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A nurse-driven method for developing artificial intelligence in "smart" homes for aging-in-place

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ABSTRACT

Objectives: To offer practical guidance to nurse investigators interested in multidisciplinary research that includes assisting in the development of artificial intelligence (AI) algorithms for "smart" health management and aging-in-place.
Methods: Ten health-assistive Smart Homes were deployed to chronically ill older adults from 2015 to 2018. Data were collected using five sensor types (infrared motion, contact, light, temperature, and humidity). Nurses used telehealth and home visitation to collect health data and provide ground truth annotation for training intelligent algorithms using raw sensor data containing health events.
Findings: Nurses assisting with the development of health-assistive AI may encounter unique challenges and opportunities. We recommend: (a) using a practical and consistent method for collecting field data, (b) using nurse-driven measures for data analytics, (c) multidisciplinary communication occur on an engineering-preferred platform.
Conclusions: Practical frameworks to guide nurse investigators integrating clinical data with sensor data for training machine learning algorithms may build capacity for nurses to make significant contributions to developing AI for health-assistive Smart Homes.

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The population of older adults in the United States (US) is growing rapidly. By 2030 one in five U.S. residents will be age 65 or older (U.S. Census Bureau, 2018). Many of these older adults wish to age-in-place (National Institute on Aging, 2017b). A growing number are interested in using sensor technology to potentially extend their independence (Demiris, Hensel, Skubic, & Rantz, 2008; Fritz, Corbett, Vandermause, & Cook, 2016; National Institute on Aging, 2017a). Health-assistive smart homes (hereafter referred to as Smart

Home; described below) may be an option that could foster the independence of older adults. Smart homes are an emerging technology designed to assist older adults with aging-in-place by monitoring their movement in the home and intervening on their behalf as needed (Cook, Crandall, Thomas, & Krishnan, 2012; Rantz & Popejoy, et al., 2014).

Using smart technologies, such as the Smart Home, to meet older adult's health care needs is gaining popularity, and nurses are increasingly called upon to be at the

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forefront of integrating new technology into the delivery of patient care. Nurses historically claim professional ownership of the space between technology and the patient (Risling, 2018), and are involved in deploying and managing these systems (Courtney, Alexander, & Demiris, 2008; Moen, 2003; Toromanovic, Hasanovic, & Masic, 2010). However, little is known about *how* nurses use their clinical knowledge to implement these emerging technologies, especially artificial intelligence (AI). AI refers to computer software algorithms capable of performing tasks normally requiring human intelligence. Despite the call for rigorous research to support the integration of AI into complex systems such as modern health care (Campolo, Sanfilippo, Whittaker, & Crawford, 2017), a key gap exists regarding transferring clinical knowledge from nursing to engineering. This knowledge gap may lead to suboptimal clinical relevance of AI and inadvertently lead to the development of deficient health-assistive smart technologies.

A paucity of nursing literature exists on *how* nurses can guide AI training for Smart Homes using their knowledge of how humans respond to illness. Specifically, a gap in the literature exists for methods describing *how to* infuse nursing clinical knowledge into the training of the AI algorithms designed to assist with health maintenance. We conducted an extensive search across Google Scholar, Semantic Scholar, PubMed, CINAHL, Cochrane, Embase, and IEEE Xplore using various combinations including: *nursing, nursing knowledge, AI, machine learning, tools, techniques, methods, design, developing, medicine, health care,* and *consumer*. A large body of knowledge exists on developing and applying AI tools for health-assistance, including Smart Homes. Within this body of literature nursing's contribution is lacking regarding their role in guiding AI training and development. Several research teams in the US use sensors and intelligent algorithms to monitor older adults as part of developing technologies for supporting aging-in-place. No literature was located from these research centers on the role of nursing in training AI or the transference of clinical knowledge to engineering for training AI. The U.S. teams include the University of Missouri-Columbia, TigerPlace; Washington State University, Center for Advanced Studies in Adaptive Systems; and the University of Texas-Arlington, SmartCare Technology Development Center; Oregon Health Sciences University, Oregon Center for Aging and Technology (ORCATECH); Georgia Tech, Aware Home; Massachusetts Institute of Technology, AgeLab; Yale University, Y-Age; Stanford University, Center on Longevity. A majority of the Smart Home literature that includes nursing comes from the work of Rantz (nursing) and Skubic (engineering) and colleagues at the University of Missouri-Columbia. Nurses are actively involved at Washington State University's Center for Advanced Studies in Adaptive Systems lab and at the SmartCare Technology Development Center at the University of Texas-Arlington. It is not clear how, or if, nurses are involved in Smart Home research at any of the other universities.

We make an attempt to fill this gap by introducing a nurse-driven method for guiding the development of AI for Smart Homes. The method was developed based on frontline experience working with a multidisciplinary team consisting of nursing, engineering, and computer science. This pragmatic experience informed the training of an intelligent algorithm that recognized three changes in health states of chronically ill persons: side effect of radiation treatment, insomnia, and a fall (Sprint, Cook, Fritz, & Schmitter-Edgecombe, 2016a; Sprint, Cook, Fritz, & Schmitter-Edgecombe, 2016b). This nurse-driven method is useful for documenting clinically relevant ground truth. Ground truth refers to information collected in real-world settings; allowing sensor data to be related to real features. Collecting ground-truth data enables calibration of remote-sensing data, and aids in the interpretation and analysis of what is being sensed in the *context* of the real-world (Bhatta, 2013). Contextualizing Smart Home data includes coupling specific attributes in sensor data to behaviors that may be associated with a human response to illness.

