Monitoring Activities of Daily Living of the Elderly and the Potential for Its Use in Telecare and Telehealth: A Review

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Original Research

Monitoring Activities of Daily Living of the Elderly and the Potential for Its Use in Telecare and Telehealth: A Review

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Abstract

Objective: *This review was designed to determine whether telemonitoring activities of daily living (ADL) of elderly people can improve quality of life and be beneficial to their healthcare.* ***Materials and Methods:*** *Electronic databases were searched for studies that monitored ADL of elderly people and preferably measured some clinical outcomes such as ability to predict key events that require intervention and for studies that assessed perception of elderly people of such telemonitoring systems. The articles were reviewed and assessed independently by two reviewers.* ***Results:*** *One hundred seventy-five unique studies were found. Sixty-seven of these were identified for potential inclusion, and 25 studies were finally included. Study characteristics, parameters monitored, outcomes, and problems encountered were summarized and discussed. The main focus was on the potential benefits of ADL monitoring on the care of elderly people.* ***Conclusions:*** *Although most studies reported on technical improvements in methods for detecting changes in ADL, few, if any, determined the benefits to the patient of telemonitoring for changes in ADL or correlation with any physiological changes. We propose sensor and system characteristics for improved user acceptance and deployment in a large-scale care plan. We present areas requiring further investigation.*

Key words: *e-health, m-health, home health monitoring, telehealth, telemedicine*

Introduction

Over the last decade, many studies on continuous monitoring of activities of daily living (ADL) of elderly people have been carried out. The main themes of the studies were health-smart homes, aging in-place, or simple activity telemonitoring. Telemonitoring ADL could improve elder care by enhancing a sense of safety and quality of life, by detecting key events (such as loss of autonomy, disease onset, and falls) and by enabling timely intervention. Moreover, long-term monitoring can also allow professionals to make informed decisions, to monitor deterioration in chronic illnesses, or to assess response to a treatment.

Changes in daily activity level (or daily habits) can provide important clues regarding functional capability, cognitive abilities, loss of autonomy/independence, deterioration in health status, or progress of an existing illness.[1] For example, people with depression tend to move less, putting weight on may limit activity level, and vice versa, a patient with chronic heart failure may be less likely to move as his or her condition deteriorates, or an elderly person with influenza may tend to spend more time in bed. An elderly person who is unable to perform ADL such as preparing a meal, eating, bathing, or climbing the stairs or exhibits poor medication adherence is more likely to suffer from a rapid deterioration of quality of life and health status and more likely to fall.[2,3]

The relationship between mobility and health status is well recognized. Increased mobility improves physiological and psychological well-being and quality of life, may prevent rapid deterioration of health status of chronically ill people,[4] and improves muscles and bones[5] (i.e., makes you become less prone to bone fractures after a fall).

Although there are significant numbers of systematic reviews and meta-analysis on telemonitoring of chronic diseases, with themes of technology or treatment effectiveness,[6–14] there are only a few reviews on ADL telemonitoring.[15,16] Telemonitoring technologies were classified into ambient sensor technologies, wearable technologies, and combinational technologies.[15] ADL monitoring was reviewed under four categories: activity, sleep, falls, and gait/posture monitoring.

The small number of reviews may be due to the fact that the studies were mainly demonstrations and/or evaluations of a new technology/approach rather than a clinical trial investigating effectiveness of the technology. Furthermore, they lack a common evaluation framework.

The objective of this review was to identify and summarize ADL telemonitoring of the elderly, determine areas that require further investigation, identify issues that need to be taken into account (including user perceptions), and review the effects of ADL telemonitoring systems on telecare of the elderly. We believe that the findings may provide useful points for the design and development of future systems and studies.

Materials and Methods

The following databases were queried for studies in English: PubMed, Scopus, and IEEE. A combination of three sets of search terms (*Table 1*) was sought in the title, abstract, and key words/MeSH terms. The first set of terms was relevant to ADL monitoring, the second set of terms to telemetry or telemedicine, and the third set to the subject age group. A separate search was carried out for user perception, using the additional set of search terms relevant to user satisfaction. Between January 1, 1995 and June 30, 2011, 256 abstracts were retrieved. Duplicate search results were eliminated, leaving 175 unique studies for abstract review.

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Table 1. Search Terms and Strategy Used (Last Updated July 2011)

DATABASE, LIMITS	SEARCH TERMS AND STRATEGY	NUMBER OF ARTICLES FOUND
Scopus	(activities of daily living OR adl) AND (telemedicine OR telemetry) AND (aged OR aging)	120
	(activities of daily living OR ADL) AND (patient satisfaction OR perception OR demands OR health services needs) AND (telemedicine OR telemetry) AND (aged OR aging)	17
Limits	Publication year, 1995– June 30, 2011; English; publication type, article, conference, or review	
PubMed	("activities of daily living"[MeSH] OR ADL OR acceleration OR activity recognition OR mobility monitoring) AND (Aged OR aging) AND ("telemedicine/methods"[MeSH] OR "telemedicine/instrumentation"[MeSH] OR "telemetry/methods" [MeSH] OR "telemetry/instrumentation"[MeSH] OR telecare) AND "humans"[MeSH]	73
	"activities of daily living*"[MeSH] AND ("patient acceptance of healthcare*"[MeSH] OR "patient satisfaction*"[MeSH] OR perception) AND ("telemetry*"[MeSH] OR "telemedicine*") AND ("aged*"[MeSH] OR "aging*"[MeSH])	16
Limits	Publication year, 1995–June 30, 2011; English	
IEEE	(activities of daily living OR mobility monitoring) AND (telemetry OR telemedicine OR biomedical telemetry OR home care services) AND (Aged OR Aging OR health services for the aged)	29
	(activities of daily living OR ADL) AND (patient satisfaction OR perception OR demands OR health services needs) AND (telemedicine OR telemetry) AND (aged OR aging)	1
Limits	Publication year, 1995–June 30, 2011; content type, conference or journal	

SELECTION CRITERIA

Only peer-reviewed publications were included. Studies that were designed to monitor ADL of the elderly, that used telemetry for transmitting relevant parameters/data, and that assessed acceptability of such monitoring systems by the users were included.

EXCLUSION CRITERIA

Studies that were not in English, studies without an abstract, studies that could not be located, studies that classified only body movements or postural transitions, studies that aimed to promote physical activity among young people or monitor athletes' performance and assist them in training activities articles, studies that assessed the effect of body movements on physiological measurements, review articles, and studies that did not present significant outcomes were excluded. Studies that used telephone calls[17]or videoconferencing to obtain relevant data were excluded. Studies that used plain sound or video signals as the main tool for ADL monitoring were also excluded[18,19] because these methods are known to raise privacy issues.

