

Inductive Content Analysis of Nurses' Interpretation of Health-Smart Home Data: Implications for Clinical Decision-Making

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Inductive Content Analysis of Nurses' Interpretation of Health-Smart Home Data: Implications for Clinical Decision-Making

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Abstract

Background: Health-smart home technologies offer real-time sensor-based monitoring of older adults, allowing for early detection of health changes. How clinicians interpret and utilize this data, particularly in visualized formats such as bar, line, and pie graphs, remains underexplored.

Objective: This study aimed to examine how nurses interpret health smart home (HSH)-generated data visualisations and their clinical implications. Specifically, it investigated how nurses engage with bar, line, and pie graphs displaying HSH sensor data, identifying key patterns in their analysis of patient activity, sleep, and mobility, as well as challenges that may impact clinical decision-making.

Methods: Using a qualitative descriptive methodology and inductive content analysis approach with a quantitative component, we analysed nurses' qualitative interpretations of existing health-smart home data from 3 older adults living with ambient whole-home sensing. Nurses provided structured written feedback on visualised trends in activity, sleep, and mobility patterns.

Results: The findings highlight both opportunities and challenges of using sensor-derived health data in older adults' care. Nurses identified key patterns in sleep, mobility, and home engagement, but interpretation difficulties, such as unclear sleep metrics and lack of clinical context, hindered decision-making. Nurses preferred bar and line graphs over pie charts for interpreting these data. Survey results show a statistically significant difference in how nurses rated different graph types ($\chi^2(2) = 17.11$, $p = 0.00019$), with pie charts rated significantly lower than both bar and line graphs ($p < 0.001$ and $p = 0.0082$, respectively). These findings underscore the need for improved data visualisation and integration to enhance clinical utility.

Conclusions: Findings indicate that nurses were able to provide accurate interpretations of the sensor-based data. However, there is a need for improved visualisation techniques and clinician training to optimize health-smart home data for early intervention. Standardized approaches to data representation could enhance nurses' ability to detect and act on subtle yet important information about older adults' health changes occurring in home settings. Clinical Trial: N/A

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Conclusion: Findings indicate that nurses were able to provide accurate interpretations of the sensor-based data. However, there is a need for improved visualisation techniques and clinician training to optimize health-smart home data for early intervention. Standardized approaches to data representation could enhance nurses' ability to detect and act on subtle yet important information about older adults' health changes occurring in home settings.

Keywords: Health-smart home, digital health, data visualisation, content analysis, nursing, aging-in-place

Introduction

With the global population aging and an increasing number of older adults living with chronic conditions, there is growing interest in health-smart home technologies to support aging in place [1-3]. Traditionally, nursing homes have been the primary setting for older adult care but concerns over quality of care in institutional settings and a strong preference in older adults to remain living at home have led to the exploration of alternative solutions. Health-smart home technologies can provide real-time, unobtrusive sensor-based monitoring of activities of daily living, offering opportunities for early detection of health changes [4, 5]. This can help address exacerbations in chronic disease early, potentially reducing hospitalizations, unnecessary emergency department

visits, and may additionally reduce costs associated with long-term residential care [6-8].

Health-smart home technologies are particularly valuable for tracking activities of daily living such as movement around the home, interest in food, toileting and hygiene, gait speed, overall activity levels, and sleep patterns [9, 10]. Deviations from typical behaviours associated with these activity patterns may indicate emerging health concerns [11]. Aging in place, facilitated by health-smart home technologies, may not only support greater independence and social connectivity but also has the potential to reduce healthcare costs associated with long-term residential care. However, while health-smart home technologies generate large volumes of sensor-based data, their clinical utility depends on how well healthcare professionals, particularly nurses, can interpret and act on this information [11].

Despite the increasing adoption of data-driven decision-making in healthcare, little is known about how nurses interact with visualized data generated by older adults living in health-smart homes—including bar, line, and pie graphs—to assess trends and patterns in activities of daily living. Previous research has focused predominately on the technical aspects of sensors that make up the health-smart home, but there remains a critical gap to understanding how nurses interpret and utilize the sensor-based data for decision-making [12]. The effectiveness of these technologies depends not only on the accuracy of sensor data, but also on how well meaningful clinical insights can be extracted from visual representations of that data [13].

This study uses a subsample dataset that includes clinicians' interpretations of smart home data that were collected for the purpose of creating a clinician-in-the-loop visual interface for nurses observing health-smart home data derived from continuous unobtrusive sensor-based monitoring of older adults at home. Quantified findings from the larger study are published elsewhere [BLINDED]. Distinctive to this work is our in-depth inductive qualitative analysis of narrative descriptions written by a subsample of nurses who provided clinical validation for the larger study's clinician-in-the-loop visual analytics. In this sub study, we seek to understand how nurses think about sensor-based data in the context of symptom presentation and illuminate challenges encountered with providing meaningful and accurate clinical interpretations. While BLINDED addressed interpretation challenges as usability barriers within a developing clinician-in-the-loop analytics system, the current sub study isolates visualisation types as a key factor influencing nurses' ability to interpret health data. Rather than refining a single system, this sub study compares different visual formats to determine which best supports clinical reasoning, providing unique insights into how nurses cognitively process health-smart home data.

Purpose of the Study

The purpose of this study was to explore (1) how nurses interpret health-smart home data derived from ambient sensors presented in bar, line, and pie graph formats; and (2) to identify the challenges nurses encounter when analysing activities of daily living data. By applying an inductive content analysis approach [14], this study aimed to uncover key themes in nurses' interpretations in three cases, assess barriers to effective data use, and provide recommendations for improving data visualisation techniques and clinician training. Findings from this study will contribute to the development of standardized, clinically relevant health-smart home data visualisations to enhance nurses' ability to identify and respond to early changes in health in clients living in a health-smart home.

Background

A global trend is emerging around providing health services to older adults in their homes. It is now common for older adults to receive home care, and the sophistication of that care is advancing. In Australia, about 17% of the population is over 65 and 20% receive formal in-home care or support [15]. In the European Union (EU), data from 2019 indicates that nearly 30% of people aged 65 and over with difficulties in personal care or household activities utilized home care services [16]. In the

United States approximately 12 million people receive home health care services annually with the majority being over 65 years [17]. The United States (U.S.) Census Bureau projects that by 2050 the number persons aged 65 and over will reach 83.9 million. Demand on home care services continues to grow. A 2020 U.S. Census Bureau survey found that between 2013 and 2020, utilisation of U.S. home health care services increased 50.5% [18].

As older adults increasingly seek to remain living at home with the support of home health services, many face the challenge of managing chronic conditions that require ongoing monitoring and timely intervention. Conditions such as cardiovascular disease, diabetes, respiratory disorders, and neurodegenerative diseases often contribute to functional decline, unplanned health care utilization, and institutionalization in nursing homes. Despite the increasing use of home care services among older adults, many experience reduced access to primary care. For instance, a study found that older adults in the U.S. generally receive good quality primary care, but challenges persist in establishing and maintaining access, as well as involving patients in disease management [19].

Traditionally, older adults with higher acuity and more advanced health monitoring needs were transitioned into nursing homes where their health status could be more closely monitored. However, because costs are increasing while access is decreasing, this option is inaccessible or impractical for many [20-23]. Additionally, a scoping review of barriers to accessing aged care services for culturally and linguistically diverse (CALD) older adults in Australia identified issues such as cultural insensitivity, language barriers, and affordability concerns, which further limits access to necessary services [24]. Similar barriers exist in the U.S. with older adults and informal caregivers affected [25]. The emergence of health-smart homes offers an alternative, allowing for continuous, unobtrusive monitoring of key health indicators while enabling older adults to remain safely in their own homes [2, 11].

The increasing adoption of digital health tools in aging-in-place models presents new opportunities for remote patient monitoring [1, 26, 27]. Data visualisation converts raw data into visually structured and easily interpretable graphics, improving comprehension, enabling trend identification, and simplifying the communication of complex information to diverse audiences.

However, while these technologies generate large volumes of quantitative data, the way nurses interpret visualized trends to inform decision-making remains understudied [12, 17, 28].