The purpose of this methodological paper is to discuss our own techniques and experiences working as a nurse researcher on a multidisciplinary Smart Home research team of engineers, computer scientists, and psychologists. We provide a blueprint for a nurse-driven method (hereafter referred to as the Fritz Method) for integrating clinical knowledge into training AI for Smart Homes. The Fritz Method leads to an expert-guided approach to machine learning resulting in clinician-based AI. Our work is value-laden, grounded in a postpositivist stance, and theoretically framed within critical realism and a pragmatic approach to frontline problem-solving (e.g., preventing falls) and clinical applications (e.g., relevant alerts, autoprompting interventions). Critical realism is based on the writings of Bhaskar (1978; 1989). It is a meta-theoretical philosophical position acknowledging the value of contextualizing aspects of human existence. Pragmatism is based on the writings of Pierce (Pierce, 1905). Pragmatism is not idealistic, nor reductionist, but rather offers a practical philosophical methodology for navigating Cartesian scientific approaches while acknowledging the influences of everyday living. Pragmatism guides our thoughts as we seek to balance the quantitative approaches of computer scientists and a nursing translation of the smart home to clinical practice. We also embrace Idhe's (1990) postphenomenology philosophy of technology: that technology impacts the end-user in a real way, influencing their everyday life. Our approach is based on a participatory, mixed methods research design that places the clinician directly in the iterative design loop for developing AI (described below). See Dermody and Fritz (2018) for more information on the conceptual framework underpinning the Fritz Method. The use of this method can guide nurse researchers to obtain consistent clinical ground truth that is auditable and coherent for engineering and computer science colleagues. We iteratively honed our

processes while working with Smart Homes deployed in the field (i.e., to independent community-dwelling older adults) from 2015 to 2018. Research studies informing this work were approved by the Washington State University Institutional Review Board.

Artificial Intelligence

The idea of "thinking machines" has been around since the 1930's. Alan Turning is credited with the development of a computing machine (The Enigma) that was able to execute algorithms considered to be intelligent. However, John McCarthy was credited with being the father of AI, coining the term in the late 1950's (McCarthy, n.d.). In our Smart Home research, we define artificial intelligence as a computer algorithm that acts as a rational agent capable of assessing human movement over time and making decisions about that person's movement, much like a human would.

Intelligent algorithms are capable of learning older adults' normal movement patterns and facilitating interventions that are clinically relevant, should abnormal patterns occur (i.e., alerting a nurse, prompting to take a medication). Examples of abnormal patterns include a significant decrease in overall activity, slower walking speed, increased bathroom use, increased activity at night, decreased entering or exiting the home, and more. (Abnormal patterns are based on the individual's normal baseline, not a population baseline.) To train AI algorithms engineers must use training data sets representative of ground truth. This is accomplished by humans who review sensor data and relate real-world features by annotating the data. To generate ground truth, humans must verify that the data chosen to train the algorithm is a good representation of the real-world event the algorithm is being trained to address. "Good representation" of data includes being able to identify clear boundaries of when an event started and ended, the degree of the event (e.g., fall with 2-hour duration versus 2-minutes), repetitive subevents (i.e., minor activities or events associated with major events), and unique attributes essential to understanding event coupling (i.e., comparing commonalities in sensor data across similar events). Good representation of an event within the sensor data is critical to also coupling what is being measured (e.g., sequential sensor activation combinations) with the event that actually occurred. For more information on training machines to identify changes in health states see (Fritz & Cook, 2017; Sprint et al., 2016a; Sprint et al., 2016b).

Smart Homes

Smart Homes use hardware (i.e., sensors, relays, and computers) and computer software to attempt to assist with health maintenance and illness prevention. Software tools include algorithms which are sophisticated probability and statistics programs that run on computers. These algorithms are referred to as activity-aware algorithms because they are capable of recognizing human behavior and daily activity patterns (Krishnan, & Cook, 2014). To accomplish this, they rapidly sort and label data derived from sensors designed to detect the state of an environment.

Smart Homes use multiple sensor types to detect movement in the home's environment. Smart Home researchers use a variety of sensors including infrared motion, door use (i.e., contact sensors), light, temperature, humidity, pressure, vibration, and more (Cook, Schmitter-Edgecombe, Jonsson, & Morant, 2018). Each sensor provides unique information important to understanding clinically relevant human behaviors and activities.

To demonstrate a nurse-driven method for training AI we highlight the WSU Smart Home that uses five environmental sensor types: infrared motion, contact, light, temperature, and humidity. (The scope of this paper excludes wearable sensor monitoring.) These sensors are used because they are unobtrusive, can continuously monitor, are low cost, and data are low fidelity and relatively easy to store and manage. This particular sensor combination is used because the compiled data provides a fairly comprehensive picture of an older adult's in-home movements and behaviors without needing to use cameras or microphones. Many older adults prefer not to be monitored with cameras and microphones (Demiris et al., 2004; Fritz et al., 2016; Mann, Belchior, Tomita, & Kemp, 2007).

Other sensors can be added to improve capturing specific movements (behaviors and activities). Floor pressure sensors can provide information about older adults' gait and walking speed, as well as falls (Jideofor, Young, Zaruba, & Daniel, 2012; Muheidat, Tyrer, Popescu, & Rantz, 2017). Vibration sensors can enhance knowledge about ambient noise levels, equipment use, and may be useful in assisting with fall detection (Cook et al., 2018). Some research teams use silhouette cameras and microphones such as Microsoft's Kinect (Bian, Hou, Chau, & Magnenat-Thalmann, 2015; Stone & Skubic, 2015). Many researchers, including our research team, use wearable devices such as smart watches or Fitbits for tracking movement outside the home.

