Title
Using Smartwatch and Bluetooth Beacons to Monitor Physical Activity of Older Adults

Author
Xie, Zhuoer

Publication Date
2019

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Using Smartwatch and Bluetooth Beacons to Monitor Physical Activity of Older Adults

A thesis submitted in partial satisfaction of the requirements for the degree Master of Science in Clinical Research

by

Zhuoer Xie

2019

ABSTRACT OF THE THESIS

Using Smartwatch and Bluetooth Beacons to Monitor Physical Activity of Older Adults

by

Zhuoer Xie

Master of Science in Clinical Research

University of California, Los Angeles, 2019

Professor Marc Adam Suchard, Chair

Objective

We used a novel Sensing At-Risk Population (SARP) system to monitor patients' physical activity and locations during post-acute rehabilitation; To (1) examine the correlation between SARP measurements and standard physical (PT) and occupational therapists (OT) and nurse (RN) evaluations; (2) examine the effectiveness of SARP to discriminate discharge dispositions.

Methods

Participants were instructed to wear the smartwatch and receive physical and occupational therapy. Spearman correlations were used to determine the associations between SARP measurements and in-person evaluations. Univariate logistic regression was used to identify predictors of discharge dispositions.

Results

SARP measurements and PT/OT/RN evaluations were correlated significantly. SARP indicated that participants were active for only 5 minutes/hour during post-acute rehabilitation. SARP significantly predicted hospital readmission (AUC>70%).

Conclusions

SARP provides physical activity information during post-acute rehabilitation in real-time. Not only is SARP significantly correlated with PT/OT/RN evaluations, but it also helps to discern discharge dispositions.

The thesis of Zhuoer Xie is approved.

Arash Naeim

David Elashoff

Marc Adam Suchard, Committee Chair

University of California, Los Angeles

2019

Table of Contents

List of Tables

List of Figures

Acknowledgements

We acknowledge support from NIH grant, DHHS Agency for Health Care Research and Quality: RO1HS024394-01. We are thankful to all authors for the study conception and design, data collection, analysis of interpretation of data, manuscript writing and approval of the final article. We would like to thank the patients from the skilled nursing facility who participated in the study.

Introduction

The U.S. population aged 65 years and greater is projected to doule to 83.7 million between 2012 and 2050[1], for whom hospitalizations numbered 13 million in 2010 [2, 3]. The rate of hospitalization rises as individuals age, and with an increase in older at-risk patients, healthcare costs are also expected to rise dramatically[4]. Older patients tend to have longer hospital stays, averaging 5.5 days[5]. Prolonged hospitalization can leave this population with significant weakness and deconditioning, preventing them from safely returning home[6].

Post-acute care, a transitional phase between the hospital and home, provides an opportunity for patients to regain muscle strength and functional independence via physical, occupational, and speech-language therapy[7]. An increasing number of older patients are discharged to skilled nursing facilities (SNFs) and receive rehabilitation[8]. However, of patients discharged to SNFs, approximately 10% do not survive, 25-30% are readmitted to the hospital due to clinical changes, and only 60% are ultimately discharged home[8, 9]. Hospital readmission from a SNF is not only costly but stressful for older adults, both physically and psychologically[8]. Therefore, enhancing healthcare outcomes after hospitalization is needed.

Tools to assess physical activity during and outside of time with SNF therapists could provide important insights to the healthcare team. Recent advances in technology allow for dynamic assessment and monitoring of older individuals across multiple environments[10-12]. This technology can monitor patients' activity continuously, transmit various types of data such as patient position, time in motion, and questionnaire responses, and provide real-time feedback about changes in patient status[10, 13, 14]. However, very few studies have focused on frail older rehabilitation patients, and those studies tend to use multiple triaxial devices that likely are not practical for long-term monitoring[15].

In this study, we investigated the use of a remote monitoring platform, Sensing At-Risk Populations (SARP), which has been described previously[16-18], to monitor frail older patients' physical activities in a SNF. By monitoring patients' activity and their indoor localization with smartwatch and Bluetooth beacons, our objectives were to (1) examine correlations between SARP and standard therapists' (PT and OT) and nurses' (RN) evaluations; (2) examine the effectiveness of SARP to discriminate discharge dispositions. We discussed that SARP could provide useful information to healthcare professionals for functional assessments during rehabilitation.

Methods

1. Participants, Discharge Dispositions and Consent Process

The UCLA Institutional Review Board approved all study procedures. This study was conducted in a SNF offering post-acute rehabilitation in Santa Monica, California. Patients were enrolled from June 2016 to November 2017. Inclusion criteria were: (1) admission for post-acute rehabilitation; (2) ability to wear a watch device; and (3) age 60 years or older. Exclusion criteria were: (1) movement disorders (e.g. Parkinson's disease); and (2) clinically unsafe to participate in the study (as determined by the therapists or medical staff). Discharge dispositions included: readmission to an acute care hospital, transfer to another nursing facility, and discharge home.

