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ORIGINAL ARTICLE

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Feasibility testing of a home-based sensor system to monitor mobility and daily activities in Korean American older adults

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Aims and objectives: This study aimed to test feasibility of a home-based sensor system that is designed to assess mobility and daily activity patterns among Korean American older adults (KAOAs; $n = 6$) and explore sensor technology acceptance among participants.

Background: Home-based sensors have the potential to support older adults' desire to remain at home as long as possible. Despite a growing interest in using home-based sensors for older adults, there have been no documented attempts to apply this type of technology to a group of ethnic minority older adults.

Design: The study employed descriptive, quantitative and qualitative approaches.

Methods: The system was deployed for 2 months in four homes of KAOAs. Study procedures included (i) sensor-based data collection, (ii) self-report mobility instruments, (iii) activity logs and (iv) interviews. To explore changes in activity patterns, line graphs and sequence plots were applied to data obtained from a set of sensors. General linear models (GLMs) were used for motion in each space of the home to examine how much variability of activities is explained by several time variables.

Results: Sensor data had natural fluctuation over time. Different 24-hr patterns were observed across homes. The GLM estimates showed that effect sizes of the time variables vary across individuals. A hydro sensor deployed in one participant's bathroom inferred various water usage activities. Overall, sensors were acceptable for all participants, despite some privacy concerns.

Conclusions: Study findings demonstrate that sensor technology applications could be successfully used longitudinally in a minority population of older adults that is not often targeted as an end-user group for the use of innovative technologies.

Implications for practice: The use of home-based sensors provides nurses with a useful tool to detect deviations from normal patterns and to achieve proactive care for some groups of older adults.

KEYWORDS
daily activities, ethnic minority older adults, feasibility testing, mobility, sensor-based monitoring, technology acceptance

1 | INTRODUCTION

Mobility is critical for maintaining independence and promoting healthy ageing. Older adults with chronic conditions are at increased risk of mobility limitation that leads to dependency in activities of daily living and other adverse health outcomes (Hardy, Kang, Studenski, & Degenholtz, 2011; Lo, Brown, Sawyer, Kennedy, & Allman, 2014; Montero-Odasso et al., 2009). Consequently, mobility limitations threaten quality of life and well-being among older adults (Webber, Porter, & Menec, 2010).

As part of prevention approaches to identify older adults at risk of mobility limitation, there have been considerable efforts to assess changes in mobility and to develop a new instrument for accurately measuring mobility. However, there are still limitations in the assessment and measurement of mobility for older adults (Abellan van Kan et al., 2009; Chung et al., 2015; Rockwood, Awalt, Carver, & MacKnight, 2000). Although functional mobility among older adults declines variably over time, it is generally captured by self-report or performance-based measurements at only a few discrete time points (Hayes et al., 2008). There is therefore a need for continuous measurement of mobility and activities in everyday life to better understand normal variability in daily functioning and to detect changes before they impact quality of life.

One alternative approach to facilitate measurement is through the use of home-based sensors. This passive monitoring can be performed continuously with less intrusion on the daily lives of older individuals (Kaye et al., 2011). Home-based sensor technologies, designed to record activities of individuals and health status in their living spaces, can detect changes in activity patterns and enable prompt intervention to prevent adverse health events resulting from mobility limitation. Continuous monitoring of motor and physical function can overcome the limitations of traditional assessment of older adult health status. Thus, monitoring multiple aspects of functional performance through sensors and intervening based on these data sets can support ageing in place (Chan, Estève, Escriba, & Campo, 2008; Kang et al., 2010; Rantz, Skubic, Miller, et al., 2013).

Despite the growing interest in using sensors for community-dwelling older adults (Chen, Harniss, Patel, & Johnson, 2014; Kaye et al., 2011; Rantz, Skubic, Abbott, et al., 2013; Reeder et al., 2013), no attempts to apply this technology to communities of ethnic minority older adults have been documented. Such inquiry is needed in a more narrow contextual focus where characteristics such as ethnicity or culture are considered. Given that technology is not culturally neutral, people's responses to monitoring technology and privacy are conceptualised differently across cultural groups. Korean Americans, for example, are such an ethnic minority, and they are one of the fastest growing immigrant subgroups in the United States (US) (Park, Roh, & Yeo, 2012). Previous research revealed that physical inactivity is one of the major health concerns in Korean American older adults (KAOAs) (Kim, Ahn, Chon, Bowen, & Khan, 2005; Sohng, Sohng, & Yeom, 2002). However, little is known about the mobility of KAOAs, so there is a need to understand trends, preferences and patterns in the mobility as well as sensor technology acceptance of the Korean American older adult population.

What does this research add to existing knowledge in gerontology?

- We have demonstrated a novel home-based methodology for assessing detection of changes in patterns of motion across the locations that could be an early sign of functional decline among older adults.
- This study suggests that innovative sensor technologies could be longitudinally installed in under-studied ethnic minority older adult populations.

What are the implications of this new knowledge for nursing care with older people?

- Nurses should consider the potential of home-based sensor technologies in designing and delivering care to support ageing in place among community-dwelling older adults.
- The importance of unobtrusive technologies and less intrusive deployment methods should be addressed when designing and deploying home-based sensor technologies.

How could the findings be used to influence policy or practice or research or education?

- Future research needs to involve a larger number of participants in an extended period of time to assess the role of sensor technologies on achieving proactive patient-centred health care for community-dwelling older adults.
- There should be an effort to identify barriers to sensor technology adoption and utilisation and to develop culturally and linguistically appropriate technology-delivered interventions for ethnic minority older adults.

The purpose of this study is to test the feasibility of a home-based sensor system that includes multiple sensors to assess mobility and daily activity patterns among older adults. We aimed to see how feasible it is to install the sensor system in real residences of community-dwelling KAOAs and whether the system generates meaningful data that can be further used to monitor activity levels and mobility. We also explored the acceptability of the home-based sensor system among KAOAs.

2 | METHODS

This study was a descriptive feasibility study conducted in a community setting. The sensor system was deployed in four homes of KAOAs. The study protocol was approved by the Human Subjects Division at the University of Washington, Seattle.

