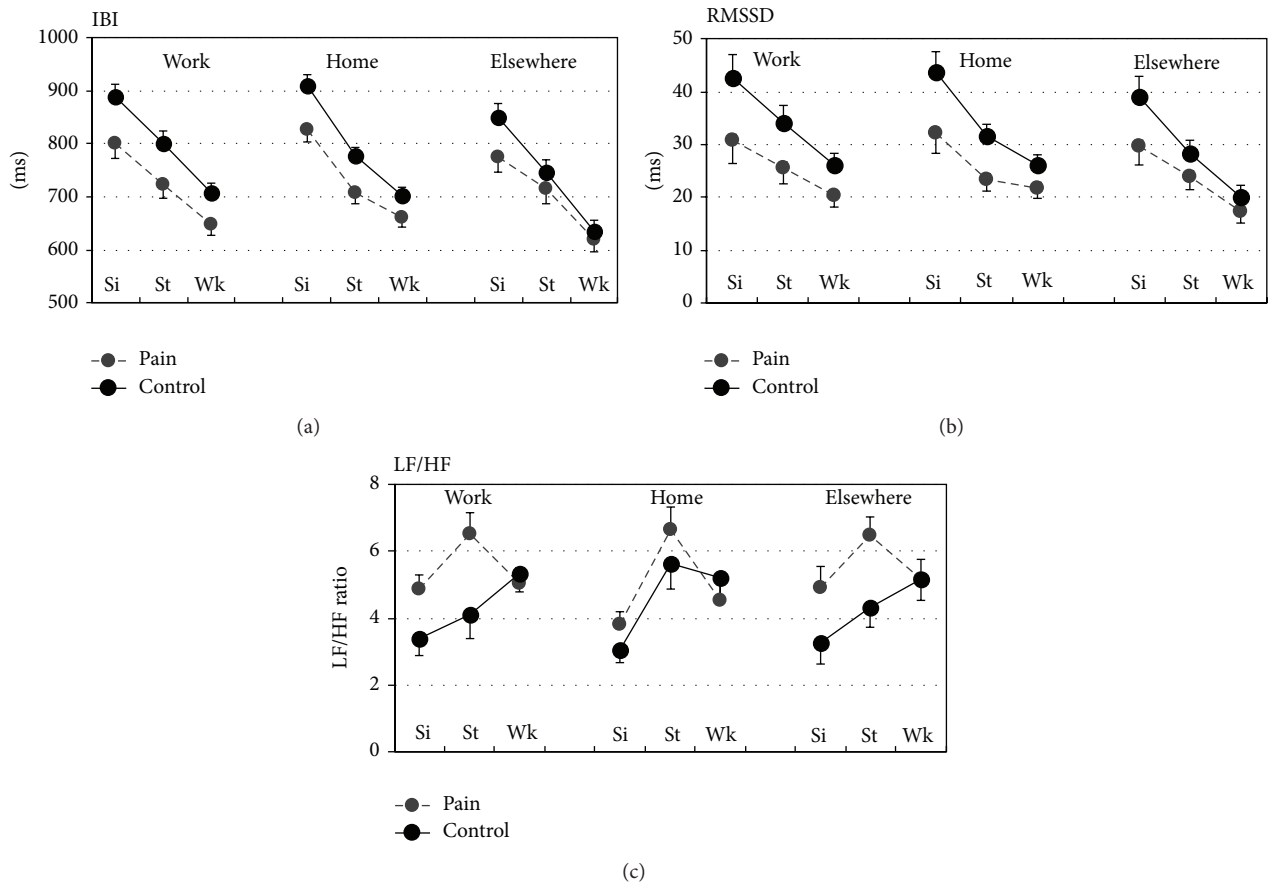

Figure 2: Heart rate variability (IBI, interbeat interval; RMSSD, root mean squared successive differences between IBIs; LF/HF, ratio between low- and high-frequency spectral power) determined for different physical activities (Si, sit/lie; St, stand; Wk, walk) during work and leisure (home and elsewhere) for the pain and control groups.

4. Discussion

The present study investigated the extent to which autonomic responses (measured through HRV) during physical activity at work and during leisure differ between subjects with and without chronic neck pain. We found that subjects with chronic neck pain had a reduced sympathetic-baroreceptor component of HRV in response to physical activity, as compared with controls, even when accounting for a wide range of potential confounders.

4.1. Autonomic Response to Sitting, Standing, and Walking. As expected, IBI (i.e., reciprocal heart rate) and RMSSD (Figure 2) decreased between lying/sitting and standing and further between standing and walking, reflecting an attenuated parasympathetic (vagal) cardiac modulation with an increase in physical activity. This activity-induced attenuation of parasympathetic activity was not significantly different between the pain and control groups, which is in agreement with laboratory studies assessing parasympathetic HRV

Table 4: Results from the ANCOVA analyses of LF/HF HRV, with p values for the main effect of group (pain versus control) and the interactions between group, activity type, and location.

Covariates	n	Group effect		Activity × group		Location × group	
		F	p	F	p	F	p
Age	42	2.1	.16	**6.1**	**.004**	1.9	.16
Gender	42	2.4	.13	**6.1**	**.004**	1.9	.16
BMI	42	—	—	—	—	—	—
METs, leisure "elsewhere"	42	—	—	—	—	—	—
Work stress, CR10	42	—	—	—	—	—	—
Mental health, SF-36	42	1.5	.23	**4.2**	**.02**	1.1	.93
Sleep quality, KSQ	42	—	—	—	—	—	—
VO_{2max}	39	0.09	.77	**6.4**	**.003**	1.7	.20

Note: all ANCOVA models are adjusted for type of work. Stepwise adjustments were made for age, gender, BMI, work stress, mental health sleep quality, and VO_{2max}.
— indicates exclusion ($p > .10$) of a covariate from the final ANCOVA model.
BMI, body mass index, MET; metabolic equivalent; SF-36, short form 36-item health survey; KSQ, Karolinska Sleep Questionnaire; HRV, heart rate variability; LF/HF, ratio between low- and high-frequency spectral powers of HRV.

indices during controlled physical exercise, that is, isometric contractions; [11, 17].

We found, however, that subjects with chronic neck pain had an aberrant LF/HF response to daily physical activity compared with healthy controls. That is, the control group showed an increased LF/HF when changing from a sedentary position to standing and walking, which corroborates previous reports [51, 52], while the pain group showed a reduced LF/HF response from standing and sitting/lying to walking (Figure 2, Tables 2–4). This indicates a reduced sympathetic-baroreceptor modulation of the heart in response to physical activity among the subjects with chronic pain. This novel finding from a field study of daily activities corroborates laboratory studies showing attenuated LF and LF/HF components during isometric contractions among people with neck pain compared with healthy controls [11, 16]. This is also consistent with two studies showing attenuated arterial blood pressure responses during static [14] and dynamic exercise [53] in people with neck pain compared to controls. In the current study, we even accounted for a wide range of important covariates, such as leisure time physical activity, work stress, mental health, sleep quality, and aerobic capacity. In addition, we adjusted the HRV indices for mean IBI, as previously recommended [54], and found that the LH/HF response remained significantly different between the pain and control groups after this adjustment.

