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Nurse-in-the-loop smart home detection of health events associated with diagnosed chronic conditions: A case-event series

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ABSTRACT

Background: Telehealth and home-based care options significantly expanded during the SARS-CoV2 pandemic. Sophisticated, remote monitoring technologies now exist that support at-home care. Advances in the research of smart homes for health monitoring have shown these technologies are capable of recognizing and predicting health changes in near-real time. However, few nurses are familiar enough with this technology to use smart homes for optimizing patient care or expanding their reach into the home between healthcare touch points.
Objective: The objective of this work is to explore a partnership between nurses and smart homes for automated remote monitoring and assessing of patient health. We present a series of health event cases to demonstrate how this partnership may be harnessed to effectively detect and report on clinically relevant health events that can be automatically detected by smart homes.
Participants: 25 participants with multiple chronic health conditions
Methods: Ambient sensors were installed in the homes of 25 participants with multiple chronic health conditions. Motion, light, temperature, and door usage data were continuously collected from participants' homes. Descriptions of health events and participants' associated behaviors were captured via weekly nursing telehealth visits with study participants and used to analyze sensor data representing health events. Two cases of participants with congestive heart failure exacerbations, one case of urinary tract infection, two cases of bowel inflammation flares, and four cases of participants with sleep interruption were explored.
Results: For each case, clinically relevant health events aligned with changes from baseline in behavior data patterns derived from sensors installed in the participant's home. In some cases, the detected event was precipitated by additional behavior patterns that could be used to predict the event.
Conclusions: We found evidence in this case series that continuous sensor-based monitoring of patient behavior in home settings may be used to provide automated detection of health events. Nursing insights into smart home sensor data could be used to initiate preventive strategies and provide timely intervention.
Tweetable abstract: Nurses partnered with smart homes could detect exacerbations of health conditions at home leading to early intervention

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1. Background

There is increasing interest in remote monitoring of the 70% of older adults diagnosed with two or more chronic conditions (Tseng, 2021). The World Health Organization and several national governments have called for bold technology-based solutions to enhance management of chronic conditions (Tseng, 2021; Barcelo et al., 2018; Pruitt et al., 2002). One innovative health technology under development is the health-assistive smart home (hereafter referred to as "smart home").

Smart homes offer features that are being employed by assisted living facilities, such as monitoring access to medication dispensers and supporting voice-activated calls for assistance (Tuory, 2017). Technologies that can distinguish normal behavior from a health crisis remain in the research phase. However, nurses should know about such forthcoming technologies so they can envision their use with various populations and participate in technology development to optimize clinical application.

The purpose of this paper is to introduce nurses to the idea of a smart home and demonstrate how this technology could assist with timely management of chronic conditions. We address the smart home's potential to assess changes in health states and facilitate "clinical triage." To show the smart home's potential for health monitoring, we describe findings derived from data retrieved as part of multiple smart home studies conducted over the last decade (2012–2022). The studies focused on developing machine learning algorithms for automated assessment and prediction of health events in adults age 60+. Smart home sensor data collected from these studies were used to present this health events case series.

1.1. Smart home terminology

Table 1 lists terms and definitions that may aid with understanding equipment, data, and methods used in this study. Fig. 1 shows the smart home kit and sensor locations in the home.

1.2. Remote detection of health events

Currently, to address a chronic condition exacerbation, providers and nurses rely on sporadic and unclear client self-report or in-person assessment, making managing chronic conditions challenging (Taniguchi et al., 2020). Thus, some providers are prescribing the use of wearable sensors. Although wearable sensors (e.g., Fitbit or Apple watch) are now routinely used to monitor an individual's vital signs (Posthuma et al., 2020; Mulas et al., 2021), analyze motor function (Rast and Labruyere, 2020), and assess cognition (Cook et al., 2018; Hafiz et al., 2020), the need to consistently wear and charge these devices limits their usability for longitudinal monitoring and assessment. In contrast to wearables, ambient smart home sensors can be embedded into everyday settings and unobtrusively collect data, telling a robust story about a client's health without requiring any direct interaction.

Researchers have used smart home sensors combined with computing and machine learning algorithms to detect changes in individuals' behaviors that are indicative of changes in health (Sprint et al., 2021; Sprint and Cook, 2016; Bakar et al., 2015; Robben et al., 2017; Dahmen and Cook, 2021; Forbes et al., 2020; Forbes et al., 2021). In one study, researchers monitored residents' socialization patterns using ambient sensors and found that decreased socialization was predictive of depression (Kim et al., 2017). In other studies, machine learning techniques identifying behavior markers such as sleep/wake behaviors and activity level were used to predict pain (Fritz et al., 2020), clinical scores (Dawadi et al., 2013), and mobility, cognition, and depression symptoms in older adults (Alberdi Aramendi et al., 2018). These behavior markers have also been used to predict fall risk, cognitive diagnosis, and dyskinesia (Darnall et al., 2012; Akl et al., 2017). Additionally, behavior changes resulting from treatment regimens for chronic conditions have been detected using smart homes (Sprint et al., 2016), thus affording the possibility that smart homes could determine prescribed treatment regimen adherence and impact.

Table 1
Terms that are used throughout this article with definitions.

Activity labels	An activity name (e.g., sleep, eat) that is assigned to a set of sensor readings.
Algorithm	A set of instructions followed by a computer.
Ambient sensor	A sensor integrated into a home that detects and reports readings related to human movement.
Artificial intelligence	Computer systems capable of performing tasks normally requiring human intelligence.
Behavior markers	Statistical measures that are extracted from sensor readings and reflect human behavior.
Behavior patterns	Sensed recurring human movement sequences.
Features	Digital descriptors that are extracted from sensor reading sequences.
Ground truth	Data collected from real-world scenarios that are used to train machine learning algorithms on related, contextual information.
Health event	A sudden change in a person's health state.
Pervasive computing	Computers embedded in everyday devices and environments.
Machine learning	A computer program that improves its own performance at a task such as detecting health events or labeling activities.
Models	The output of a computer algorithm after it analyzes data to find predictive patterns.
Sensor reading	A timestamped, reported value of a sensed entity.
Shannon entropy	The amount of information in a variable. For this case series, it reflects the proportion of each type of sensor in a sequence of 30 consecutive sensor readings. It is calculated as negative one times the sum of $p_i \times \log(p_i)$, where p_i represents the probability (estimated by its proportion) of the *ith* sensor. Shannon entropy equals zero when any $p_i = 1$ and is maximum when all p_i are equal.
Smart home	A home that can sense and reason about the state of the environment and residents.