During admission, a therapist pre-screened patients for eligibility prior to research staff approaching participants for consent. Research staff provided a study summary and reviewed the study materials with eligible participants. If interested, participants completed the informed consent process. The consent procedure occurred one to four days after admission depending on the timing of pre-screening and the availability of research staff.

A total of 251 participants were screened and 50 did not meet inclusion criteria. Among the 201 eligible subjects, 17 (8%) declined to participate. To compare the baseline SARP measurements with the first time in-person evaluations and yield a consistent comparison, we required SARP measurements to be available within 3 days of the first therapist evaluation. Of the 184 participants, 99 (54%) met this criterion and were included in the analyses.

2. SARP System

The specifications of SARP system included: (1) a wearable sensor technology: Sony 3 Bluetooth enabled smartwatch with in-built em7180 $\pm$ 2g triaxial accelerometer, 420mA battery and Bluetooth module; (2) Proximity-based Bluetooth Low Energy (BLE) beacons (MCU ARM Cortex-M4 32-bit processor with FPU); (3) a smartwatch application to read Bluetooth beacons and track accelerometer changes for remote patient monitoring; (4) secured real-time data transmission; (5) a central data processing and analytics engine[16-18]. Figure 1 shows the smartwatch, Bluetooth beacons and the SNF floor plan.

2.1.Smartwatch and Bluetooth Beacons

The smartwatch has a built-in 3-axis accelerometer, samples acceleration at 16Hz, and records patient movements. The magnitude of the acceleration signal is processed according to the following formula where the physical activity is inferred

$SM = \sqrt{acc_x^2, acc_y^2, acc_z^2}$ where acc indicates acceleration force around x, y, z axes. The signal magnitude (SM) is then fed to a Band-pass filter with 0.5 and 8 Hz cut-off points, thereby highlighting human motion frequency components. Mean Absolute Deviation (MAD) of the resultant signal, in window intervals of 10 s, is then calculated with the following formula.

$MAD = \frac{1}{N}\sum_{i=1}^{N=160} | x_i - x_{ave}|$ where 160 is the number of samples in 10 seconds. MAD denotes the statistical dispersion of acceleration from the mean where the unit is $\frac{m}{s^2}$, and it quantifies the acceleration movements. MAD is proportionate to force applied to the watch by patient and hence proportionate to relative work and energy. In this study, we refer to MAD as ENERGY.

BLE Beacons were placed in the locations of interest. The smartwatch Bluetooth module reads the signal strengths broadcasted from the beacons. Based on the signal strengths, the proximity of watch (patient) to each location of interest was calculated and the closest location was highlighted. This way, SARP produced the indoor localization of patients. This algorithm was refined to achieve > 80 % accuracy over the course of 6 months at the SNF [16-18].

2.2.SARP Data Collection, Storage and Process

Each participant was provided a smartwatch labeled by a device number. Research staff placed the smartwatch on participants at 9 am and retrieved it at 6 pm. The smartwatches were charged at night and returned to participants the next morning. Participants were asked to wear the smartwatch until they were discharged. The de-identified sensor data were transmitted wirelessly to a secured server and maintained in a central data processing engine hosted at University of California, Los Angeles.

2.3.SARP Measurements

The daily smartwatch wear time was recorded as “uptime” (i.e., approximately 8 hours). Two summary metrics and four location metrics were used for data analysis:

(1) Total active time (ACTIVE) summarized the total active minutes in a day; an empirically produced threshold of 0.02 $\square/\square^{2}$ determined Active/Non-Active status. In case the

MAD of acceleration signal exceeded 0.02 in 10 seconds, participants' status was considered active.

(2) Daily energy expenditure (ENERGY) was estimated as the sum of MAD of the accelerometer signal in a day.

(3) Time spent in different locations was summarized based on the Bluetooth beacons location. Time spent in the bedroom was further classified into (a) time spent in the bed, (b) bathroom, and (c) toilet. Table 1 displays the SARP measurements and their definitions.

We divided daily SARP measurements by "uptime" of each particular day. The purpose of normalization is to develop generic metrics which are independent of the variability in adherence in wearing the watch between users.

3. Nursing (RN) and Therapist (PT/OT) Evaluations

Participants' device number, consent date and study completion date were recorded in REDCap[19]. Minimum Data Set (MDS)[20], part of the U.S federally mandated clinical assessment of all residents in Medicare or Medicaid certified nursing homes, was used to obtain participants' age, gender, race/ethnicity, height, weight, date of birth, body mass index, number of active diagnoses, presence of pain, education level, and length of post-acute rehabilitation. Functional status evaluated by a RN on admission including bed mobility, transfers, dressing, eating, toilet use, personal hygiene, bathing, walk in the room, walk in the corridor, locomotion on the unit, and locomotion off the unit, was also obtained from the MDS. Function levels were scored on a five-point scale for data analysis purpose: total dependence; extensive assistance; limited assistance; supervision and independent. It was considered missing if documented as "activity did not happen or activity happened only 1-2 times".