The group difference in LF/HF response to physical activity suggests an aberrant sympathetic-baroreceptor function in subjects with chronic neck pain, according to studies indicating that LF/HF is a sensitive measure of sympathetic-baroreceptor activity during experimentally induced pain [6]. The onset and continuation of a physical activity bout are accompanied by a reduced IBI, as confirmed by our data, which is due to a shift in autonomic balance favoring sympathetic over parasympathetic predominance [55]. During physical activity, the arterial baroreflex regulates arterial blood pressure via changes in sympathetic and parasympathetic cardiac modulation [21], as reflected in LF and HF indices of HRV [56]. The interplay between the baroreflex and the ANS is, in turn, under the influence of central networks [57] involving, for instance, the anterior cingulate and insular cortices and the thalamus, as well as structures in the brain stem (periaqueductal grey, medulla), which are also engaged in central pain processing and descending pain inhibition [58, 59]. Thus, baroreceptor regulation of blood pressure during physical activity is associated with adaptive hypoalgesia, which may be inhibited in conditions of chronic pain [4, 18, 60, 61], including neck pain [62].

Thus, our findings point to the involvement of a central dysregulation in chronic neck pain, including aberrant interactions between the ANS, baroreflex, and central pain processing mechanisms. We suggest future studies to investigate this further in experimental and prospective designs.

4.2. Association between Leisure Time Physical Activity and Parasympathetic Activity. We found that the subjects with chronic neck pain were less physically active (i.e., having lower estimated METs) than the controls, particularly during leisure time. This corroborates previous findings from our research group [12, 13]. However, the present study is, to our knowledge, unique in showing that "inactivity" among subjects with pain does not occur during work or at home, but only in other geographical locations (i.e., leisure "elsewhere"). We also found an increased heart rate (lower IBI) and reduced parasympathetic activity (RMSSD) for leisure "elsewhere" compared to leisure "at home," which most likely reflects an increased intensity of physical activity "elsewhere." In addition, there was a significant interaction between physical activity level (i.e., estimated MET) and location on RMSSD, which indicates an enhanced parasympathetic cardiac modulation during work, but not during leisure, among those being more physically active in their leisure time. These findings may encourage future interventions to stimulate leisure time

physical activity in chronic neck pain populations and to evaluate intervention effects on HRV and pain.

The subjects with chronic neck pain had shorter IBIs and a trend towards reduced RMSSD compared with the controls (Tables 2 and 3), particularly when sitting or lying (Figure 2). We have previously demonstrated a reduced basal parasympathetic activity among people with chronic neck pain in comparison with asymptomatic controls, as assessed using HRV indices during controlled rest or during sleep [11, 13]. However, the group differences in IBI and RMSSD observed in the present sample were less clear when adjusting for leisure time physical activity "elsewhere" in the ANCOVA models. Nevertheless, the observed association between physical activity levels and HRV may have mechanistic implications with respect to the onset and persistence of chronic neck pain. Parasympathetic activation appears to be involved in the inhibition of inflammatory processes, that is, via activation of the cholinergic anti-inflammatory pathway [63]. Thus, resting HRV is negatively associated with systemic levels of proinflammatory cytokines [64, 65]. Based on animal models, proinflammatory markers have been proposed to contribute to work-related muscle pain [66], and some studies show higher concentrations of proinflammatory cytokines among persons with upper-extremity pain [67–69], including work-related neck pain [70]. Thus, we suggest that this possible connection between physical activity, parasympathetic regulation, and inflammation should be further investigated in prospective studies in chronic neck pain populations.

4.3. Methodological Discussion. The assessment of HRV combined with long-term continuous recordings using accelerometry and GPS is an obvious strength of the present study. This allowed us to analyze HRV in response to different activity types across different spatial contexts in an approach that was entirely dependent on the access to continuous data for extended periods. Separating leisure time physical activity "elsewhere" from that "at home" led to a more stringent measure of physical activity during leisure, as confirmed by its clear association with HRV. Thus we could appropriately adjust HRV data for objectively measured levels of physical activity. Given the abundance of studies showing that leisure time physical activity is, in its own right, associated with increased HRV (e.g., [26–28]), adjustment for this factor is crucial. A further strength is the recruitment of subjects with and without pain from the same company, while also minimizing confounding due to recruitment bias.

Our study suffers some limitations which need to be acknowledged. We estimated periods of sitting/lying, standing, and walking from the accelerometer recordings, while any further level of detail in discriminating different types of physical activities was not considered feasible. It is possible that further detail, including identification of, for example, periods of swimming, could have led to an even better understanding of factors influencing HRV. Further, the fact that sitting and lying were not separated may also muddle the interpretation of HRV findings, since HRV can change substantially between sitting and supine positions [71]. Our study design does not allow inferences about causal relationships between HRV and neck pain, even if data of HRV, physical activity, and GPS were collected for several days. Such inferences need to be based on experimental designs or prospective studies using repeated sampling of pain characteristics across a longer time span, for example, following the progression of symptoms from an asymptomatic state to chronic pain. Our study also lacks data on pain sensitivity, which precludes us from determining whether changes in HRV were associated with insufficient pain modulation or not. However, we did not consider it feasible to assess pain sensitivity during different activity types across several days. As our assessment methods were selected to be as nonobtrusive as possible, we did not assess ambulatory blood pressure, and, thus, possible relationships between changes in blood pressure and pain could not be tested. Thus, further studies are recommended to resolve these issues. Finally, as data was collected during the brighter part of the year (i.e., primarily in May and June), caution should be paid in generalizing our results to the spring and winter seasons, where patterns of physical activity and inactivity may differ considerably from those during summer.

5. Conclusion

We found that subjects with chronic neck pain showed an attenuated LF/HF response to physical activity compared with asymptomatic subjects, even after adjustment for essential confounders. This suggests an aberrant sympathetic-baroreceptor function among subjects with chronic neck pain. In order to further investigate this theory, interventions or experimental protocols manipulating autonomic regulation need to be evaluated with respect to their possible effect on chronic neck pain. Our results were critically dependent on the access to data collected continuously for prolonged periods of time, and so we recommend using long-term monitoring of physical activity, spatial location, and pain even in future prospective investigations of the physiological and behavioral determinants of chronic neck pain.

Conflict of Interests

The authors declare that there is no conflict of interests.

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Research Article

The Discriminant Value of Phase-Dependent Local Dynamic Stability of Daily Life Walking in Older Adult Community-Dwelling Fallers and Nonfallers

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The present study compares phase-dependent measures of local dynamic stability of daily life walking with 35 conventional gait features in their ability to discriminate between community-dwelling older fallers and nonfallers. The study reanalyzes 3D-acceleration data of 3-day daily life activity from 39 older people who reported less than 2 falls during one year and 31 who reported two or more falls. Phase-dependent local dynamic stability was defined for initial perturbation at 0%, 20%, 40%, 60%, and 80% of the step cycle. A partial least square discriminant analysis (PLS-DA) was used to compare the discriminant abilities of phase-dependent local dynamic stability with the discriminant abilities of 35 conventional gait features. The phase-dependent local dynamic stability λ at 0% and 60% of the step cycle discriminated well between fallers and nonfallers (AUC = 0.83) and was significantly larger ($p < 0.01$) for the nonfallers. Furthermore, phase-dependent λ discriminated as well between fallers and nonfallers as all other gait features combined. The present result suggests that phase-dependent measures of local dynamic stability of daily life walking might be of importance for further development in early fall risk screening tools.

1. Introduction

Falls among older people are an important reason for dependence in daily life, reduced quality of life, and admission to hospitals or nursing homes. At a European level, the annual costs of falls among older persons are estimated to be 30 Billion Euro [1]. Early prediction of falls amongst community-dwelling older persons could provide opportunities for early fall prevention. Thus, considerable efforts have been made for early fall risk assessment and fall prediction in older persons.