The analysis of smart home sensor data combined with clinical assessments for the purpose of detecting and anticipating clinically relevant health events remains underexplored (Fritz and Dermody, 2019), limiting the translation of smart home technologies into real-world settings where a growing number of persons are diagnosed with chronic conditions. A further knowledge gap is that studies to date have not focused on monitoring individuals with a diverse set of chronic health conditions in natural settings. Instead, they are limited to controlled settings or are focused on a single health condition.

2. Methods

2.1. Study design

2.1.1. Case series (Current study)

This health event case series used existing sensor-based data collected from two parent studies; one *ongoing* smart home research study [Clinician-in-the-Loop study; sample of $N = 30$] and one *completed* study [Age-Matched study; sample of $N = 20$]. See Section 2.2 for parent study sensor data collection methods. The studies were approved by the Washington State University Institutional Review Board.

This retrospective secondary analysis used existing data to determine if smart home sensor data could provide clinically relevant behavior information to support automated monitoring and timely interventions for older adults with chronic conditions. We analyzed nine health events that may provide insight for a variety of common conditions and their related exacerbations in an older adult population. We defined a health event as any sudden change in health state reported by the participants that resulted in a change in behavior routine. Cases were chosen by three nurses and one engineer who were familiar with participants' sensor data and associated health data. Secondary data analysis was conducted on the subset of data pertaining to the nine health event cases presented here. To preserve anonymity, we assigned participants' codes S1 through S8. Two health events (Case 5 and 8) use data from Participant S5. All participants were living in retirement communities either in the United States (U.S.) or Australia.

2.2. Data acquisition (Parent studies)

To be included in either the *ongoing* Clinician-in-the-Loop study (participants with chronic health conditions) or *completed* Age-Matched (healthy older adult participants) parent studies, participants needed to understand English and sign an informed consent; live alone in a community home; be Internet-connected; not own pets that roam the house; and agree to have smart home sensors installed for at least 12 months.

For the *ongoing* Clinician-in-the-Loop parent study (sample $N = 30$), smart home sensors were installed in the homes of adults age 65+ in the U.S. and Australia between October 2016 and August 2020 as part of an ongoing research collaboration. No comparisons between the countries' participants were made. Of the 30 participants whose participation was completed by the time of this paper, 25 had one or more chronic conditions that required ongoing medical management, including but not limited to congestive heart failure,

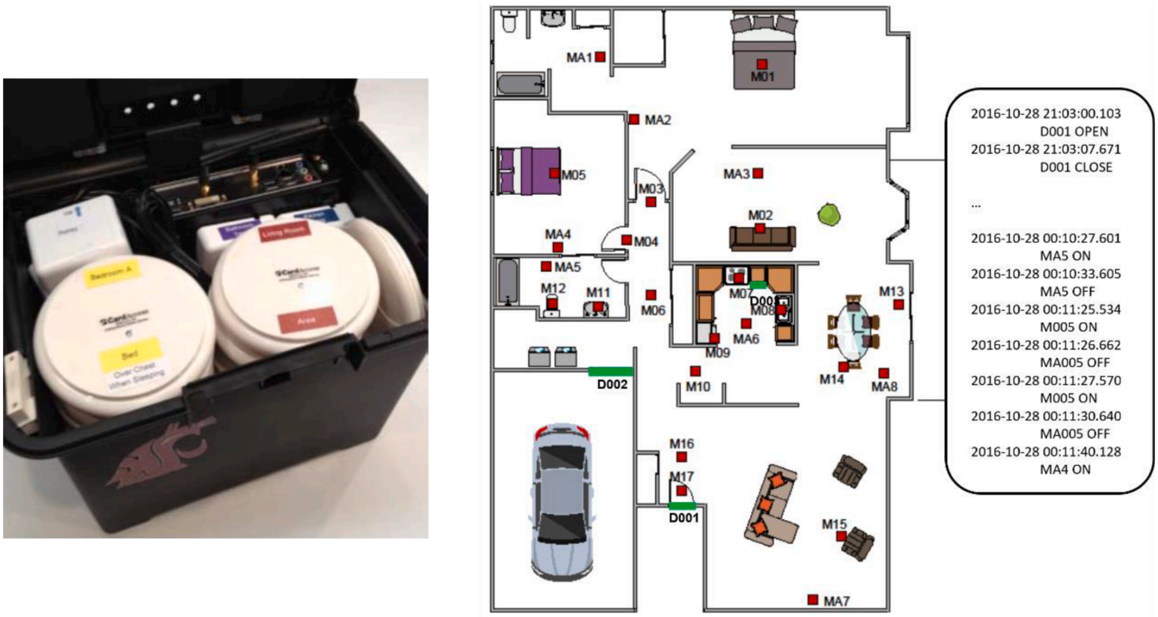

Fig. 1. (Left) Smart home monitoring kit, (middle) sensor locations in a typical home, and (right callout) examples of sensor readings generated by the smart home as a participant moves around the home.

chronic obstructive pulmonary disorder, irritable bowel syndrome, cancer, diabetes, diverticulitis, atrial fibrillation, arthritis, epilepsy, ulcerative colitis, Parkinson's, Sjogren's, or restless leg syndrome.

For the *completed* Age-Matched parent study (sample of $N = 20$), smart home sensors were installed in the homes of 20 adults age 65+ without a chronic condition in the U.S. between 2011 and 2017. The same smart home and sensor installation strategies were used for all participants in both studies.