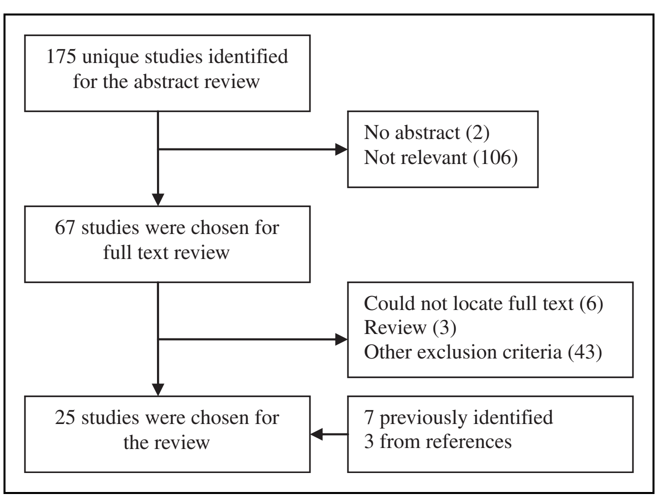

Fig. 1. Study selection process.

The authors independently retrieved the abstracts and assessed these based on the inclusion criteria. This resulted in 67 studies for full text review (*Fig. 1*). Seven further studies previously identified were included. The selected articles were reviewed independently by each researcher, and those that did not meet the selection criteria were excluded. Reference lists of the retained publications were hand-searched for further publications that might be relevant and assessed for inclusion using the criteria. Three further studies were determined from the review process. Twenty-five studies were finally included in the review.

Results

From the selected articles (*Fig. 1*), we extracted data on the following items:

1. Study characteristics, including number of subjects, subject characteristics, laboratory or home environment, follow-up duration, and study type
2. Monitoring device and telemonitoring characteristics, including any user interaction required, decision support capability, emergency detection capability, approaches for proactive

treatment, level of support (education, regular contacts, reminders), and alarms
3. Monitored parameters (e.g., ADL, body movements, physiological data) and sensor characteristics
4. Outcomes: relation between changes in habit data and health status, sensitivity and/or specificity for predicting events requiring intervention or fall detection, rates of false alarms, user perception of such monitoring systems, effectiveness of the intervention, and technical problems experienced

We placed the selected studies into three main groups according to the parameters that were monitored:

- Group 1—those that monitored only activity level (11 studies)[20–30]
- Group 2—those that monitored both activity level and physiological parameters (9 studies)[31–39]
- Group 3—those that evaluated user perception of activity telemonitoring systems (5 studies)[40–44]

We consider the selected studies in three aspects:

1. Study characteristics
2. Parameters monitored and sensors used
3. Outcomes

The element on the parameters that were monitored was further categorized into the type of measurement: activity measurements, physiological data measurements, and self-rated symptoms. The element on outcomes was divided into alarms, user perception, and relating the activity data to well-being.

Tables 2–4 list the details of the studies that met the inclusion criteria, including the characteristics of the subjects, follow-up duration, parameters monitored, sensors, and outcomes for Groups 1–3, respectively. Those studies that had a small number of subjects and short follow-up duration or only undertook the validation of a device are not presented in *Tables 2* and *3*. The studies that used workshops and focus groups or surveys to determine user preferences are not presented in *Table 4*.

STUDY CHARACTERISTICS

Certain feasibility studies were included as they were among the first attempts on activity telemonitoring for the elderly.[20,21] The former reported the preparation phase of a three-phase project; the latter described a system for assessing the ability to live alone/independently.

The purpose and evaluation methods of the studies reviewed varied significantly (*Tables 2* and *3*). Some focused on validation of a system or platform,[22–24,28,31,35,37,39] some had as their aim the detection of changes in behavioral pattern,[26,29,30] and others investigated physiological measurements and self-rated symptoms in order to better predict subjects' well-being.[32,33,38] Some studies had more specific aims: monitoring nighttime activities of subjects with cognitive disabilities,[25] monitoring restlessness after surgery,[27] measuring functional capacity of cardiac rehabilitation patients,[34] and predicting key medical events.[36]

Two of five studies on user perception detailed the experience of participants with involved actual telecare technologies[40] or smart home technologies.[41] The other three studies used workshops and focus groups[42,43] or questionnaires[44] to elicit user perception.

The number of subjects included in studies in Group 1 was low (*Table 2*).[22–25,27–30] The studies in Group 2 tendeded to have more subjects, and all but one[39] used more than 20 (*Table 3*). The studies on user perception of activity telemonitoring systems used 13–30 subjects[40–43] (*Table 4*) but would be considered statistically insufficient. The questionnaire survey for acquiring symptoms[44] was performed on 477 subjects.

Studies attempting to associate activity data with physiological data or aim to evaluate user perception tend to use subjects only from a highly targeted group. This includes almost all studies in Group 3,[21,25–27,29,30,32,34,36,38,39] and it would be difficult to generalize findings to other populations. Those evaluating accuracy of a device used volunteers[24,31,35,37] and so are self-selecting and again would preclude generalization of results.

Follow-up durations varied significantly from minutes[24,31,35] to years.[27,29,36,38,40,41] Studies evaluating a new wearable device tended to have shorter follow-up durations, whereas studies evaluating ambient sensors and aiming to relate activity patterns to health status tended to have longer follow-up durations.

ACTIVITY MEASUREMENTS

Most of the studies monitoring ADL addressed loss of autonomy or well-being. The indicators of loss of autonomy included difficulties in performing ADL (e.g., meal preparation, personal hygiene, bathing, and dressing) without help from a caregiver, deterioration in cognitive abilities (e.g., forgetting to turn off electrical appliances, poor medication adherence), or pathological behavior linked to cognitive impairments.[1]

Indicators of well-being/general health status included mobility, frequency of bathroom visits, sleep patterns, in-bed restlessness, level of nocturnal activities, medication adherence, meal preparation activities, and falls. For example, persistent increase in nocturnal activity and irregular eating patterns may be linked to declining cognitive abilities or onset of dementia.[30,45,46] Too much time spent in a particular room can be related to depression, fatigue, an illness, or a possible fall. Likewise, there are links between insufficient sleep and increased risk of fall, forgetfulness, or irregular behavior.[46]

Interviews with over 40 expert practitioners and discussions with elderly people indicated four ADL to be important to monitor: medication adherence; up-and-around transference; bathroom use; and meal preparation.[22] Relative importance placed on activities varied depending on the practitioner. On the other hand, the elderly themselves placed the greatest emphasis on those activities that gave them a sense of empowerment and helped them to remain independent.