Motion Sensors

Infrared movement-detecting sensors are much like motion-activated porch lights that are found outside of a home. In the Smart Home, this sensor detects when the resident is moving around within the home. Some motion sensors detect any movement occurring in an entire room while others only detect motion occurring near the sensor, and within its direct line-of-sight. These sensors send automated text messages over the internet regarding their current ON/OFF state

(i.e., when motion is detected an ON message is sent). Infrared motion sensors can provide information on the resident's location, time spent in a single location, sequential movement, frequency of toilet use, sleeping, and overall activity levels (Cook & Das, 2004; Ghods et al., 2018; Lê, Nguyen, & Barnett, 2012; Skubic, Guevara, & Rantz, 2015). Walking speed can be calculated using this data. This information becomes knowledge when combined with AI tools such as activity-aware algorithms (Krishnan, & Cook, 2014) providing information about an older adult's movement that does not fit the individual's normal pattern. Knowledge of abnormal motion could inform efficacious care decision-making (Rantz, Lane, et al., 2015; Skubic et al., 2015).

Contact Sensors

Similar to chair and bed alarms, these sensors use magnetic relays (i.e., a switch) to capture when two magnets are in close proximity to each other allowing current to flow. When the magnets are in close proximity, current flows and the alarm is *not* activated. When the magnet is pulled away, current does not flow and the alarm is activated. Similarly, contact sensors (placed on doors in the Smart Home) can provide information about whether the door is OPEN or CLOSED. When the door is open, the magnet is not in close proximity and current cannot flow and the text message will indicate the door is OPEN. Magnets in contact sensors are low power and do not interfere with other signals or electronics, such as implantable cardioverter defibrillators. Contact sensors provide information regarding door use behavior patterns related to entering and exiting the home and opening or closing cabinet doors. Information on older adults' door use can lead to knowledge about depression (Kaye et al., 2011), social isolation (Demiris et al., 2004), and medication use (Wagner, Basran, & Dal Bello-Haas, 2012).

Light, Temperature, Humidity Sensors

A light sensor placed inside the refrigerator provides information about potential interest in food, eating patterns, and food-related routines (e.g., retrieving creamer for coffee every morning at 5:30 A.M.). Light sensors located throughout the home (e.g., office, bedroom, living room) provide information on the ambient light level in that room by time of day. This information augments understandings of the resident's activity levels during the day or night.

Combining temperature, humidity, and motion sensor data provides information on activities involving use of the kitchen stove and bathroom showers. This information informs understandings of eating patterns, bathing, and grooming. It also allows the intelligent algorithm (AI agent) to assess when a stove may have been accidently left on (e.g., the air temperature around the stove rises significantly and no motion has been detected in the kitchen in the last 30 minutes).

Data, Ground Truth, and AI Tools

Data

The goal for the Smart Home is to identify and/or predict a change in health state so a caregiver or nurse can proactively intervene and a negative health event can be avoided or mitigated. To accomplish this, large amounts of data of persons experiencing health events are needed. We define "health event" as any change in health state with the potential to cause harm if not treated. We collect health event data by monitoring older adults with multiple chronic conditions. Exacerbations of chronic conditions have well-known symptoms that result in typical behaviors. These behaviors are associated with physical, observable movements that motion sensors can detect, and motion patterns that AI algorithms are capable of recognizing.

Both qualitative and quantitative data are needed to train the Smart Home to recognize changes in health states. We conduct semistructured and unstructured health interviews and physical assessments, and extract health information from medical records. These data are recorded as qualitative text-based language. Examples are: the story of a fall (where, when, how, time duration, associated injuries, and outcome); description of feeling sad or lonely during the first holiday without a spouse of 60 years (i.e., situational sadness); description of weakening legs and increased dyskinesia of a person with Parkinson's, and the effect on daily activities and routines; and, effects of a medication changes. Such descriptions are recorded and organized on a spreadsheet capturing each major body system (e.g., respiratory, cardiac, and musculoskeletal). We also assess (and search the medical record for) functional status, use of assistive equipment, socialization, and multidisciplinary care planning. From the medical record, we extract information about previous surgeries or injuries, symptom complaints, medications, and symptom response to pharmacological treatment.

Quantitative data includes ambient ubiquitous sensor data from the five types of sensors mention above (motion, contact, light, temperature, humidity) and quantifiable nursing assessment data such as vital signs and Timed Up and Go Tests (time in seconds). Copious amounts of ambient sensor data are collected. Each sensor is capable of activating multiple times per second as the resident moves about within the home. Sensors are labeled and appear as discrete text-based data of ON/OFF activations that include the date and time the sensor was activated (e.g., "2018-02-19 05:06.23.0955587 LivingRoomAArea ON"; representing movement in the living room at on February 19, 2018 at 5:06 A.M.).

Ground Truth

Ground truth documentation of the human response to illness and the associated events are critical to training clinically efficacious AI (Liao, Hsu, Chu, & Chu, 2015; Pearl, Glymour, & Jewell, 2016; Risling, 2018). Additionally, choosing appropriate data representing real-world events is important (Brynjolfsson & Mitchell, 2017). Sensor data alone tell an incomplete story, leaving the AI agent at risk of unreliable decision making. Accordingly, the "full story" can only be understood within the context of the older adult's experience of the health event. Reliable ground truth is obtained through: (a) listening to the participant's story; (b) recording reported symptoms; (c) conducting a physical nursing assessment; (d) reviewing medical records (as needed); and, (e) asking probing questions designed to elicit event-specific information about changes in movement and motion patterns that can be measured using sensor data. (See the Telehealth Visits section below for examples of probing questions.)

To communicate reliable clinical ground truth to engineers, our nurses keep a log of all health events (i.e., anything that is a significant change from norm; Table 1) and annotate prelabeled sensor data (Figure 1). Multiple characteristics of health events are captured on a spreadsheet that is made available to the engineering team via a HIPAA compliant web-cloud.

Nurses are uniquely positioned to provide an important clinical perspective and description of events for training the AI agent because of their holistic training, clinical knowledge, and the frontline expertise. Annotated data sets and the health event log inform shared interdisciplinary decisions regarding the choice of training data sets (Figure 1).