2.2.1. Ambient sensors

Data were collected by ambient sensors, including passive infrared motion detectors, light, magnetic door use, and temperature sensors. Selected sensors tracked motion of the whole-home, ambient light by day and night, opening and closing of doors, and temperature changes near the kitchen stove and in the bathroom. Sensor placement was determined based on the floor plan and room size and adjusted to monitor the participant's normal utilization of the space (Fig. 1). The goal for sensor placement locations was to sense movement in all areas of the home. Each room contained at least three sensors attached using removable adhesive strips; approximately 15–20 sensors were installed in a typical 2-bedroom, 2-bathroom home. An area motion sensor (360-degree sensing area) was placed on the ceiling in each room to capture motion anywhere in the room. At least two additional motion sensors were placed with narrower (1-meter) fields of view to capture motion in smaller, regularly utilized spaces (e.g., recliner chair, bathroom sink). In all homes, motion sensors were installed above the kitchen sink, stove, beds, seating areas, bathroom sinks, toilets, and shower. The opening and closing of the home's main entrance was captured by magnet-driven switches placed on the doors and door jams. Refrigerator use was captured by placing a motion sensor inside the refrigerator.

Each sensor sampled its environment at 1.25 Hz and reported its state (ON/OFF, OPEN/CLOSED, temperature/light levels) in response to sensed environmental changes like new heat-based motion in its field of view, door use, change in light level, or change in temperature. The generated binary ("ON" or "OFF") or numeric (temperature in Fahrenheit) readings were transmitted to a computer, labeled with timestamps and sensor identifiers (Fig. 1), and securely encrypted and transmitted to an off-site server. Homes generated 1500–2000 sensor readings each day per participant.

2.2.2. Vital sign devices

For each of the cases presented here, digital blood pressure monitors, pulse oximeters, and weight scales were used by participants. These data supported nurses' understanding of the relationship between sensor data and participant well-being.

2.2.3. Nursing assessments

The research team included five nurses that met weekly with each participant. During initial home visits, nurses collected health histories, conducted physical assessments, and wrote summaries of participants' daily routines. Summaries were updated quarterly.

Weekly telehealth visits consisted of semi-structured interviews seeking information about participants' health conditions and any health events occurring in the week prior. Recorded participant information included vital signs (heart rate, oxygen saturation, blood pressure, weight); pain ratings; overall or specific changes in their health; medication changes; visits to providers or emergent care; health of each body system (eyes/ears/nose/throat, neuro, cardio, respiratory, genitourinary, gastrointestinal, musculoskeletal, endocrine, integumentary, psychosocial); health concerns; health-related events; and social activities such as visitors or attending an exercise class. Nurse telehealth visits lasted approximately 10–25 min, depending on the complexity of health changes.

Nurses asked, "Tell me how your health has been this last week. Any changes?" Participants were primarily asked about known health conditions or situations previously shared with the nursing team. For example, if the participant was diagnosed with a movement disorder and prone to falls, the nurse asked, "How have you been moving this last week? Any falls?" They also asked, "How have you been sleeping? Any particular nights that weren't good?" Nurses collected information about the date, time, location, and duration of health events, and how the health events impacted participant routines (e.g., sleep, leaving home). If participants could not recall details, this was noted. Generally, participants could recall the days, times, and locations of their health events (i.e., what happened, when, and where). All participant health events were added to a master list, from which a convenience sample was selected for this case series.

2.3. Data analysis and preparation

2.3.1. Nursing analytics (Current study)

2.3.1.1. Health data. The nursing record provided context for the sensor-based data collected during an identified health event. We focused on symptom manifestations related to bathroom use, sleep disturbances, time out of the home, and navigation patterns, because these behaviors can be defined by temporal and locational context, captured by timestamped sensor readings. We also focused on symptom manifestations related to these behaviors because they are common across a diverse range of conditions and acute exacerbations, thus positioning these sensor-derived "symptoms" to play an essential role in evidence-based nursing and symptom science (Cashion et al., 2016; Dorsey et al., 2019) regarding community-based care of older adults.

Health events representing a participant's chronic condition were chosen for this case series. Not all health events reported by participants and recorded by nurses were analyzed. Some were excluded due to insufficient nursing descriptions or because the event occurred in conjunction with other confounding events requiring analysis beyond the scope of this paper.

2.3.1.2. Sensor data. We analyzed the raw sensor readings to describe participant behavior at baseline and during health events. For each case event, one nurse-researcher (NurseA) re-reviewed the weekly health assessment record to verify the time of the health event and associated participant-reported behavior change. NurseA also selected one week of baseline data for the individual; the first complete week of data identified by the assigned parent study nurse and confirmed by the participant as "normal" (no health events, extra visitors, travel, holiday activities, or behavior variations). In some cases, to better illuminate the health event, the baseline week was compared to the week in which the health event occurred. Nursing data were shared with the engineer who used the context and sensor-based date and time event parameters to compute quantifiable routine changes.

2.3.2. Machine learning (Parent studies)

As part of the aims of the parent studies, an increasingly expansive and accurate set of activity labels were automatically assigned to smart home sensor readings. These labels provided a vocabulary for expressing and tracking participant behavior patterns. Activity models were created by a machine learning algorithm based on two months of labeled data provided for 68 homes (from the two parent studies and one other smart home study). These homes were chosen for activity modeling because the same sensor deployment strategies were used. Additionally, at least one month of data were manually labeled for each home by a research team member who assigned an activity category (e.g., sleeping, bathing) to each sensor reading. These labels provide ground truth activity categories for training the machine learning algorithm.

Data used to train the machine learning algorithm consisted of features that were extracted from rolling sequences of 30 consecutive sensor readings (similar to the process of rolling averages). Features extracted from each sequence were time of day (seconds past midnight), day of the week, time duration, elapsed time for each sensor since its latest reading, most recent participant location, most dominant sensor (sensor generating the most readings), Shannon entropy was calculated as negative one times the sum of $p_i \times \log(p_i)$, where p_i represents the proportion of each type of sensor in the sequence of 30 consecutive sensor readings, number of location changes, and the number of readings generated by each sensor (Sprint et al., 2021). Using leave-one-home-out cross validation, modeling the 11 activities of bed-toilet transition, cook, eat, enter home, leave home, personal hygiene, relax, sleep, wash dishes, work, and other resulted in a 92% accuracy for the 68 homes. The leave-one-home-out validation method reflects the expected accuracy of the model should it be used in a new home where labeled training data are not available.