The method of acquiring activity data varied (*Tables 2* and *3*) and included passive infrared (PIR) motion sensors,[25,27,29,30,32,33,38] electricity consumed by lights and appliances,[28] radiofrequency identification technology,[24] accelerometer-based devices,[23,31,34,35] a pedometer,[37] and a self-rated mobility questionnaire.[36] Some of the studies used a compact, wearable device with activity sensor and

Table 2. Summary of Characteristics and Results of Studies That Monitored Activity Data Only

REFERENCE (YEAR)	SUBJECT NUMBERS (AGE), CHARACTERISTICS, FU PERIOD	SENSORS AND TOOLS USED, ACTIVITIES MONITORED, FEATURES EXTRACTED	RESULTS, INCLUDING USER PERCEPTION AND RECOMMENDATIONS
Mathie et al.[23] (2004)	6 (80–86 years) Healthy elderly FU: 13 weeks	TA waist-mounted; weekly self-reported health status by COOP/WONCA questionnaire, fall diary, daily health questionnaire; a routine of directed movement (standing, sitting, lying, walking) Activities and features: falls, metabolic energy expenditure	A moderate correlation ($r = -0.51$) between weekly self-reported health status and energy expenditure was found. Out-of-range data loss was experienced. User perception: TA unit unobtrusive, comfortable, and easy to use; compliance rate high (worn 88% of the days); fall detection feature valuable; initially nervous about using the technology Recommendations: (1) a small dedicated unit instead of a computer and receiver will be better; (2) a TA unit with a wider radio coverage
Chan et al.[25] (2005)	4 (76–94 years) 1 dependent, 1 with dementia, and 2 with Alzheimer's disease FU: 8 months	PIR sensors Activities and features: nighttime activities between 9 p.m. and 7 a.m., including in-bed restlessness, visiting toilets, going out	There is a correlation between in-bed restlessness and getting up or going out of the bedroom. User perception: NI Recommendations: (1) new alarm criteria with more subjects need to be set, (2) diagnosis software modules need to be developed, (3) current events and past normal events should be compared in real time, and (4) in the case of behavioral deviations, warning alarm should be send to the caregivers.
Suzuki et al.[26] (2006)	1 (72 years) Living alone in her home FU: 6 months	IR sensors, door/window sensors, photoelectric sensors to detect when someone came within 2 m, a wattmeter to detect when the TV is on Activities and features: presence. A baseline rhythm was established using daily questionnaires and sensor output statistics for 12 days. A typical day was determined as sensor outputs being within mean ± 3 SD.	From the baseline data, a day is divided into four periods: sleeping (23:00–5:00 h), getting up/breakfast (5:00–9:00 h), indoor activities/going out (9:00–17:00 h), and dinner/going to bed (17:00–23:00 h). Twenty-nine atypical days were detected. She had to see the doctor twice: once was due to increased BP and poor sleep, the other due to a painful foot. The former resulted in lower sensor outputs, whereas the latter resulted in large sensor outputs. The total steps taken indoors and total sensor counts were highly correlated. The histogram of counts of sensor outputs for each hour and each room showed activity level over time. User perception: NI Recommendations: NI
Tyrer et al.[27] (2007)	2 (80 and 82 years) Initially independent FU: 14–16 months	PIR sensors Activities and features: presence, restlessness (using time and event-frequency)	The restlessness data were related to the activities recorded by the residents (e.g., increase in bedroom activity after a knee surgery or frequent bathroom visits after change of medication). One resident showed deteriorating health including several hospitalizations for CVA events. User perception: NI Recommendations: additional sensor data need to be analyzed and modeled.

(continued)

Table 2. Summary of Characteristics and Results of Studies That Monitored Activity Data Only *continued*

REFERENCE (YEAR)	SUBJECT NUMBERS (AGE), CHARACTERISTICS, FU PERIOD	SENSORS AND TOOLS USED, ACTIVITIES MONITORED, FEATURES EXTRACTED	RESULTS, INCLUDING USER PERCEPTION AND RECOMMENDATIONS
Franco et al.[28] (2008)	13 (mean, 80 years) Volunteers, but 1 with moderate Alzheimer's disease FU: 6.4 months	Electricity used by lights and appliances Activities and features: presence from the room lights; certain activities from the use of electrical appliances	Seasonal changes in activity level were insignificant. Average number of rooms visited was 8 for sedentary and 43 for very active person. It was possible to differentiate a person with Alzheimer's disease: nocturnal activity of the person with Alzheimer's disease was higher and included visiting the garage and kitchen. User perception: (1) 8 of 13 thought that the installation period was too long; (2) 2 of 13 thought that too many cables were in some rooms; (3) 12 of 13 did not like being monitored; (4) 10 of 13 forgot about the equipment once the cables were hidden; and (5) all wanted feedback on results. Recommendations: NI
Virone et al.[29] (2008)	22 (>65 years; mean, 83.8 years) 7 from memory care, 15 from non–memory care unit; all living alone FU: 3 months–1 year	PIR sensors Activities and features: presence, activity level, establishes a behavior pattern (CAR), detect deviations from normal behavior by using four thresholds: S_1, S_1*, S_2, and S_2* where [S_1*, S_1] = [mean ± 1.5 SD], [S_2*, S_2] = [mean ± 2 SD]	It was possible to detect deviations from CAR and set off an alarm to caregivers. Quality of sleep, sleep disorders, wandering, and meal activity could be inferred from CAR information. Noise was the main weakness of the system. User perception: NI Recommendations: (1) user ID data to differentiate visitors, (2) study sleep behavior from the bed monitor data, (3) measure time spent outside using GPS, (4) calculate sensitivity and specificity of the method, and (5) render the model using data fusion and/or data mining (e.g. clustering)
Franco et al.[30] (2010)	1 (80 years) Elderly, living alone FU: 6 months	PIR sensors Activities and features: presence; daily routine model; detects temporal shifts by comparing two sequences of activities; triggers an alarm in case of significant deviations from normal	Proposes a new tool for detecting pathological behavior (e.g., loss of autonomy in Alzheimer's disease patients and early dementia onset) by detecting significant deviations from normal; 15-min processing window more sensitive to shifts User perception: NI Recommendations: (1) use additional sensors (e.g., bed, chair, kettle, TV, etc.) for more accurate detection, (2) study seasonal effects, and (3) a study with a longer FU on a wider population including demented and nondemented elderly

BP, blood pressure; CAR, circadian activity rhythm; CVA, cerebrovascular accident; FU, follow-up; IR, infrared; NI, no information; PIR, passive infrared; SD, standard deviation; TA, tri-axial accelerometer.