Conceptual Perspectives

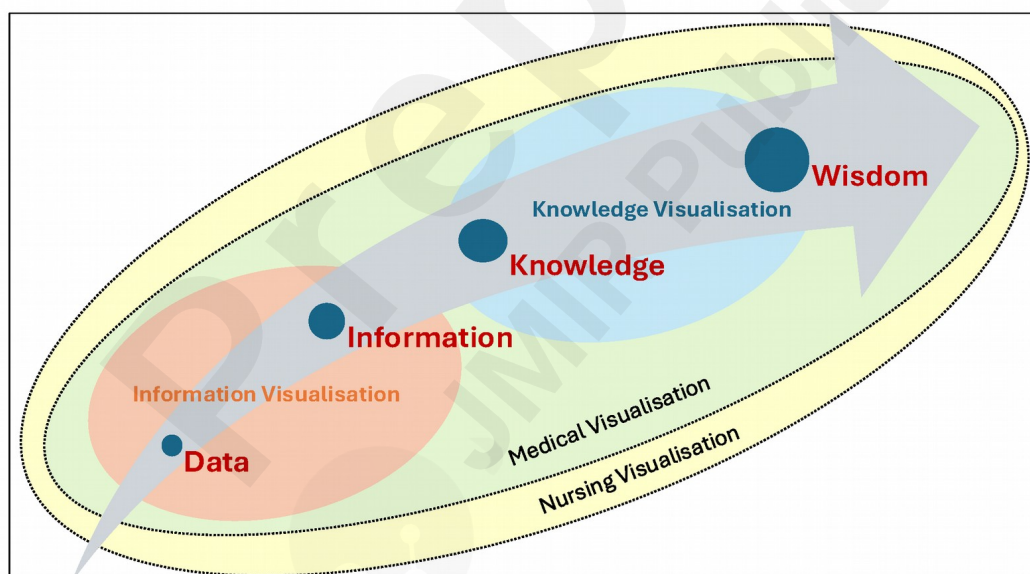
In the context of health-smart home technologies, poorly designed visualisation interfaces—whether overly complex, visually cluttered, or misaligned with clinical needs—can obscure critical insights, delaying or even compromising patient care. Optimising data visualisation for nurses requires a balance of information density, intuitive design, and real-time interpretability to ensure digital health tools enhance, rather than hinder, decision-making and workflow efficiencies [12, 29]. However, a significant gap exists in the literature regarding health-smart home nursing visualisations. Thus, a propensity to solely rely on medical visualisations exists.

The medical visualisation field aims to advance communication of complex medical data in a way that is understandable and actionable for healthcare professionals (graphs, interactive visuals). Included in this work are advances Human-Computer Interaction (HCI) [28, 29]. Recent advances influencing medical visualisation include artificial intelligence and machine learning (AI-ML), the growth of wearable and ambient sensor technology, demand for telehealth and remote monitoring, integration of augmented and virtual reality (AR, VR), computational power and cloud infrastructure, and personalized medicine. Examples of frequently used medical visualisations include statistical data (bar, line and pie graphs) such as those used in Patient Reported Outcome Measure (PROMS), quality indicator data [30], as well as time series graphs (ECG)[31] and spatial imaging (CT, MRI) [32]. Heatmaps and colour maps are used for quickly identifying patterns in biological data collected from chemical analysis [33].

Just as statistical visualisations can mislead, suggesting false patterns or concealing key trends [34], similar risks exist in sensor-derived health data. Traditional medical visualisations—such as fever

charts, ECG waveforms, and blood pressure trends—focus on single physiological measures, making them intuitive for clinical interpretation. In contrast, health-smart home data integrates multiple variables (e.g., sleep, mobility, room occupancy), requiring a more complex and contextual interpretation process. Unlike a fever chart that clearly shows temperature fluctuations, smart home data visualisations must convey multiple dimensions without overwhelming users or obscuring key insights. If poorly designed, they risk misinterpretation—either overemphasizing anomalies or concealing meaningful trends. Nurses must connect disparate data points, recognize patterns, and determine clinical relevance, making the choice of visualisation format critical. In addition to engaging nurses with sensor-based visualisations, it is important to understand how their cognitive process interprets the data. Clinical reasoning in this context requires pattern recognition, contextual knowledge, and judgment about what is clinically significant as seen in the visualisations. Effective visualisations must support, not hinder, this process, ensuring that critical health insights are easily identified and acted upon. When designing visualisations, it is important to consider the data to wisdom continuum and how information visualisation (transforming data into useful information and knowledge visualisation (transfer of knowledge between humans) play key roles in assisting with wise clinical decision-making [12, 35-38]. The data to wisdom model, illustrates the progression of raw data to valuable, actionable insights [39]. For nurses working with sensor data, the transformation from data wisdom goes beyond medical information to include patients' in-home situational context (i.e., social and economic health determinates) [Figure 1].

Figure 1 Data to wisdom continuum in the context of health-smart home data visualisations, which includes medical visualisations and much needed nursing visualisations.



Data Visualisation in Healthcare Decision-Making

Previous research has explored the relationship of data visualisation dashboards and quality of care and clinicians' satisfaction. Findings suggests that well-designed data visualizations improve efficiency by reducing cognitive load, enhancing pattern recognition, and supporting predictive analytics for patient care [12]. While data visualisation tools are well-established in acute care settings such as adult intensive care units (ICUs) [12, 38], their application in community-based settings such as home care remains underexplored. As healthcare increasingly shifts toward aging in place and remote monitoring, a growing opportunity exists to leverage health-smart home technologies to enhance care coordination [40]. Health-smart homes equipped with passive sensor-

based monitoring systems are capable of providing real-time data on activities of daily living, mobility patterns, and other key health indicators [41]. Integrating remotely collected data streams into meaningful visual representations, clinicians—particularly nurses—could be enabled to effectively interpret trends, identify early signs of health deterioration, intervene proactively, and work more efficiently [42]. This transition from institutional to home-based data visualisation introduces new challenges and opportunities in designing user-friendly, clinically relevant interfaces that support remote decision-making and optimize patient outcomes.

Nurses' Role in Remotely Collected Sensor Data Interpretation

For decades nurses have provided healthcare services to people in their homes. They collect physiological, psychosocial, and functional data that informs healthcare decisions [43].

Integrating remotely collected health-smart home sensor data of community-dwelling clients into nursing practice could enhance patient monitoring, speed up the recognition of changes in health, promote early, and proactive interventions. Studies have demonstrated that continuous sensor-based monitoring in home settings enables automated detection of health events, allowing nurses to initiate preventive strategies and provide timely interventions [11]. Additionally, research indicates that in-home sensor systems can detect early signs of health changes, sometimes even before patients become aware, facilitating early detection and management of health deterioration [26]. These findings support the potential of health-smart home technologies to augment traditional nursing assessments, leading to improved patient outcomes and supporting aging in place [11, 27].

Equally critical is the design of health-smart home collected data visualisations, which must strike a balance between simplicity and utility (Dowding et al., 2019). For nurses to leverage these tools effectively under the time pressures and cognitive demands of clinical practice, visualisations must be intuitive and accessible, requiring minimal training to interpret, while retaining the depth and precision necessary to support meaningful interpretation and decision-making [28]. Poorly designed interfaces—whether overly complex, visually cluttered, or functionally clunky may result in nurses not having actionable insights—a risk undermining the very efficiencies and improvements that digital health tools aim to deliver [29]. Thus, understanding nurses' interaction with data visualisations and optimizing design are twin imperatives for advancing care delivery in technology-enabled settings.

Research Questions

This study aimed to explore how nurses interpret HSH-generated data visualisations and the clinical implications of their interpretations.

- How do nurses interpret bar, line, and pie graphs displaying HSH sensor data?
- What patterns and challenges emerge in their analysis of patient activity, sleep, and mobility?

Methods

Study Design

This study utilised a qualitative descriptive design with inductive content analysis, an approach well-suited for exploring participants' experiences, perceptions, and insights [14, 44]. Qualitative descriptive research focuses on exploring participants' experiences and perspectives, staying close to their words and meanings without extensive interpretation or theoretical abstraction [45], making it particularly valuable in healthcare research where understanding practical applications and real-world experiences are essential.

Sample and Recruitment

This study employed a combination of purposive and convenience sampling to recruit participants with relevant expertise in nursing practice, health informatics, and education. Purposive sampling was used to ensure the inclusion of Registered Nurses (RNs) with experience in clinical decision-making and exposure to health informatics, while convenience sampling was applied due to the accessibility of participants within academic and professional networks. Recruitment was conducted via course announcements, professional networks, and targeted email invitations.