Table 2 lists behavior markers used for the cases presented in this paper, the learned activity labels that defined each marker, and the statistical measures used to quantify the marker. Sample data and activity recognition software are available at casas.wsu.edu.

2.3.3. Machine learning (Current study)

Behavior markers associated with health events were calculated using sensor readings that were automatically labeled with an activity category by the activity recognition algorithm described in Section 2.3.2. Table 2 provides definitions of the behavior markers and the automated activity labels used for each. For example, bathroom usage was measured as the number of sensor readings labeled daily as a bathroom-related activity (personal hygiene or bed-toilet transition), and sleep movements were based on the number of sensor readings labeled "sleep." For some cases, we also reported the number of distinct occurrences of a labeled activity. This relied on segmenting the data into non-overlapping instances of an activity category. Data were segmented based on time and location. If the elapsed time between two consecutive readings and the same activity label was less than five minutes, they were grouped into the same activity occurrence; otherwise, they were considered two distinct occurrences.

We also reported sleep interruptions and per-day time spent out of the home. Sleep interruptions were defined as broken-up "sleep"

Table 2
Behavior markers used in this case series.

Behavior marker	Definition and activity label(s)	Descriptive statistics
Bathroom usage	Count of sensor readings labeled with bathroom-related activity labels.*	Count per day, mean count over multiday time period (e.g., baseline).
Bathroom use occurrence	A distinct "trip" to the bathroom as a sequence of consecutive readings labeled with bathroom-related activity labels.* Time between each reading is <5 min.	Count per day, mean daily count over multiday time period.
Bathroom use duration	Duration in seconds of a single bathroom use occurrence.	Mean duration of occurrences within given time period.
Sleep movements	Count of sensor readings with activity label "sleep."	Mean daily count over multiday time period.
Sleep interruption	Two occurrences of sleep activity (i.e., consecutive readings labeled "sleep") during the same night which were separated by a sequence of sensor readings in a different location than the sleep activity. Each interruption lasted at least two minutes and typically involved the "bed-toilet transition" activity label but may have also involved any activity label that was not "sleep."	Mean daily count over multiday time period.
Sleep interruption duration	Duration in minutes of an instance of sleep interruption.	Mean duration of interruptions within given time period.
Bed-toilet activities	A sleep interruption specifically involving sensor readings labeled "bed-toilet transition"	Mean daily count over multiday time period
Time out of home	Time elapsed in seconds between a sensor reading with activity label "leave home" and a sensor reading with activity label "enter home"	Total time per day, mean daily total time over multiday time period.

*The activity recognition algorithm used in this study combines all bathroom-related activity under the single label "personal hygiene." This activity label is not exclusive to just hygiene activities as understood by nurses but encompasses any activity associated with the bathroom location.

activity during the same night, where the sequence of readings was broken across two different locations. Interruptions were included only if they were at least two minutes in duration. Time out of home was calculated as the elapsed time between “leave home” and subsequent “enter home” activities.

For the case events below, we report descriptive statistics, including means and standard deviations for daily activities at baseline and percent changes in activity associated with the case events. Z-scores highlight activity outliers compared to baseline or a healthy population. For some events, to better exhibit the behavior patterns related to a chronic health condition, we compared the individual’s activity to that of a healthy older adult population (referred to as the *healthy sample*). For some case events spanning multiple days, a z-score was calculated for the average daily activity over the event days. For other cases with multiple multi-day events, a z-score was calculated for the activity on the first day of each event to indicate the significance of the departure from baseline. For some cases, qualitative descriptions of movement trajectory in the home were also presented.

3. Health event reports

3.1. Smart home detection of bathroom use cases

3.1.1. Case 1, cardiac

Participant S1, a female age 75–80 (age range to protect privacy), was monitored for 24 months with smart home sensors in her one-bedroom, one-bath apartment. S1 was diagnosed with congestive heart failure, atrial fibrillation, dysphagia, and hyperglycemia. She was prescribed a diuretic, and on five occasions of varying duration ($M = 3.6$ days, SD = 2.2), her daily diuretic dose was temporarily increased to treat excess fluid retention. These episodes were characterized by urinary frequency and an increase in bathroom usage activity during the increased diuretic dose.

Based on this measure, bathroom usage increased by 27.8% over the mean during the baseline week for this participant (baseline $M = 1789.6$ sensor readings, SD = 258.5). Similarly, daily bathroom use increased in number (10.9% increase) over baseline ($M = 21.6$, SD = 3.1) and duration (16.7% increase) over baseline ($M = 466.7$ s, SD = 521.6). Examination of bathroom usage during the first day of each episode revealed z-scores ranging from 1.05 to 5.21 with respect to the baseline week. The z-scores for three of the days (60% of the cases) were >2.0, suggesting that these health events were statistically significant departures from the participant’s baseline and might indicate that the participant experienced expected results after taking the diuretic.

3.1.1.1. Clinical application. In the context of a prescribed diuretic for congestive heart failure, nurses using inductive reasoning can infer increased bathroom use in sensor data is an indicator of probable fluid retention leading to taking the prescribed diuretic. Understanding the frequency and duration of such events is valuable when planning care.

3.1.2. Case 2, cardiac

Participant S2, a female age 70–75, was diagnosed with atrial fibrillation with congestive heart failure. She was monitored for 22 months with smart home sensors in her one-bedroom, one-bath apartment. She weighed daily in the mornings and was prescribed a diuretic as needed for any >2 lb weight gain. This as-needed prescription was later converted to a daily dose to treat ongoing issues with fluid retention. Throughout observation, the participant reported a total of 54 days of diuretic use, with participant-reported urinary frequency decreasing over time. On days that the participant took the diuretic, bathroom usage increased 15.7% over baseline ($M = 782.6$ readings, $SD = 155.6$). Bathroom use duration also increased by 16.7% (baseline $M = 268.4$ s, $SD = 355.4$). Bathroom usage z-scores for the first day of the events ranged from 0.08 to 2.63 and 10 of the days yielded a z-score > 2.0, which indicated a moderate change in behavior during treatment periods. The low frequency of significant z-scores was possibly due to the highly variable diuretic use as well as decreased effectiveness of the treatment over time, which would support the participant’s own report of waning urinary frequency. The number of days she was on the treatment plan (54 days, or 10% of the monitored time period) may also have impacted the lack of significance of the behavior change.