More than 400 risk factors for falls have been reported (e.g., [2]). Most risk factors have been assessed in laboratory settings or in clinical test situations, and fall risk assessment tools have been developed based on these assessments [3–6]. However, most of these screening tools reflect the performance of the older person at a specific moment in time or they are based on self-report. Furthermore, falls in older persons are often experienced during activities of daily living [7, 8]. Thus, monitoring of behaviour in daily life, rather than assessment by performance tests and self-report, may be important for furthering evidence-based recommendations for fall risk assessment and screening for fall prevention interventions.

Daily life activities, like lying, sitting, standing, and walking, can be identified by body-fixed sensors containing inertial sensors like accelerometers and gyroscopes [9]. Features of the acceleration signal within these activities and in the transition between activities might be important in fall risk assessment [10]. Several measures of gait stability and variability are significantly different between elderly fallers

and nonfallers [11–13]. Amongst these is the measure of local dynamic stability that has been suggested to be one of the most sensitive measures of gait instability in older persons [14]. Local dynamic stability λ is defined as the rate of exponential increase in infinitely close distances between trajectories in the reconstructed state space of the gait dynamics [15]. These distances are considered as infinitesimal perturbations and, thus, local dynamic stability defines the reaction of the gait dynamics to these perturbations. The gait dynamics are local dynamic stable when $\lambda < 0$, indicating an exponential decrease in the distance between neighbouring trajectories. In contrast, the gait dynamics are local dynamic unstable when $\lambda > 0$, indicating an exponential increase in the distance between neighbouring trajectories. Recent extensions of computational methods for local dynamic stability λ indicate that λ is phase dependent and changes within the gait cycle [16, 17]. Despite promising results, the discriminating ability of phase-dependent λ has not been compared to the discriminating abilities of other features of daily life walking.

The main aim of the present study is to compare phase-dependent λ with conventional gait features in their ability to discriminate between the daily life walking of community-dwelling elderly fallers and nonfallers.

2. Methods

2.1. Participants and Data Collection. Inertial sensor data previously studied by Weiss et al. [13] were reanalysed in the present study. The data can be downloaded at http://www.physionet.org/. The data consist of 3 days of 3D-acceleration data from 71 community-dwelling older persons (mean age: 78.36 ± 4.71 yrs; range: 65–87 yrs; gender: 64.79% women; mean height: 1.62 ± 0.07 m; mean weight: 71.98 ± 12.88 kg). None of the participants included had been diagnosed with gait or balance disorders or had cognitive impairments (i.e., Mini Mental State Examination score > 24). The participants were classified as fallers or nonfallers based on retrospective self-report. Participants reporting 2 or more falls in the year prior to testing were considered as fallers; this definition was used to ensure a clear distinction between the two groups and to focus on (multiple) fallers and nonfallers, excluding older adults who may be in an intermediate, less well-defined, and more ambiguous state with respect to their fall history. There was no difference between fallers and nonfallers in age, gender, years of education, height, weight, or body mass index, but a difference in in-lab preferred gait speed (nonfallers: 1.19 ± 0.24 m/s; fallers: 0.97 ± 0.30 m/s). The acceleration along the anterior-posterior (AP), mediolateral (ML), and vertical (V) axes was sampled at 100 Hz by a small inertial sensor (DynaPort Hybrid, McRoberts, The Hague, Netherlands; 87 × 45 × 14 mm, 74 g). The sensor had a range and resolution of ±6 g and ±1 mg, respectively. The acceleration signals were recorded on a Secure Digital (SD) card at a sample frequency of 100 Hz and later transferred to a personal computer for further analysis using Matlab (MathWorks, Natick, MA). The sensor was fitted without any difficulties on a belt on the center of lower back, at the L5 level. The sensor had to be removed during the shower and swimming and occasionally during sleep. The participants received a diary for tracking when and why they took off and put on the device. No specific problems were evident during data collection and retrieval.

2.2. Preprocessing of the Data. The classification procedure was restricted to the walking bouts of duration ≥ 60 seconds, identical to those originally analysed by Weiss et al. [13]. This size was chosen to ensure that these were indeed walking segments and that the acceleration derived measures would be robust. The walking bouts were identified by using two filters: one filter was based on the acceleration-magnitude, and the other filter was based on the energy in the frequency domain [13, 18]. The activity bouts were visually observed to ensure that these were indeed valid walking segments. A mean of 28.3 walking bouts (range: 5 to 90) with duration ≥ 60 seconds was identified for each of the participants. There was no significant difference in number of walking bouts between fallers and nonfallers. The reader is referred to Weiss et al. [13] for further details about the participants, protocols, and preprocessing of the 3D-acceleration data.

Intrastep 3D-velocity was estimated from the 3D-acceleration signal. The 3D-acceleration was detrended using an orthogonal wavelet procedure that preserved intrastep variation in the 3D-velocity but removed interstride non-linear trends [19]. This detrending procedure provides stationary 3D-velocity signal necessary for computation of local dynamic stability [20]. The local maxima of the vertical velocity were defined as the beginning of a step. This step identification method provided similar results to the autocorrelation method used in previous studies based on comparison of the mean step time [12, 21].

2.3. State Space Construction Methods. Two 6D state spaces were constructed for each walking bout by the two following methods [20].

Method 1. Differential coordinate embedding was defined as $\mathbf{x}(t) = [a_{\mathrm{AP}}(t), a_{\mathrm{ML}}(t), a_{\mathrm{V}}(t), v_{\mathrm{AP}}(t), v_{\mathrm{ML}}(t), v_{\mathrm{V}}(t)]$, combining both acceleration signal $a(t)$ and velocity signal $v(t)$ in AP, ML, and V directions. The local dynamic stability λ_{diff} computed from state space construction Method 1 has the subscript diff in the result section.

Method 2. Delayed coordinate embedding was defined as $\mathbf{x}(t) = [v_{\mathrm{AP}}(t), v_{\mathrm{AP}}(t + l\Delta t), v_{\mathrm{ML}}(t), v_{\mathrm{ML}}(t + l\Delta t), v_{\mathrm{V}}(t), v_{\mathrm{V}}(t + l\Delta t)]$, where $v(t)$ is the velocity signal, $\Delta t = 0.01$ s is the sampling interval, and l is the time lag. This delayed coordinate embedding combines the velocity signal $v(t)$ in AP, ML, and V directions for the velocity signal and uses a short time lag, $l = 3$, to prevent the blending of phases within the gait cycle. The local dynamic stability λ_{lag} computed from state space construction Method 2 has the subscript lag in the result section.

2.4. Computation of Phase-Dependent Local Dynamic Stability λ. Phase-dependent local dynamic stability was defined

according to a method developed by Ihlen et al. [16] and based on two equations:

$$\lambda = \frac{\langle \ln \langle d_i(t) \rangle \rangle_{\text{step}}}{t}, \quad (1)$$

$$\lambda = \frac{1}{t_n} \ln \frac{\langle \langle d_i(t_n) \rangle \rangle_{\text{step}}}{\langle \langle d_i(0) \rangle \rangle_{\text{step}}}, \quad (2)$$