Study participants (n=14) were experienced RNs either (1) enrolled in a Doctor of Nursing Practice Family Nurse Practitioner program at a university in the Pacific Northwest region of the U.S. who were completing a graduate course in health informatics or (2) nursing faculty from various schools of nursing (associate, bachelor's, or graduate nursing degree programs) in the Pacific Northwest region of the U.S. All participants held a bachelor's or higher nursing degree from accredited nursing schools in the U.S. and all were female. Age was not obtained. The sample for this sub study is a subset of a total RN sample of (N=60) described elsewhere [BLINDED]. Nursing text-based data analysed here was provided by the n=14 nurses who provided clinical validation for the larger study.

Ethical Considerations

This study was determined to be exempt research by the BLINDED Office of Research Assurances (IRB #16457). Participation was voluntary, and participants could withdraw at any time before submitting their responses, ensuring autonomy and adherence to ethical research principles. For those enrolled in courses, participation had no bearing on grades or academic standing, ensuring that responses were given freely and without obligation. After participants submitted their responses, all written responses were de-identified, and the associated email was deleted, making it impossible to retract or exclude a response after submission. Compensation was not offered.

Research Team and Reflexivity

Both researchers (RF and GD) held academic positions in research-intensive universities, where they taught in various nursing programs. They are females and RNs with PhDs and have extensive clinical nursing experience spanning several decades. They have expertise in deploying health-smart homes and conducting qualitative, and mixed research. Additionally, they have personal experience caring for frail older family members, including those with dementia, which informs their vested interest in advancing the integration of health-smart homes into new models of care. RF introduced the study and full study purpose to the potential participants. Participants were not interviewed, instead they provided written responses.

Data Collection Approach

Nurses who consented to the study were sent an asynchronous email with a Power Point™ document (without audio-video) with a five-slide, written explanation of the health-smart home as well as a short instruction manual on how to use the interactive data visualisation tool prepared using Grafana™ which was accessible using a web-link. All study activities were completed in the private time of the participants. The Power Point™ presentation introduced three participant cases, each including biologic sex, age, primary diagnosis, and a specified seven-day period for analysis. Nurses were provided with background information, a home floorplan with sensor placements, and multiple Grafana-generated visualisations, including bar graphs for activity levels and sleep duration (weekly and monthly), line graphs for sleep interruptions and walking speed (weekly and monthly), and pie charts representing time spent in different home locations (weekly and monthly). Nurses accessed the Grafana Dashboard to review these visualisations and respond to structured questions based on the specific data window required.

Sensor data for Grafana dashboard. The data used in the visualisations for this study were from the homes of community-dwelling older adult participants from multiple health-smart home studies conducted at Washington State University's Center for Advanced Studies in Adaptive Systems [46]. An example of the visualisations provided to participants is shown in Figure 2.

Figure 2 Exemplar visualisations that RN-participants were asked to interpret.



Sensor derived data included passive infrared motion (PIR), temperature, humidity, light, and door use (magnetic) contact sensors placed on the ceilings and walls of older

adults' residences. To facilitate data exploration and pattern identification, Grafana™ was used to generate a dashboard with interactive visualisations of the sensor-derived data. The details on how the visualizations were developed are described elsewhere [47]. Grafana™ is an open-source data visualisation and monitoring platform that integrates with various data sources, including Prometheus (a monitoring system for collecting and querying time-series data), InfluxDB (a high-performance database designed for time-stamped health and sensor data), and MySQL (a widely used relational database for structured data storage). These integrations enable Grafana™ to aggregate and display real-time and historical health-related data, making it a valuable tool for nursing research, digital health applications, and smart home health monitoring.

Participants responded to a combination of nine structured questions (one open-ended), and a 7-point Likert scale survey, adapted specifically for this study [48], which was not pilot tested. The structured questions (Table 1) aimed to assess nurses' interpretations of the visualised data and their perceptions of its usability. Participants were asked to identify any changes in health status or events, describe their clinical interpretations based on the graphs, and specify which charts they used in their decision-making. Additional questions explored graph interpretability, including which visual

formats were easiest to use, how the graphs could be improved, and whether alternative graph types would better represent specific data points (e.g., activity level, sleep duration, walking speed). Participants also provided general feedback on the overall usefulness of the visualisations, indicated whether any relevant information was missing or unnecessary, and offered suggestions for redesigning the graphs (e.g., modifications to colours, axis scales, or graph types). Finally, participants recorded the approximate time spent on the tasks, providing insight into the cognitive workload associated with interpreting the data.

Table 1 Structured Questions

(1) What change in health status or health event (if any) do you identify in for this patient?
(2) What clinical interpretations would you make about this patient based on these graphs?
(3) Which charts did you use to make your interpretations?
(4) Which types of graphs were easiest to interpret? How could these graphs be improved to make them easier and more efficient to interpret?
(5) Would it be more useful to see any of the characteristics (i.e., activity level, sleep duration, sleep interruptions, walking speed, percentage of time spent in locations) represented by a different type of graph?
(6) Please comment on the overall usefulness of the graphs.
(7) Is there any information you would like to see on the visualization that is not present? Is there any existing information on the visualization that was not useful to you?
(8) Please provide any comments and/or suggestions you have about how you would redesign this visualization (e.g., colors, type of graph/chart, scales of x and y axes).
(9) Please record the approximate amount of time you spent working on these tasks.

Survey

The Post-Study System Usability Questionnaire (PSSUQ), developed by Lewis (1992), is an 18-item instrument designed to evaluate user satisfaction with system usability, structured around three factors: System Usefulness (SYSUSE), Information Quality (INFOQUAL), and Interface Quality (INTERQUAL). The scale employs a seven-point Likert format (1 = Strongly Agree, 7 = Strongly Disagree), with high internal reliability (Cronbach's alpha = 0.97)[48]. For this study, an adapted version of the PSSUQ was used, comprising 11 selected items tailored to assess nurses' perceptions of smart home data visualizations. The modifications ensured relevance to clinical usability, ease of interpretation, and decision-making support while maintaining the original scale's structure and reliability. The survey was used to gain preliminary insights into the participants views on the usability and clinical relevance of the different visualisation types including bar, line and pie graphs (Table 2 Health-Smart Home Survey). The selected 11 items align with established principles of usability assessment, particularly in the context of health informatics and clinical decision support tools. These questions assessed key domains of visualisation effectiveness, ensuring that the presented data supports accurate interpretation and informed clinical decision-making. Participants were instructed to rate each statement for each visualisation graph type (bar, line pie) on a seven-point Likert scale, with response options of 1 (Strongly Agree), 2 (Agree), 3 (Somewhat Agree), 4 (Neutral), 5 (Somewhat Disagree), 6 (Disagree), and 7 (Strongly Disagree). A numbered scale from 1=strongly agree to 7=strongly disagree was displayed at the top of the questionnaire to ensure clarity in response options. In selecting a seven-point Likert scale over a five-point scale, the goal was to enhance response sensitivity and capture more nuanced participant perceptions. However, the primary goal of this study was not to generalize statistical findings, but rather to provide contextual and quantifiable information to gain additional insights into the qualitative exploration of nurses' interpretations of health data visualisations. The idea was that the Likert-scale responses would offer structured insights into the qualitative perceptions of usability and data clarity while maintaining the exploratory nature of this research.

Table 2 Health-Smart Home Survey

Comprehensibility & Ease of Use	
(1) "Overall, I am satisfied with how easy it is to understand the visualization of the data." (6) "The information provided by the visualization was easy to understand." (7) "The organization of the visual data was clear."	These items assess cognitive load and how intuitively nurses can interpret the data without additional explanation, an essential factor in clinical decision support.
Interpretation & Clinical Meaning	
(2) "I was able to efficiently interpret the visual data." (9) "The visual data is presented in a clinically meaningful way." (10) "I am confident that visualizing data in this format would allow me to identify clinically meaningful change in health status."	These items measure the effectiveness of the visualisation format in enabling clinicians to recognise trends, patterns, and health changes in a way that informs practice.
Usability & Workflow Integration	
(3) "I felt comfortable interpreting this visualization." (4) "I believe I could become productive quickly using this visualization." (5) "It was easy to find the information I needed in this visualization."	These statements reflect usability heuristics, such as learnability, efficiency, and confidence in decision-making, which are critical for technology adoption in nursing.
Data Completeness & Satisfaction	
(8) "The visualization contains all of the information I would expect it to have." (11) "Overall, I am satisfied with this visualization."	These items assess perceived completeness and user satisfaction, which influence engagement and continued use of visualisation tools in clinical settings.