3.1.2.1. Clinical application. This case highlights why including a nurse in the loop is important when utilizing sensor data. A nurse using smart-home data might notice a lack of significant change in bathroom behavior in an individual with known diuretic use as evidence to help troubleshoot issues with diuretic efficacy. Sensor-derived activity measures could provide helpful prompting for nurses to conduct focused follow-up to support an individual’s self-management of their chronic condition.

3.1.3. Case 3, urinary tract infection

Participant S3, a female age 80–85, was diagnosed with multiple conditions, including atrial flutter with an implanted defibrillator, hypertension, anemia, osteoporosis, and asthma, with a history of stroke. She was monitored for 14 months in her two-bedroom, one-bath apartment. S3 reported a case of urinary tract infection during this time, resulting in a fall and hospitalization. For this case, we focused on data related to the urinary tract infection rather than fall detection. The amount of bathroom activity on the event date (the first day of symptoms, one day before a fall) represented a 101.3% increase over baseline (baseline $M = 1308.8$ readings, $SD = 549.9$). The z-score for bathroom activity on this date was 2.4, representing a statistically significant outlier for this participant. Accompanying the increase in bathroom activity was a corresponding 44.6% increase in duration of bathroom use occurrences (baseline $M = 460.0$ s, $SD = 601.1$), although the number of occurrences of this activity subsequently decreased by 3.0% from the baseline ($M = 20.6$, $SD = 3.5$).

3.1.3.1. Clinical application. Urinary tract infections often include symptoms of urgency, frequency, difficulty initiating voiding, and pain. Any combination of symptoms would increase variability in bathroom use, especially frequency and duration of time in the bathroom. In this case, an initial increase in bathroom occurrences followed by decreased occurrences with longer duration tracked a common symptom trajectory for urinary tract infections: onset of initial urgency followed by flow difficulties.

3.1.4. Case 4, ulcerative colitis

Participant S4, a female age 80–85, was diagnosed with colitis and anemia. She was monitored for 16 months in her one-bedroom, one-bath apartment. During this time, the participant reported fourteen colitis health events with associated diarrhea. The mean event duration was 4.3 days (*SD* = 5.1). As with Cases 1–3, colitis events were also characterized by changes in bathroom activity. The first day of the reported events represented a 168.4% increase in bathroom activity over the baseline week *(M* = 427.4 readings, *SD* = 266.2). The first-day values correspond to z-scores ranging from 0.66 to 6.14. Ten of the z-scores are >2.0 (71% of the values), indicating that these events occurred as outliers with respect to the participant's baseline.

3.1.4.1. Clinical application. This information could support early detection of a colitis attack and promote quick, effective treatment.

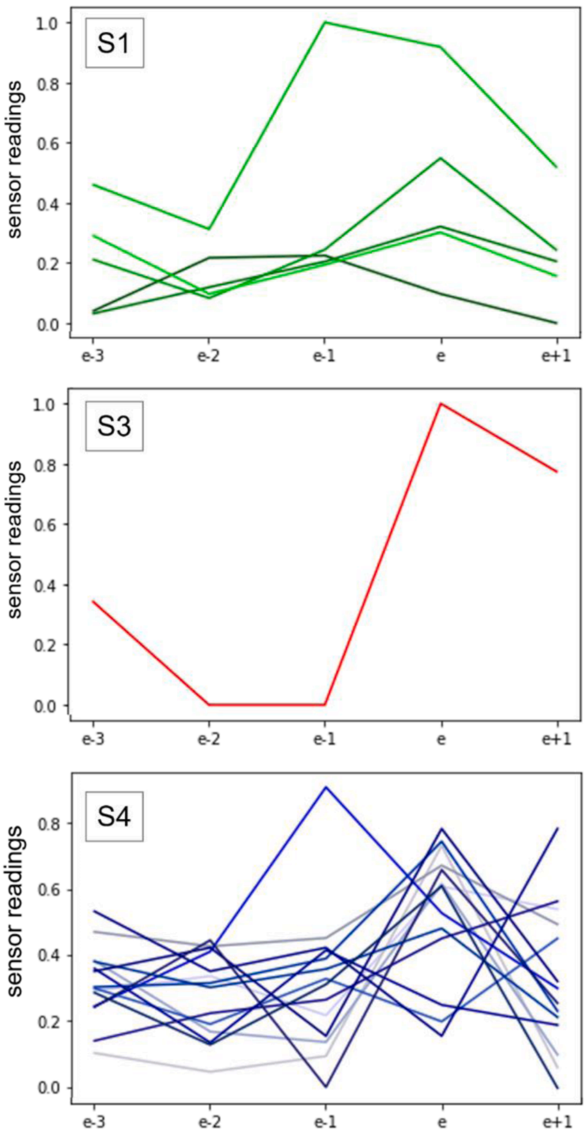

Fig. 2. Amount of toileting activity for cardiac and gastrointestinal cases (top) 1, (middle) 3, and (bottom) 4. The x axis represents individual days, where e indicates the first day of the reported event. The y axis represents the number of bathroom use sensor readings. For S3, the solid line is the number of daily bathroom use sensor readings of the event. For S1 and S4, the lines represent the number of bathroom use readings on the corresponding day of the reported health events.

For these cases, we compared daily statistics against a "normal" one-week baseline to discover health event anomalies. However, as Fig. 2 illustrates, nurses could also use smart home-reported information to detect the onset of these health events by comparing with the recent past. Fig. 2 plots the number of "personal hygiene" sensor readings averaged over the event first days (day *e* in the graph) together with the previous three days and the following day. As the graphs indicate, a noticeable increase in bathroom activity occurred when the health event began. For participant S4, the increase continued into the subsequent day due to the multi-day duration of diarrhea and the many bathroom activities throughout the night.