2.1 | Sample

The participants for this study comprised of six KAOAs. To be included in the study, participants needed to be (i) community-dwelling individual residing in the greater Seattle metropolitan area, (ii) born in Korea and immigrated to the United States, (iii) aged 65 or older and (iv) able to speak and read Korean. Exclusion criteria included having (i) a known life expectancy of 6 months or less, (ii) inability to provide written informed consent or (iii) unwillingness to install the sensor technology in the home. We did not apply exclusion criteria based on type of residence or home environment, living arrangement (e.g. single, married or living with a family), or pet ownership, as we wanted to deploy the sensor system in real residences of older individuals. Participants were recruited through convenience and snowball sampling methods. Information sessions were held at regular membership meetings of Korean immigrant senior associations and churches to explain the study. At the sessions, interested individuals identified themselves to the principal investigator for later initial eligibility screening via phone. All presentations and screening were conducted in Korean.

2.2 | Sensor system description

The system consisted of a study laptop, a wireless Internet router, and a set of motion sensors. Figure 1 shows a sensor system deployment in one of our study sites. These sensors capture various events in which a participant may be involved. Motion sensors were commercially available, wireless passive infrared sensors (MS 16A, X10.com) that have been used and validated in other home-based monitoring studies (Reeder et al., 2013; Kaye et al., 2011, 2012; Rantz, Skubic, & Miller, 2009). These sensors were placed in rooms frequently trafficked by participants to detect changes in motion through changes in ambient temperature when an individual moves around. These sensors detect motion in a cone-shaped area with a range of approximately 20' from the lens of the sensor and fire every 6 s as long as motion is sensed.

One of our study sites had a water consumption sensor (hydro sensor) in addition to motion sensors. The hydro sensor is a pressure-based sensing solution for monitoring water consumption and fixture-level use (Froehlich et al., 2011). This sensing approach can infer flow using a model of the pressure drop in the house as well as using the high-frequency resonances generated from the use of water fixtures in the home. These resonances provide additional information about the valve characteristic of the water fixture and its uniqueness in the homes based on the propagation characteristics in the home. In a previous study, the hydro sensor showed 90% accuracy in classifying real-world water usage (Froehlich et al., 2011). The hydro sensor was installed by screwing the pressure and flow sensors onto an exterior hose pipe, water heater drain valve or utility sink faucet. By analysing differential water pressure caused by various water-based activities, the hydro sensor is able to identify different activities involving water usage, such as taking a shower, using a toilet and dishwashing.

All data were time-stamped at the same computer (i.e. sharing the same wall clock to avoid possible temporal skew) and automatically uploaded once at night through a secured Internet connection back to the secure university server. During the study, the laptop was left on all the time for buffering and logging the sensor data.

2.3 | Procedures

The first visit occurred at baseline. After collecting informed consent, the floor plan of the house was measured and the sensor system was deployed. We tried to install sensors in minimally intrusive places. Demographic data were collected for age, gender, history of chronic conditions, current medications and assistive device use. To validate the sensor system, participants were required to fill out activity logs continuously for 2 weeks during study enrollment. They were asked to record where they had been and what they had been doing every 30 min during the 14 days. These logs were used as ground truth data.

Participants were asked to participate in the study for 2 months. Study data were collected through self-report instruments, interviews and monthly fall calendars filled out by participants. Table 1 shows the data collection schedule. We also conducted an individual interview at

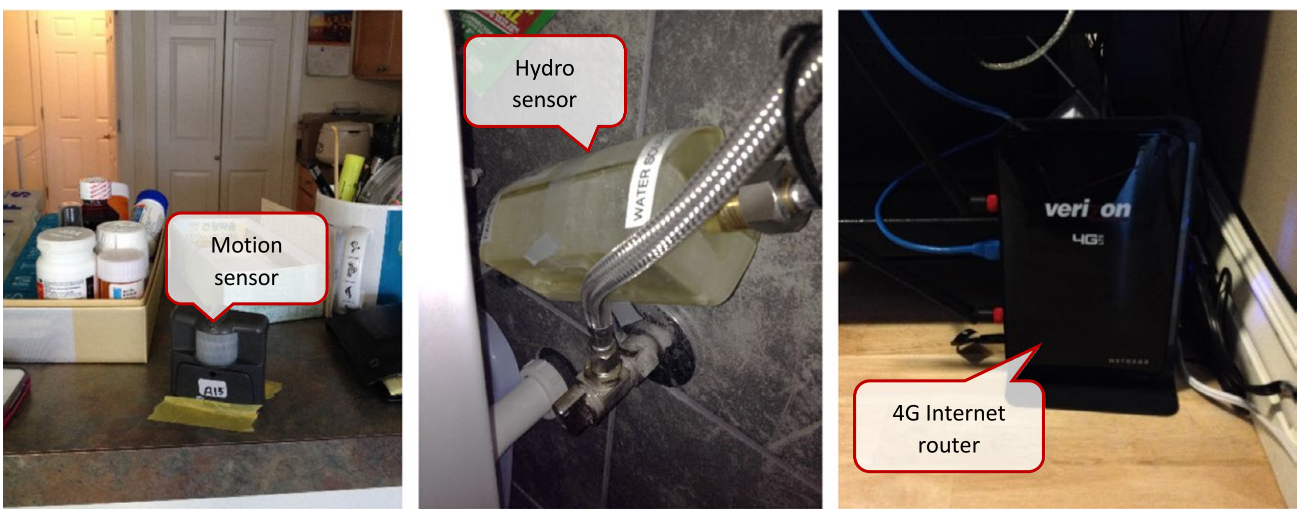

FIGURE 1 A deployment of a home-based sensor system in one of our study sites. (Left) motion sensor in a dining room; (Middle) hydro sensor in a bathroom; (Right) Internet router in a living room. Please note that these are actual pictures, not staged pictures

1 month (mid-point visit) and 2 months (exit visit) that explored participant perceptions of home-based sensor technologies using a series of semi-structured open-ended questions. Interviews were digitally recorded. Sensor systems were removed during the exit visit at the end of the study.

2.4 | Data analysis

The goals of this analysis were to characterise participant mobility and activity trends in each area of the home over 2 months of follow-up.

2.4.1 | Sensor data preparation

Activity data were acquired from six to nine motion sensors located in each room and in pathways of the participant's home. The motion sensor data set includes an activity time stamp (in milliseconds), location stamp and status ('on' or 'off'). The hydro sensor data set has information regarding each water-based activity, including which water source was turned on (e.g. kitchen faucet, toilet, shower), start-time stamp, end-time stamp and event duration. We aggregated the collected sensor into two files for each day (one for motion data and one for water activity data). The data set for each home therefore consisted of a set of daily files. As part of data preparation, the daily files were merged into one sheet per home and then cleaned to remove invalid values. Two variables were created indicating the day of week and time of day. Sensor data were first aggregated to a minute level. Then, we also aggregated the data to an hourly level by counting the number of minutes in the hour with at least one sensor 'on' event in that minute. We did not exclude days in which there was no motion detection from the analysis. All data cleaning and analyses were performed with SPSS, version 19 (SPSS Inc., Chicago, IL).