Data Analysis Approach

Text-Based Evaluation Data

This study employed general inductive content analysis [14] to analyse nurses' written feedback on structured questions related to sensor-derived graphs depicting sleep, activity, and mobility trends of three smart home participant cases. Content analysis is a systematic and objective research method used to describe and quantify phenomena, often applied to document analysis.

It enables researchers to organise data into meaningful categories, assuming that words and phrases classified together share a common meaning [14, 49]. This approach helps test theoretical concepts, derive insights, and generate practical knowledge [50]. By applying an inductive content analysis approach this study aimed to uncover key themes in nurses' interpretations, assess barriers to effective data use, and provide recommendations for improving data visualisation techniques and clinician training. The goal of the researchers was to capture the breadth and depth of participant feedback to ensure a comprehensive understanding of the data. Accordingly, for this study, data saturation was not the intended criterion for determining adequacy of data' rather, the approach focused on ensuring exploration of participant perspectives and identifying patterns and variations in responses. Therefore, the analysis aimed to reflect the full range of participant experiences rather than achieving theoretical saturation. Data were analysed by **GD and RF** following a three-phase

inductive process described by Thomas (2006). In Phase 1 (Open Coding), two researchers (GD and RF) independently reviewed participants' responses, identifying key statements and applying initial descriptive codes. In Phase 2 (Categorisation), similar codes were grouped by GD and RF into broader categories to reflect patterns in how nurses engaged with the visualisations. In Phase 3 (Theme Development), categories were synthesised (GD and RF) into higher-order themes, representing overarching interpretations of how the visual data were perceived and used. Throughout the process, the researchers engaged in reflexive discussions to ensure that the themes emerged from the data rather than being imposed. To enhance trustworthiness and rigour, both researchers independently coded the data and then met to compare interpretations, resolving discrepancies through discussion. Manual coding was used by GD and RF to maintain close engagement with the data, rather than relying on qualitative analysis software. Representative participant quotations were selected to illustrate each theme, ensuring transparency in how interpretations were derived from the raw data. Participants were not asked to provide feedback on the findings.

Survey

Descriptive statistics were computed using SPSS (Statistical Package for the Social Sciences, version 30) to summarize participants' perceptions of the three visualisation types (Bar, Line, and Pie). Mean and standard deviation values were calculated for each of the 11 survey items across the three visualisation types. Given the Likert scale structure (1 = Strongly Agree, 7 = Strongly Disagree), lower mean scores indicate stronger agreement with a statement, while higher mean scores indicate greater disagreement. These summary statistics provided an initial assessment of perceived usability, interpretability, and clinical relevance across the three visualisation types. Since participants responded to the same set of 11 survey items for all three visualisation types, the dataset was treated as repeated measures, allowing for within-subject comparisons.

A Friedman test was conducted to determine whether there were significant differences in ratings across the three visualisation types. The Friedman test is a non-parametric alternative to repeated-measures ANOVA, appropriate for ordinal Likert-scale data and small sample sizes ($N = 14$). To ensure that within-subject variability was preserved, each individual response across all 11 survey items was included in the analysis rather than averaging responses at the participant level. If a significant difference was detected, post-hoc pairwise comparisons were conducted using the Wilcoxon signed-rank test, a non-parametric test for paired samples, to identify specific differences between graph types (bar vs. line, bar vs. pie, and line vs. pie). An alpha level of 0.05 was used to determine statistical significance for all analyses (Gibbons & Chakraborti, 2014; Pallant, 2020).

Findings

Text-Based Evaluation Data

All RNs ($n=14$) responded to the structured questions for each of the three smart home participant and completed the 11-question Likert scale survey. No participants withdrew. All participants answered all structured qualitative questions in writing across the three smart home participant cases and completed the 11 survey questions for bar, line and pie visualisations. The average time reported by participants spent working on reviewing the health-smart home data visualisation across all three smart home participant cases and providing written responses was 71 minutes.

Inductive Content Analysis of Nurses' Evaluations

Case 1

The qualitative analysis of nurses' evaluations of sensor-derived health data visualisations for smart home participant Case 1 revealed four overarching themes: (1) Sleep disruptions and nocturnal activity, (2) mobility declines and fatigue-related activity fluctuations, (3) home environment usage and social engagement, and (4) challenges in interpreting smart home data. These themes reflect how nurses interpreted the patient's sleep, mobility, and activity patterns, as well as the challenges they encountered in using sensor-based data for clinical decision-making.

Sleep Disruptions and Nocturnal Activity Nurses identified significant sleep disturbances in smart home participant Case 1, particularly in relation to the patient's radiation treatment cycle. Sensor data showed erratic sleep patterns, with poor sleep the night before treatment and longer rest post-treatment, which nurses linked to fatigue and recovery. Additionally, frequent nocturnal awakenings and bed-to-toilet transitions were observed, leading nurses to speculate on possible urinary issues, discomfort, or pain-related sleep disruption. One nurse noted, *"sleep is being interrupted,"* (p12) while another highlighted the increasing bed-to-toilet transitions, stating, *"she had less transitions from bed to toilet after her radiation and then slowly increased in frequency over the week"* (p04). One participant noted that more information is needed to make clinically relevant inferences noting, *"only looking at night-time use of bathroom does not give me a good enough clinical picture. Was there something that occurred during the before the nighttime of increased bathroom use that would explain it? (increased consumption of liquids, change in meds?) To many unknowns to draw meaning here"* (p14). In addition, a recurring challenge was distinguishing true sleep from inactivity, as nurses noted uncertainty in interpreting whether long sleep durations indicated restful sleep or prolonged immobility due to illness or fatigue. One participant expressed this challenge, stating, *"It is hard to tell if she is getting up or just rolling around"* (p02). Some nurses suggested anxiety before treatment may have contributed to pre-treatment sleep loss, as one remarked, *"The patient slept very little and poorly the night before radiation treatments"*(p05).

Clinical Implications: Nurses linked sleep disturbances in smart home participant Case 1 to health status and treatment effects, emphasising the need for improved sleep monitoring methods.

They suggested potential interventions to address nocturia and anxiety-related sleep loss, highlighting the importance of assessing sleep in conjunction with other clinical indicators. However, one participant noted that more information was needed to make clinical inferences, *"patient with more sleep interruptions last ½ of month. This could be clinically relevant, depending on the diagnosis and medications/doses (or changes in meds/doses). Need more context. As is, cannot infer anything"* (p14).

Mobility Decline and Fatigue-Related Activity Fluctuations Sensor data for smart home participant Case 1 indicated progressive mobility decline, which nurses interpreted because of radiation-related fatigue. A noticeable reduction in walking speed was observed throughout the treatment cycle, with the slowest movement occurring on the fourth and fifth treatment days. One nurse noted, *"by Thursday and Friday (4-5 treatments of Radiation), the patient's walking speed slows due to fatigue, pain, and/or discomfort"* (p05) and *"the patient takes a significantly longer time getting to the bathroom at day 4 or 5 of Radiation"* (p05). Another participant observed *"the participant's walking speed declined progressively throughout the treatment week, with the slowest movement observed on the fourth and fifth treatment days"* (p03). Nurses also noted increased sedentary behaviour, as smart home participant Case 1 spent more time *"less activity on the third and sixth days of this week"* (p10), or sitting post-treatment, which they attributed to fatigue, pain, and overall physical decline. One participant described this as, *"the patient spends a lot of time watching TV and being sedentary in the living room"* (p05). Additionally, delayed and more difficult bathroom transitions were observed, leading some nurses to express concern about increased fall risk, particularly towards the end of the treatment week. One nurse warned, *"this patient could experience an increased risk for falls due to the number of bed transfers"* (p04).

Clinical Implications: Nurses emphasized the need for closer monitoring of mobility patterns in smart home participant Case 1, particularly in relation to fall risk and functional decline. They suggested that gait assessments and tracking bathroom transitions over time could provide early warning signs of worsening fatigue and mobility impairments.