3.1.5. *Case 5, diet and antibiotic side effects*

Participant S5, a female age 85–90, was diagnosed with atrial fibrillation, hypertension, asthma, and diverticulosis. She was monitored for 18 months in her three-bedroom, two-bath duplex cottage. She reported two diarrhea events occurring at home during this time due to a high-fiber diet and side effects from antibiotic use. Activity-labeled smart home sensor data reflected a corresponding 20.1% increase in bathroom activity over baseline during these events ($M = 463.0$, $SD = 121.7$). However, the z-scores for these days were 1.9 and 0.9, indicating these events are not a significant departure from baseline. The number of bathroom use occurrences decreased by 2.7% from baseline during the events, and the durations reflected a slight increase of 15.1% (occurrence $z = 0.3$, duration $z = 0.1$). In this case, the most notable change was in the time spent out of the home, per the sensors. During these health events, the participant spent 93.9% less time out of the home compared to baseline ($M = 195.8$ s, $SD = 81.0$). The time-out-of-home z-scores were -1.97 and -2.27, reflecting that these were outlier behaviors.

3.1.5.1. Clinical application. Using these data, nurses could deduce that the individual does not need an immediate intervention for acute colitis. However, should social isolation from increased bathroom use continue, it may be a sign of an acute exacerbation requiring intervention. Regardless of the underlying cause, the pattern of social isolation accompanying bowel symptoms indicates an opportunity for timely bowel symptom identification and management.

3.2. *Smart home detection of disrupted sleep*

3.2.1. *Case 6, restless legs*

Participant S6, a female age 70–75, was diagnosed with Type 2 diabetes mellitus, hypertension, arthritis, and restless leg syndrome. She was monitored for 17 months in a two-bedroom, one-bath apartment. During the monitoring period, the participant reported restless leg syndrome events that occurred during the late evening or early morning hours. A mean of 1.1 sleep interruptions was

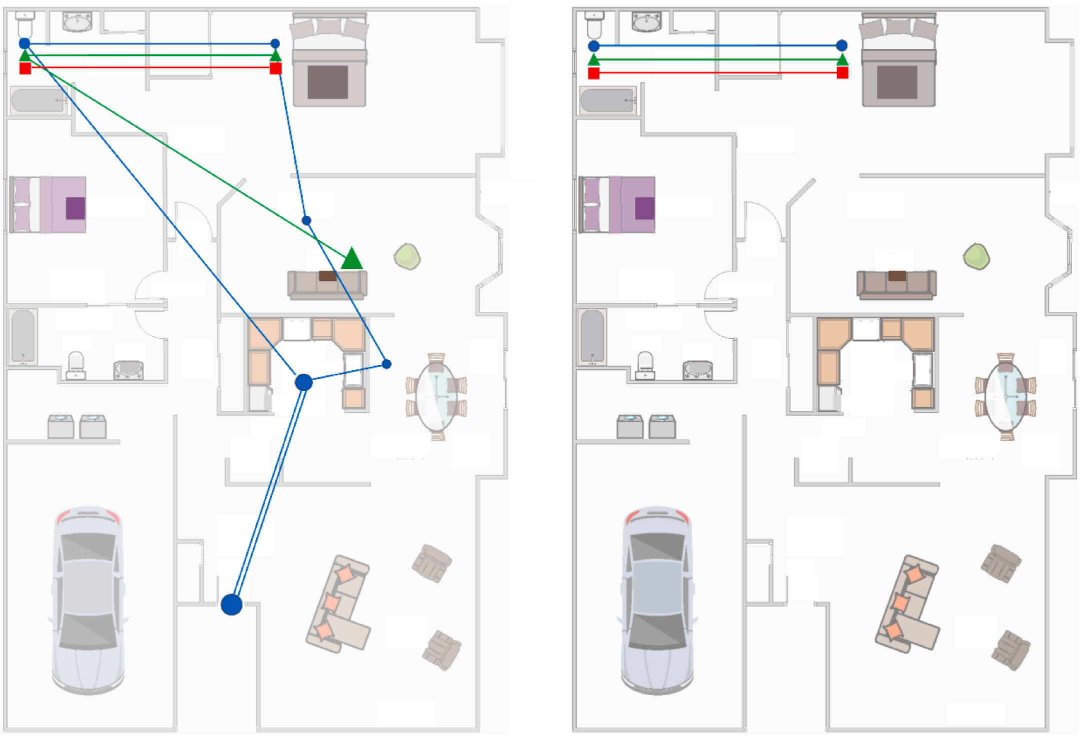

Fig. 3. Night-time movement pattern for S5 (red), S6 (blue), and S7 (green). Graphs are based on a typical home floorplan and shape sizes (left) indicate the relative amount of time spent in each location during sleep interruptions (larger icon indicates more time). In the graph participants S5 and S7 experienced more frequent and prolonged sleep interruptions than the healthy sample (right) and visited more rooms each night (left).

observed during the baseline period ($SD = 0.4$).

For this participant, the sleep interruptions at baseline were lengthy and complex, with a mean duration of 16.3 min ($SD = 3.6$). They typically consisted of a bed-toilet transition, followed by the participant spending time in the kitchen and outside the apartment before returning to the kitchen and eventually back to bed. Fig. 3 illustrates the typical trajectory for sleep interruptions. On three evenings when restless leg syndrome was reported, the number of interruptions averaged 2.7 times per night, a 133.3% increase over baseline ($z = 4.4$), with an average duration of 33.5 min, a 106.1% increase over baseline ($z = 4.8$), representing a statistically significant departure from baseline behavior. Additionally, S6's overall amount of sleep movement was high and did not differ significantly between baseline and periods with restless legs.

3.2.1.1. Clinical application. Comparing smart home sensor data for similar behaviors between persons can help nurses better understand the chronic conditions that individuals are managing. Many participants managing chronic conditions experience frequent sleep interruptions; thus, we compared S6 sleep patterns with a healthy older adult sample ($N = 20$). The mean number of daily sleep movements for S6 was 396.0. This number represents a 141.8% increase over the mean number of 163.7 for the healthy sample (SD=133.2, $z = 1.7$). This could be an important finding in an older adult because frequent sleep interruptions and restless sleep could increase fatigue and confusion, leading to a greater potential for falls and affecting the ability to manage their health.