2.4.2 | Estimates of mobility and daily activity patterns

We were less interested in comparing one participant's activity pattern to that of another participant than in exploring changes in mobility and activities of each home over time. To this end, line graphs and sequence plots have been applied to data obtained from motion sensors. These graphs are used to display motion sensor events in each space and at the whole home level. Sensor firing events per home were aggregated to a daily level. Therefore, activity trends can be visualised or tracked at different time scales (i.e. for 24-hr patterns or pattern changes over time). For hydro sensor data, frequency and daily mean of sensor firings by each valve were calculated.

Furthermore, general linear models (GLMs) were used as within-home linear model fits to estimate, for each room or sensor, the effect size of the 24-hr time-of-day (TOD) effect, the day-of-week (DOW) effect and the interaction effect of these two time variables (TOD*DOW). The TOD effect is modelled as a general home-specific 24-hr pattern described by 24 hourly mean values. The DOW effect allows a general home-specific weekly pattern described by 7 daily values. The TOD*DOW effect describes variations from the overall 24-hr pattern by day of week. The effect size measure used was eta-squared (partial eta^2), which can be interpreted as the partial R^2 for each effect controlling for all the other variables in the model. The total within-home R^2 for the {TOD, DOW and TOD*DOW} model is also reported. That is, we examined the effects of time variables on changes in activities over time in each room of the home. GLMs were based on within-home data, but we did not intend to examine the effect at the whole home level. Also, because the motion sensor data were collected within each unique home, no statements of probability are reported. The hourly counts of the number

TABLE 1 Mobility parameters and data collection schedule

Instrument	Description	Scoring	Schedule
Korean version Katz scale of activities of daily living (Sohn, 1998)	Six items focused daily activities	0 (unable to do) to 2 (no help) for each item	Baseline, 1, 2 months
Rosow-Breslau scale (Rosow & Breslau, 1966)[a]	Three items focused on walking	1 (very easy) to 4 (very difficult) for each item	Baseline, 1, 2 months
Nagi disability scale (Nagi, 1976)[a]	Three items focused on stooping, reaching and lifting	1 (no difficulty at all) to 5 (unable to do it) for each item	Baseline, 1, 2 months
Life-space assessment of mobility (LSA) (Baker, Bodner, & Allman, 2003)[a]	Focused on the spatial extent, frequency and independence of individual movement within their environments	0 (mobility restricted to the bedroom) to 120 (independence enabling travel to out of town)	Baseline, 1, 2 months
–	Fall calendars	–	Monthly; retrieved at 1, 2 months
–	Interviews	–	1, 2 months
–	Activity logs	–	Completed for 2 weeks during study enrolment; retrieved at 1 month after baseline

[a]indicates instruments that were translated into Korean by the author and back translated into English by another researcher to check translation accuracy

of minutes with at least one sensor firing event were used as a dependent variable in models testing for significance of the time effects.

2.4.3 | Perceptions of home-based sensor technologies

Recordings were transcribed verbatim in Korean by the primary author (JC) of the research team. The transcript was translated into English by a bilingual speaker and checked for accuracy by another member of the team by discussing the meanings of questionable translations with the primary author. Thematic analysis was conducted to identify themes related to perceptions of technology and potential concerns related to in-home use of sensors. Transcripts for six mid-point interviews were coded to create a codebook. Codes from the codebook were reviewed for content validity by two researchers (GD & HT). Then, all transcripts were coded according to a modified codebook. The codebook was updated following each coding of one transcript. After all 12 interviews were coded, final results were summarised and reviewed by the research team.

3 | RESULTS

We aimed to explore the feasibility of implementing in-home mobility monitoring sensors in real-world settings of ethnic minority older adults living in the community. All participants completed every component of the study successfully, and their data are included in this study. However, due to limited prototype availability, a hydro sensor was only installed in one home (Home 1). Participant homes were followed for up to 84 days (mean = 64.8 ± 14.3) to detect changes in activity patterns. More than 6,000 home-hours of continuous activity data were collected during this study. All study participants were ambulatory and cognitively intact at baseline. Table 2 describes participant and housing characteristics, sensor deployments and participant mobility scores.

TABLE 2 Housing characteristics with sensor placement and participant mobility scores

							Mobility scores				
Home	Housing Type (# of bedroom and bathroom)	Sensors	Monitoring days	Total events	Participant	Gender/ Age	Assessment	Katz ADL[d]	RB scale[e]	Nagi scale[f]	LSA[g]
1	House (1/1)	1 hydro sensor; 7 motion sensors[a]	67[b]	120,091 (motion); 2,768 (hydro)	1	F/79	Baseline	12	9	12	90
							Mid-point	12	10	11	84
							Exit	12	9	16	102
2	Apt (1/1)	6 motion sensors	56	62,735	2	F/75	Baseline	12	6	7	74
							Mid-point	12	6	8	92
							Exit	12	5	9	100
3	Town home (2/2)	8 motion sensors	52	231,608	3	F/68	Baseline	12	4	8	72
							Mid-point	12	6	6	112
							Exit	12	4	5	80
					4	M/74	Baseline	12	6	5	72
							Mid-point	12	6	6	120
							Exit	12	6	5	80
4[c]	House (3/3)	9 motion sensors	84	613,827	5	F/69	Baseline	12	5	8	78
							Mid-point	12	4	8	80
							Exit	12	5	9	74
					6	M/79	Baseline	11	9	15	63
							Mid-point	10	10	19	46.5
							Exit	9	9	17	55

ADL = Korean version Katz Activities of Daily Living; RB scale = Rosow-Breslau Scale; LSA = Life-Space Assessment of Mobility.
[a]A motion sensor in the bathroom was installed later.
[b]Water usage data were collected for 26 days.
[c]Couple used separate bedrooms and bathrooms.
[d]Higher scores indicate independence in activities of daily living (range = 0–12).
[e]Higher scores indicate difficulty in walking-related mobility (range = 3–12).
[f]Higher scores indicate functional disability (range = 3–15).
[g]Higher scores indicate better life-space mobility (range = 0–120).

3.1 | Mobility and activity patterns captured by sensors

As shown in Fig. 2, each home has a different level of motion sensor firings over time. Activity sensor data in each home have natural fluctuation over time, without any significant decrease or increase. Obviously, homes with a single participant (Home 1 & 2) have a lower number of sensor firings compared to homes with couples (Home 3 & 4). Sequence plots for different areas of the home also show variable, but natural fluctuation in activities over time, meaning that there was no increase or decrease in overall mobility level or activity trend over the monitoring period (graphs not shown).