Home Environment Usage and Social Engagement Smart home sensor data for smart home participant Case 1 provided insights into daily routines and home environment use. Nurses observed consistent room usage, with most time spent in the bedroom and living room, while minimal time was spent in the kitchen and dining areas. One participant noted, *"Minimal time in the bathroom and*

kitchen. Equal time in living room and bedroom. Time is spent outside"(p01). This led to speculation about possible reduced meal preparation and food intake, suggesting potential nutritional concerns. Limited outdoor activity was also noted, with smart home participant Case 1 leaving home primarily for medical appointments. Some nurses speculated that frequent door openings could indicate smoking habits or social visits, though this remained unclear. One participant questioned, *"There were periods of time where the door would open and close and then open and close again minutes later throughout the day, I wondered if possibly the patient was going outside to smoke but that could just be my bias"*(p11).

Clinical Implications: Nurses highlighted fatigue-related lifestyle changes that may require nutritional support and strategies to promote social engagement for smart home participant Case 1. Understanding patterns of home and community interaction may provide useful indicators of overall well-being and functional status.

Challenges in Interpreting Smart Home Data

Despite the valuable insights provided by the sensor data, nurses faced multiple challenges in interpretation for smart home participant Case 1. Walking speed metrics were particularly difficult to assess, as nurses questioned whether changes reflected fatigue, pain, or another condition. One participant expressed confusion, stating, *"I do not know how to interpret walking speed. What is the unit of measure? Does walking slower mean the patient was in pain? More sleepy? Less alert?"* (p06). Sleep data interpretation was another challenge, with nurses struggling to differentiate between sleep and prolonged inactivity, and lacking more context, making it harder to determine true sleep quality. *"Is the baseline specific to the patient? Or is it a standardized baseline? I wonder why the slow increase in sleep hours in the week?"* (p13). Another participant noted *"On the previous graph, 11/30 showed that the patient slept more hours than usual. I think perhaps what the graph was showing was how many hours they were in bed and not how many hours they were sleeping as this graph shows the patient was up 6 times to go to the bathroom"* (p06). One participant remarked, *"patient with more sleep interruptions last ½ of month. This could be clinically relevant, depending on the diagnosis and medications/doses (or changes in meds/doses). Need more context. As is, cannot infer anything"* (p14).

Regarding data visualisation, nurses found that line graphs and trend analyses were more useful, whereas pie charts were seen as less informative. One participant stated, *"I used the graph charts and the links to the sensor data. The pie chart didn't provide much information"* (p01). Additionally, nurses noted that raw sensor data alone lacked sufficient clinical context, reinforcing the need for integrating sensor-based data with clinical benchmarks to enhance usability. *"Not sure what was happening on 11/26, was the patient not home? I could look at the raw sensor data, but not sure if that would answer the question"* (p13).

Clinical Implications: Nurses emphasised the need for enhanced data visualisation techniques, including clearer reference values for mobility metrics and improved methods for interpreting sleep data for smart home participant Case 1. They also highlighted the importance of pairing sensor-based assessments with clinical evaluations to ensure that findings are clinically meaningful and actionable. In summary, nurses effectively used smart home sensor data to identify key patterns related to sleep, mobility, and home activity in smart home participant Case 1, linking these trends to radiation therapy effects, fatigue, and potential health risks. However, challenges in data interpretation highlighted the need for improved contextualisation, enhanced data visualisation, and clearer clinical benchmarks to optimise the integration of smart home technology into patient care.

Case 2

The qualitative analysis of nurses' evaluations of sensor-derived health data visualisations for smart home participant Case 2, a 92-year-old female living alone with a diagnosis of non-specific insomnia, revealed four overarching themes: (1) Chronic sleep disruptions and nighttime activity, (2) nighttime bathroom usage and health implications, (3) activity patterns: stability with periodic declines, and (4) low engagement and reduced activity levels. These themes illustrate nurses'

interpretations of the patient's sleep, mobility, and home environment usage while highlighting the challenges they encountered in making clinical assessments using sensor-derived data.

Chronic Sleep Disruptions and Nighttime Activity Nurses identified severe sleep disturbances in smart home participant Case 2, with erratic sleep patterns making it difficult to establish a consistent sleep schedule. Sensor data revealed alternating periods of no sleep and oversleeping, suggesting disordered sleep cycles. Frequent nocturnal awakenings were also common, with the participant waking between 2 to 8 times per night. One nurse noted, *"On average there were 5 hours of sleep and a few times there were 9 hours or below 2 hours"* (p01). Another participant highlighted the frequency of awakenings, stating, *"Frequently disturbed sleep, with some periods of being considerably disrupted"* (p02). Poor sleep hygiene was also a concern, with some nurses speculating that bedroom use patterns indicated non-sleep activities, such as watching television. Additionally, nurses noted inconsistencies in sensor-detected sleep, with one nurse commenting, *"She does not appear to have a decrease in sensor activity that would allow me to interpret her amount of sleep"* (p04). This raised concerns about whether sensor data could reliably differentiate true sleep from stillness or inactivity. The potential relationship between different patterns such as insomnia and slower walking was noted *"most of the month she is moving slower than her norm. Not sure this has anything to do with insomnia, or maybe insomnia is only one of the factors affecting walking speed"* (p14).

Clinical Implications: Nurses recommended improved sleep monitoring techniques to better distinguish sleep from prolonged stillness. Additionally, they suggested potential sleep hygiene interventions to optimise conditions for sleep and reduce nighttime awakenings. Given the frequent disruptions, some nurses also proposed further evaluation for nocturia or an overactive bladder as a possible contributor to fragmented sleep.

Nighttime Bathroom Usage and Health Implications A consistent finding in smart home participant Case 2 was the impact of frequent nighttime bathroom trips on sleep quality. The participant exhibited high rates of nighttime bed-to-toilet transitions, with increased bathroom visits before and after sleepless nights. One nurse observed, *"Her bed-to-toilet transitions are above her baseline over 50% of the time"* (p04). Another nurse noted, *"Patient's sleep interruptions varied from being below her baseline half of the month and spikes in the middle and end of the month showing she was interrupted more frequently to go to the bathroom (6-8 times)"* Why is the baseline different for the week and the month?" (p08). Some nurses speculated that the participant may have undiagnosed urinary issues, such as nocturia or an overactive bladder, that exacerbated insomnia. One nurse suggested, *"She has an overactive bladder and needs evaluation to rule out other possibilities related to her urinary health or dietary plan (too much caffeine)"* (p12). Fluctuations in bathroom visit frequency were also noted, with spikes occurring at certain times of the month, raising questions about whether this pattern correlated with medications, sleeplessness, hydration habits, or other health factors. *"More trips to the bathroom occur when the patient is not sleeping well, or does the patient not sleep well because always getting up to the bathroom?"* (p13).

Clinical Implications: Nurses recommended further clinical evaluation for nocturia or overactive bladder, given its potential role in disrupted sleep patterns. They also suggested tracking fluid intake, medication use, and other behavioural factors to assess whether they contributed to nighttime awakenings. However, additional clinical correlation was deemed necessary to determine whether nocturia was a primary cause of sleep disturbances or a secondary effect of another condition.

Activity Patterns: Stability with Periodic Declines The overall activity levels for Patient Case 2 remained relatively stable, but nurses observed fatigue-related fluctuations that affected mobility. The patient's baseline activity level was generally consistent, but some days exhibited extreme drops. One nurse noted, *"The patient was close to her baseline activity most of the month with 4 days of increased activity. She had 7 days of the month where she was below her activity baseline"* (p07). Fatigue-related declines in mobility were particularly evident after nights of poor sleep, leading nurses to speculate that sleep deprivation contributed to daytime inactivity. One participant stated,

“Walking speed decreased for about one week out of the month” (p02).

However, occasional spikes in activity were also noted, leading some nurses to question whether these fluctuations were linked to medication effects, visitors, or anxiety-related restlessness. One nurse commented, *“This patient had a huge increase in their relative walking speed the week in focus compared to the entire month” (p04).*

Clinical Implications: Nurses emphasised the need for regular mobility assessments to monitor gait stability and assess fall risk. Some nurses suggested that walking speed data required clearer reference points to determine whether changes were clinically significant or within normal variability. Others proposed that increased mobility episodes could be linked to anxiety or restlessness, warranting further evaluation.