Participants had daily physical and occupational therapy. The first therapist evaluation was typically at the time of admission or one day later. During each therapist encounter, three to seven metrics from gait, transfer, bed mobility, hygiene, toileting, upper and lower body dressing were evaluated. Research staff extracted participants' physical activity data evaluated by therapists from the medical records. Data quality was assessed by a physician biweekly to verify missing values, field validation errors, outliers or incorrect values.

Only metrics that were evaluated consistently (the most commonly assessed metrics evaluated by therapists) were determined acceptable for data analysis. With this requirement, we reported 11 PT and OT metrics. For data analysis purpose, we coded these metrics on a seven-point scale from 1, representing total assistance, to 7, denoting complete independence based on the functional independence measure (FIM) instrument[21]. Table 1 contains the most commonly used measurements and their definitions.

4. Statistics and Data Analysis

Descriptive statistics were computed for sociodemographic variables and study measures (PT/OT/RN/SARP). We compared the PT/OT/RN/SARP metrics among discharge dispositions via one-way ANOVA tests (SARP) or Kruskal-Wallis Tests (PT/OT/RN).

Spearman correlations were used to determine the association between SARP and PT/OT/RN metrics. The Benjamini-Hochberg false discovery rate (FDR) was computed to account for multiple hypotheses. A threshold of FDR< 0.2 was used for reporting of results.

Univariate logistic regression was used to identify predictors of discharge dispositions (discharge home and transfer to other nursing facility were considered as one outcome for this analysis). Area Under the ROC Curve (AUC) was used to evaluate the ability of the predictors to discriminate discharge dispositions.

Two-sided p values were reported and comparisons were considered statistically significant if $p<0.05$. All analyses were performed using STATA 15.

Results

Table 2 shows participant demographics. Participants' mean age was 80.6 (SD 9.2) years, 30.3% were male, and 79.8% were white. Of the 99 participants, 77.6% had more than 10 active diagnoses. Almost all participants required assistance for their activities of daily living. The mean length of post-acute rehabilitation was 23.4 (SD 15.7) days. Seventy percent of the participants were discharged home, 12.1% were readmitted to the hospital, and 17.2% were transferred to another nursing facility.

1. Associations between SARP and PT/OT/RN Evaluations

Of the 44 correlations computed, nine were significant with FDR <0.2 correction between SARP and PT/OT/RN evaluations, seven for SARP ACTIVE and two for SARP ENERGY (Table 3).

2. Discharge Dispositions as a Function of PT/OT/RN and SARP Evaluations

Five of six PT metrics, five of six OT metrics, and nine of 11 RN metrics differed significantly between the three discharge dispositions ($p<0.05$; Table 4). SARP ACTIVE, ENERGY and Time in Bedroom, but not three other in-room SARP metrics, differed significantly between the discharge dispositions ($p<0.05$). Participants readmitted to the hospital spent 8 more minutes/hour in the bedroom than those discharged home (home 49.2 minutes v. hospital 57 minutes v. other nursing facilities 55.8 minutes, $p=0.03$). The participants readmitted to the hospital were active for only 3.6 minutes/hour, whereas those discharged home and to other nursing facilities were active 6.6 minutes/hour and 6 minutes/hour, respectively ($p=0.007$) (Table 4).

3. Univariate Logistic Regression Model

All in-person evaluations except RN-rated Eating and OT-rated Hygiene significantly predicted hospital readmission, and their AUC ranged from 0.58 to 0.85. SARP metrics ACTIVE and ENERGY significantly predicted hospital readmission, with AUC 0.75 and 0.71, respectively (both $p<0.05$).

Discussion

This study demonstrates that SARP, a novel remote sensing system using a smartwatch based single triaxial accelerometer and Bluetooth beacons, could continuously measure older patients' physical activity as well as time spent in different locations during post-acute rehabilitation. Not only is SARP significantly correlated with PT/OT/RN evaluations, but it also helps to discern discharge dispositions. Some features predicted hospital readmission with more than 70% accuracy.

Research with commercial devices such as Fitbit One and Apple Watch has shown that using a fitness tracker can provide reliable activity and energy expenditure data, but those studies were conducted with young and healthy populations[22, 23]. Parvaneh et al.[14] and Schwenk et al.[24] used chest-worn wearable technology to identify frailty status in community-dwelling older adults and predict fall risk in older dementia patients. In contrast, our target population was at-risk older frail patients during post-acute rehabilitation, and the device was a single wearable smartwatch, which is promising for future studies as it is capable of continued monitoring at home after hospital discharge.