AI Tools

Our engineers use a combination of AI tools to train the Smart Home AI agent (Table 2). They supervise the machine as it learns; referred to as supervised learning techniques. These techniques use algorithms that are essentially sophisticated probability and statistics tools capable of solving computations so large that it would take a human several months, even years, to complete the task. However, computers can complete the task in seconds or minutes.

Our engineers use a combination of AI techniques to train the AI agent. Techniques listed in Table 2 have achieved statistical significance across multiple health events at the point in time the event reportedly occurred. For more information on this process see Sprint et al. (2016a).

Ambient Sensor Data Collection

In this section, we provide a description of the Fritz Method, a nurse-driven method to support training a rational AI agent whereby we identify training data sets that accurately represent health events. We begin by providing a blueprint for efficient collection of both quantitative and qualitative data that includes mapping our visits with participants and highlighting important considerations at each step. Following this section, we discuss data analysis and annotating for ground truth. A pilot study including 10 Smart Homes and hundreds of sensors serves to develop the methodology needed by nurse researchers to interpret Smart home data.

Recruiting Visit (Phone or Home Visit)

To obtain the necessary health event data for training the AI agent, we include participants age 55 and over with two or more chronic conditions, living independently, having internet, and having no plans for

Table 1 – Clinical Ground Truth for Health Events. Documentation Recorded on a Consolidated Sortable Form Including All Health Events							
Participant Code	Date	Health State	Anomaly Detection Category	Diagnosis	Start Time Stamp	End Time Stamp	Notes
P1*	5/29/2017	Fall	Fall	Parkinson's	2101	2119	Gaps in data during fall; while P1 on floor
P2	11/15-16/2017	Leg cramps	Sleep	Parkinson's	2354	0537	Interrupted sleep
P3	1/29-31/2018	Med change; IM injection antibiotics	GI/GU	UTI	1/29 @ 1039	1/31 @ 1247	Home health nurse
P4	2/28/2018	Fall	Fall	Parkinson's	2235	2254	Normal routine described
* This fall is represented in Figure 1.							

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Per patient Fall around 9p; broken hip; was "on the way from bathroom"

2017-05-26 21:01:27.257814      HallwayA        ON
2017-05-26 21:01:30.433048      HallwayA        OFF
2017-05-26 21:01:30.941226      LivingRoomAArea ON

Fall begins here, per pt report during interview on 6/6/17; see Assessment Spreadsheet; pt fell while
attempting to sit down in recliner chair, fell toward kitchen table and kitchen chair, 20 minute downtime
before medics removed him to ambulance

2017-05-26 21:01:34.695532      LivingRoomAArea OFF
2017-05-26 21:04:44.232883      LivingRoomAArea ON
2017-05-26 21:04:45.211312      LivingRoomAChair        ON
2017-05-26 21:04:45.470087      KitchenADiningChair     ON
2017-05-26 21:04:46.337140      LivingRoomAChair        OFF
2017-05-26 21:04:46.590135      KitchenADiningChair     OFF
2017-05-26 21:04:46.857620      LivingRoomAArea OFF      6 min gap in data here
2017-05-26 21:10:41.846734      KitchenADiningChair     ON
2017-05-26 21:10:41.930689      KitchenADiningChair     OFF

EMS arrives; below, multiple concurrent sensor activations representing multiple persons in residence

2017-05-26 21:19:18.025476      MainEntryway    ON
2017-05-26 21:19:19.893615      MainEntryway    OFF
2017-05-26 21:19:20.457500      MainEntryway    ON
2017-05-26 21:19:22.475317      HallwayA        ON
2017-05-26 21:19:22.516994      MainEntryway    OFF
2017-05-26 21:19:24.396811      MainEntryway    ON
2017-05-26 21:19:24.512413      HallwayA        OFF
2017-05-26 21:19:26.326339      LivingRoomAArea ON
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Figure 1 – Segment of the sensor data of the fall of a person with Parkinson's with clinical ground truth annotations made by a Registered Nurse. The fall occurred in the living room May 26, 2017 at approximately 9 P.M.

extended vacations (greater than one month) while the Smart Home is installed in their home. We prefer participants living alone but no stipulations are specified regarding other people in the home (i.e., partners, caregivers, and visitors). Most of our participants live alone but some have spouses, partners, or live-in caregivers. We prefer a home visit for recruiting community-dwelling independent participants because home visits allow us to immediately observe the layout of the home. Additionally, we can assess the older adult's internet connection and whether they live alone or have pets (how many and what kind). [Persons living alone, without pets that move about the home (i.e., bird versus cat), provide "cleaner" data that is easier to analyze. Sensors activated by pets have more erratic patterns than humans, making the data difficult to interpret and use for training the AI agent. We make team decisions regarding the value of admitting a more data-complex case into the study.]

We involve community stakeholders (e.g., a continuing care retirement community organization [CCRC]). Many CCRC leaders are interested in the potential benefits of Smart Homes and we find they are often open to hosting the research. Utilizing CCRCs simplifies many aspects of the research. CCRCs may provide: (a) large sample populations available in one location; (b) advertising and recruiting of interested participants; (c) staff who are excellent resources on residents' health and functional status; (d) introduction of researcher to participant; and (e) assistance with installation and maintenance technicalities (e.g., connecting to secure Wi-Fi, changing batteries).

Table 2 – Tools for Training Smart Home AI	
Hidden Markov Models	Computes the probability that an environmental state is occurring based on secondary observations instead direct observations.
Naive Bayes Classifiers	Using statistics to predict the likelihood that an event will occur in a given data classification with specific classification attributes. Assumes that all variables are independent.
Gaussian Mixture Models	Using statistics modeling to capture the distribution of a cluster of data (a pattern) while accounting for both mean and variance.
Conditional Random Fields	Probabilistic model used to analyze structured data and to discriminately label and segment sequential data. Independence is *not* assumed for current output observations in time-series analysis.
Time-Series Forecasting Models	Uses statistics modeling to predict future values based on previously observed data.
Decision Trees	A decision flow chart with possible outcomes for each branch of the chart. Similar to the decision tree used in an Advanced Cardiac Life Support course.
Leave-one-home-out	Tests the generalizability of the learned model by training the model on all but one home and testing it on the remaining homes, then repeating and averaging the results over all of the test homes.