where $\langle d_i(t) \rangle$ is the reaction curve of the initial perturbation $\langle d_i(0) \rangle$ and the outer brackets $\langle \cdots \rangle$ are the mean across all steps in the walking bout. The initial perturbation was defined as the distance $d_i(0)$ between the reference point and the ith neighbourhood trajectory within a small neighbourhood of predefined size (see Figure 1(a)). The initial perturbation was considered at 0%, 20%, 40%, 60%, and 80% of the step cycle (see Figures 1(b) and 1(c), e.g., for 0% and 60%). The reaction distance $d_i(t)$ of the initial distance $d_i(0)$ was traced to the next starting point of a step. The average reaction distance $\langle d_i(t) \rangle$ was computed across all ith neighbourhood trajectories. The reaction distance, $\langle d_i(t) \rangle$, for less than 10 neighbourhood trajectories or with instantaneous stride time outside the 5% and 95% percentiles was excluded for further analysis. The portion of excluded $\langle d_i(t) \rangle$ was less than 10% of the total number of strides for all participants and these strides were typically short periods of deviating patterns of the acceleration and velocity signals due to large deviations from normal patterns. In (1), the remaining $\langle d_i(t) \rangle$ was normalized to step time before λ was assessed as the linear regression slope for the first 10% of the step cycle (see Figure 1(b)). In (2), the remaining $\langle d_i(t) \rangle$ was not normalized and $\langle d_i(t) \rangle$ was the reaction distance at time t_n equal to 10% of the step cycle. The first 10% of the step cycle was considered to prevent influence of curvatures in state space trajectories [22]. The median of λ was computed across all walking bouts for each participant. In addition, the conventional phase-independent λ_{wolf} was computed by the method of Wolf et al. [23]. Wolf's method was applied to the acceleration signal in the AP, ML, and V directions, separately. A 6D delayed coordinate embedding was used with time lag, $l = 8$, which was the mean lag for the first minima of the average mutual information function [24]. The Matlab code for the phase-dependent measures, λ_{diff} and λ_{lag}, is available at http://www.physionet.org/.

2.5. Test-Retest Reliability of Phase-Dependent Local Dynamic Stability λ. Different circumstances of walking, like turns, walking surfaces, obstacles, variations in walking speed, and dual tasking, may introduce random fluctuations in phase-dependent local dynamic stability λ between walking bouts. Even though the median of each selected feature across several walking bouts will reduce these fluctuations, it is uncertain if the median has sufficient reliability across walking bouts within a 3-day period. Thus, the test-retest reliability of the median of local dynamic stability λ was assessed by interclass correlation (ICC) absolute agreement for the first and the last 1/3 of the walking bouts within the 3-day recording period.

2.6. Partial Linear Square Discriminant Analysis (PLS-DA). PLS-DA relates the predictor matrix $\mathbf{X}$ of gait features with the response $\mathbf{Y}$ of fall status (see Figure 2). PLS-DA is able to identify a low-dimensional latent structure ($\mathbf{T}$) from a large number of gait features $\mathbf{X}$ which discriminates between fallers and nonfallers. In contrast to other regression approaches, PLS-DA is designed to perform discriminate analyses based on a large set of noisy and collinear predictors $\mathbf{X}$ and is therefore suitable for the large number of gait features investigated in the present study. The present study used a nonlinear iterative partial least square (NIPALS) algorithm extended by a target projection (TP) as summarized in Figure 2 [25–27]. The TP-loadings define the contribution of each gait feature in the PLS model. A TP-loading closer to −1 or 1 indicates that the gait feature has a strong influence in discriminating between fallers and nonfallers, whereas a TP-loading close to 0 indicates that the feature has little or no influence in discriminate analyses. Thus, the TP-loading provides a ranking list of the most influential gait features for the classification of fallers and nonfallers. Three different predictor matrices $\mathbf{X}$ were defined for the PLS-DA to compare the discrimination ability of phase-dependent local dynamic stability with other gait features (see Table 1). All gait features in the predictor matrices $\mathbf{X}$ were converted to z-scores before the application of PLS-DA. A PLS-DA cross-validation procedure was used to estimate how well the model would generalize to new samples from the same population [28]. Four latent variables provided the minimum error of the cross-validation for all predictor matrices $\mathbf{X}$ and were used in the PLS-DA. Sensitivity and specificity and area under the ROC curve (AUC) were defined based on the real and predicted outcome variables from PLS-DA. All analyses were performed in Matlab R2014a.

3. Results

Figure 3 shows the mean reaction curve of the fallers and nonfallers for initial perturbation at 0%, 20%, 40%, 60%, and 80% of the step cycle. The figure indicates that the reaction distance curve for both elderly fallers and nonfallers has a phase-dependent shape. The nonfallers had a significantly larger local dynamic stability, median λ, compared to the fallers at 0%, 20%, and 60% of the step cycle, irrespective of the state space reconstruction method and definition of λ (see upper and lower panels in Figure 3). The TP-loadings of all 46 included gait features indicate that phase-dependent λ at 0 and 60% of step cycle was most influential in discriminating between elderly fallers and nonfallers (see green bars in Figure 4). The conventional measures of local dynamic stability had less influence in the discrimination analysis compared to the phase-dependent λ (compare red bars of λ_{wolf} with green bars of λ_{lag} and λ_{diff} in Figure 4). Increased error, decreased specificity, and decreased AUC were found when the phase-dependent measures, λ_{diff} and λ_{lag}, were removed (see Table 2 and Figure 5). Furthermore, the eight phase-dependent measures, λ_{diff} and λ_{lag}, performed as good as all the 38 gait features together in classification of fallers and nonfallers (see third column in Table 2 and the red ROC curve in Figure 5). In addition, all the phase-dependent