To our knowledge, this is the first study in which wearable sensor measurements were compared with PT/OT/RN evaluations. Previous work examined the relationship between technology-based evaluation and specific standardized ratings. For example, Simila. H et al. used accelerometer data and Berg balance score to predict fall risk[25], and Parnandi. A et al. used inertial unit measurement to predict functional ability from the Wolf motor function test[26]. One study demonstrated that wearable sensor data combined with patients' admission clinical information achieved a higher prediction accuracy on FIM scores than the clinical information alone in a rehabilitation facility[27]. In the present study, sensor measurements (ACTIVE and ENERGY) were moderately correlated with PT/OT/RN evaluations. Other than the scheduled time with therapists, SARP demonstrates that the participants are active only for an average of 5 minutes/hour during post-acute rehabilitation. This result is similar to that of Rand et al., who used raw activity counts from accelerometers to monitor physical activity in older post-stroke patients and found that patients had very low activity levels[28].

Another innovation is the combination of the physical activity data from smartwatch and the indoor location data from Bluetooth beacons. Although research exists using wearable sensor to monitor physical activity[26, 29], the use of Bluetooth beacons remains experimental[30, 31]. Komai et al. used a fixed scanner and moveable Bluetooth beacons, which were embedded in patients' name cards, to monitor patients' movement from each location in a Japanese daycare center. The small study (N=2) showed that the system could identify each individual's locations[32]. We were able to distinguish the location data of 99 participants. Moreover, our study is the first study that real-time location data and physical activity data were gathered along with clinical outcomes. We found that participants readmitted to the hospital spent almost 100% of time in their bedroom, with 75% of the time in the bed.

Prolonged bed rest contributes to general deconditioning, decreases muscle strength and often leads to complications[33]. Physical activity is associated with quality of life, health outcomes, and functional independence in patients who are in the recovery phase after hospitalization, whereas lack of physical activity is related to poor functional recovery[34, 35]. The inability to accomplish activities of daily living is associated with hospital readmission[33, 36], which is a common and costly discharge disposition from SNFs[8]. Patients readmitted to an acute care hospital from a SNF also have the highest one-year mortality rate (approximately 50%)[9]. Many of these issues can be addressed proactively through promotion of medically-indicated physical activity. The Physical Activity Guidelines for Americans recommend that all adults, including those with disabilities and older adults to have at least 150 minutes a week of moderate–intensity aerobic physical activity[37]. Improving out-of-room/bed activities has the potential to increase recovery and overall health benefits among older adults. The location data adds value to the smartwatch data as it assists healthcare professionals to understand where the physical activity is occurring and the duration of bed rest. This could alert therapists to the importance of out-of-room/bed activities, and allows clinicians to use this information in treatment.

In the near future, the supply of trained medical personnel is projected to be insufficient to meet the demands of the growing population[38]. Data from smartwatch and location sensors can provide insight into a patient's functional status and its associated declines or improvements without extra staff time. Therefore, SARP may serve to augment and complement traditional in-person measurement and provide novel opportunities to offer personalized medicine to improve the quality of interventions during post-acute rehabilitation. Counter to the concern regarding older adults' uptake of technology[39], most participants were interested in and able to wear the smartwatch with minimal training.

Study Limitations

The study has several limitations. We normalized SARP metrics to generate generic metrics which are independent of participants. The date of informed consent varied, due to a limited number of research staff. In order to allow consistent comparison between baseline SARP and in-person evaluations, we limited the analytic sample size. The smartwatches were charged in the evening, so no data were collected at night. Finally, patients admitted to a SNF have lower tolerance for therapy and activity in general than do patients admitted to acute rehabilitation, who can expect to work with therapists for three or more hours on five of seven days[40]. Therefore, caution is needed when applying the findings to other populations.

Conclusions and Future Research

This study used a smartwatch and Bluetooth beacons to monitor older adults' physical activity and locations during post-acute rehabilitation. SARP integrates continuous, objective and personalized data into therapist evaluations, and predicts hospital readmission. Research is ongoing on whether SARP can monitor individual changes that might serve as evidence of incremental decline in functional independence. Providing the trending data from SARP to care providers might be beneficial, in that medical professionals could provide early intervention early and optimize patients' outcome. The present findings add to the wearable sensor research base, especially on older adults during post-acute rehabilitation, provide insight into patients' activity levels, and have implications for enhancing physical activity during rehabilitation.