Enrolling Participant Visit *(Home Visit)*

Here, we explain to the participant the level of sophistication and realistic capabilities of the Smart Home. Many smart homes used in research are not yet capable of alerting researchers to a health event (e.g., a fall). Advising participants on the Smart Home's specific capabilities is important. We advise them to call the emergency help line or follow the CCRC's protocol in the event of an emergency.

Environmental Considerations for Sensor Placement

In-home assessments provide baseline information on the participant's routine activities and behaviors and the use of space within the home. We look for health and safety risks such as lighting, throw rugs, clutter, shower mats, condition of food, heating and cooling, and more. Knowledge of these items informs data analysis and interpretations around events such as falls. This knowledge guides thoughts of how and where events may occur within the home. We perform the full home assessment only when enrolling participants. Thereafter, targeted home assessments are performed, based on clinical findings.

The number and type of sensors needed to construct the Smart Home is based on the floorplan, placement of furniture, and the resident's use of the space. Furniture locations are marked on the floor plan. The participant's favorite locations in each room are also recorded; including, the favorite dining room chair,

living room chair, side of bed, bathroom and/or bathroom sink (Figure 2). Labeling participants' favorite locations helps with discriminating one person's movements from another when multiple people are in the home (i.e., spouse or visitors).

We note the type and location of each sensor, as well as where the server will be located. We create a digital file of the labeled floorplan for the engineering team so the individualized Smart Home can be assembled. Typically, a two-bedroom two-bath home requires a total of 15 to 20 sensors (Table 3).

Sensors are placed on ceilings, walls, and doors. One motion *area* sensor and multiple motion *direct* sensors are placed in every room. *Area* motion sensors have a 360-degree visual field and they activate anytime there is motion in the room. *Direct* motion sensors require the resident to be in close proximity (<2 meters) to the sensor. A *direct* sensor is placed at the entry of each interior room (to detect someone entering the room) and one or two *direct* sensors are placed near the resident's favorite location in that room. *Direct* sensors are necessary for tracking sequential motion throughout the home. A *direct* sensor is placed just inside the bathroom door and above the sink and the toilet to monitor use of each. An *area* and a *temperature-humidity* sensor are placed in the bathroom as well. The *temperature-humidity* sensor provides information about bathing (e.g., taking a shower increases the temperature and humidity in the bathroom). (There are no cameras or microphones in the smart home.) A *light* sensor is placed inside the refrigerator to inform understandings of eating patterns. A *temperature-humidity* sensor

Figure 2 – Floor plan of residence with field notes of furniture locations and the plan for sensor location by type *(Left)* and a digital copy that is created after the visit *(Right)*. ⊙ direct sensor ceiling; ◖ direct sensor wall; ● area sensor; [R] relay; [T] temperature-humidity.

Table 3 – Sensor Locations and Types

Area	Direct	Area	Contact	Light	Humidity	Temp.
Entry door			✓			
Hallway	✓	✓				
Living room entrance	✓	✓				
Favorite living room chair	✓					
Office entrance	✓	✓				
Office chair	✓					
Dining room	✓	✓				
Favorite dining room chair	✓					
Kitchen entrance	✓	✓				
Kitchen sink	✓					
Kitchen stove	✓				✓	✓
Refrigerator				✓		
Bathroom Entrance	✓					
Bathroom Sink	✓					
Toilet	✓					
Shower					✓	✓
Bedroom entrance	✓	✓				
Favorite side of bed	✓					

is placed on the wall by the kitchen stove. A *contact* sensor is placed on the main door entering the home. Command Strips attach sensors to walls, ceilings, and doors.

Sensor data is relayed from the sensor to an onsite server via a secure Wi-Fi network. The onsite server then sends data over a secure internet connection to our main servers, which are kept in a temperature controlled secure room on the university campus. Our sensor network does not interfere with commercial home security systems because each system has its own unique digital identifiers that secure data. Additionally, our infrared motion sensors are passive (not emitting infrared) so they do not interfere with home security systems detecting infrared.

Nursing Assessment Visits

Nurses conduct interviews and complete targeted assessments during weekly telehealth and monthly in-home nursing visits. In the first monthly home visit, we initiate a year-long monitoring process. We conduct a comprehensive nursing interview and physical assessment. The initial assessment establishes a baseline for health and daily routines. We obtain a health history tailored to the participants' physical conditions and diagnoses. Semistructured and open-ended questions are asked such as "Tell me about your health both recently and in the past," and "Have you been diagnosed with anything, or had any surgeries, and so forth?," and "Tell me about your medications and how long you have been taking them?" and "Tell me about your daily schedule or routines? Weekly?" We document: (a) medications, (b) functional status, (c) balance and gait speed, (d) use of assistive personnel and/or equipment, usual daily routines (e.g., normal wake time), (e) reported sleep quality, (f) a head-to-toe physical assessment, and (g) the participant's perception of their overall health. We also assess psychosocial well-being and record reported interactions/relationships with family, friends, visitors, social engagements, and perceived stressors and levels of stress. We use reliable scales so comparisons between participants can be made if needed. We use the Timed-Up-and-Go, Tinetti Balance Assessment Tool, Hedva Barenholtz Levy (HbL) Medication Risk Questionnaire, Geriatric Depression Scale, and the Katz Index of Independence in Activities of Daily Living. During routine monthly visits, we perform a physical assessment and ask about changes to health in the previous week. Weekly telehealth visits are shorter and address recent changes (within the last 7 days) and record vital signs.