Figure 3 shows a 24-hr activity pattern of the living room for each home. Data were averaged for all monitoring days. As seen in the graphs, different 24-hr patterns were observed across homes with variable shapes and peak points allowing the identification of signature patterns. For example, a couple in Home 3 usually used the living room early in the morning, during lunch and in the evening over the week.

Twenty-four-hour patterns from sensor data (both averaged over all days and specified by day of the week) were compared with completed activity logs that were considered the ‘ground truth’ for location within the home and time of the activity. We were able to validate that sensor data were highly correlated with the activity logs.

3.2 | Within-home variations in motion by the time-of-day and day-of-week effects

Table 3 is a summary of linear model effects for a 24-hr time time-of-day (TOD), day-of-week (DOW) and the interaction (TOD*DOW) model for motion events captured by individual sensors in each home.

When we analysed the sensor data using separate GLMs for each space in Home 1, the results indicated that the time-of-day (TOD) variable explained a considerable amount of living room activity (partial eta squared = .46, R^2 = 51; Table 3), indicating that the resident of Home 1 had shown a quite regular activity trend over time in a living room area. As seen in Fig. 4, this participant occupies her living room more at night than daytime, and thus, it has an increasing trend when averaged over 24 hrs.

As indicated in Table 3, the activity pattern of the resident living in Home 2 was variable over time with no more than 3% of DOW effect and no more than 12% of TOD effect explaining her activities in every space. Her activity logs indicate that different days had different patterns over the 2-month follow-up period. For example, she had irregular sleep duration, time to get in bed or get up from the bed, and meal time. Variability in her life pattern is well detected by the in-home sensors.

As for residents in Home 3, the estimates indicate the regularity in their daily activities, with most of R^2 in each room being greater than .50 and partial eta squared for TOD in every room larger than .30 except for the activities in a main bedroom and office (Table 3). Figure 5a indicates that they usually used the living room early in the morning, during lunch and in the evening over the week, even though different days have different peak points. Similarly, the kitchen activity was quite patterned, with increased sensor events during the breakfast, lunch and dinner times (Fig. 5b). However, in Fig. 5b, 2 of 7 days (Monday and Thursday) every week show different patterns from other days, contributing to increasing the partial eta squared for the interaction of DOW and TOD to .37.

The couple in Home 4 used separate bedrooms and bathrooms due to different sleep schedules between them caused by the husband’s Parkinson’s disease. In communal areas (living room, dining room and kitchen), the partial eta squared for the TOD was larger than .35, reflecting the strong day and night activity effects. Even though the activity was not patterned in husband’s and wife’s bedrooms, there were increased sensor events at about 10 pm throughout the week, which means the regular bedtime for the couple (graphs not shown). The partial eta squared for the DOW was less than .01 in every space, indicating different patterns in different days.

3.3 | Water usage activities captured by a hydro sensor

A hydro sensor deployed in one participant’s bathroom inferred real-world water usage activities in her home. We collected a total of 2,768 labelled water events, where an event is one occurrence of a valve open. Table 4 shows a breakdown of valve activity by fixture. Using a hydro sensor, we extrapolated what types

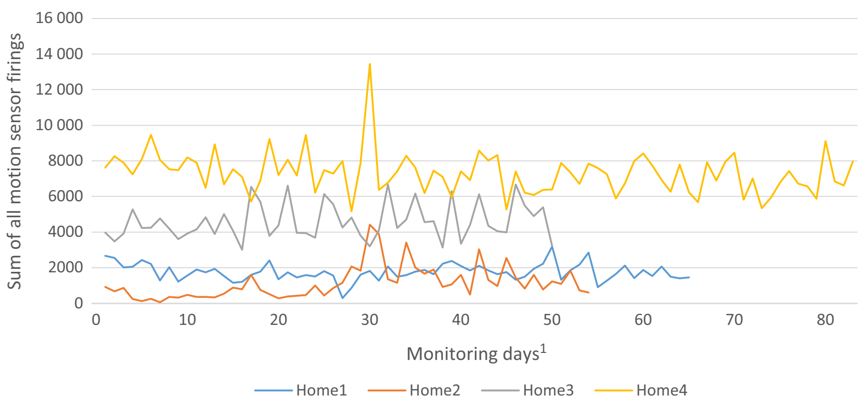

FIGURE 2 Example graph of motion sensor firings over time. [1]From all days, days containing complete 24-hr data were included