medical/physiological sensors,[31,35] and some used only ambient sensors.[22,25,28–30,32,33,36,40,41] Ambient sensors were used in some studies to better distinguish activities (e.g., PIR motion and door sensors)[35] or door sensors on the refrigerator door and silverware drawers to detect meal preparation[22,41] or on the wardrobe to detect dressing activities.[21]

Table 5 identifies the sensors used for ADL monitoring. The most popular sensors, in order of popularity, were PIR sensors, accelerometers, chair sensors, bed sensors, medication adherence sensors, and door sensors. In some instances, use of some sensors was discontinued because of discomfort or unreliability or additional hazards introduced by the sensor itself, for example, unreliable floor

Table 3. Summary of Characteristics and Results of Studies That Monitored Activity and Physiological Data

REFERENCE (YEAR)	SUBJECT NUMBERS (AGE), CHARACTERISTICS, FU PERIOD	SENSORS AND TOOLS USED, PARAMETERS MONITORED	RESULTS, INCLUDING USER PERCEPTION AND RECOMMENDATIONS
Alwan et al.[32] (2006)	22 (one 49 years, the rest 65–93 years; mean, 83.8 years) Assisted living residents FU: 3 months	PIR sensors, temperature sensor at stove top, bed sensor Activity: presence, meal preparation, showering, bathroom visits, fall Physiologic: pulse via the bed sensor Alerts: forgotten stove burner; fall (if no activity for 45 min following bed exit); low pulse, <35 beats/min for 45 min; high pulse, >100 beats/min for 10 min	The system was effective in memory care units. False alert rates were high. No false fall alerts were generated. Changes detected in ADL levels were found to be due to either rectal bleeding or urinary tract infection, both of which had required hospitalization. Activity data of a CHF patient who complained of being tired frequently showed that he was sleeping in his chair instead of the bed. Increased restlessness in 1 case was due to pain from osteoarthritis. User perception: Fear of fall and not receiving timely help were common concerns (95%). For some, the system enhanced sense of security and hence perceived QoL. Recommendations: High false alerts rates need to be dealt with.
Biddis et al.[36] (2009)	45 (≥60 years) Elderly with CHF FU: 18 months	Questionnaire for mobility and health status; BP, W, PR Activity: self-rated mobility Physiologic: BP, W, PR; self-rated symptoms Alerts: 15 types of alerts. They were based on thresholds for physiological measurements and on deterioration from the usual state for diet and symptoms.	A multivariate logistic regression model was developed to predict key medical events. The model could predict with 75% sensitivity and 74% specificity. Self-rated health status and mobility improved prediction accuracy from 61% to 75%. Number of alerts was 8,576, but only 171 were key events, and only 24 of them required immediate intervention. The strongest predictor was the cumulative number of system alerts generated in a given week. User perception: NI Recommendations: Larger datasets are required to develop more accurate, robust, and generalized models that can predict the level of severity of the event as well.
Merilahti et al.[37] (2009)	36 (17 working age, mean of 55 years; 19 elderly, mean of 78 years) All volunteers FU: 3 months	An activity detector on wrist, pedometer, air temperature sensor; BP, W, HR, PR, and beat-to-beat HR variability; daily wellness diary for manually entering data from devices Activity: sleep/awake activity classification; step count Physiologic: BP, W, HR, PR, beat-to-beat HR variability	Wireless connection between sensors and computer was unreliable. User perception: Daily reporting and manual data entry were found to be laborious. The elderly preferred paper-based reporting. There were more human errors than technological malfunctions. Start-up scheme for HR monitor was complex and too demanding for the elderly. Most valuable variables were BP, W, and exercise. Wrist activity detector was found to be uncomfortable by 35–38%, and HR belt was found to be uncomfortable by 65% of working age; 29% of working age thought that the system was disturbing at home, whereas none of the elderly thought so. The working age group wanted feedback and to view their data. Recommendation: The health monitoring system should be fully automated, with minimal and simple device interactions. New things that the elderly have to learn should be minimized.

(continued)

Table 3. Summary of Characteristics and Results of Studies That Monitored Activity and Physiological Data *continued*			
REFERENCE (YEAR)	SUBJECT NUMBERS (AGE), CHARACTERISTICS, FU PERIOD	SENSORS AND TOOLS USED, PARAMETERS MONITORED	RESULTS, INCLUDING USER PERCEPTION AND RECOMMENDATIONS
Skubic et al.[38] (2009)	34 (70–95 years) 3 married couples, the remaining single; 90% with a chronic illness, 60% with multiple illnesses; all living in a community for aging in place FU: >2 years for some	PIR, bed, chair, stove sensors, video sensor net, floor mats, floor vibration sensors Activity: presence, forgotten stove burner, sleep quality through four levels of bed restlessness; motion density maps; background-subtracted silhouette imagery to monitor gait patterns, walking speed, balance, and posture and for detecting falls Physiologic: qualitative pulse and respiration through the bed sensor; low pulse if <30 beats, high pulse if >100 beats	Abnormal increases in activity data were observed for 2 subjects just after they had surgery: in-bed restlessness and bed tachypnea after a bypass surgery and in-living room motion and bed tachypnea after a knee replacement surgery. Motion density maps for a month exhibited irregular patterns for someone with cognitive problems. Changes in density map were related to change in well-being (e.g., decrease in the density to increase in depression level in 1 case). Problems experienced: The computers were unplugged. Sensors stopped transmitting. Computers stopped logging. A stove sensor failed. User perception: (1) People don't want extraneous sensors, wires, and computers cluttering up their space. (2) The residents with the sensor network felt safer. (3) Residents wanted to have control on granting access to the data. Recommendations: (1) Custom configuration is necessary due to the differences in flats. (2) Connection between sensor data and health events is necessary.

ADL, activities of daily living; BP, blood pressure; CHF, congestive heart failure; FU, follow-up; HR, heart rate; NI, no information; PIR, passive infrared; PR, pulse rate; QoL, quality of life; W, weight.

mats to avoid hazards of tripping,[38] malfunctioning chair sensors,[38] bed sensors,[39] and electrocardiogram leads and electrodes.[34]

Wearable activity sensors were mainly used to monitor or differentiate activities related to body movements or metabolic energy expenditure. Activities detected varied depending on the position of the sensor. Waist-worn accelerometers were used to detect falls, classify body movement (standing, sitting, lying, and walking), estimate metabolic energy expenditure, monitor functional balance, and/or investigate whether estimated energy expenditure was related to self-reported health.[23,34] A wrist-worn unit could only differentiate simple body movements such as walking, running, resting, immobility, or dangerous fall[31] and could manage sleep/awake classification.[37] An ear-worn accelerometer based unit[35] could classify activities into four groupings: very low-, low-, mid-, and high-level activities.