3.2.2. Case 7, restless legs

Participant S7 was a female age 80–85. She was diagnosed with osteoarthritis with thoracic collapse and chronic obstructive pulmonary disorder as well as restless leg syndrome. She was monitored for 14 months with smart home sensors in her one-bedroom, one-bath apartment. This participant reported frequent episodes of restless leg syndrome and insomnia. On nine days of reported restless leg syndrome, the participant had a mean of 1.2 sleep interruptions ($SD = 0.4$), a 14.5% decrease from baseline ($M = 1.4$, $SD = 0.5$, $z = -0.4$). On the other hand, the length of the sleep interruptions averaged 10.2 min, a 107.6% increase from baseline ($M = 4.9$, $SD = 1.4$, $z = 3.6$). As with Case 6, sleep patterns during restless leg events exhibited a significant change from baseline. Comparing S7 with the healthy sample, this participant generated an average of 323.3 motion sensor readings while sleeping, an increase of 97.4% over the healthy sample ($z = 1.2$). As Fig. 3 illustrates, sleep was distributed between the bedroom and the living room during restless leg events.

3.2.2.1. Clinical application. Understanding and detecting restless leg through these sensor-observed behavior patterns is important because restless leg syndrome is treatable. Automated recognition could afford early intervention opportunities so participants can experience improved sleep, which improves quality of life (Sella et al., 2021), lessens chronic condition severity (Centers for Disease Control and Prevention 2018; Du et al., 2021), and reduces night-time falls.

3.2.3. Case 8, nocturia and restless leg syndrome

Participant S5, a female age 80–85, was diagnosed with atrial fibrillation, hypertension, asthma, and diverticulosis. She was monitored for 18 months in her three-bedroom, two-bath duplex. The participant reported nocturia and restless legs through the monitoring period. This person's night-time events were characterized by sleep interruption patterns. Compared to baseline, the number of sleep interruptions (all bed-toilet activities) increased by 85.3% (baseline $M = 2.4$, $SD = 0.7$, $z = 2.9$). Similarly, the duration of the sleep interruptions increased by 69.6% (baseline $M = 5.9$ min, $SD = 5.2$, $z = 0.8$).

Next, we analyzed the overall night-time behavior patterns for participant S5. Unlike S6 and S7, this participant slept in the bedroom each night, and the overall mean number of motions during sleep was 40.0, a 75.6% decrease from the healthy sample ($z = -0.9$). However, the number of overall bed-toilet activities averaged 2.5, which was higher than participants S6 and S7. This number also represents a 162.5% increase over the mean for the healthy sample ($z = 2.0$). The participant reported no cardiac symptoms during this time and showed signs of sleeping well. However, signs of having an overactive bladder at night were noted and confirmed by the nurse during the weekly telehealth visit.

3.2.3.1. Clinical application. Falls are commonly associated with night-time urination frequency and urgency. Nocturia is treatable if the provider knows it is happening. As indicated in this case, smart homes may automate reporting of nocturia.

3.2.4. Case 9, midnight fall

Participant S8 was a male age 85–90. He was diagnosed with Parkinson's disease, Sjogren's disorder, and torticollis. He was monitored for 24 months with smart home sensors in his one-bedroom, one-bath apartment. The participant experienced recurring falls in the home, commonly after getting up from a nap or in the middle of the night when going to the kitchen for a drink. This smart home resident experienced a mean 2.7 sleep interruptions each night during the baseline period with no reported health events. This value represents a 171.4% increase over the mean for the healthy sample ($z = 2.2$). The baseline mean interruption duration was 23.3 min ($SD = 21.2$). Sleep locations were distributed between the living room and bedroom, sometimes sleeping in both these locations in a single evening. A typical night-time trajectory is illustrated in Fig. 4.

Three recorded night-time fall events occurred around 1:00am. The falls were detected as statistical anomalies because duration of the sleep interruptions averaged 103.7 min ($z = 3.8$). In one case, a second piece of evidence was provided by the fact that the participant spent 15 min in front of the kitchen stove, as indicated by the corresponding motion sensor. Because this participant did not cook, the longest continuous period spent in this region of the kitchen on baseline days was 3 min.

Additionally, multiple falls were noted as occurring between 9:00pm and 10:00pm. During this time, the participant got up from a nap and moved to the kitchen to take medicine. Like the night-time falls, one of these events was detected as an anomaly because the participant, who did not cook, lingered in front of the kitchen stove for 14 min. However, other events were characterized by the opening of the external door after 10:00pm when medical personnel came to provide treatment. Immediate detection of falls is key to recovery for older adults.

3.2.4.1. Clinical application. Predicting falls based on unexpected activities could facilitate interventions to mitigate these falls.

4. Discussion

Remote health monitoring using smart homes may afford new opportunities for clinical insight into symptoms experienced by older adults between office visits. These technologies offer the possibility of extending the reach of nurses into the home where individuals are often managing chronic conditions without assistance. In this health event case series, we demonstrated ways nurses might use smart home data as evidence to recognize clinically relevant changes in an individuals' health and treatment.

With respect to diuretic management, the number of bathroom-related sensor readings and the number and mean duration of distinct bathroom visits may provide insights regarding the use and efficacy of diuretic treatment. In our cases, S1 demonstrated a more prominent departure from baseline than S2 during treatment. This corroborates the reported experiences of participants where S1 reported successful resolution of her fluid retention symptoms after each diuretic event, whereas S2 reported lesser response or resolution of fluid retention with her diuretic use over time. Using sensor-based monitoring of bathroom use for older adults with congestive heart failure can provide nurses near real-time information about the use of prescribed diuretics at home, between office visits. Although weight scale data provides data about exacerbations in congestive heart failure, it is common for individuals to forget to weigh themselves and report changes to their provider. Smart home sensor monitoring does not require diuretic use reporting. A nurse managing individuals with diuretic treatment could monitor sensor-derived bathroom use measures to detect large departures from baseline.

Secondary issues such as dizziness and dehydration (Mayo Clinic. Dehydration. 2021) are associated with changes in bladder and bowel habits (Przydacz et al., 2020). These changes can lead to falls (Mayonewsreleases, 2013), as occurred in Case 3. A smart home could detect changes such as the number of bathroom sensor readings on the first day of urinary tract infection symptoms and trigger a nurse to evaluate clients for other signs/symptoms of acute exacerbation and initiate treatment before a fall occurred. Post-fall care costs impact individuals, families, communities, and country-level resources (Davis et al., 2010; World Health Organization 2021), emphasizing the need to automatically monitor behavior patterns and changes with a goal of decreasing exacerbations leading to costly, life-changing situations.