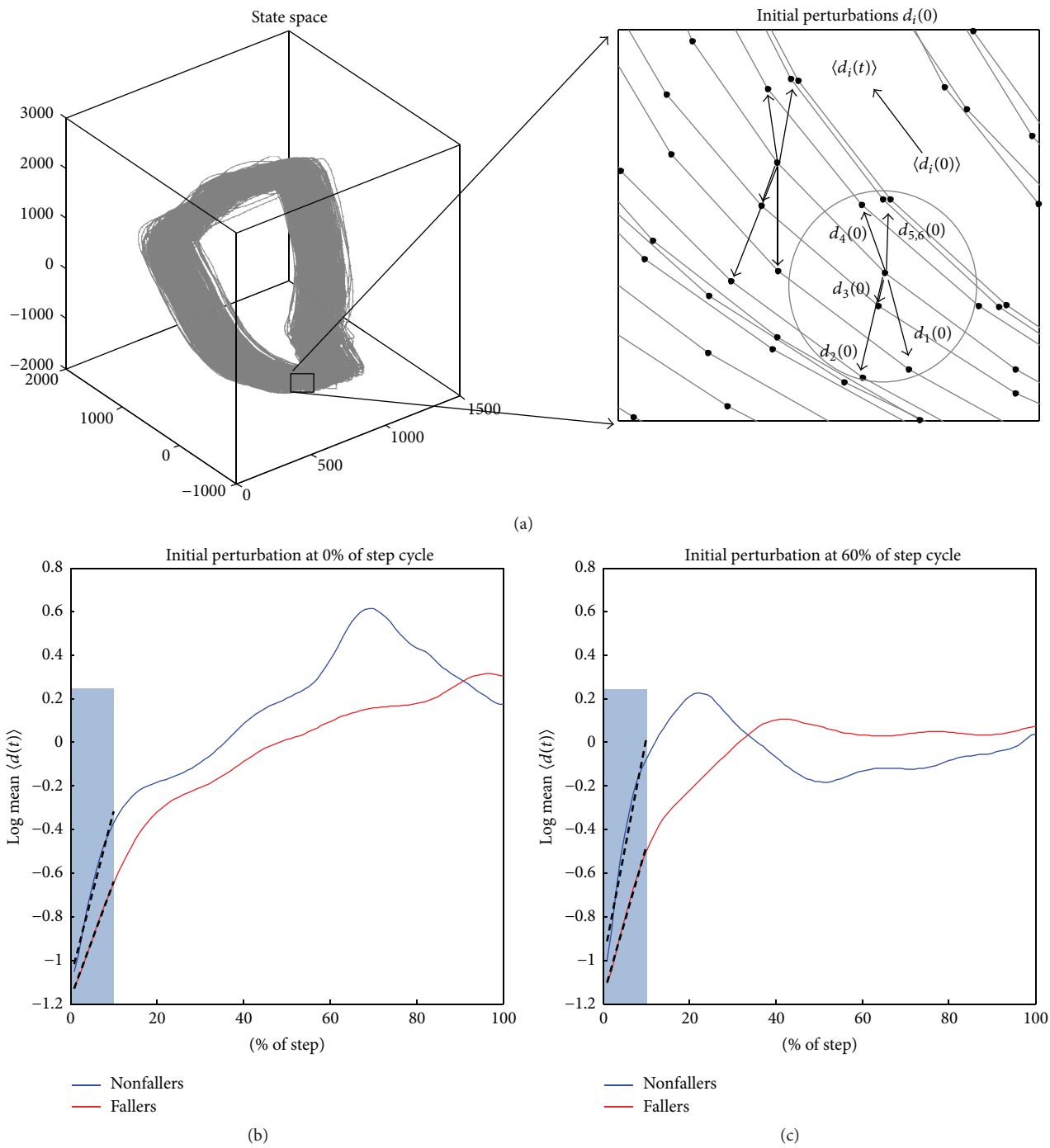


FIGURE 1: (a) A schematic representation of the reaction distance $\langle d_i(t)\rangle$ based on i trajectories within a small neighborhood (gray circle) of the state space. The initial average perturbation distance $\langle d_i(t)\rangle$ was computed from multiple distances $d_i(t)$ within the neighborhood. Note that the left panel illustrates a 3D state space reconstruction where the computations of $\langle d_i(t)\rangle$ are based on a 6D state space reconstruction. (b) A representative example of a log-reaction curve normalized to the step cycle for a faller (*red*) and a nonfaller (*blue*) for initial perturbation at 0% of the step cycle. (c) The same example of a log-reaction curve for initial perturbation at 60% of the step cycle. The slopes of the regression lines for the initial 10% (black lines in shaded areas of (a) and (b)) were defined as the local dynamic stability according to (1).

measures, median λ_{diff} and λ_{lag}, included in the discriminate analysis had high test-retest reliability (ICC coefficients > 0.80; see Table 3). Thus, phase-dependent local dynamic stability seems to be an important feature for the classification of fallers and nonfallers in community-dwelling older persons.

4. Discussion

The main purpose of the present study was to compare phase-dependent local dynamic stability measures with more conventional gait features in their ability to discriminate

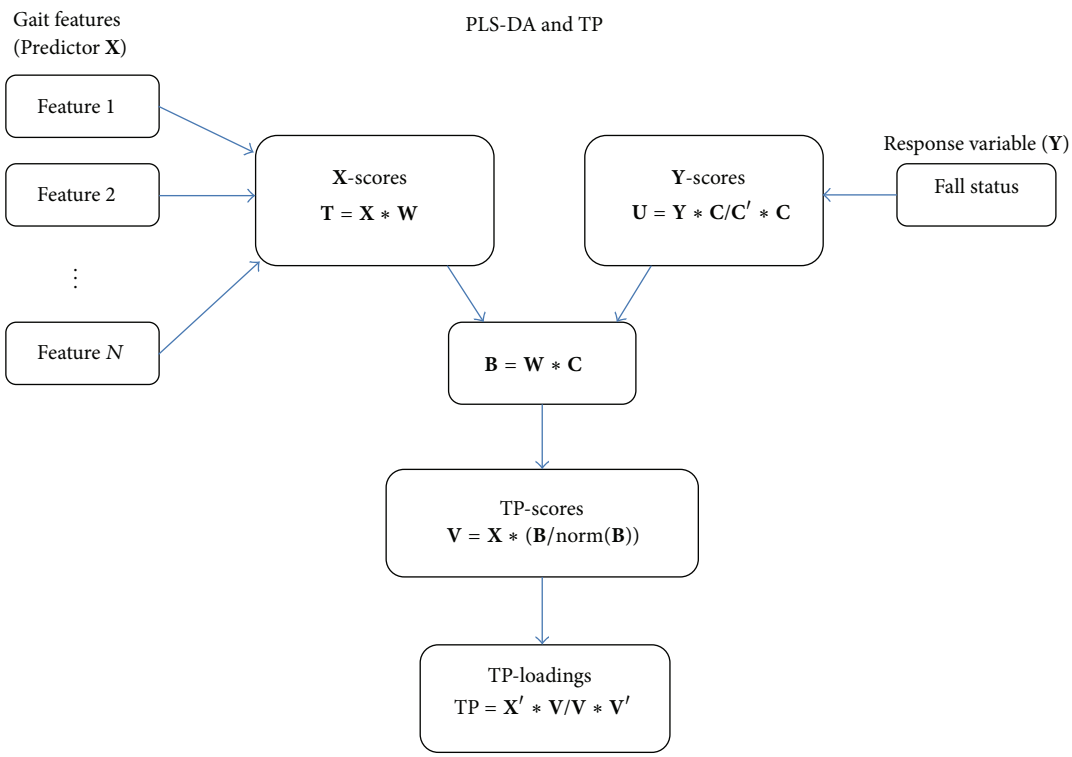


Figure 2: A schematic illustration of partial least square discriminant analysis (PLS-DA) and target projection (TP) used in the present study. The prediction matrix **X** has a number of columns equal to the number of gait features and number of rows equal to the number of participants. The high number of gait features is projected to a small number of principle axes in the feature space and this projection is defined as the **X**-scores (**T**). The projection is provided by a weight matrix **W** for the gait feature matrix **X** and by a weight matrix **C** for the categorical (faller and nonfaller) response variable **Y**. The target projection method combines the weight matrices **W** and **C** in order to define the influence of each gait feature in the discrimination between fallers and nonfallers. The cross-product **B** of weights **W** and **C** is used to calculate the target projection scores **V**, which is a variable containing one score for each older person which maximizes the discrimination between fallers and nonfallers. The target projection score **V** is used to define the target projection loadings TP containing one loading for each gait feature that denotes its influence on the target projection score.

between community-dwelling elderly fallers and nonfallers. The phase-dependent λ_{diff} and λ_{lag} at 0% and 60% of the step cycle had the best classification performance and considerably improved the PLS-DA, compared to the 38 conventional features of daily life walking.

In a treadmill study, Ihlen et al. [17] found that healthy older persons had larger phase-dependent λ_{diff} and λ_{lag} compared to young adults. In contrast, in the present study, the phase-dependent λ_{diff} and λ_{lag} were larger in older nonfallers compared to fallers. These contrasting findings may be due to several reasons. First, a recent study indicates that gait characteristics obtained in in-lab studies are different from those recorded for daily life walking [29]. Thus, the more unstable gait dynamics of elderly nonfallers might be due to a more heterogeneous and challenging walking environment for this group including more frequent turns and multitasking while walking. These factors might contribute to the larger λ_{diff} and λ_{lag} compared to the fallers but might also indirectly reflect subtle decline in balance and mobility in the fallers group. Second, the increased local dynamic stability found for the fallers might also reflect adaption in the gait dynamics towards more cautious gait including less frequent turns and multitasking while walking and less challenging walking environment. However, the present study cannot conclude whether the larger λ_{diff} and λ_{lag} in the nonfallers are due to differences in external environmental factors or internal neuromuscular factors or a combination of these two. Further studies are needed to include contextual information of daily life walking in community-dwelling older persons.