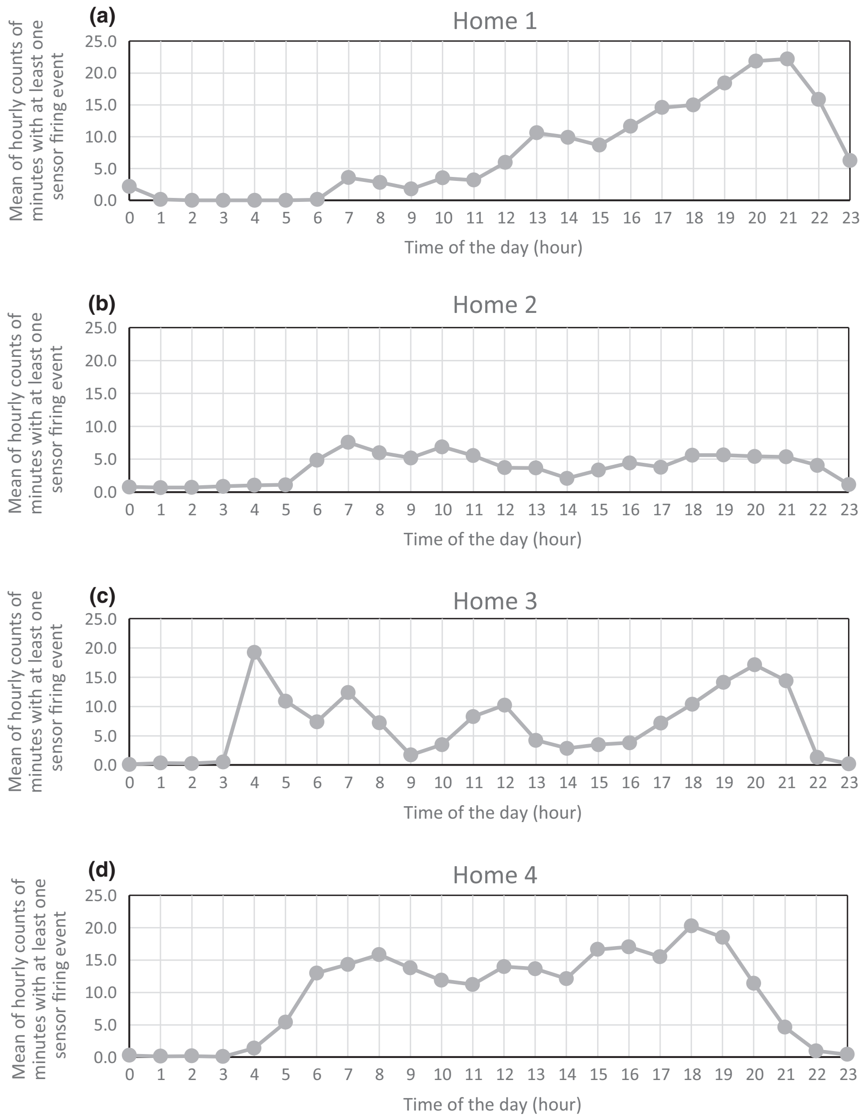

FIGURE 3 Twenty-four-hour activity patterns in the living room detected by a motion sensor. These graphs are based on the time of day on the 24-h clock

of water-involving activities were conducted at the time when a motion sensor in kitchen or bathroom fired. For example, the fact that either a laundry or kitchen sink use was detected by a hydro sensor allowed us to infer what specific activity was conducted in kitchen when the participant's activities were sensed by a motion sensor in kitchen.

3.4 | Acceptability of a home-based sensor system

Thematic analysis of the interview transcripts (six mid-point and six exit visits) resulted in four emergent themes: perceived usefulness, privacy concerns, use of sensor data and design recommendations.

3.4.1 | Perceived usefulness

A majority of the participants agreed that there was potential usefulness of sensor-based monitoring. The technology, however, was reported to be most useful only in later life or when health declines, as exemplified by the following quote: 'I don't think I would need these types of technologies before I become really sick'. Other factors affecting perceived usefulness of sensor technologies include cost of the equipment or maintenance, living situation, understanding about technology functions and trust in researchers or engineers. Interestingly, gaining and building trust with participants throughout the monitoring period was mentioned as a main motivator before they consider the use of sensors and decide to participate in the study: 'If there was a possibility of invasion of privacy, you (researcher) wouldn't allow us to do this study'.

In terms of cultural roles, family perceptions of the technology appeared to affect older adult acceptance of sensor technology, even though none of the participants were living with their family other than spouse. For example, one participant who was living alone in one of the two units in her son's house commented, 'My son once said the sensors were bothersome and cluttered (laughing). … It seems like he thinks they (sensors) are a little bit messy. He asked me when the study is finished. (Because of the sensor system,) there are more cords on the floor than we usually had'. On the other hand, one participant regarded in-home sensors as unnecessary due to her fear

TABLE 3 Proportion of variance in activity levels by room

Space	Home 1	Home 2	Home 3	Home 4
Master bedroom[a]	DOW = .16 TOD = .01 Interaction = .13 R^2 = .26	DOW = .02 TOD = .06 Interaction = .18 R^2 = .23	DOW = .01 TOD = .22 Interaction = .24 R^2 = .38	DOW = .01 TOD = .18 Interaction = .07 R^2 = .23
Master bathroom[a]	DOW = .00 TOD = .16 Interaction = .19 R^2 = .30	DOW = .02 TOD = .12 Interaction = .27 R^2 = .34	DOW = .00 TOD = .39 Interaction = .31 R^2 = .52	DOW = .01 TOD = .10 Interaction = .09 R^2 = .18
Living room	DOW = .01 TOD = .46 Interaction = .13 R^2 = .51	DOW = .03 TOD = .11 Interaction = .19 R^2 = .28	DOW = .03 TOD = .47 Interaction = .27 R^2 = .56	DOW = .01 TOD = .37 Interaction = .08 R^2 = .41
Kitchen	DOW = .01 TOD = .05 Interaction = .09 R^2 = .14	DOW = .02 TOD = .07 Interaction = .15 R^2 = .21	DOW = .10 TOD = .42 Interaction = .37 R^2 = .58	DOW = .01 TOD = .36 Interaction = .07 R^2 = .39
Dining room	–	–	DOW = .03 TOD = .47 Interaction = .28 R^2 = .57	DOW = .01 TOD = .35 Interaction = .06 R^2 = .38
Office	DOW = .01 TOD = .48 Interaction = .11 R^2 = .51	DOW = .01 TOD = .07 Interaction = .12 R^2 = .18	DOW = .02 TOD = .11 Interaction = .14 R^2 = .23	DOW = .01 TOD = .07 Interaction = .06 R^2 = .13
Bedroom[b]	–	–	–	DOW = .01 TOD = .20 Interaction = .07 R^2 = .25
Bathroom	–	–	DOW = .00 TOD = .33 Interaction = .31 R^2 = .49	DOW = .01 TOD = .18 Interaction = .06 R^2 = .22
Entrance	DOW = .00 TOD = .20 Interaction = .14 R^2 = .30	DOW = .02 TOD = .07 Interaction = .14 R^2 = .21	-	-
2nd Living room	–	–	–	DOW = .00 TOD = .13 Interaction = .08 R^2 = .19

R^2 is a within-home measure.
[a]Main bedroom and main bathroom in Home 4 were used mainly by wife.
[b]This bedroom in Home 4 was used mainly by husband.

of consequences of future technology advancements, leading her to comment ‘I think science should be stopped here at this point in time. If there are more developments, humans will become slaves to the machine’.

3.4.2 | Privacy concerns

When asked about privacy concerns, mixed opinions were observed. Some participants explicitly stated that sensors installed in their homes did not bother them, while others reported they had been worried about privacy mostly at the beginning of the study. Most participants (n = 5) explicitly stated that their behaviours had not been changed by the existence of the sensors, but all participants reported obtrusiveness related to perceived invasion of privacy with varying degrees of the feeling. Also, sensors were perceived physically or psychologically prominent or an impediment to daily routines, leading to this comment: ‘It should have been placed in an out-of-the-way spot if I used the system longer… Because this is noticeable’. Three participants expressed their privacy concerns related to a motion sensor in the bathroom, as exemplified by the following quote: ‘When I undress or dress at the bathroom, I kept thinking about my privacy, even though I heard that the sensor did not take pictures. Whenever I felt uncomfortable, I covered the sensor with a towel’.