Suppliers

Sony 3 Bluetooth enabled smartwatch with in-built em7180 $\pm$ 2g triaxial accelerometer, 420mA battery and Bluetooth module;

Proximity-based Bluetooth Low Energy beacons (MCU ARM Cortex-M4 32-bit processor with FPU);

Table 1. SARP, RN, PT and OT Metrics and Definitions

	Metrics	Definition
SARP	ACTIVE	Total active minutes in a day.
	ENERGY	The sum of mean absolute deviation of the accelerometer signal in a day.
	Time in Bedroom	Total time in a day spent in the resident room. It is the sum of the time spent in bed, toilet and bathroom.
	Time in Toilet	Total time in a day spent in the his/her toilet.
	Time in Bed	Total time in a day spent in the his/her bed.
	Time in Bathroom	Total time in a day spent in the his/her bathroom.
RN	Bed Mobility	How resident moves to and from lying position, turns side to side, and positions body while in bed or alternate sleep furniture.
	Transfer	How resident moves between surfaces including to or from: bed, chair, wheelchair, standing position (excludes to/from bath/toilet).
	Dressing	How resident puts on, fastens and takes off all items of clothing, including donning/removing a prosthesis or TED hose. Dressing includes putting on and changing pajamas and housedresses.
	Eating	How resident eats and drinks, regardless of skill. Do not include eating/drinking during medication pass. Includes intake of nourishment by other means (e.g., tube feeding, total parenteral nutrition, IV fluids administered for nutrition or hydration).
	Toilet	How resident uses the toilet room, commode, bedpan, or urinal; transfers on/off toilet; cleanses self after elimination; changes pad; manages ostomy or catheter; and adjusts clothes. Do not include emptying of bedpan, urinal, bedside commode, catheter bag or ostomy bag.
	Personal hygiene	How resident maintains personal hygiene, including combing hair, brushing teeth, shaving, applying makeup, washing/drying face and hands (excludes baths and showers).
	Bathing	How resident takes full-body bath/shower, sponge bath, and transfers in/out of tub/shower (excludes washing of back and hair). Code for most dependent in self-performance and support.
	Walk in the Room	How resident walks between locations in his/her room.
	Walk in the corridor	How resident walks in corridor on unit.

	Locomotion on unit	How resident moves between locations in their room and adjacent corridor on same floor. If in wheelchair, self-sufficiency once in chair.
	Locomotion off unit	How resident moves to and returns from off-unit locations (e.g., areas set aside for dining, activities or treatments). If facility has only one floor, how resident moves to and from distant areas on the floor. If in wheelchair, self-sufficiency once in chair.
PT	Gait: Level Surfaces	How resident ambulates in level surfaces.
	Bed Mobility: Supine to Sit	How resident moves to and from lying position, turns side to side, and positions body while in bed or alternate sleep furniture.
	Transfer: Sit to Stand	How resident moves between surfaces including to or from: sit to stand or stand to sit.
	Transfer: General	How resident moves between surfaces including to or from: bed, chair, wheelchair, standing position.
	Transfer: Bed to Chair	How resident moves between surfaces: bed to chair or chair to bed.
	Gait Distance (Feet)	The distance that resident could walk.
OT	Bed Mobility: Sit to Stand	How resident moves from sitting to standing or standing to sitting
	Bed Mobility: Supine to Sit	How resident moves from supine to sitting or sitting to supine
	Dressing: Upper body and Lower body	How resident puts on, fastens and takes off all items of clothing, including donning/removing a prosthesis or TED hose. Dressing includes putting on and changing pajamas and housedresses.
	Hygiene	The ability to attend to the cleansing of his/her body and access the necessary tools in the educational environment.
	Toileting	The ability to anticipate the need and uses the bathroom.

Table 2. Sociodemographic Data of Study Subjects

Characteristics	N (%)
Mean Age (SD)	80.6 (9.16)
Gender (%) • Male • Female	 30 (30.3) 69 (69.7)
Race/Ethnicity (%) • American Indian/Native • Hispanic/Latino • Asian • Native Hawaiian/Pacific Islander • African American • White	 1(1) 1 (1) 4 (4) 4 (4) 10 (10) 79 (79.8)
Pain Present (%) • No • Yes	 23 (34.9) 43 (65.2)
Active Diagnosis (%) • <10 • >=10	 22 (22.5) 76 (77.6)
Urinary Incontinence • Always continent • Occasionally incontinent • Frequently incontinent • Always incontinent • Not rate	 77 (78.6) 2 (2) 8 (8.2) 9 (9.2) 2 (2)
Bowel Continence • Always continent • Occasionally incontinent • Frequently incontinent • Always incontinent • Not rate	 82 (83.7) 2 (2) 4 (4.1) 9 (9.2) 1 (1)

Table 3. Significant Correlations between SARP Metrics and PT/OT/RN Evaluations

SARP Metrics	**PT/OT/RN Evaluations**	**N**	**rho**
ACTIVE	Gait: Level Surfaces	75	0.37
ACTIVE	Bed Mobility: Supine to Sit	91	0.33
ACTIVE	Transfer: Sit to Stand	85	0.3
ACTIVE	Bed Mobility: Sit to Stand	77	0.31
ACTIVE	Gait: Distance	91	0.28
ACTIVE	ADL Walk in the Hallway	87	0.29
ACTIVE	ADL Walk on the Unit	92	0.27
ENERGY	Bed Mobility: Supine to Sit	91	0.27
ENERGY	Gait: Level Surfaces	75	0.28