Rispens et al. [12] found that local dynamic stability, λ_{wolf}, computed by the method of Wolf et al. [23] for the acceleration signal in the V direction was able to discriminate between fallers and nonfallers. However, in the present study, the phase-dependent λ_{diff} and λ_{lag} were found to be more sensitive to falls status of community-dwelling older person compared to λ_{wolf}. In contrast to the findings of Rispens et al. [12], λ_{wolf} did not influence the classification of fallers and nonfallers in the present study.

The present study also shows the potential of PLS-DA for the comparison of the influence of different gait features to discriminate between fallers and nonfallers. Numerous features of gait stability and variability have been introduced in the last decades, but their abilities to discriminate between fallers and nonfallers are seldom compared [11]. The TP-loadings in Table 2 are able to rank the influence of the different gait features in the classification of elderly fallers and

Table 1: The gait features contained in the three predictor matrices **X** used in the partial least square discriminatory analysis (PLS-DA) of elderly fallers and nonfallers. The gait features written in italic style are the same features used in Weiss et al. (2013) [13].

Predictor matrix $\mathbf{X}_1$ (46 gait features)	Predictor matrix $\mathbf{X}_2$ (38 gait features)	Predictor matrix $\mathbf{X}_3$ (8 gait features)
λ_{diff} (phase: 0%, (1))	—	λ_{diff} (phase: 0%, (1))
λ_{diff} (phase: 0%, (2))	—	λ_{diff} (phase: 0%, (2))
λ_{diff} (phase: 60%, (1))	—	λ_{diff} (phase: 60%, (1))
λ_{diff} (phase: 60%, (2))	—	λ_{diff} (phase: 60%, (2))
λ_{lag} (phase: 0%, (1))	—	λ_{lag} (phase: 0%, (1))
λ_{lag} (phase: 0%, (2))	—	λ_{lag} (phase: 0%, (2))
λ_{lag} (phase: 60%, (1))	—	λ_{lag} (phase: 60%, (1))
λ_{lag} (phase: 60%, (2))	—	λ_{lag} (phase: 60%, (2))
λ_{wolf}*	λ_{wolf}*	—
*Acceleration range**	*Acceleration range**	—
*Acceleration root-mean-square**	*Acceleration root-mean-square**	—
*Amplitude of dominant frequency**	*Amplitude of dominant frequency**	—
Average stride duration	*Average step duration*	—
Average step duration	*Average step duration*	—
Cadence	*Cadence*	—
*Harmonic ratio**	*Harmonic ratio**	—
Median walking bout duration	*Median walking bout duration*	—
Median number of steps for bout	*Median number of steps for bout*	—
*Slope of dominant frequency**	*Slope of dominant frequency**	—
*Step symmetry**	*Step symmetry**	—
*Step regularity**	*Step regularity**	—
*Stride regularity**	*Stride regularity**	—
Total number of steps	*Total number of steps*	—
Total number of walking bouts	*Total number of walking bouts*	—
Total percent of walking duration	*Total percent of walking duration*	—
*Width of dominant frequency**	*Width of dominant frequency**	—

*Gait feature defined for AP, ML, and V direction, separately.

Table 2: Classification performance for predictor matrices $\mathbf{X}_1$, $\mathbf{X}_2$, and $\mathbf{X}_3$ (see Table 1 for their definitions).

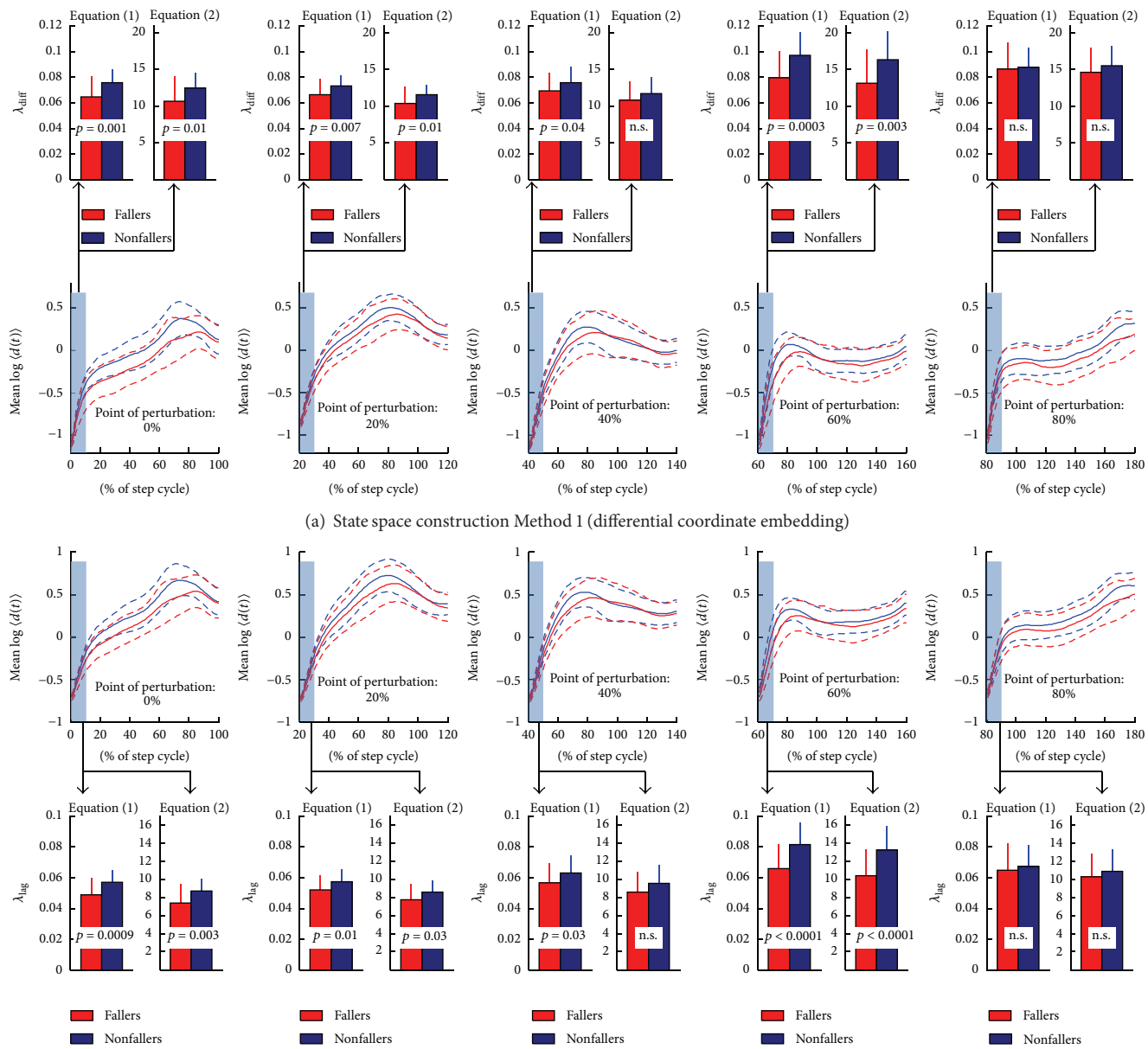
	Predictors $\mathbf{X}_1$	Predictors $\mathbf{X}_2$	Predictors $\mathbf{X}_3$
Sensitivity	0.72	0.72	0.69
Specificity	0.90	0.79	0.87
AUC	0.93	0.84	0.83
Error (1 – accuracy)	0.18	0.24	0.21

Table 3: Interclass correlation (ICC) coefficient and its 95% confidence interval (CI) for the phase-dependent local dynamic stability measures, λ_{lag} and λ_{diff}.