Additionally, the number and duration of sleep interruptions, time out of home, and night-time movement patterns may indicate chronic condition exacerbations. Sleep patterns change with age (Tatineny et al., 2020); changes can be detected through movement patterns at night and interruption monitoring. As older adults manage insomnia and other sleep issues (Tatineny et al., 2020), changes can lead to falls and the need for higher levels of care environments.

While sensor-derived measures can identify abnormal behavior patterns compared to healthy population norms, Cases 7 and 8 highlight the potential of sensor-based monitoring as a tool for precision health. Both cases illustrate a significant departure from the individual's baseline sleep interruption pattern or duration during restless leg events despite not showing any significant deviation from healthy nightly sleep movement norms.

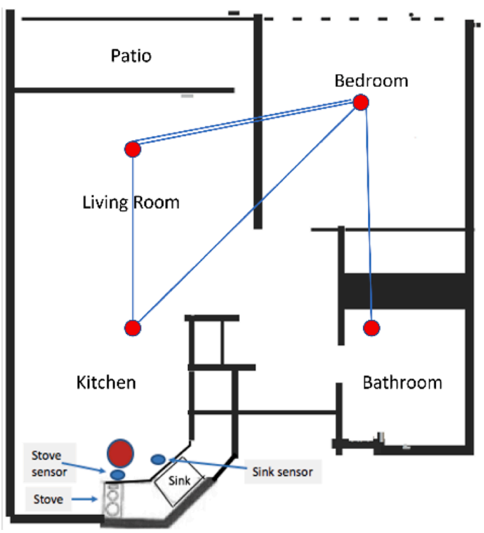

Fig. 4. Typical night-time movement patterns for participant S8. The red circle above the stove sensor indicates the location of a night-time fall.

Despite their potential, smart homes have not been widely adopted by healthcare systems or countries where much of the research has been conducted (Dermody et al., 2021). Older adults prefer that smart homes address specific health needs rather than offering generalized monitoring (Choi et al., 2021). This article highlights specific uses for a health-focused smart home. The connection between sensor-derived biobehavioral metrics and clinical guidelines used by providers is lacking. These cases demonstrate that smart-home data could inform clinical guidelines for chronic conditions by providing real-time evidence of an individuals' responses to their condition and to pre-post treatment regimens. Clinical guideline organizations such as the Institute for Clinical Systems Improvement (ICSI 2021) or the European Observatory on Health Systems and Policies may benefit from sensor-derived information. We have demonstrated that smart health technology used by nurses improves the interpretation and use of sensor data. Nurses are well-positioned to become the "data-brokers" of information derived from ambient sensors. Applying nurse insights about human illness response to smart home data can inform new methods for remote care and provide a new approach to evidence-based practice.

We have demonstrated in this case series that ambient sensors placed in one's home can remotely detect clinically relevant health events. Smart homes could aid in monitoring individuals with chronic health conditions and support remote management of a larger number of clients effectively. While the detected health events were characterized by patterns and anomalies in an individual's movement patterns, these sensors would not be effective at monitoring events not accompanied by behavior changes. Additional analytical methods are needed to distinguish health-related behavior changes from changes due to other internal or external influences. While events such as changes in glucose or a stroke will eventually have a behavioral impact, ambient sensing alone would not allow timely interventions for some acute events. Smart home sensors can be accompanied by wearable physiological sensors to broaden their effectiveness.

5. Limitations

The current "personal hygiene" activity does not distinguish between toilet use and other bathroom activities such as grooming. When translating to practice, an additional activity label should specifically categorize toilet use.

The cases presented here were chosen for two reasons: (1) nursing field notes contextualizing events, were detailed and deemed reliable; and (2) they provided a variety of exemplars for clinically considering sensor data. Activity measures presented here are a subset of the possible measures that could track health events and further research is necessary to determine which measures are best in terms of reliability, change sensitivity, and association with chronic condition exacerbations. Additionally, we did not conduct an in-depth within-subject analysis of the correlation between activity trends and event trends. Case 2 shows the limitation of calculating statistics for an aggregate of events across a long-time span. A more in-depth analysis would likely reveal deeper insight regarding her waning diuretic response in association with other heart failure symptoms. In addition, there may be differences in activity patterns between Australian and U.S. participants with chronic conditions.

This case series does not provide guarantees that smart home sensors combined with machine learning will consistently detect health events, nor does it comprehensively define the categories of events that can be sensed and detected. Further research is needed to investigate additional types of health events and quantify the predictive performance of these technologies.

6. Conclusion

Smart homes using ambient sensors with machine learning capabilities may afford nurses the opportunity to better support older adults who are managing chronic conditions at home. In this paper, we presented nine cases where sensor-based data tell a compelling "symptom-story" of the human response to a change in a chronic condition. We observed that ambient sensor data showing bathroom use could illuminate the onset of (a) exacerbations in congestive heart failure and one's use of diuretics; (b) urinary tract infections; and (c) bowel issues associated with colitis and bowel-related side effects of medications like antibiotics. We observed that ambient sensor data showed disrupted sleep and illuminated experiences with restless leg syndrome, insomnia, and nocturia. We also found ambient sensor data could aid in recognizing falls by showing changes in motion trajectory patterns. Combining clinical insights and sensor-based data offers new understandings of how, and when, individuals are experiencing health events at home requiring nursing interventions for optimal health outcomes.

What is already known

- Timely interventions supporting self-management of chronic conditions can reduce burden.
- Ambient sensors can unobtrusively collect continuous data in home settings reflecting behavior patterns associated with health states.

What this paper adds

- We provide examples of how nurses could interpret and use sensor data in the clinical setting.
- With these cases, we demonstrate how nurses could utilize continuous ambient sensor data from smart homes for helping individuals self-manage their chronic conditions.
- Machine learning and computing techniques could aid nurses in understanding health changes before an individual presents to a healthcare facility.

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Declaration of Competing Interest

None

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