Low Engagement and Reduced Activity Levels Smart home sensor data revealed patterns of low engagement and limited activity within the home environment. Nurses observed that Patient Case 2 spent most of the time in the bedroom and living room, with minimal time in the kitchen or other areas. One nurse noted, *“Majority of time is in bedroom, rarely outside. Not using work area (not sure what this is). Little time in kitchen but could be prepping food and eating in another room” (p01).* Another participant speculated that this pattern reflected social withdrawal or reduced motivation for daily activities, *“Patient spends the majority of her time in her bedroom and living room. She spends very little time in the other rooms. She is in the bathroom more than she is in the kitchen and dining room. She doesn’t go outside or lets in visitors much” (p07).* While activity levels remained mostly low and stable, occasional short bursts of movement were observed. Some nurses speculated that these brief periods of increased movement might be linked to anxiety, discomfort, or external factors.

Clinical Implications: Nurses recommended further assessment of the patient’s social and emotional well-being to determine whether isolation, depression, or other mental health factors contributed to low engagement. Additionally, some suggested that light physical activity or a structured daily routine might help reduce prolonged sedentary behaviour. Given the minimal kitchen use, nurses also recommended tracking mealtime routines to assess for dietary concerns.

In summary, nurses interpreted sensor-derived health data from smart home participant Case 2 to identify chronic sleep disruptions, frequent nighttime awakenings, fluctuations in mobility, and patterns of low engagement. While the sensor data provided valuable insights into daily routines and health behaviours, nurses faced challenges in data interpretation, particularly in distinguishing true sleep from stillness, assessing the clinical significance of mobility changes, and linking nocturnal bathroom usage to underlying conditions. These findings highlight the need for improved contextualisation, enhanced data visualisation techniques, and clearer clinical reference points to optimise the integration of smart home technology into patient care.

Case 3

The qualitative analysis of nurses’ evaluations of sensor-derived health data visualisations for smart home participant Case 3, an 89-year-old female living alone without medical history provided, revealed five overarching themes: (1) Fluctuating sleep and activity patterns, (2) increased nighttime bathroom trips and their impact on sleep, (3) walking speed decline and mobility variability, (4) home usage patterns and sedentary lifestyle, and (5) challenges in data interpretation and clinical context. These findings reflect nurses’ interpretations of the patient’s sleep, mobility, and home environment usage, as well as the limitations they faced in drawing clinical insights due to missing medical history.

Fluctuating Sleep and Activity Patterns Nurses observed erratic sleep behaviours and inconsistent activity levels, making it difficult to establish a stable daily routine for Case 3.

Sensor data indicated persistent low sleep levels, with frequent awakenings affecting rest. Sleep duration ranged from as little as three hours to over seven hours, with no discernible pattern. One nurse noted, *“Average 5-7 hours’ sleep. Few greater and one 3 hours” (p01).* Additionally, nighttime restlessness was evident, as sensor activity remained high even during supposed sleep periods. One

nurse noted *“great variety in sleep with more fluctuation towards the end of the month”* (p06). Another nurse noted an interesting pattern of insomnia and then sleep recovery stating, *“patient is having some nights where she doesn't sleep much but tends to follow this with a good sleep day (recovery)”* (p14). There were concerns about whether sensor-detected inactivity truly reflected sleep. *“Over the month, sleep interruptions hovered close to baseline. There was one spike mid-month where her sleep interruptions increased dramatically to 20 times”* (p07). Furthermore, activity levels varied significantly, with some days showing increased movement followed by sharp declines, making overall behavioural patterns difficult to interpret *“I am unable to make any interpretations based off of this information”* (p04).

Clinical Implications: Nurses suggested that erratic sleep cycles could contribute to fatigue, cognitive impairments, and reduced mobility. They recommended further assessment of sleep hygiene and potential interventions for insomnia or anxiety. Additionally, tracking factors such as caffeine intake, medication effects, or psychological stressors could help clarify the underlying causes of sleep disturbances.

Increased Nighttime Bathroom Trips and Their Impact on Sleep A key finding in nurses' interpretations was the high frequency of nighttime bed-to-toilet transitions, which appeared to correlate with poor sleep quality. Smart home participant Case 3 woke up multiple times per night, with some nights exceeding 20 trips to the bathroom. One nurse stated, *“the patient barely slept on 3 of 7 days and 4 other days patient slept 7 to 9 hours”* (p03). Another participant noted *“the patients transfers [to toilet] increased over 50% of their baseline during the week in observation. With days 10/03/17 & 10/07/17 showing less than baseline activity”* (p04). Nurses speculated that the frequent nocturnal awakenings could indicate undiagnosed urinary health issues, such as nocturia, an overactive bladder, or a possible urinary tract infection (UTI). One nurse commented, *“possible UTI or increased diuresis? Patient awakens in spikes to use the bathroom at night”* (p06). Additionally, nurses noted a clear correlation between bathroom use and sleep disruptions, where nights with fewer bathroom trips were associated with longer and more restful sleep.

Clinical Implications: Nurses recommended further assessment of urinary function, hydration patterns, and medication side effects to determine if nocturia was a primary cause of sleep disturbances. They also suggested dietary adjustments (e.g., limiting caffeine intake) and nighttime toileting strategies to help mitigate sleep disruptions.

Walking Speed Decline and Mobility Variability Nurses examined walking speed data to assess mobility and potential health risks, identifying notable trends for smart home participant Case 3. The participant exhibited significant fluctuations in walking speed, with some days showing markedly slow movement followed by brief spikes in speed. One nurse noted, *“Walking speed fluctuated greatly throughout the week”* (p06). There was a clear correlation between bathroom trips and walking speed, with nurses observing that on nights with fewer bathroom trips, walking speed was faster, whereas frequent nighttime awakenings led to slower movement. One nurse stated, *“The patient walks more quickly on nights that she gets more sleep. This could be due to urgency”* (p11). Another participant added, *“The patient walks quickly on the nights that she goes to the bathroom less”* (p05). Additionally, a gradual decline in mobility over time was noted, with nurses raising concerns about fatigue, potential muscle weakness, or an undiagnosed condition. One nurse commented, *“Significant decreased walking speed overall”* (p01).

Clinical Implications: Nurses highlighted that variability in walking speed could indicate episodic changes in energy levels, urgency, or discomfort. They recommended tracking patterns between sleep, fatigue, and mobility changes to provide insights into the patient's overall health status. Further assessment for fall risk or muscle weakness was suggested to identify early mobility decline.

Home Usage Patterns and Sedentary Lifestyle Sensor data provided insights into smart home participant Case 3's daily movement within her home, revealing low engagement and limited room usage. The participant spent most of her time in the bedroom and living room, with minimal movement to the kitchen, dining room, or office. One nurse noted, *“Most of the time spent at home.*

Equal time in living room and bedroom” (p01). Another participant added, *“Majority of time is in bedroom, rarely outside” (p03).* Nurses speculated that limited home engagement could be a sign of social withdrawal, cognitive decline, or fatigue-related lifestyle changes. One participant remarked, *“the patient spent less time in the office and more time in the bathroom during the week where she had two nights of poor sleep. She also spent much less time in the kitchen and less time outside” (p05).* Additionally, some nurses observed that periods of poor sleep or increased bathroom trips correlated with reduced movement throughout the home during the day, further reinforcing the connection between nighttime disruptions and daytime fatigue.

Clinical Implications: Nurses suggested encouraging structured movement, social interaction, or small daily tasks to help increase activity levels. Additionally, tracking longitudinal changes in home usage could provide insights into potential cognitive, emotional, or functional declines.

Challenges in Data Interpretation and Clinical Context While sensor data provided valuable insights, nurses faced several challenges in interpretation, particularly due to missing medical history and unclear reference points. Unclear sleep patterns made it difficult to determine whether periods of inactivity represented true sleep or simple rest without movement. One nurse noted, *“Decreased sensors when asleep, with no clinical data hard to draw on inferences.”* Assessing walking speed was another difficulty, as standardised clinical benchmarks were lacking. One participant questioned, *“Uncertain of the difference in pace as defined by the seconds?”* Additionally, some nurses struggled to interpret erratic activity trends, as short bursts of movement occurred without an obvious explanation. One nurse stated, *“The graphs do not show any patterns that would identify any health status change in the patient.”* Finally, the lack of medical history made it challenging to draw conclusions about sleep, mobility, and bathroom usage patterns.