Features	ICC	ICC (95% CI)
λ_{diff} (phase: 0%, (1))	0.90	[0.84, 0.94]
λ_{diff} (phase: 0%, (2))	0.89	[0.82, 0.93]
λ_{diff} (phase: 60%, (1))	0.92	[0.88, 0.95]
λ_{diff} (phase: 60%, (2))	0.90	[0.85, 0.94]
λ_{lag} (phase: 0%, (1))	0.86	[0.77, 0.91]
λ_{lag} (phase: 0%, (2))	0.85	[0.76, 0.91]
λ_{lag} (phase: 60%, (1))	0.93	[0.88, 0.95]
λ_{lag} (phase: 60%, (2))	0.92	[0.87, 0.95]

nonfallers. Table 2 indicates that many of these features have significantly different mean values for fallers and nonfallers, while the discriminatory power is low (i.e., TP-loading < 0.5). A consensus on a procedure to compare the abilities of different gait features in the classification of elderly fallers and nonfallers, like PLS-DA, might have important value for evaluation of new features of gait stability and variability. Furthermore, procedures like PLS-DA might also be helpful for the identification of fall risk profiles for different groups of older people, and the procedures might be extended to include clinical test scores and demographic variables.

The present study has several limitations. First, the present study did only distinguish between fallers and nonfallers based on retrospective fall reports from a relatively small sample of community-dwelling older adults. The specificity, sensitivity, and AUC reported in the present study are in the upper end of values that could be expected from a perfect fall prediction model [30]. Thus, it is likely that specificity, sensitivity, and AUC will decrease for λ_{diff} and



(a) State space construction Method 1 (differential coordinate embedding)

(b) State space construction Method 2 (delayed coordinate embedding)

FIGURE 3: (a) Mean ± 1SD of the log-median $\langle d_i(t) \rangle$ for fallers (*red*) and nonfallers (*blue*) defined by the state space reconstruction Method 1 (differential coordinate embedding) for initial perturbation at 0%, 20%, 40%, 60%, and 80% of the step cycle. The smaller upper subplots show mean ± 1SD of local dynamic stability λ_{diff} for fallers (*red*) and nonfallers (*blue*) together with p values. (b) Mean ± 1SD of the log-median $\langle d_i(t) \rangle$ for fallers (*red*) and nonfallers (*blue*) defined by the state space reconstruction Method 2 (delay coordinate embedding) for initial perturbation at 0%, 20%, 40%, 60%, and 80% of the step cycle. The smaller upper subplots show mean ± 1SD of local dynamic stability λ_{lag} for fallers (*red*) and nonfallers (*blue*) together with p values.

λ_{lag} in a prediction model of prospective falls. Consequently, further studies on larger samples with prospective fall data are necessary before concluding that phase-dependent λ_{diff} and λ_{lag} will improve fall prediction models or early fall risk assessment in the population of community-dwelling older adults.

Second, demographic variables and variables of clinical tests used for fall risk assessment, like tests of balance and mobility performance, were not included in the classification procedure. Inertial sensor based tools for unsupervised in-home test of physical function, including mobility and balance, could also contribute to the improvement of early fall risk assessment in community-dwelling older adults [31]. However, former studies have shown that features of daily life walking improve the risk assessment when combined with instrumented tests of mobility performance [10, 13]. Nevertheless, falls have multifactorial causes including medication, urinary control, vision, footwear, environmental hazards,