Some of the studies attempted to detect falls in addition to other ADL.[21,23,31,32,34,38] The general approach for fall detection was to use an accelerometer- or gyroscope-based wearable device and use a threshold-based approach.[23,31,34,47–49]

Other methods to detect falls included floor vibration sensors,[38,50] gait characteristics,[51] sound source height information gathered through an array of acoustic sensors,[52] and background-subtracted silhouette imagery.[38] A "possible fall" was suspected by detecting inactivity for 45 min following a bed exit.[32] The common problem with fall detectors was the high rate of false alerts (i.e., low specificity).

PHYSIOLOGICAL DATA MEASUREMENTS

The most common physiological parameters measured were blood pressure, heart/pulse rate, respiratory flow/rate, and weight (*Table 6*). Other measurements included saturation of peripheral O_2, electrocardiography,[31,34] and HR variability.[34,37] Some studies measured the heart and respiratory flow rate through the bed sensor and used these parameters to support activity monitoring.[32,33,38,39]

SELF-RATED SYMPTOMS

Self-rated symptoms involved questionnaires and/or wellness diaries, either paper[23,39] or with a monitoring device.[36,37] Some studies attempted to determine whether sensor data could provide independent measures for health status. For this purpose, symptoms were correlated with variables from sensor data (e.g,, weekly self-reported health status with energy expenditure information calculated from accelerometer data[23] or self-reported sleep times with the bed sensor data[39]). Symptoms were directly used for generating alerts.[36]

Table 4. Summary of Characteristics and Results of Studies on User Perception			
REFERENCE (YEAR)	SUBJECT NUMBERS (AGE), CHARACTERISTICS, FU PERIOD	PARAMETERS MONITORED, TOOLS USED	RESULTS
Brownsell et al.[40] (2008)	24 (73 ± 11 years) telecare/28 (77 ± 8 years) control Elderly FU: 12 months	Fall detection, house safety and security, presence, and movement Tools: Front door remote access with CCTV camera, fall detectors, bed and chair sensor, extreme temperature, movement, door sensors, electricity usage, and automatic light switch; an Internet café; fall efficacy scale to measure fear of fall; SF-36 health survey	There were insignificant changes in fear of falling and in 8 domains (out of 9) of the SF-36 scale. Social functioning was 8% higher in the intervention group. Feeling of safety was improved. Many were unhappy to wear the fall detector. There were 22 real and 88 false alerts. Sensor uptake rates by 29 participants who chose telecare equipment: 100% for CCTV, intruder alarm, flood detector, and movement detector; 93% for door usage and electricity usage; 90% for extreme temperature, 52% for bed sensor, 38% for chair sensor, and 28% for fall detector Recommendations: methods for matching user needs to telecare provision need to be established; a reliable feedback mechanism to users, carers, and healthcare professionals needs to be developed
Demiris et al.[41] (2008)	14 (> 65 years) Elderly living in sheltered housing for "aging in place" FU: 12 months	Presence, activity levels, sleep patterns, and potential emergencies; detections of fall, fire, left on stove, and intruders; an event-driven video sensor to reduce false alarms Tools: motion sensors, sensor mat, cabinet door switches, bed sensor, stove temperature sensor, gait monitor, and an event-driven video sensor; focus group sessions on user perception, data ownership, and permission for installation of the sensors in their home	Participants are focused on the emergency detection feature of the technology rather than their capability of proactive monitoring. They preferred smaller sensors and unobtrusive devices because of the fear for stigmatization. Participants who had no fall history could not see the benefit of fall detectors. There were concerns about the accuracy of devices, privacy violation, stigmatization, and the need to balance safety with privacy. Data ownership and access: 1 subject wanted to see the data first and then have full control of its distribution. Most of them wanted the healthcare providers to have the information: 6 wanted close family member to see the data, and 4 of them wanted to have an access.

CCTV, closed circuit TV; FU, follow-up; SF-36, Short Form 36 health survey to evaluate a person's health and ability to do everyday activities.

A wide range of self-rated symptoms was used with elderly congestive heart failure patients.[36] These included angina, shortness of breath, swollen ankles, bloated stomach, dizziness, cough, urine excretion, eating well, medication taken, and need for an extra pillow. Symptoms relevant to stress, sleep, exercise, and sickness[37] and those relevant to sleep quality, daily activities, pain, and rehabilitation program activities[39] were collected. Weekly health status was obtained[23] through the COOP/WONCA health questionnaire,[53] which comprises 5-point charts in six domains: physical fitness, feelings, daily activities, social activities, overall health, and change in health status.

Only a small percentage of alerts were key events.[36] Symptoms such as swollen ankles, urine excretion, need for an extra pillow at night, and cough were most often correct in predicting a key event. On the other hand, diet was the least accurate indicator of a key event. Personalized and optimized thresholds were suggested in order to reduce false alert rates.

OUTCOMES

Only one study considered the impact of passive health status monitoring technology on cost of care and efficiency of professional

Table 5. Sensors Used for Monitoring Activities of Daily Living

SENSOR CLASS	SENSORS AND THEIR FUNCTIONALITIES
Occupancy sensors	PIRs and electricity consumed by lights
Body movement sensors	Accelerometer-based, wearable units: classifies body movements and postural transitions and detect falls
Sensors detecting use of specific objects	Medication dispenser to monitor medication adherence Electricity used by appliances[28] Bed sensors to detect in-bed restlessness and sleep patterns[38,39] Chair sensors Door sensors on refrigerator door and silverware drawer to detect meal preparation[22] Door sensors on wardrobes/chest of drawers to detect dressing or grooming[21] RFID tags on objects[24] and an RFID reader (glove based)
Pressure sensors	In the form of floor mats and smart tiles to detect falls and presence or shoe pads to detect steps[21]
Video sensors	Video cameras: to monitor activities and detect falls, or it can be just an event-driven camera to time-stamp events[41] or can be used to extract the imagery silhouette[38] to monitor gait, walking speed, balance, and posture and to detect falls
Sound sensors	Microphones: to detect sounds in the residence or just to discriminate sounds of daily activities from normal speech,[19] to detect stress of the resident,[18] or to detect falls[52]
Optical sensors	Detect use of mirrors or sinks[21]; optical/ultrasonic system to detect gait speed and direction of the subject when passing through a doorway
Emergency button	To ask for help in case of an emergency. It can be integrated into a wearable device,[21] which may be in the form of a watch or pendant.