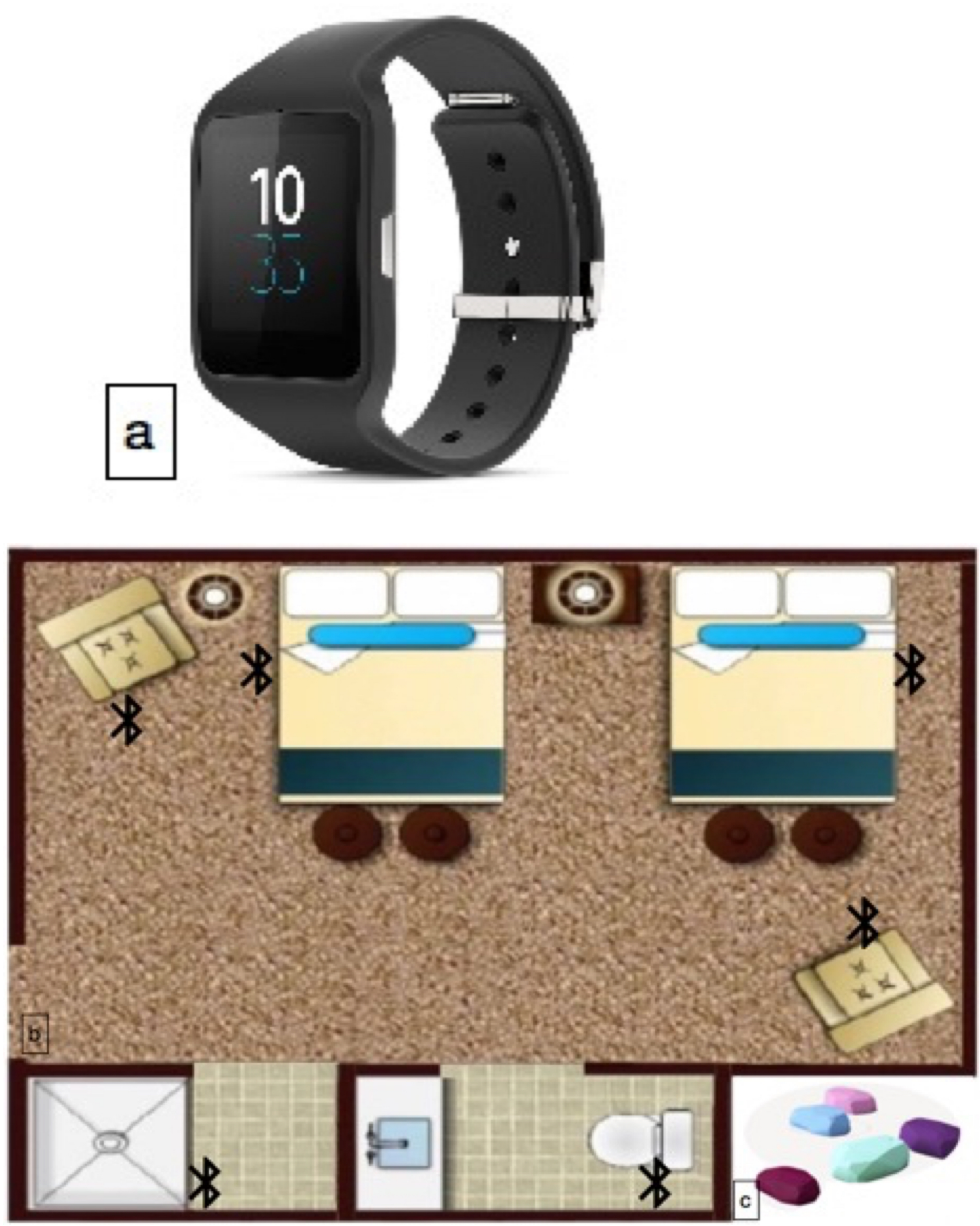
Table 4. PT/OT/RN/SARP Evaluation Differences Based on the Discharge Dispositions