Clinical Implications: Nurses highlighted the need for better integration of sensor data with medical records and clinical notes to improve interpretation accuracy. Additionally, they suggested that more intuitive visualisations and standardised reference values for sleep, activity, and mobility metrics could enhance clinical decision-making.

In summary, nurses used sensor-derived health data to evaluate Case 3’s sleep, mobility, and home engagement patterns, identifying frequent nighttime awakenings, walking speed variability, and reduced engagement in daily activities. However, challenges in data interpretation—including unclear sleep metrics, lack of medical history, and difficulties with mobility data interpretation—limited the ability to make definitive clinical judgments. These findings underscore the importance of improved contextualisation, enhanced data visualization, and the integration of sensor-based assessments with clinical evaluations to support the use of smart home technology in patient care. Across all cases, data interpretation challenges limited clinical decision-making. Nurses encountered ambiguities in sleep data, questioning whether sensor-detected inactivity truly reflected sleep. Similarly, walking speed fluctuations were difficult to assess due to the lack of standardised clinical reference values.

The absence of medical history in some cases further hindered interpretation, as sensor data alone lacked sufficient context to support definitive clinical conclusions. These findings highlight the need for better integration of sensor-derived data with medical records, improved data visualisation techniques, and clear clinical benchmarks to enhance usability for healthcare professionals.

Survey Results

A total of 14 nurse-participants were included in this study, each of whom evaluated all three graph types (Bar, Line, and Pie). The 11-item 7-point Likert scale questionnaire provided preliminary insights into participants’ perceptions of sensor-derived data visualisations. Given that each participant responded to all 11 items for each of the three graph types, this resulted in 154 total responses per graph type (14 participants × 11 items), yielding a dataset of 462 responses across all graph types. There were no missing data, and each response was complete, ensuring data integrity. Descriptive analysis (Table 3) revealed differences in perceived usability and clinical relevance across the three visualization types. Bar graphs and line graphs were rated the most favourably, with

participants generally agreeing that they were easy to understand and clinically useful (Bar: $M = 3.64$ – 4.57 , $SD = 1.49$ – 2.22 ; Line: $M = 3.93$ – 4.86 , $SD = 1.55$ – 2.28). In contrast, pie charts were generally rated less favourably, with more neutral to somewhat disagree responses ($M = 4.14$ – 5.29 , $SD = 2.10$ – 2.44), particularly for ease of finding information and overall clarity. The lowest-rated item for pie charts was “The organization of the visual data was clear” ($M = 5.29$, $SD = 2.23$), indicating potential difficulties in interpreting structured information. These findings suggest that bar and line graphs are more effective for clinical decision-making, whereas pie charts may require design improvements to enhance interpretability and usability.

Table 3 Results of Survey Questions

(N=14)	Bar Mean (SD)	Line Mean (SD)	Pie Mean (SD)
Overall, I am satisfied with how easy it is to understand the visualization of the data	4.07 (2.02)	4.36(1.74)	4.86(2.38)
I was able to efficiently interpret the visual data	4.07 (1.94)	4.43(1.55)	4.57(2.44)
I felt comfortable interpreting this visualization	3.79 (2.22)	4.14(2.28)	4.93(2.2)
I believe I could become productive quickly using this visualization	4.07 (2.16)	4.21(2.08)	4.71(2.3)
It was easy to find the information I needed in this visualization	4.14 (1.96)	4.43(1.65)	5.14(2.21)
The information provided by the visualization was easy to understand	4 (2.18)	4.21(1.72)	5(2.15)
The organization of the visual data was clear	4.57 (2.03)	4.86(1.83)	5.29(2.23)
The visualization contains all of the information I would expect it to have	3.71 (1.49)	3.93(2.02)	4.14(2.32)
The visual data is presented in a clinically meaningful way	4 (1.88)	4.36(1.91)	4.64(2.21)
I am confident that visualizing data in this format would allow me to identify clinically meaningful change in health status	3.64 (1.82)	4(2.11)	4.14(2.25)
Overall, I am satisfied with this visualization	3.86(1.83)	4.07(1.82)	4.43(2.1)
Response options: 1 (Strongly Agree), 2 (Agree), 3 (Somewhat Agree), 4 (Neutral), 5 (Somewhat Disagree), 6 (Disagree), and 7 (Strongly Disagree).			

The Friedman test was conducted to determine whether there were significant differences in participants' ratings of the three visualization types. Each participant's individual ratings across all 11 questions for the three visualization types (Bar, Line, and Pie) were included in the test to account for within-subject variability.

The results indicated a statistically significant difference across the three visualisation types ($\chi^2(2) = 17.11$, $P < .001$), confirming that participants rated Bar, Line, and Pie charts differently in terms of usability and clinical relevance. Post-hoc Wilcoxon signed-rank tests were conducted to determine which visualisation types differed significantly in participant ratings. The results indicated that there was no significant difference between Bar and Line graphs ($W = 2857.0$, $P = .10$), suggesting that both were perceived similarly in terms of usability and clinical relevance. However, Pie charts were rated significantly lower than both Bar graphs ($W = 1437.0$, $P < .001$) and Line graphs ($W = 2678.5$, $P = .008$), confirming that participants found Pie charts less useful for clinical decision-making. These findings support the qualitative feedback that Bar and Line graphs were more effective in conveying sensor-derived data, whereas Pie charts presented challenges in clarity and interpretation.

Merging of Inductive Content Analysis Findings with and Survey Results

The findings from the three cases illustrate both the potential value and challenges of using sensor-derived health data to assess sleep, mobility, and home engagement in older adults. Across all cases, nurses were able to identify key patterns, such as frequent nighttime awakenings, fluctuations in mobility, and variable home engagement, demonstrating how smart home technology can provide real-time insights into health status and functional changes. However, common challenges in data interpretation—including unclear sleep metrics, difficulties distinguishing true rest from inactivity, lack of clinical context, and limitations in mobility assessments—highlight the need for improved contextualisation and integration of sensor data with clinical evaluations.

The survey results broadly confirm the qualitative findings from the inductive content analysis, particularly in relation to the challenges nurses faced when interpreting sensor-derived data visualisations and their preferences for certain visual formats. However, the extent of this alignment varies across specific themes. The survey results confirm several key findings from the qualitative analysis, particularly in relation to challenges in interpreting smart home data.

The Friedman test indicated a statistically significant difference in how nurses rated different graph types ($\chi^2(2) = 17.11$, $P < .001$), with pie charts rated significantly lower than both bar and line graphs ($P < .001$ and $P = .008$, respectively). This supports nurses' qualitative feedback that pie charts were less useful and harder to interpret for clinical decision-making. Nurses explicitly stated that line graphs and trend analyses were more useful, whereas pie charts lacked sufficient information, as highlighted in statements such as: "The pie chart didn't provide much information."

Further, the survey results confirmed difficulties in interpreting sleep and mobility data, with *"The organization of the visual data was clear"* receiving the lowest rating for pie charts ($M = 5.29$, $SD = 2.23$). This aligns with qualitative concerns that sensor-based sleep and mobility data were difficult to interpret without additional clinical context. Nurses struggled to differentiate true sleep from inactivity and had difficulty interpreting walking speed metrics, questioning whether variability was due to fatigue, pain, or another factor. Statements such as: *"I do not know how to interpret walking speed. What is the unit of measure?"* directly reflect the survey results, where participants rated clarity and interpretability lowest for pie charts. Additionally, the survey results confirmed that both bar and line graphs were rated similarly in terms of usability and clinical relevance, with no significant difference between the two. This supports the qualitative finding that both formats were generally effective for clinical interpretation. Nurses preferred visualisations that allowed them to track trends over time, reinforcing the survey finding that bar and line graphs provided more clinically meaningful insights than pie charts. This was further validated by qualitative statements such as: *"I used the graph charts and the links to the sensor data. The pie chart didn't provide much information."* These findings collectively suggest that bar and line graphs are more effective for clinical decision-making, while pie charts may not provide sufficient clarity or actionable insights in this context.

Discussion

The integration of smart home technologies in healthcare presents significant opportunities for enhancing the remote monitoring and management of older adults with chronic diseases. However, the effectiveness of these technologies is closely tied to the design of data visualisations and the proficiency of nurses in interpreting and acting upon this data.