PIR, passive infrared; RFID, radio frequency identification.

caregivers. The average number of hospital visits, hospital days, and cost per subject for assisted living subjects were less than those for usual-care subjects.[33]

RELATING ACTIVITY DATA TO PHYSIOLOGICAL DATA AND WELL-BEING

Some studies[21,23,25–30,32,33,36,38] attempted to relate activity level to well-being or health status. For example, excessive bathroom visits and increase in restlessness during the night were related to rectal bleeding or urinary tract infection,[32] pain from osteoarthritis,[33] and surgery.[27] Likewise, the number of times the elderly opened/closed their wardrobe/drawers was related to their dressing ability,[21] weekly self-reported health status to energy expenditure calculated from accelerometer data,[23] in-bed restlessness to increased bedroom activities,[25] persistent increase in nocturnal activity to declining cognitive abilities or onset of dementia,[28,30] and heart rate variability at night to sleep quality.[34] Tiredness of a congestive heart failure patient was associated with sleeping in the chair during the night.[32]

ALARMS

Some monitoring systems had emergency detection capabilities, including cessation of activity,[20,25] falls,[21,23,31–34] high pulse and low pulse,[32,33] and forgotten stove burner.[32,33] Fifteen types of alarms were noted,[36] pertaining to physiological measurements, medication adherence, diet, and symptoms. Some systems were able to provide reminders for particular activities (e.g., lock doors, take medication on time, and turn off appliances).[22]

Few methods were used for detecting changes in activity pattern, but included (1) comparing two sequences of activities,[30] (2) relative increase or decrease,[27,28,32–34,38] and (3) detecting deviations from a statistically identified normal pattern.[25,26,29,30] The normal pattern was usually defined as the interval of mean $\pm$ 2 SD or mean $\pm$ 3 SD, where SD is the standard deviation.

USER PERCEPTION

Two of 11 studies in Group 1 and 5 of 9 studies in Group 2 presented results on user perception of monitoring systems. The results were concerned with comfort of a wearable device,[23,31,34,37] comfort of bed sensor,[39] reliability,[31] ease of use,[23,37] obtrusiveness at home,[28,37] and visual aspects.[31] Detailed results on various aspects of user acceptability are reported.[23,28,38]

Preferences differed between an elderly and a working age group.[37] For example, none of the elderly thought that the monitoring system was disturbing at home compared with 29% of the working age group (*Table 3*).

All preferred an assistive technology rather than one that took away their sense of control and confidence or was constantly reminding/telling them what to do.[42] Simple, quick installation and no maintenance were among the preferred features for systems.[42] One participant said that interaction with the system should be as simple as "push a button."[43]

There were concerns regarding ownership of the data,[22,38,41,42] who has access to the data, and "who decides what to monitor."[25,42] Healthcare providers and close family members were the desired recipients of the data.

Discussion

This review summarizes the characteristics, outcomes, and limitations of 25 studies on telemonitoring ADL of the elderly. Almost all of the studies observed some benefits in the use of telemonitoring for changes in the ADL. However, it was not possible to combine studies in a meta-analysis because of heterogeneity of parameters, outcomes, and methodological approaches. Nevertheless, the outcomes of the studies provide important guidance on an optimum or improved strategy for future trials.

Table 6. Summary of Physiological Data Measurements

REFERENCE (YEAR)	BP	SPO_2	WEIGHT	HR/PR	ECG	BTB HV	RESPIRATORY FLOW RATE	SKIN TEMPERATURE
Anliker et al.[31] (2004)	•	•			•		•	•
Alwan et al.[32] (2007)				•[a]				
Alwan et al.[33] (2007)				•[a]			•[a]	
Bidargaddi and Sarela[32] (2008)		•		•	•	•	•	
Atallah et al.[35] (2009)	•	•	•					
Biddiss et al.[36] (2009)	•		•	•				
Merilahti et al.[37] (2009)	•		•	•		•		
Skubic et al.[38] (2009)				•			•	
Junnila et al.[39] (2010)	•		•	•[a]			•[a]	

[a]Obtained through the bed sensor.

BP, blood pressure; BTB HV, beat-to-beat heart rate variability; ECG, electrocardiography; HR, heart rate; PR, pulse rate; SpO_2, saturation of peripheral O_2.

This is the first review on the potential benefits of ADL monitoring on the elderly and identifies a significant gap in research in the field: whether monitoring ADL and physiological data together could improve management of elderly people's care and health. This question requires larger, long-term studies with clinically relevant outcomes and common methodology.

In the following parts we discuss the findings of the study characteristics, parameters to monitor, preferred sensor and system characteristics, and recommendations on these for future research.

STUDY CHARACTERISTICS

Although some studies monitored activities for a period of 6 months or longer, the need for even longer evaluation periods is advocated.[30] Studies should develop tools or a knowledge base for decision support by analyzing data retrospectively. Studies should use subjects selected on objective metrics from real target groups (i.e., elderly people or the chronically ill) with longer follow-up durations.[37] Development and evaluation studies should follow common methodology and ideally be based on randomized controlled trials, with carefully selected relevant outcome measures, in order to assess the actual benefits of using such systems compared with conventional care.

PARAMETERS MONITORED AND SENSORS USED

Activity measurements. Important home ADL to monitor include dressing, self-hygiene, toilet use, meal preparation, medication management, communication ability, functional mobility (up-and-around transference, move in bed, stand, bending, etc.), and home management (house cleaning, laundry, finances).[1] Some may not need continuous monitoring (e.g., communication ability, bending, dressing) because periodic evaluation or temporary monitoring may suffice. Continuous monitoring would be appropriate for the following: toilet use, meal preparation, medication management, up-and-around transference, movements in bed, chair use, and falls.

Sensors used were mainly environmental, except for accelerometers and some physiological sensors. Ambient sensors could not differentiate the subject from visitors, as opposed to wearable activity sensors. Noise and artifacts due to body motions reduced clinical accuracy of physiological data from wearable sensors and their ability to distinguish body movements.[31,34,35] Wearable activity detectors could only distinguish simple activities (e.g., walking, running, resting, fall, or total lack of movement[31]) or simple classes like very low-, low-, mid-, or high-level activities.[35] These activity classes did not provide information about the capability of the subject for independent living (e.g., meal preparation, performing self-hygiene, or frequency bathroom visits). There were also issues including discomfort, and sensors were not worn during certain activities (e.g., shower or in bed).[25,30,31,34,35] The wearable sensors were thought to be unsuitable for cognitively impaired patients as the sensors are likely to be forgotten or thrown away.[25,30] Therefore, ADL monitoring requires use of a combination of ambient sensors (i.e., PIR, medication dispenser, door sensors).