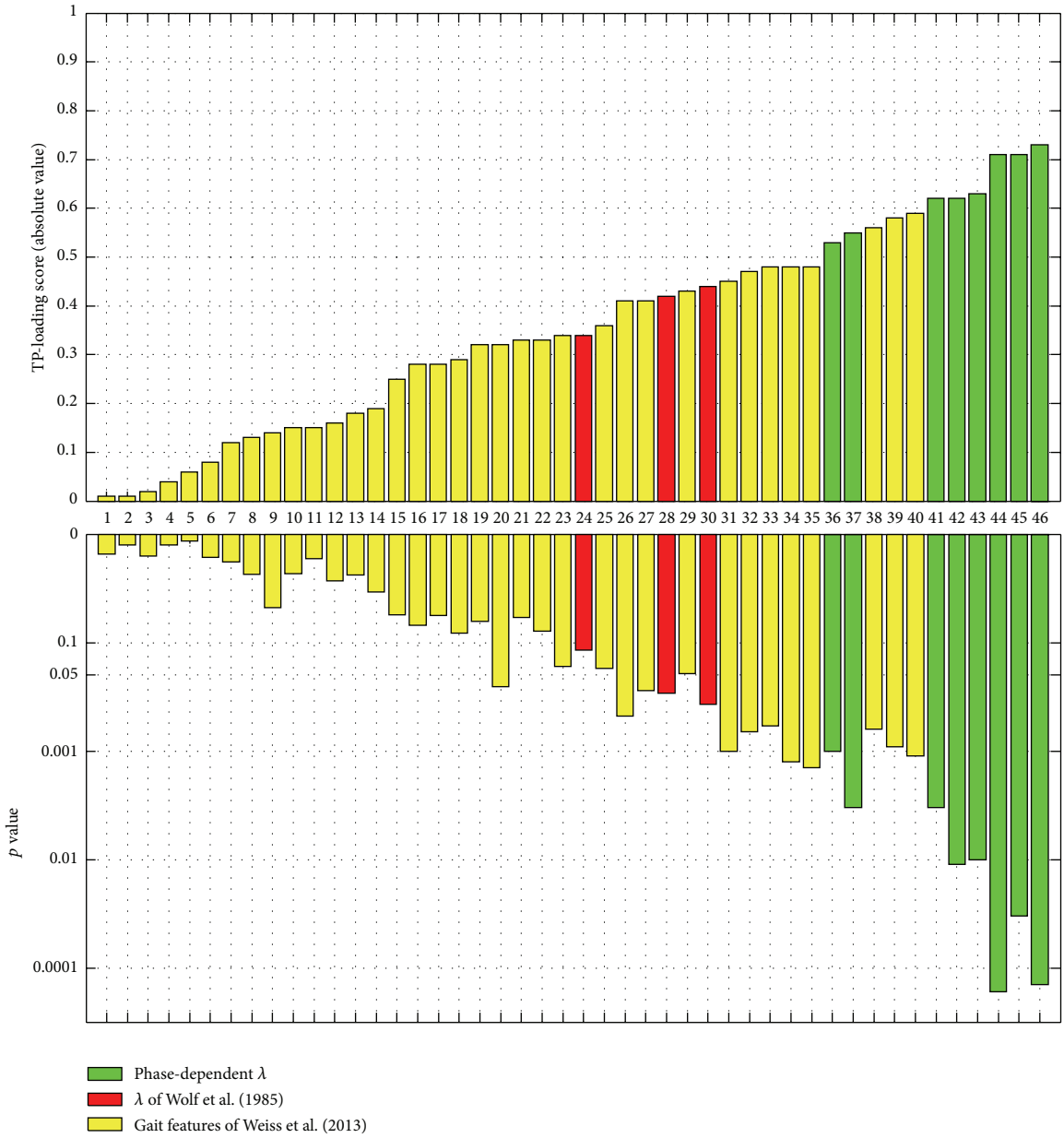


Figure 4: The TP-loading scores and corresponding p values for 46 gait features (predictor matrix $\mathbf{X}_1$ in Table 1). The feature numbers in the middle are linked to the list of gait features as follows: (1) total number of walking bouts, (2) ML harmonic ratio, (3) total percent of walking duration, (4) V step symmetry, (5) AP amplitude of dominant frequency, (6) ML step regularity, (7) V acceleration root-mean-square, (8) ML acceleration root-mean-square, (9) total number of steps, (10) V harmonic ratio, (11) ML step symmetry, (12) AP acceleration root-mean-square, (13) AP slope of dominant frequency, (14) AP stride regularity, (15) ML stride regularity, (16) V step regularity, (17) ML acceleration range, (18) V stride regularity, (19) AP step symmetry, (20) median walking bout duration, (21) V acceleration range, (22) AP harmonic ratio, (23) ML width of dominant frequency, (24) V λ_{wolf}, (25) AP step regularity, (26) V slope of dominant frequency, (27) V width of dominant frequency, (28) ML λ_{wolf}, (29) AP width of dominant frequency, (30) AP λ_{wolf}, (31) V amplitude of dominant frequency, (32) ML amplitude of dominant frequency, (33) ML slope of dominant frequency, (34) median number of steps for bout, (35) AP acceleration range, (36) λ_{diff} (phase: 0%, (2)), (37) λ_{lag} (phase: 0%, (2)), (38) Cadence, (39) average stride duration, (40) average step duration, (41) λ_{diff} (phase: 60%, (2)), (42) λ_{lag} (phase: 0%, (1)), (43) λ_{diff} (phase: 0%, (1)), (44) λ_{lag} (phase: 60%, (1)), (45) λ_{diff} (phase: 60%, (1)), and (46) λ_{lag} (phase: 60%, (2)). The phase-dependent local dynamic stability measures, λ_{lag} and λ_{diff}, are represented as *green bars* whereas conventional local dynamic stability measures, λ_{wolf}, are represented as *red bars*. The yellow bars represent gait features used in Weiss et al. (2013).

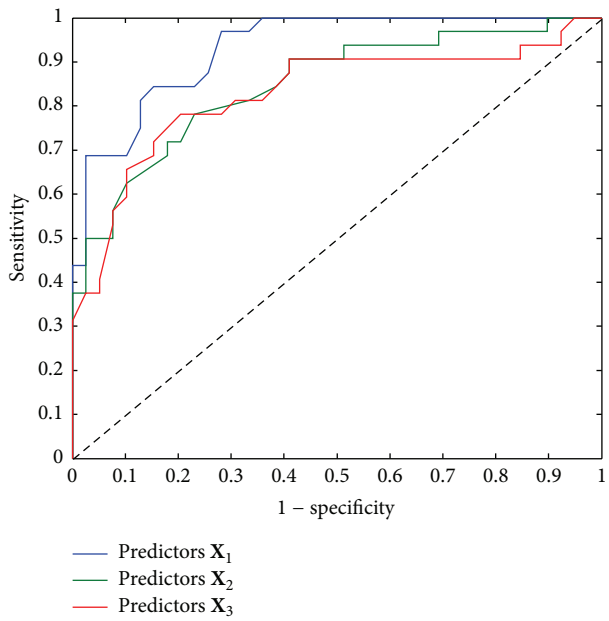


Figure 5: ROC curves summarizing the performance of the PLS-DA for the predictor matrix $\mathbf{X}_1$ (*blue*), predictor matrix $\mathbf{X}_2$ (*green*), and predictor matrix $\mathbf{X}_3$ (*red*) of gait features (see Table 1 for their definitions).

cognitive function, mental health, and fear of falling, to mention but a few, and it is therefore likely that a combination of outcomes of clinical tests and features of daily life activities will optimize fall risk assessment and fall prediction models. Even though the inclusion of λ_{diff} and λ_{lag} might further improve the fall risk assessment when combined with clinical tests, issues like cost (and maintenance cost) of accelerometers, unsupervised device handling in an in-home setting, provision and retrieval from patient in a clinical setting, and the potential for an easy-to-use online estimation of λ_{diff} and λ_{lag} will decide the feasibility of the use of λ_{diff} and λ_{lag} in fall risk assessment tools. Thus, further studies and cost-benefit analyses have to be conducted to determine the usability and feasibility of these analyses when implemented in smartphone and desktop application and the gain in accuracy of fall risk assessment needed to compensate potential decline in clinical feasibility.

Third, the relationship between phase-dependent stability λ_{diff} and λ_{lag} and variables related to the health status of the older adults was not investigated. Investigation of these relationships would be important to improve the clinical interpretation of λ_{diff} and λ_{lag} and thus should be included in further studies. In addition, assessment of λ_{diff} and λ_{lag} could be combined with experimental in-lab research of stability, like experimental perturbation studies of in-lab gait, as well as studies on neurophysiological mechanisms in animal models to improve the understanding of the underlying mechanisms of λ_{diff} and λ_{lag} [32, 33].

Fourth, the time consumption of the computational steps (i.e., gait bout identification, preprocessing, and estimation procedure) to assess λ_{diff} and λ_{lag} was not recorded. The time consumption of these steps would be important to decide the possibility for online computation of λ_{diff} and λ_{lag} which is necessary for clinical feasible smartphone and desktop application.

Fifth, even if the present study did investigate the test-retest reliability of λ_{diff} and λ_{lag} based on the first and the last 1/3 of the walking bouts during the 3-day recording, this is a considerable shorter test-retest interval compared to the 1-week test-retest interval considered in Rispens et al. [12]. ICC for 1-week test-retest might be weaker compared to the ICC found in the present study and further studies should investigate test-retest reliability of the local divergence features for longer test-retest intervals.

Sixth, the accuracy of the phase-dependent λ_{diff} and λ_{lag} is dependent on the reliability of the step identification. The inertial sensor was placed on the lower back which makes heel strike and toe-off events more difficult to identify within the gait cycle. Thus, the phase-dependent λ_{diff} and λ_{lag} in Figure 3 were not defined according to single and double support phases within the gait cycle, but according to the local peaks of the vertical velocity. The employment of advanced step identification algorithms might define the phase-dependent λ_{diff} and λ_{lag} according to heel strike and toe-offs, but further validation of these algorithms is necessary [34]. Furthermore, as inertial sensors become smaller and more wearable, further studies should include an additional sensor on the lower extremities and/or insole data to identify heel strikes and toe-offs and thereby single and double support phases.

Seventh, the sample size used in the present study is small. Rispens et al. [12] were not able to replicate the results of Weiss et al. [13] for some of the spectral features for another study with a larger sample size. A similar contrast in results might be present for phase-dependent local dynamic stability when replicated for different groups of community-dwelling older persons. Thus, further studies should replicate these initial findings on cohorts of community-dwelling older persons with different health status. Finally, the present study suggests that phase-dependent λ_{diff} and λ_{lag} are related to falls status and might be important to include in fall risk assessments and fall prediction models. Several studies indicate that measures of gait stability and variability improve fall risk assessment and fall prediction models when compared to assessments and models based on clinical tests and fall history [12, 13]. Thus, further application of phase-dependent λ_{diff} and λ_{lag}, to track changes in falls status and to prospectively identify fallers, is needed to determine their influence in fall risk assessments and fall prediction models.

5. Conclusions

The present study compared phase-dependent measures of local dynamic stability of elderly fallers and nonfallers in daily life walking with existing features of gait stability and variability. These phase-dependent measures had the best classification performance of all included gait features and improved the discrimination between elderly fallers and nonfallers compared to all other features of daily life walking. Thus, phase-dependent measures of local dynamic stability might be of importance for further development in early fall risk assessment, fall prediction, and fall prevention amongst

community-dwelling older persons. The present results set the stage for follow-up prospective studies in larger cohorts and clinical feasibility studies to further assess the potential of these metrics.

Conflict of Interests

The authors declare that no conflict of interests is associated with the present study.

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