	Variables	Discharge Dispositions			
		Home N=70	**Hospital N=12**	**Others N=17**	**p**
RN	Bed Mobility	3 (3, 3)	2 (2, 2.5)	3 (3, 3)	<0.001
	Transfer	3 (3, 3)	2 (2, 2)	3 (3, 3)	<0.001
	Dressing	2 (2, 3)	2 (2, 2)	2 (2, 3)	0.04
	Eating	5 (5, 5)	4.5 (5, 5)	5 (5, 5)	0.35
	Toilet Use	3 (2, 3)	2 (2, 2)	3 (2, 3)	<0.001
	Personal Hygiene	3 (2, 3)	2 (2, 2.5)	3 (3, 3)	0.004
	Bathing	2 (2, 3)	2 (2, 2)	2 (2, 2)	0.12
	Walk in the Room	3 (3, 3)	2 (2, 2)	3 (3, 3)	<0.001
	Walk in the corridor	3 (3, 3)	2 (2, 2)	3 (3, 3)	<0.001
	Locomotion on Unit	3 (3, 3)	2 (2, 2)	3 (3, 3)	<0.001
	Locomotion off Unit	3 (2, 3)	2 (2, 2)	3 (3, 3)	<0.001
PT	Transfer General	4 (3,4)	2 (2,3)	4 (3,4)	0.02
	Transfer: Sit to Stand	4 (3,4)	2 (2,4)	4 (3,4)	0.05
	Transfer: Bed to Chair	4 (3,4)	2 (2,4)	4 (3,4)	0.04
	Gait: Level Surfaces	4 (3,4)	2 (2,3)	4 (4, 4)	0.001
	Bed Mobility: Supine to Sit	4 (3,4)	2 (2,4)	4 (3,4)	0.03
	Gait Distance‡	40 (10, 60)	0 (0, 27.5)	50 (30, 50)	0.01
OT	Bed Mobility: Sit to Stand	4 (3,4)	2 (2,3)	4 (3,4)	0.0002
	Bed Mobility: Supine to Sit	4 (3,4)	2 (2, 3.5)	4 (4,4)	0.01
	Dressing: Upper body	4 (4,4)	4 (3,4)	4 (4,4)	0.03
	Dressing: Lower body	3 (2,4)	2 (1,3)	3 (2,3)	0.047
	Hygiene	4 (4,4)	4 (3,4)	4 (4,4)	0.1
	Toileting	4 (2,4)	2 (2,3)	3 (3,4)	0.01
SARP	Active*	6.6 (3.8)	3.6 (2.2)	6 (3.0)	0.007
	Energy	47.2 (18.3)	33 (14.9)	43.1 (14.2)	0.03
	Time in Bedroom*	49.2 (13.1)	57 (4.8)	55.8 (6.4)	0.03
	Time in Toilet*	9.6 (11)	4.2 (5)	9.6 (8.5)	0.19
	Time in Bed*	34.2 (18)	42.6 (18.8)	37.2 (17.5)	0.3
	Time in Bathroom*	4.8 (8.0)	5.4 (8.0)	9.6 (17.3)	0.25

* Data presented as minutes per hour

‡ Gait Distance's unit is feet.

Figure 1. Image of the SARP system: (a) Smartwatch; (b) Skilled Nursing Facility Floor plan; (c) Bluetooth beacons; is the Bluetooth beacons location in the residents' room.



References

1. Ortman, J.M., V.A. Velkoff, and H. Hogan. *An Aging Nation: The Older Population in the United States Population Estimates and Projections Current Population Reports*. 2014.
2. Statistics, N.C.f.H., *National Hospital Discharge Survey Data 2010.* 2012.
3. Gorina, Y., et al. *Hospitalization, Readmission, and Death Experience of Noninstitutionalized Medicare Fee-for-service Beneficiaries Aged 65 and Over*. 2015.
4. Yamamoto, D.H., *Health Care Costs*. 6/2013, Health Care Cost Insitute.
5. Center for Health Statistics, N. *Vital and Health Statistics Series 13, Number 165 (December 2007)*. 2005.
6. Covinsky, K.E., et al., *Loss of independence in activities of daily living in older adults hospitalized with medical illnesses: Increased vulnerability with age.* Journal of the American Geriatrics Society, 2003. **51**: p. 451-458.
7. *Post-Acute Care - California Hospital Association.*
8. Mor, V., et al., *The Revolving Door Of Rehospitalization From Skilled Nursing Facilities.* Health Affairs, 2018. **29**: p. 57-64.
9. Hakkarainen, T.W., et al., *Outcomes of Patients Discharged to Skilled Nursing Facilities After Acute Care Hospitalizations.* Annals of surgery, 2016. **263**: p. 280-285.
10. Benedetti, M.G., et al., *Physical activity monitoring in obese people in the real life environment.* Journal of neuroengineering and rehabilitation, 2009. **6**: p. 47.

11. Albert, M.V., et al., *Monitoring daily function in persons with transfemoral amputations using a commercial activity monitor: a feasibility study.* PM & R : the journal of injury, function, and rehabilitation, 2014. **6**: p. 1120-1127.

12. Yang, C.-C.C. and Y.-L.L. Hsu, *A review of accelerometry-based wearable motion detectors for physical activity monitoring.* Sensors, 2010. **10**: p. 7772-7788.

13. Najafi, B., et al., *Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly.* IEEE transactions on bio-medical engineering, 2003. **50**: p. 711-23.