Co-Designing Health-Smart Home Data Visualisations with Nurses

Involving nurses in the co-design of health-smart home data visualisations is crucial. Nurses play a pivotal role in patient care and are increasingly engaged in remote health monitoring. Their insights can ensure that data visualisations are intuitive, relevant, and actionable [51]. By collaborating with nurses in the design process, visualisations can be tailored to meet clinical needs, thereby enhancing the quality of remote monitoring and patient outcomes [52]. This collaboration enhances the usability of tools and reduces cognitive load through features like color-coded alerts. It ensures that data are presented in ways that not only provide information but also support holistic knowledge of the older

adult and their life contexts. Such knowledge is needed for rapid clinical decision-making in an era of precision medicine, and where emphasis is placed on patients' autonomy and right to self-determination.

Furthermore, as patient advocates, nurses can shape visualisations to facilitate communication with older adults and their families, translating complex sensor data into meaningful, actionable insights for themselves. Addressing challenges like data overload or technical scepticism through co-design can also foster trust in these systems, ultimately enhancing adoption and positive end-user experiences.

Enhancing Nurses' Proficiency in Remote Monitoring

The efficacy of smart home systems in detecting health changes is significantly influenced by nurses' proficiency in utilizing data dashboards, alongside access to clinical history and in-person collected data. A study examining nurses' practices in remote monitoring of chronic patients found that nurses use data in the form of graphs, alerts, questionnaires, and messages to personalize care [53]. This underscores the necessity for comprehensive training programs that equip nurses with the skills to interpret complex sensor derived data and integrate it with traditional clinical assessments, and medical history. Furthermore, the development and implementation of nurse-based remote patient monitoring programs have demonstrated that dashboards available through software platforms allow RNs to monitor patients effectively, viewing and responding to real-time alerts when data falls outside predefined limits. This integration of technology into nursing practice not only enhances patient care but also supports nurses in making informed decisions based on a combination of real-time data and clinical expertise [54].

New Types of Evidence for Evidence-Based Practice

Introducing nurses to data derived from unobtrusive, continuous ambient sensing is important to growing their knowledge about how to utilize this new type of data as evidence for evidence-based decision-making. Nurses and other healthcare team members are currently not trained to use this type of data. This will result in the need for training to increase comfort with relying on the data and associated visuals (graphs, charts). We posit that obtaining knowledge and comfort with information provided by smart homes will require similar changes to thinking about data that the introduction of smart infusion pumps, automated medication dispensing machines, and other information derived from remote patient monitoring equipment. Embracing a growth mindset as new forms of data emerge, including information outputs from devices featuring artificial intelligence, will position nurses for the future of healthcare.

Nurses as Future Data Brokers

Given that artificial intelligence capabilities will continue to rapidly change how and when we receive information about the health of patients, and given nurses are currently the information hub for most complex cases (e.g., case managers), they are well-positioned to be future healthcare information data brokers. Nurses already utilize scientific principles, mathematical concepts and cutting-edge technology featuring artificial intelligence to assess, diagnose, and plan patient care [55]. As nurses become experts in new, and more sophisticated technologies, they will likely lead their healthcare teams in translating data and sensor-derived information into knowledge that reliably informs care decisions and interventions.

Limitations

The small sample size and characteristics restricts generalizability of the findings, and participants' perspective may not reflect the experiences of nurses in different clinical settings. Additionally, the study relied on self-reported interpretations, which introduces the potential for bias. No participants had prior experience working with smart home data, however, all were experienced nurses. Additionally, the scenarios chosen for this study were vetted by a nurse scientist (RF) having experience working with smart home sensor data and creating visualisations. Scenarios were purposively chosen containing data about health events that subjectively represented easy, medium, and hard to interpret data. No scenarios were presented that were deemed impossible to interpret.

Future research should examine how nurses with varying levels of data literacy and technology exposure engage with smart home health data visualisations, incorporate objective usability assessments and comparative studies to strengthen the reliability of findings, and should explore how training in data literacy and digital health tools impacts nurses' ability to use sensor-based health information effectively.

Conclusion

This study provides new insights into nurses' interpretation of health-smart home-generated data, revealing key challenges in sleep, mobility, and activity trend analysis. Findings highlight the need for improved visualisation techniques, clinician training, and standardized benchmarks to optimize sensor-based clinical decision-making in home care settings.

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Conflict of Interest Declaration

The authors have no conflicts of interest.

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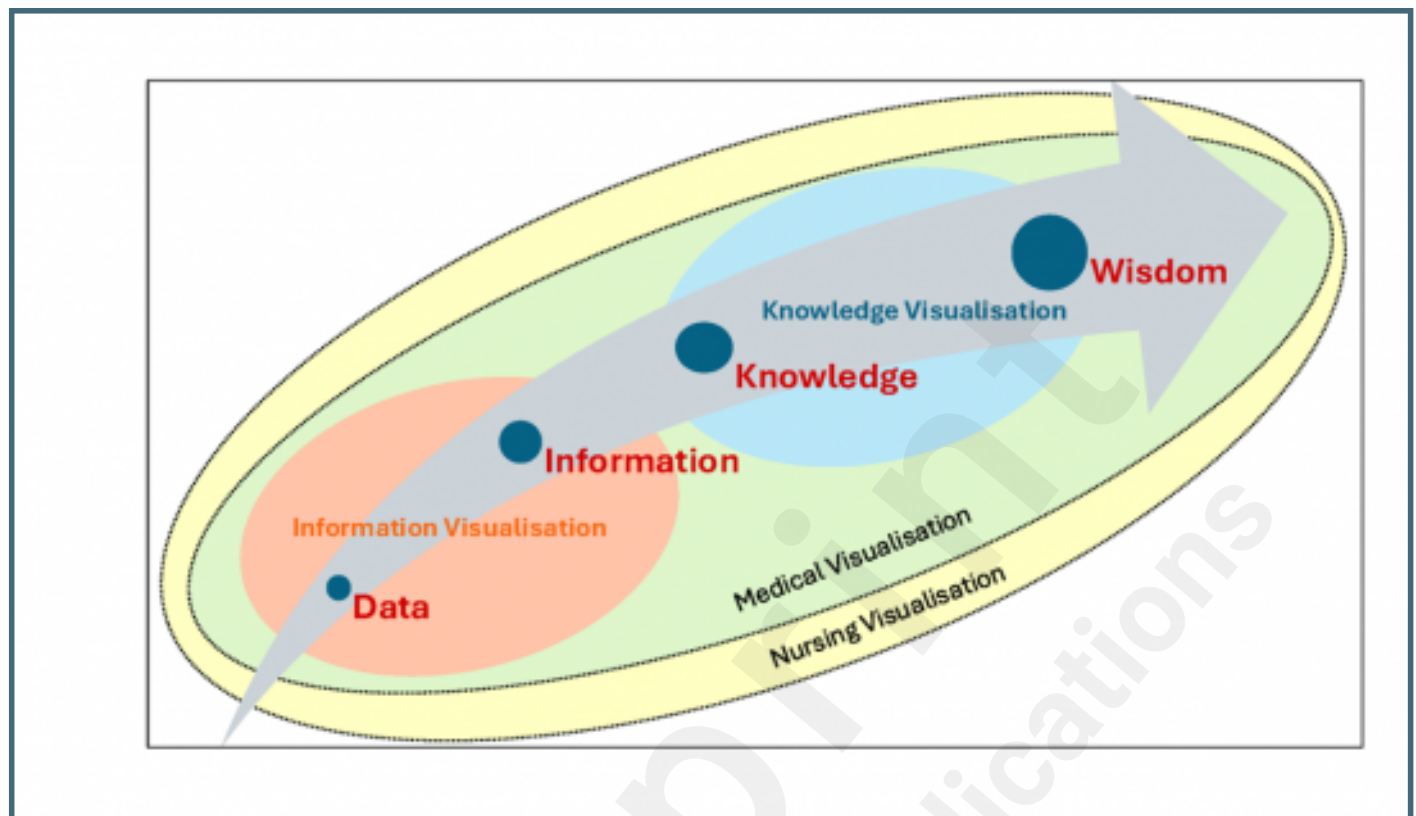
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Supplementary Files

Figures

Data to wisdom continuum in the context of health-smart home data visualisations.



Exemplar visualisations RN participants were asked to interpret.



CONSORT (or other) checklists

Coreq checklist.

URL: <http://asset.jmir.pub/assets/d7fc19d66d9b283bf9942dc8406b8bd8.pdf>