In addition, in-home sensors were perceived as a main source of privacy invasion if the technology had the ability to distinguish different postures, like a camera or video camera. One subject stated ‘because it does not capture all of my private things– if the sensors

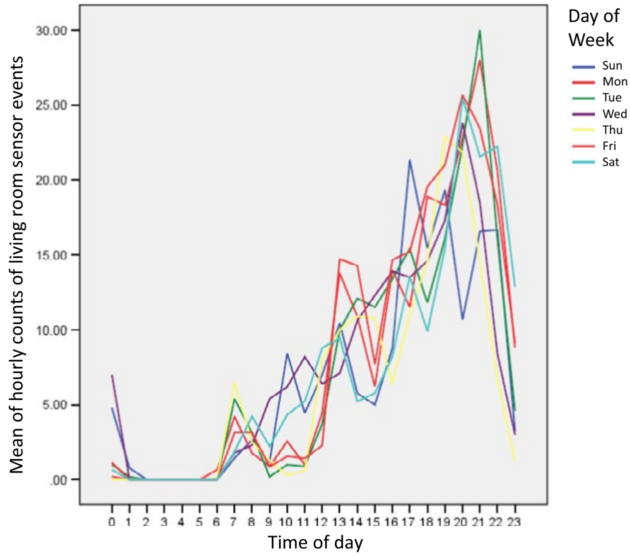

FIGURE 4 Twenty-four-hour pattern of living room activity in Home 1

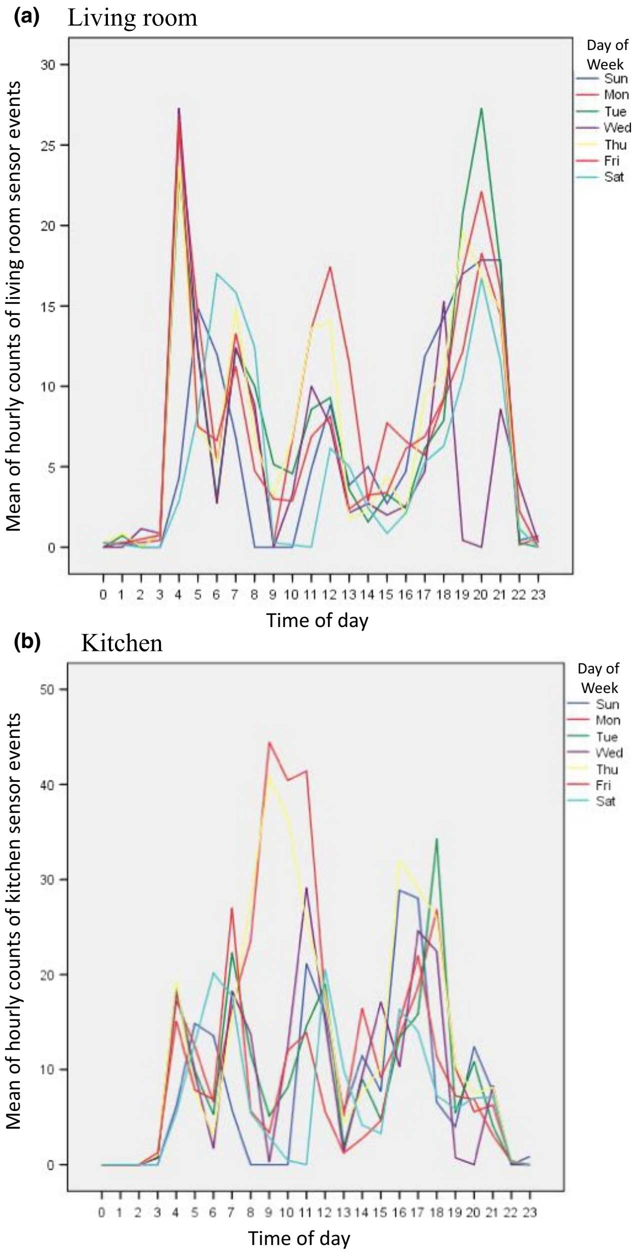

FIGURE 5 Twenty-four-hour activity pattern detected by sensors at home 3. DOW = Day of Week

show all things about my life, I would be very careful about it, but it's not that. I think it's okay'.

Some participants wished to have the ability to control the technology on or off mostly because they did not want to feel that they were being continuously monitored. One person voiced that they would want to turn the system off in specific circumstances, such as when taking a shower or changing clothes. On the other hand, another participant cited a different reason for having this function, 'Without controlling it, I do things unconsciously. …Older adults need such a means. We eat breakfast, lunch, and dinner without thinking what we are doing. If I was able to control the system, I could be better concentrating on my life'.

3.4.3 | Use of sensor data

All participants expressed their interests in accessing their own sensor data. Desired frequency of data access varied among participants, from daily (n = 1) to seasonally (n = 3). Potential uses of sensor data were also identified, including health or activity monitoring, support for active and healthy living, or prevention of adverse health events. Interestingly, one subject wanted to have her own data because 'the data would help me remember what I did, and understand why something happened, and remind what I shouldn't have done. It may make me reflect upon what I did [chuckles]. In other words, seeing the data may help me look back on my past'. Similarly, she wanted to share her data with her children in a hope that the data can be used as a means for reminiscence by her family.

Most participants (4 of 6) stated their willingness to share data with family members and/or healthcare providers. The reason for data sharing includes home safety, a need for somebody who can monitor an older individual's health and potential support for healthcare providers to set up care plans.

3.4.5 | Design recommendations

The interviews identified some technology features as a barrier to technology acceptance. For example, the red light of the wireless motion sensor bothered one participant while she was using the bathroom. All participants were concerned about the potential that the system in their homes would record their images or audio, exemplified by the following quotes: 'if it recorded what I am saying, then I would be very careful about every single word I say. Or, I would say something in a polite way every time' and 'later on I become comfortable after I heard again the sensors are not able to take pictures'. In addition, participants preferred sensors being installed in a location that is not noticeable or they cannot touch for obtrusiveness concerns.

TABLE 4 A summary of water-involving activities detected by the hydro sensor in the first home

Fixture	Frequency (%)	Daily Average
Bathroom sink	2134 (77.1)	82.1
Dishwasher	6 (0.2)	0.2
Kitchen sink	265 (9.6)	11.5
Shower	24 (0.9)	0.9
Toilet event	334 (12.1)	12.9
Washing machine	5 (0.2)	0.2

Daily averages were calculated based on 26 days.