We keep detailed records of participants' self-reported patterns (e.g., wake times, eating, napping, and sleep) and their activities of daily living (e.g., exercise class, shopping, book-keeping, arrival and departure of visitors). These activities and movement habits express how a person moves through space over time. Attributes associated with these activities can be measured and tracked, and regular patterns can be recognized in the sensor data by both humans and the AI agent. We conduct a new and nursing interview specifically regarding routines quarterly.

Telehealth Visits *(Phone or Video Call)*

We use telehealth equipment to collect vital signs and weight. Using a telehealth system allows the nurse researcher to obtain a direct report of objective measures like vital signs without making weekly in-home visits. Using telehealth makes this type of study more feasible. We ask participants to recall only one week at a time because it is easier for them to remember details with closer time-distance to an event. Weekly telehealth visits are made between monthly telehealth visits (Figure 3). We schedule telehealth visits for the
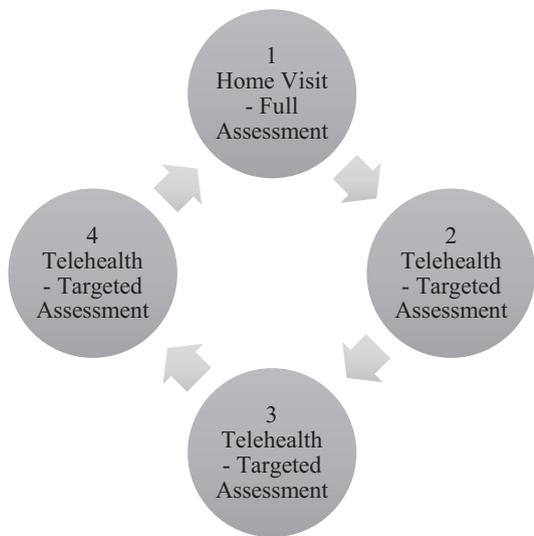
Figure 3 – Monthly visit cycle. Weekly phone or audio-visual telehealth visits are made between monthly home visits.

same day and time each week. Monthly home visits are scheduled a month in advance. This results in few missed appointments. Missed appointments often result in a struggle to recall event details.

A semistructured interview guides weekly telehealth visits. This guide is designed to elicit information from participants about recent changes in health and functional status; changes occurring in the previous seven days (Table 4). If a change is reported, probing questions are asked, and participant responses are entered on a spreadsheet containing information organized by body systems.

Each visit, participants are asked how they feel about the sensors and being monitored. They are reminded that data collection can cease immediately by unplugging the server should they become uncomfortable with the presence of the sensors. Unplugging the server results in discontinuing participation in the study. Subsequent removal of the equipment is scheduled. Weekly telehealth visits are typically <10 minutes unless a major health event occurred. Reporting of health events require longer visits.

Data Processing and Analysis

We use investigative techniques to accurately determine aspects of health (and associated movements) that can be measured with environmental sensors. Understanding how sensors work and what they can detect is required to successfully implement this method. In using these techniques, the nurse must keep in mind the type of data sensors produce and what can be measured. Key to the process, is the need to couple quantifiable measurements of motion sensor data to an actual health event. To do this, the nurse elicits details from participants to illuminate changes in behaviors and activities, which are demonstrated in movement patterns.

Two data types are analyzed in parallel: qualitative (nursing interviews, assessments, medical records) and quantitative (discrete ON/OFF sensor labels, health data such as vital signs). An interplay occurs between the two data types (Figure 4). Data derived from nursing assessments informs review of sensor data. The nurse uses nurse-documented dates, times, locations, and durations of health events to guide navigation to specific locations within the sensor data to begin the process of identifying the associated event. Once data representing the event is located, the nurse looks for beginning and ending boundaries of the event. These are annotated and the event is labeled (e.g., fall begins here).

Additionally, the nurse labels the participant's movement during the event (Figure 5). This provides detailed information regarding data clusters and attributes associated with the event (i.e., sensor activation combinations associated with certain events). Nurses also communicate any patterns or commonalities they note emerging across events. For example, in Figure 5 the repeated activation of a single sensor (BedroomAArea) is common across multiple fall data sets.

We provide further context on the spreadsheet where all events are recorded along with analytic notes (Table 1). This documentation includes how the event directly relates to participants' health and/or diagnosis, reported symptoms at time of event, and