Researchers have tried to extract further information from PIR data.[29] Using only person in room sensors it was possible to monitor habits and deviations from normal behavior pattern and so infer bathroom use, sleep quality, in-bed restlessness, wandering, and meal activity and provide alerts for timely intervention. PIR sensors are less intrusive than worn sensors, and owing to an added security feature they are highly accepted by elderly.[40,41] However, without user identification, they cannot differentiate multiple residents or residents from visitors. Therefore, in their current form, they are most suitable for people living alone. Activity data when visitors were present were considered to be too noisy for accurate analysis.[28,29] Such noisy intervals can be excluded from the data if they can be detected (e.g., through increased activity rate when visitors are present as suggested by Franco et al.[28]). For future large-scale deployment purposes, a radiofrequency user identification feature can be added to such ambient sensors.

Additional sensors can be used, and outputs from these can be combined with PIR data in order to obtain more accurate information about the activity being performed. This would include sensors to detect use of specific objects such as bed, chair, door, kettle, and TV[21,22,25,30] and electronic medication dispensers.[22]

There are no clear indications of the usefulness of some of the activity sensors (e.g., video sensors, sound sensors, and pressure mats other than crude presence detection).[20,38] Computational complexity inherent in video signal processing is an issue.[54] Video and sound also present issues around privacy for use in places such as bedroom and bathroom—two important rooms for fall detection[55] and ADL monitoring.

User preferences for fall detection were inconsistent across the studies. Their acceptance was diminished primarily by the high rate of false alarms; some found them uncomfortable to wear, and some raised issues such as stigmatization. Some studies showed a lower preference for fall detectors than security-enhancing sensors.[40,41] In another study, some participants thought that they were not old enough to need such tools.[42] However, in studies where the main focus was fall detection, it was concluded that users valued the fall detection feature.[23,32]

Improving the specificity of wearable fall detectors is problematic because to subject-to-subject and instance-to-instance dependency of the fall events. Furthermore, although high detection accuracy can be achieved in the laboratory environment, performance decreases significantly in the actual environment. Moreover, falls are usually simulated by healthy volunteers, and there are many differences in gait or postural transition characteristics between the healthy and the elderly. Likewise, unsupervised or personalized testing and training of fall detectors using machine learning methods are difficult to perform because of the rarity of fall events.[47] Retrospective analysis of data from large-scale deployment of such systems may provide a solution. Meanwhile, a solution for detecting serious falls would be to use a combination of ambient presence sensors (e.g., PIR motion sensors) and an alert button worn around the neck or on wrist. The long response time associated with presence sensors may be circumvented by the alert button on many occasions, and the presence sensors would detect instances when a user may be unable to raise the alert (or not wearing the device).

There were further problems with wireless devices being out-of range[23] and having short battery life. These undermined perceived reliability of the monitoring systems and hence user acceptance. The out-of-range problem can be solved by using wireless networks that support extension to coverage. Use of power-efficient designs and low-power sensors and sending processed data rather than raw data were among the solutions suggested to overcome short battery life.

Physiological data measurements. There are many studies in the literature that report on only physiological data but relatively few that monitor both physiological and ADL data. Although in this review we report nine studies that monitored both physiological and activity data, three of them only tested accuracy of their wearable multisensor devices that also measured a physiological parameter.[31,34,35] Four of them[32,33,38,39] monitored pulse rate and respiratory flow rate via the bed sensor. However, these were not used for clinical purposes; rather, they were designed for supporting presence and fall detection (absence from bed). The remaining two monitored multiple parameters of ADL and physiological data[36,37]: Biddiss et al.[36] used self-rated mobility, and Merilahti et al.[37] considered sleep/awake classification and step count as activity data. There remains a need for studies that assess the benefit of combined monitoring of activity and physiological data.

It is beneficial to monitor daily blood pressure, heart rate, and weight of the elderly, depending on disease. Saturation of peripheral O_2 may also be measured for chronic obstructive pulmonary disease patients or blood glucose for a diabetic person. A physician will normally determine which physiological data are to be monitored. Long-term studies will reveal which physiological data are valuable to monitor continuously and at what frequency.

Self-rated symptoms. Self-rated symptoms have long been used for diagnosis, assessing the progress of an illness, or measuring the response to a treatment. They can also be used in telecare. For example, in Biddiss et al.,[36] self-rated rated physical and psychological symptoms were found to be more indicative of the need for medical intervention than the physiological measures.

Symptoms relevant to general health can be monitored (e.g., swollen ankles, dizziness, cough, urine excretion, pain, sleep quality, etc.). However, their daily monitoring can be laborious. Instead, users should be encouraged to report any change in their status of well-being and health. Valuable symptoms to monitor and monitoring frequency will depend on the current health status of the subject and can be determined through interviews and/or questionnaires with carers, doctors, and research. However, eliciting symptom data can become burdensome over extended periods of time, and, where possible, alternative nonintrusive techniques are to be preferred.

OUTCOMES

Relating activity data to physiological data and well-being. Some studies related the ADL to well-being of the subjects or to psychological parameters.[21,25,26,28,29,32–34,38] Findings show that changes in several ADL (e.g., bedroom and bathroom activities, in-bed restlessness, and nocturnal activities) provided important clues to the subjects' well-being. However, none of the studies provided a description or a model of their approach toward their decision process. Rather, they analyzed the data retrospectively to identify intervals over which the activity data were abnormal and then attempted to determine a reason for the change[32–34] or observed the changes in ADL following a known change in health status or medication.[27,38]

Almost all of the ADL telemonitoring studies have reported some benefits for care of the elderly. With such a significant percentage of the elderly having chronic disease (or comorbidities) or being under an increased risk of developing one, any telemonitoring intervention aiming to improve quality of care of the elderly should consider monitoring medication adherence and illness related physiological parameters.

Alarms. Detecting changes in an activity pattern or physiological parameters is important. There is no well-established method, and the area requires further research. For the former, the approach of detecting deviations from a statistical normal can be adopted.[25,26,29,30] A normal behavior pattern can be established based on sensor statistics over 10–15 days. If the sensor statistics are outside the normal (i.e., mean ± 2 SD or mean ± 3 SD,) an alarm can be raised. The cumulative number of complaints or worsening symptoms over a period (e.g., a week as in Biddiss et al.[36]) can be used to predict the time of intervention. For monitoring blood pressure and glucose level, existing guidelines can be adopted, until a better method is found.