4 | DISCUSSION

Findings from this study demonstrate the feasibility of passive home-based monitoring of mobility, as evident by the successful deployment of a home-based sensor system for monitoring mobility and daily activities among community-dwelling KAOAs. By continuously monitoring older adults through the use of unobtrusive home-based sensor technologies, we have been able to observe multiple parameters of activity and mobility patterns of individuals. In addition, the data indicate that no participants experienced decline in their activity levels or mobility over the data collection period. This is likely due to the inclusion criteria and also partly because our study period was relatively short for observing meaningful changes in health parameters. However, an overall increase in the life-space assessment of mobility (LSA) scores for residents in Home 2 and 3 was consistent with an increasing trend for these homes in all motion sensor firing graphs (Fig. 2). These results support further testing of the sensor technology with a larger cohort of older adults during an extended period of time or in those at high risk of mobility limitations to detect changes in activity patterns and physical functioning. It could allow capturing meaningful trend changes caused by natural ageing process or environmental influences (Kaye et al., 2011).

We used an individual GLM for motions in each space of the home to examine how much variability of activities over time is explained by several time variables. The model estimates showed that the effect sizes of two time variables (day-of-week and time-of-day) and the interaction of these two in a specific location (e.g. bedroom, bathroom, living room) vary across homes. In addition, only 18%–34% of the variance of the activities was explained by the time factors in the second home, while the GLMs in the most spaces of the third home explained more than 50% of the variance. It indicates that different people have different life patterns, in terms of space occupancy duration, sleep pattern, the number of bathroom visits, and indoor and outdoor activity ratios. Although we did not aim to compare the variability across homes, the data might reflect greater heterogeneity in activity patterns and mobility within one ethnic group that is usually considered culturally homogeneous. The heterogeneity of these trends suggests the next step, which may examine determinants of the variability in older adults' activity and behaviours.

Installing a hydro sensor in addition to motion sensors was an innovative, non-obtrusive approach to monitoring older adult daily activities in the home setting. The motion sensor itself has a limitation that data are often ambiguous, detecting movement in a location without identifying specifically which activity was conducted. The hydro sensor used in this study allowed us to infer activities based on water usage patterns. This innovative sensor technology has the potential to support ageing in place by monitoring real-world activities of daily living in the home (e.g. toilet use, bathing, cooking) (Fogarty et al., 2006). Furthermore, the hydro sensor allowed us to collect detailed logs of daily activities from an unobtrusive single installation point.

Some participants expressed privacy concerns particularly regarding the motion sensor in the bathroom. This recognised concern seems to be related to the installation method. The motion sensors were installed on the toilet bowl or furniture at a height of 2 to 4 feet. Therefore, when participants were taking a shower or using a toilet, they noticed the presence of the sensor and perceived it as violation of privacy even though they explicitly expressed their understanding of how the technology works. From participant responses, we confirm the importance of unobtrusive technologies for monitoring activities. Future work should use only the hydro sensor to detect bathroom activity with less intrusive deployment methods for verification as needed (e.g. motion sensor placed outside the bathroom).

All participants were retained to study completion even though the study protocol could have been perceived as intrusive and burdensome to some participants. The high retention of the participants may be because of multiple factors, including the availability of research staff in the client's native language and the convenience of home visits. When participants wondered how the system works and if there is a risk of privacy invasion, research staff was able to address those concerns by providing detailed information in their native language. Communicating efficiently through their native language may have motivated participants to remain in the study. Given the growing population of racial and ethnic minority older adults (U.S. Census Bureau, 2014), this suggests the need for linguistically appropriate technology interventions for older adults who have language barriers or feel more comfortable with their native language. For example, developers should include instructions written in various languages and/or simplified diagrams for installation regardless of language.

We found that there are challenges to sensor data analysis. Due to technical issues, activity data for some days were not transmitted to the server. Also, there is an issue of labelling the data from multiple residents in the home. We recruited participants without restriction based on their living arrangements because we wanted to see the feasibility of the system in real-life settings. Sensors in a couple's home do not tag for personal identification. Therefore, different activities from different persons in one home were recorded into the same data set. This would be important because we are unable to figure out whether there is a signal from a couple's sensor data that indicate the risk of deteriorating health or abnormal life patterns. For example, in Fig. 3c, the activity pattern from the sensors does not allow us to discern when the wife goes to bed as her data are conflated with her husband's data. Therefore, activity logs were useful to determine whether sleep is an issue for the wife given she gets up very early. Previous studies reported similar challenges in data analysis (Kaye et al., 2011; Pavel, Hayes, Adami, Jimison, & Kaye, 2006). The reliability in recognising different persons in multiple person households will be improved when algorithms to disambiguate the data are fully available. Alternatively, minimal on-body instrumentation of wearable sensors could mitigate this issue.

As a feasibility study, this study has several limitations. Firstly, our activity measures pertain to indoor activity only, although most subjects were also active outside the home. Secondly, the generalisability of the findings is limited because we included a small number of participants from one ethnic group. Finally, the 2 months of sensor-based monitoring period were not enough to detect meaningful changes in activity levels. Despite these limitations, to the best of our knowledge, this is the first study targeting use of in-home technology assessment in ethnic minority older adults.

5 | CONCLUSION

The results strongly suggest that continuous monitoring of activity patterns in the home, and variance in daily activity or 24-hr activity pattern, might provide a useful tool to detect deviations from normal activity patterns that could be an early sign of functional decline. Furthermore, the combination of activity logs and assessment of various mobility parameters would allow validating the accuracy of sensor data. Finally, the results of the current study suggest that technology applications could be successfully installed for a long-term monitoring period in this under-studied minority older adult population. Given the feasibility demonstrated in this study, future research needs to involve a greater number of participants in an extended period of time to assess the important role of home-based sensor technologies on achieving proactive patient-centred health care for community-dwelling older adults. Also, there should be an effort to identify adoption and utilisation barriers as well as facilitators when developing care models delivered through sensor-based monitoring technologies among older adults from racial and ethnic minority groups.

Implications for practice

- The clinical implications from our findings suggest that preventive interventions based on sensor-based activity data could likely be effective in changing lifestyle behaviors for improving mobility and overall health in older adults. Given that different cultural backgrounds affect perceptions and acceptability of technology differently among people, ethical issues or other challenges related to technology adoption, such as privacy, data gathering and sharing, and informed decision making, should be considered prior to the intervention and discussed with multiple stakeholders in communities.

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DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflict of interests with respect to the research, authorship and/or publication of this article.

CONTRIBUTIONS

Study design: JC, GD, HT; Data collection and analysis: JC, GD, HT, KC, RB; Manuscript preparation of this paper: All.