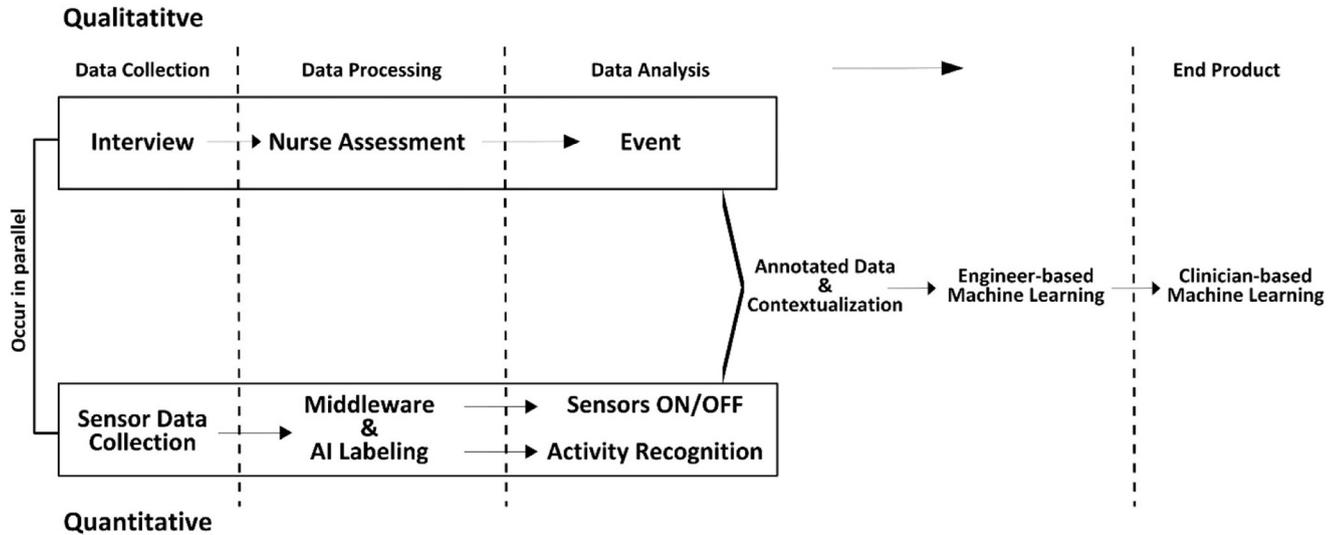| Table 4 – Semistructured Weekly Telehealth Interview Questions	
General Questions	Telehealth Interview Questions
Health & functional status in the previous 7 days	• "How are you feeling?" • "Tell me about any changes in your health this last week?"
Probing questions if changes have occurred	• "Tell me about how this has changed your routines, or how you go about your day?"
Perceptions about sensors	• "How is it going with the sensors, any issues?" • "Are the sensors bothering you in any way?"
Targeted questions (CHF)	**Associated detected sensor motion**
Has there been a change in your medication this week?	Number of trips to bathroom, walking speed, sleep/wake times, sleep location
Have you gained more than 2 pounds since we last talked?	Walking speed, sleep location
Are you experiencing shortness of breath?	Walking speed, interrupted walking
Are you sleeping in your bed at night?	Sleep location

Qualitatitve

Data Collection | **Data Processing** | **Data Analysis** | → | **End Product**

Occur in parallel

Interview → ▸ Nurse Assessment → ▸ Event

Annotated Data & Contextualization → Engineer-based Machine Learning → Clinician-based Machine Learning

Sensor Data Collection → Middleware & AI Labeling → Sensors ON/OFF / Activity Recognition

Quantitative

Figure 4 – Parallel processing of qualitative and quantitative data in the Fritz Method. The nurse collects qualitative data to contextualize quantitative sensor data for training the Smart Home AI agent. The middleware (software) receives ON/OFF text-based data and identifies individual sensors. Sophisticated activity-aware algorithms label incoming data (e.g., grooming, sleeping, and leaving home). Nurse annotated data sets are used to train the machine to recognize a change in health state.

anomalies noted by the nurse in the sensor data. If needed, when data are unclear, we conduct a postevent interview with the participant to further illuminate event start-end times as well as movements during the event. This is accomplished during the proceeding nursing visit. Completed analysis is then sent to the engineering team to be used for training the AI agent (i.e., annotated data and spreadsheet). This is a nonlinear, interactive, iterative, and dynamic process driven by the health event and situational context. The goal of coprocessing the data (by nurses and engineers) is to build a "clinically" intelligent smart home. The coprocessing also enhances engineers' knowledge of clinical aspects of chronic illness and the effect on movement and motion patterns.

Understanding the details of an event (i.e., how it affected movement, location, and time in location) significantly increases the accuracy of the nurse's ground

truth annotations. In turn, the accuracy impacts training data set choices, which ultimately impacts the efficacy of the AI agent. Here, nurses are well-positioned to elicit key information about how the individual responded to illness and to ascertain how that response is revealed in the sensor data. Several components enhance nurses' ability to provide ground truth. Knowing the individual's health and activity baseline and health information is a key. A holistic baseline includes a clear understanding of normal routines and use of space (based on the floorplan).

Abnormal movement is identified after normal baselines are understood. We locate and use any measures already identified in the literature that sensors can detect regarding specific diagnoses (e.g., walking speed for cognitive decline). We annotate data that are known to include sensor activations of visitors if they were present in the home near the time of the event.

```
2017-03-07 15:51:42.220648      BedroomAArea      ON
2017-03-07 15:51:43.349622      BedroomAArea      OFF
2017-03-07 15:51:45.220753      BedroomAArea      ON
2017-03-07 15:51:46.269012      BedroomAArea      OFF
2017-03-07 15:57:26.440501      BedroomAArea      ON
2017-03-07 15:57:27.569257      BedroomAArea      OFF


Pt reports fall starts here; was sitting on end of bed working with papers and became
"frozen" tried to move to head of bed but fell on floor between bed and closet


2017-03-07 16:00:19.022263      BedroomAArea      ON
2017-03-07 16:00:20.047158      BedroomAArea      OFF
2017-03-07 16:01:47.594651      BedroomAArea      ON
2017-03-07 16:01:48.725696      BedroomAArea      OFF
2017-03-07 16:01:50.783879      BedroomAArea      ON
2017-03-07 16:01:51.908606      BedroomAArea      OFF
```

Figure 5 – Data showing sensor activations of a participant who fell in their bedroom on March 7, 2017 about 4:00 P.M. In the lower section of data, the participant is moving after falling but before getting up.

When two people reside in the smart home, we annotate a sample data set showing each resident's discriminative data. We also verify the sensor data is reliable; meaning, there was good connectivity and sensor batteries were working at the time of the event. Finally, we conduct a scoping review of the sensor data to identify event beginning and ending points and any changes in baseline occurring in the pre-event data. Improving understanding of patterns in pre-event data may be important to future work that regards predicting events. (For a more in-depth discussion on the annotation process, see Fritz & Cook, 2017).