High rates of false alerts were a common problem, especially those related to falls. These were attributed to the noise and artifacts in the data due to body movements for wearable sensors or visitors for ambient sensors. Algorithms that can deal with noisy data and data fusion are anticipated as a solution to the problem.[29,31,34] Although many mentioned high false alert rates, only one study[36] provided sensitivity and specificity values for its prediction algorithms.

User perception. Three main determinants of user perception were user needs and concerns, familiarity of the user with the sensors/tools, and sensor characteristics. User needs and concerns included age, illness, comorbidities, and experience from previous adverse health/safety events. For example, correct detection of fall was appreciated by a person who felt helpless after a previous serious fall.[41] User needs will also determine which activities to monitor and how to monitor. For example, any technology targeting the elderly should be "elderly friendly" (i.e., have a minimal user interface, be very simple to use, and have large displays) or be completely passive (i.e., only ambient sensors) for people with dementia[30] as they are likely to forget any wearable sensors.

Concerns of elderly people, in descending order, were found to be security, safety, well-being, falls, and ownership of the data.[40–42] These affected the perception of the monitoring systems/sensors or smart houses and sensors that they are willing to adopt. They wanted to adopt certain sensors, such as PIR, stove top temperature sensor, closed circuit TV at the front door, intruder alarm, flood detector, movement detectors, and door sensors.[22,32,40,41] Furthermore, system features such as detecting an emergency or having safety-enhancing features helped to overcome their initial reluctance to the idea of being monitored.[41]

Initial reluctance toward monitoring technologies was also an issue. Reasons for this include privacy concerns, stigmatization,[43,47] unfamiliarity with the tools and technology,[37,43,44] and inconvenience or disturbance it may cause at home.[28,38,42]

People, especially the elderly, tend to prefer tools with which they are familiar. For example, the elderly may prefer paper questionnaires to those answered via a Web site or mobile text message.[44] Likewise, familiar measurements (blood pressure, weight, and exercise) were thought to be the easiest and the most interesting ones.[37]

There were clear indications that participants were against invasive tools (i.e., videocameras and microphones).[28,41] Even an event-driven Web camera to reduce false alarm rates was not accepted owing to privacy concerns.[41] However, approaches that would guarantee anonymity (e.g., background-subtracted silhouette imagery for monitoring in Skubic et al.[38]) were found to be acceptable.

Sensor characteristics that affect user acceptance include comfort of wearable sensors, noninvasiveness, accuracy, reliability, ease of use, whether the sensors enhance the sense of security and well-being,[32,40,41] and whether they have emergency capabilities.[32,41] Preferred sensor characteristics are as follows:

- Accuracy and reliability. High false alarm rates and clinically inaccurate sensor data undermine user acceptability.[31,41]
- Easy to understand and use. It should be easy to restart if it goes wrong,[37] preferably with self-integration capability (into the system).
- Comfortable to wear and use.[23,31,37] Uncomfortable devices may not be worn, even if the devices were for treatment (e.g., electrocardiography monitoring device in Bidargaddi and Sarela[34]).
- Invisible to visitors (or easy to hide) if possible.[28,41] This is to avoid stigmatization, inconvenience, or disturbance at home.[28,38,42]
- Lighter and smaller devices/sensors[41]
- Nonintrusive if possible (i.e., no videocamera or microphone[28,41])
- With a memory to log the measurements in case they cannot be sent straight away[39]

Acceptability by health professionals depends on whether the monitoring system improves the effectiveness of treatment or healthcare and whether it reduces their work load. They prefer a system that supports their decision process without increasing their work load, a system presenting clinically useful/relevant information rather than a vast amount of clinically irrelevant data. Moreover, any change in care management will introduce organizational challenges. Therefore, the benefits from the change should justify the effort of the change.

From the outcomes on user perception, recommendations on design and preferred characteristics of a system can be made. First, a long-term health monitoring system should be fully automated so as to minimize human interaction and hence human errors. For example, manual data entry and daily reporting can be found to be laborious.[37] Second, device interactions and recovery from faults should be as simple as possible. Third, the things that the elderly have to learn should be minimized as they prefer tools with which they are familiar.[23,37,44] Fourth, data/information feedback should be available for those interested (e.g., the young,[37] those who want to take control of their healthcare,[28] or those who want ownership of the data[38,41]). Finally, data security should be implicit.

Recommendations for systems for use in large-scale telemonitoring can be made. First, a large-scale long-term deployment will require a system with decision support tools (i.e., a system with automatic reasoning and knowledge extraction features) in order to support healthcare professionals. Second, the system should be easily configurable according to the user needs (i.e., should enable pick and mix sensor combinations or enable custom configuration due to differences in user needs and in layouts of residences). Third, the system should be easily scalable and interoperable. Scalability requires lower cost, including equipment, installation, and operational and maintenance costs. Short battery life and out-of-range problems have to be dealt with. Finally, the system should be able to perform remote software upgrades and maintenance and monitor battery status of wireless devices.

Conclusions

This is the first review on whether monitoring ADL of elderly people is beneficial to their well-being and healthcare. Findings of some studies are encouraging. However, for more conclusive findings, there is a need for better-designed studies with larger sample size, longer follow-up durations, clinically relevant outcomes, and comparable outcome measures that are indicators of efficacy (effectiveness of care plan) and quality of the study. The studies should measure indicators of success of the new intervention, including participation rate (adherence statistics or drop out), sensitivity/specificity for any prediction tool, hospital visits, hospitalization rate, user satisfaction, and well-being of patients during follow-up (either periodically or at least at the baseline and end of the study). Studies should consider inclusion criteria of participants and ideally be based on severity of frailty, and outcomes should be correlated on objective metrics such as the Edmonton Frail Score.[56] It is important that common terminology is adopted, such as the International Classification of Functioning, Disability and Health of the World Health Organization,[57] to ensure comparability of studies.

Wearable technologies require much improvement in their accuracy and reliability and in particular the sensitivity and specificity of fall detectors and key event predictors, and these should be reported in outcomes.

Future studies should look to develop rule-based decision support tools that are based on combinations of activity information, physiological data, and self-rated symptoms. Important areas for further investigation include the following:

- Determining correlation between changes in ADL, physiological parameters, and well-being/health status (i.e., extracting useful information relevant to subjects' well-being)
- Determining relevance of activity data, physiological data, and self-rated symptoms for effectiveness of the intervention
- Determining the most effective set of sensors

Development of these new approaches will take time, which may undermine the credibility of such systems at early stages of adoption. Legal issues (ethical, data security, and ownership of the data) and organizational challenges due to the changes in healthcare management may require consideration to enhance acceptance of such systems by users.

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