REFERENCES

Abellan van Kan, G., Rolland, Y., Andrieu, S., Bauer, J., Beauchet, O., Bonnefoy, M., … Vellas, B. (2009). Gait speed at usual pace as a predictor of adverse outcomes in community-dwelling older people an International Academy on Nutrition and Aging (IANA) Task Force. *Journal of Nutrition, Health & Aging*, *13*, 881–889.

Baker, P. S., Bodner, E. V., & Allman, R. M. (2003). Measuring life-space mobility in community-dwelling older adults. *Journal of the American Geriatrics Society*, *51*, 1610–1614.

Bureau, U. S. C. (2014). 2014 National Population Projections. Retrieved February 11, 2015, from http://www.census.gov/population/projections/data/national/2014/summarytables.html

Chan, M., Estève, D., Escriba, C., & Campo, E. (2008). A review of smart homes—Present state and future challenges. *Computer Methods and Programs in Biomedicine*, *91*(1), 55–81.

Chen, K.-Y., Harniss, M., Patel, S., & Johnson, K. (2014). Implementing technology-based embedded assessment in the home and community life of individuals aging with disabilities: A participatory research and development study. *Disability and Rehabilitation. Assistive Technology*, *9*(2), 112–120.

Chung, J., Demiris, G., & Thompson, H. J. (2015). Instruments to assess mobility limitation in community-dwelling older adults: a systematic review. *Journal of Aging and Physical Activity*, *23*(2), 298–313.

Fogarty, J., Au, C., & Hudson, S. E. (2006). Sensing from the basement: a feasibility study of unobtrusive and low-cost home activity recognition. Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology. Montreux, Switzerland: ACM.

Froehlich, J., Larson, E., Saba, E., Campbell, T., & Atlas, L.. (2011). A longitudinal study of pressure sensing to infer real-world water usage events in the home. Proceedings of the Ninth International Conference on Pervasive Computing. 50–69.

Hardy, S. E., Kang, Y., Studenski, S. A., & Degenholtz, H. B. (2011). Ability to walk 1/4 mile predicts subsequent disability, mortality, and health care costs. *Journal of General Internal Medicine*, *26*(2), 130–135.

Hayes, T. L., Abendroth, F., Adami, A., Pavel, M., Zitzelberger, T. A., & Kaye, J. A. (2008). Unobtrusive assessment of activity patterns associated with mild cognitive impairment. *Alzheimer's & Dementia*, *4*, 395–405.

Kang, H. G., Mahoney, D. F., Hoenig, H., Hirth, V. A., Bonato, P., Hajjar, I., Lewis, A. L., for the Center for Integration of Medicine Innovative Technology Working Group on Advanced Approaches to Physiologic Monitoring for the Aged. (2010). In situ monitoring of health in older adults:

Technologies and issues. *Journal of the American Geriatrics Society*, *58*, 1579–1586.

Kaye, J., Mattek, N., Dodge, H., Buracchio, T., Austin, D., Hagler, S., … Hayes, T. (2012). One walk a year to 1000 within a year: Continuous in-home unobtrusive gait assessment of older adults. *Gait & Posture*, *35*(2), 197–202. doi:10.1016/j.gaitpost.2011.09.006

Kaye, J. A., Maxwell, S. A., Mattek, N., Hayes, T. L., Dodge, H., Pavel, M., … Zitzelberger, T. A. (2011). Intelligent systems for assessing aging changes: Home-based, unobtrusive, and continuous assessment of aging. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *66B*(suppl 1), i180–i190.

Kim, M. J., Ahn, Y.-H., Chon, C., Bowen, P., & Khan, S. (2005). Health disparities in lifestyle choices among hypertensive Korean Americans, non-Hispanic Whites, and Blacks. *Biological Research for Nursing*, *7*(1), 67–74.

Lo, A. X., Brown, C. J., Sawyer, P., Kennedy, R. E., & Allman, R. M. (2014). Life-space mobility declines associated with incident falls and fractures. *Journal of the American Geriatrics Society*, *62*(5), 919–923.

Montero-Odasso, M., Bergman, H., Beland, F., Sourial, N., Fletcher, J. D., & Dallaire, L. (2009). Identifying mobility heterogeneity in very frail older adults. Are frail people all the same? *Archives of Gerontology and Geriatrics*, *49*, 272–277.

Nagi, S. Z. (1976). An epidemiology of disability among adults in the United States. The Milbank Memorial Fund Quarterly. *Health and Society*, *54*, 439–467.

Park, J., Roh, S., & Yeo, Y. (2012). Religiosity, social support, and life satisfaction among elderly Korean immigrants. *The Gerontologist*, *52*, 641–649.

Pavel, M., Hayes, T. L., Adami, A., Jimison, H., & Kaye, J. (2006). Unobtrusive assessment of mobility. Conference Proceeding of the 28th IEEE Annual International Conference, 1, 6277–6280.

Rantz, M. J., Skubic, M., Abbott, C., Galambos, C., Pak, Y., Ho, D. K. C., … Miller, S. J. (2013). In-home fall risk assessment and detection sensor system. *Journal of Gerontological Nursing*, *39*(7), 18–22.

Rantz, M. J., Skubic, M., & Miller, S. J. (2009). Using sensor technology to augment traditional health care; Paper presented at the Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE; Sep 3-6, 2009

Rantz, M. J., Skubic, M., Miller, S. J., Galambos, C., Alexander, G., Keller, J., & Popescu, M. (2013). Sensor technology to support Aging in Place. *Journal of the American Medical Directors Association*, *14*, 386–391.

Reeder, B., Chung, J., Lazar, A., Joe, J., Demiris, G., & Thompson, H. J. (2013). Testing a theory-based mobility monitoring protocol using in-home sensors: a feasibility study. *Research in Gerontological Nursing*, *6*(4), 253–263.

Rockwood, K., Awalt, E., Carver, D., & MacKnight, C. (2000). Feasibility and measurement properties of the functional reach and the timed up and go tests in the Canadian study of health and aging. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences*, *55*(2), M70–M73.

Rosow, I., & Breslau, N. (1966). A guttman health scale for the aged. *Journal of Gerontology*, *21*, 556–559.

Sohn, S. (1998). *Differences in cognitive function and activities of daily living between two groups with and without depression among patients with senile dementia*. Unpublished master's thesis, Yonsei University, Seoul, Korea.

Sohng, K. Y., Sohng, S., & Yeom, H. A. (2002). Health-promoting behaviors of elderly Korean immigrants in the United States. *Public Health Nursing*, *19*, 294–300.

Webber, S. C., Porter, M. M., & Menec, V. H. (2010). Mobility in older adults: A comprehensive framework. *Gerontologist*, *50*, 443–450.

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