14. Parvaneh, S., et al., *Postural Transitions during Activities of Daily Living Could Identify Frailty Status: Application of Wearable Technology to Identify Frailty during Unsupervised Condition.* Gerontology, 2017. **77030**.

15. Cheung, V.H., L. Gray, and M. Karunanithi, *Review of accelerometry for determining daily activity among elderly patients.* Arch Phys Med Rehabil, 2011. **92**(6): p. 998-1014.

16. Moatamed, B., et al., *Low-cost indoor health monitoring system.* BSN 2016 - 13th Annual Body Sensor Networks Conference, 2016: p. 159-164.

17. Bouchard, K., R. Ramezani, and A. Naeim, *Features based proximity localization with Bluetooth emitters.* 2016 IEEE 7th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference, UEMCON 2016, 2016: p. 1-5.

18. Bouchard, K., et al., *Evaluation of Bluetooth beacons behavior*, in *2016 IEEE 7th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*. 2016, IEEE. p. 1-3.

19. Harris, P.A., et al., *Research electronic data capture (REDCap)--a metadata-driven methodology and workflow process for providing translational research informatics support.* Journal of biomedical informatics, 2009. **42**: p. 377-381.

20. *DRAFT MINIMUM DATA SET, Version 3.0 (MDS 3.0) FOR NURSING HOME RESIDENT ASSESSMENT AND CARE SCREENING*.

21. Linacre, J.M., et al., *The Structure and Stability Independence Measure of the Functional.*

22. Diaz, K.M., et al., *Fitbit®: An accurate and reliable device for wireless physical activity tracking.* International Journal of Cardiology, 2015. **185**: p. 138-140.

23. El-Amrawy, F. and M.I. Nounou, *Are Currently Available Wearable Devices for Activity Tracking and Heart Rate Monitoring Accurate, Precise, and Medically Beneficial?* Healthcare Informatics Research, 2015. **21**: p. 315.

24. Schwenk, M., et al., *Sensor-derived physical activity parameters can predict future falls in people with dementia.* Gerontology, 2014. **60**: p. 483-492.

25. Simila, H., et al., *Accelerometry-Based Berg Balance Scale Score Estimation.* IEEE Journal of Biomedical and Health Informatics, 2014. **18**: p. 1114-1121.

26. Parnandi, A., E. Wade, and M. Mataric, *Motor function assessment using wearable inertial sensors.* Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, 2010. **2010**: p. 86-9.

27. Sprint, G., et al., *Predicting Functional Independence Measure Scores during Rehabilitation with Wearable Inertial Sensors.* IEEE Access, 2015. **3**: p. 1350-1366.

28. Rand, D., et al., *How Active Are People With Stroke? Use of Accelerometers to Assess Physical Activity.* 2008.

29. Van Kasteren, T.L.M., et al., *An activity monitoring system for elderly care using generative and discriminative models.* Personal and Ubiquitous Computing, 2010. **14**: p. 489-498.

30. Huh, J.-H. and K. Seo, *An Indoor Location-Based Control System Using Bluetooth Beacons for IoT Systems.* Sensors (Basel, Switzerland), 2017. **17**.

31. Magistro, D., et al., *A Novel Algorithm for Determining the Contextual Characteristics of Movement Behaviors by Combining Accelerometer Features and Wireless Beacons: Development and Implementation.* JMIR mHealth and uHealth, 2018. **6**: p. e100.

32. Komai, K., et al., *Beacon-based multi-person activity monitoring system for day care center.* 2016 IEEE International Conference on Pervasive Computing and Communication Workshops, PerCom Workshops 2016, 2016: p. 1-6.

33. Greysen, S.R., et al., *Functional Impairment and Hospital Readmission in Medicare Seniors.* JAMA Internal Medicine, 2015. **175**: p. 559.

34. Mayo, N.E., et al., *Activity, participation, and quality of life 6 months poststroke.* Archives of Physical Medicine and Rehabilitation, 2002. **83**: p. 1035-1042.

35. Fox, K.R., *The influence of physical activity on mental well-being.* Public Health Nutrition, 1999. **2**: p. 411-418.

36. Depalma, G., et al., *Hospital readmission among older adults who return home with unmet need for ADL disability.* Gerontologist, 2013. **53**: p. 454-461.

37. *2008 Physical Activity Guidelines - health.gov.*

38. Reinhardt, U.E., *Does The Aging Of The Population Really Drive The Demand For Health Care?* Health Affairs, 2003. **22**: p. 27-39.

39. Wildenbos, G.A.A., L. Peute, and M. Jaspers, *Aging barriers influencing mobile health usability for older adults: A literature based framework (MOLD-US).* International Journal of Medical Informatics, 2018. **114**: p. 66-75.

40. Levant, S., K. Chari, and C.J. DeFrances, *Hospitalizations for patients aged 85 and over in the United States, 2000-2010.* NCHS data brief, 2015(182): p. 1-8.