Engineers use the information provided by nurse researchers for training the AI agent. They use: (a) anomaly detection categories to classify events the AI agent is being trained on; (b) the event timestamps to locate pre-event and event data; (c) time stamps to select time windows for the automatic detection of clinically relevant health events; (d) routine and change in routine comparisons to inform choice of juxtaposed training set examples (event versus routine data); and, (e) the measures (i.e., sensor activation combinations) to inform choice of tools and techniques.

Discussion

Privacy is a concern for many older adults (Boise, 2013; Courtney, 2008; Demiris, 2009; Fritz et al., 2016). In-home monitoring with sensors could increase privacy concerns. Older adults are generally more open to sensor monitoring than monitoring that includes cameras or microphones (Boise, 2013; Courtney, 2008; Demiris, 2009; Demiris et al., 2004; Fritz et al., 2016). Some older adults agree to cameras and microphones if they can choose where they are located in the home (University of Washington School of Nursing, 2017). If the older adult desires cameras and microphones, they want them in the main living areas (i.e., kitchen, living room, and entry) and not in the bedroom, bedroom closet, or bathroom (Demiris et al., 2004). Although we do not use cameras of microphones, we do place sensors in the bathroom. With data from bathroom sensors, we can determine when someone is showering or using the toilet and for how long. We cannot discriminate between voiding and defecating (additional sensors would need to be placed in the toilet to determine this) and we cannot see or hear bathroom activities. Maintaining this level of privacy, has been acceptable to our participants. Despite privacy concerns, older adults indicate they are open to Smart Home monitoring for extending independence if it is individualized and works as intended (Fritz et al., 2016), is secured against identity theft and other criminal intent (Seelye, Schmitter-Edgecombe, Das, & Cook, 2012; Wagner et al., 2015), and not cost prohibitive (Steggell, Hooker, Bowman, Choun, & Kim, 2010).

Nursing Implications

The move to value-based care models (Center for Medicare and Medicaid, 2018) and the shortage of care providers (American Association of Colleges of Nursing, 2017) will continue to catalyze the use of smart environments and AI in delivering health care. Clinical nursing knowledge will need to be incorporated to optimize meaningful health-related features and functionality. The stakes are high when using AI to monitor and assist older adults in managing their health at home. However, without assistive technologies many older adults may face a premature transition to care facilities, resulting in greater cost to self and society.

Nursing Research

The Fritz Method is designed to guide nurse researchers who are the clinical expert in an expert-guided approach to training AI. Further development of this method should focus on: (a) increasing the number changes in health states that algorithms can detect; (b) providing ground truth for predicting changes in health states (requires annotating data in the hours, days or weeks before an event occurs); (c) compiling a list from the literature of all sensors used to detect health states or symptoms by diagnosis or health condition; (d) expanding anomaly detection categories; (e) honing communication with engineers; and, (f) validating clinical usefulness.

Limitations

A major limitation is that this method has not been validated for clinical usefulness. Literature is scarce regarding: (a) anomaly detection categories, (b) the association between motion characteristics, specific diagnoses, and sensor activation combinations, and (c) AI algorithms capable of identifying changes in health states. Our anomaly detection categories are chosen based on logic and clinical expertise. Many of the motion characteristics (detectable by sensors) that relate to specific diagnoses are chosen based on clinical knowledge and knowledge of how sensors work, not validated tools. Additionally, few nurses have been trained to use the method ($n = 5$) in a small sample size ($n = 10$).

Nursing Education

Nurses are the workforce that will most likely be called upon to implement smart technologies so their involvement in research and design is critical. Currently, nursing education provides limited exposure to using data beyond patient alarm systems and electronic health records informatics (Fetter, 2009). This may leave nurses unprepared to imagine and explore uses for new types of data (derived outside of electronic health records). The lack of exposure may also limit nurses' ability to function at the design table

where they are desperately needed. To better position nurses for this role, nurse educators must expand coursework to include training on AI. Specifically, students should understand how AI uses sensor data and how AI training works. Future nurses need to comprehend AI's potential, impact on health care delivery, and how it fits within precision health paradigms. They should also understand Smart Homes may be capable of "measuring" patient outcomes and therefore play a major role in the move toward value-based care. Nurses will need to combine knowledge of Smart Homes capabilities and new care models to optimally advocate for patients' right to privacy, autonomy, and self-determination.

Undergraduate prelicensure nurse educators should consider introducing the general concept of AI and should facilitate discussing primary applications in health care (e.g., clinical decision support). Graduate nursing faculty should master and teach concepts that regard turning sensor data-driven information into knowledge about health. Nursing instructors who feel unqualified to this could consider using guest lecturers who are AI-experts (e.g., engineering and computer science faculty) or showing free online videos created by academic researchers regarding managing sensor data for data-driven health. A good resource is the "SERC WSU" YouTube channel. Optimal courses for integrating AI content are informatics, community health, gerontology, ethics, and research design. Evidence-based practice and theory courses may also be suitable places to integrate AI content. Nursing education will need to keep pace with technology to prepare future nurses (Risling, 2017).

Conclusion

Humans cannot analyze copious amounts of motion data and they are not well-suited to provide continuous in-home monitoring over weeks, months, and years. However, intelligent machines trained in activity recognition, are capable of this. Conversely, machines are unable to intuitively understand and incorporate context. For this, humans are needed. To train a Smart Home AI agent, data sets are required representing ground truths that have been labeled by experienced nurse-clinicians.

Smart environments and Smart Homes will likely be part of the future of integrated models of care. Health-assistive Smart Homes using less sophisticated AI are already being marketed. The push to use Smart Homes in the delivery of in-home care will likely intensify as more people age and AI becomes more sophisticated. It is critical that expert nursing knowledge be integrated in AI training so accurate detection of risky changes in health can be achieved. The Fritz Method is a practical approach to integrating critical nursing knowledge into the Smart Home's AI agent.

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Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.outlook.2018.11.004.

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