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Feasibility of sensor technologies data to enhance digital comprehensive geriatric assessment system

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Abstract

Background: As Canada's population ages, delivering high-quality, personalized care to older adults, particularly in home and community settings, has become increasingly important. The interRAI Home Care (RAI-HC) assessment is widely used to evaluate older adults' health, functional status, and ability to live safely at home. However, its effectiveness can be limited by infrequent updates, administrative burden, and reliance on episodic data collection. Integrating sensor technologies into a digital version of the RAI-HC may help address these challenges.

Research aim/question(s): This study examines the technical and conceptual feasibility of using sensor-generated data to support selected components of the interRAI Home Care (RAI-HC) assessment, as a foundation for developing a Digital Comprehensive Geriatric Assessment (D-CGA) system.

Methods: A five-stage feasibility framework was applied. First, commercially available technologies were identified through structured searches of major Canadian consumer-facing online platforms, alongside AGE-WELL–affiliated technologies. Second, a structured extraction matrix was developed to document sensor characteristics, data types, interoperability features, and validation evidence. Third, sensor-derived data were mapped to geriatric health domains based on existing literature. Fourth, these literature-informed domains and data types were analytically aligned with RAI-HC assessment sub-domains and questions using the interRAI Version 10.0 Standard Edition. Finally, initial clinical validation was conducted through consultation with a clinician experienced in RAI-HC implementation.

Results: Eighty-three sensor technologies (49 commercial and 34 AGE-WELL) were retained. Mapping identified 15 RAI-HC assessment questions for which sensor-derived data could potentially contribute. Clinical validation indicated that five questions could be fully supported by sensor data, five partially supported, and five required clinical judgment.

Conclusions: Sensor technologies show selective potential to support components of the interRAI Home Care assessment, while many RAI-HC items remain dependent on clinical interpretation. These findings support the feasibility of partial digitization, rather than full automation, of comprehensive geriatric assessment within a future D-CGA system.

Keywords: RAI-HC, comprehensive geriatric assessment, sensor technology, digital health

Introduction

As the population ages, delivering high-quality, timely and personalized care to seniors has become increasingly important. Comprehensive geriatric assessments (CGAs) are central to identifying the medical, psychological, functional, and social needs of seniors, especially those receiving home care (Panza et al., 2018). The interRAI Home Care instrument (RAI-HC) is widely used in Canada and internationally, offering a standardized way to evaluate older adults in home and community care settings (Salahudeen & Nishtala, 2019). Currently, RAI-HC assessments are typically conducted in person by health care professionals through interviews and direct observations (Canadian Institute for Health Information, 2025). Several articles have shown that RAI-HC is effective in guiding care planning, allocating resources, and monitoring the quality of care (Guthrie et al., 2019; Harman et al., 2019; Yamada et al., 2014).

However, the effectiveness of the RAI-HC is often limited by infrequent data collection, administrative burdens, and inconsistencies in data quality (Guthrie et al., 2019). The digitization of RAI-HC may overcome these challenges by enabling more timely and accurate assessments (Sinn et al., 2022). Recent studies of interRAI implementation suggest digital approaches can streamline workflows and improve assessment consistency (Sinn et al., 2022). Moreover, there are some arguments around the integration of sensor technologies that can provide real-time, objective data on daily activities and health status, which supports evidence-based care planning (Stoop et al., 2019). Recent research has shown that integrating sensor technology into CGA could improve accuracy and responsiveness (Sinn et al., 2022; Stoop et al., 2019).

Literature review

Traditionally, CGA is conducted in person by healthcare professionals. However, this conventional approach faces several limitations, such as restricted accessibility, discontinuity of care, and outdated data. In response to rising demands in home care and persistent staffing shortages, digital health solutions, particularly those integrating sensor technologies, have garnered growing attention (Ulate et al., 2021).

Over the past two decades, digital health solutions supporting CGA have evolved significantly, reflecting rising needs in healthcare and advances in technology (Stoop et al., 2019). Early efforts primarily focused on telemedicine and basic electronic health records to facilitate remote consultations and data sharing (X. Wu et al., 2024). As technology advances, more sophisticated tools like mobile health applications and web-based platforms have emerged, supporting multidimensional assessments and improved care coordination (Meng et al., 2023; Silva et al., 2018). In recent years, the integration of wearable sensors, artificial intelligence, and internet of things (IoT) devices has further altered CGA, showing a promising future for continuous, real-time monitoring of older adults' daily activities and health status (Patel et al., 2012). These innovations have enhanced the accuracy and timeliness of assessments and demonstrated a clear evolution from basic digital support to comprehensive approaches in CGA (Tsiachristas et al., 2017).

Sensor technologies, defined as devices or systems that detect and respond to physical stimuli such as movement, temperature, or physiological signals, are increasingly being integrated into healthcare to enable real-time monitoring and data collection (Patel et al., 2012). Sensor technologies are increasingly proposed as viable tools for supplementing or partially automating sections of the CGA. A study by Meng et al. (2023) demonstrated the feasibility of using AI-driven sensor networks to track geriatric health indicators such as mobility, sleeping patterns, and fall risks, showing alignment with CGA components like Activities of Daily Living (ADLs) and cognitive assessments. The integration of sensor monitoring tools enables continuous data capture, overcoming the limitations of periodic manual assessments and reducing reliance on self-reporting, which can be biased or inaccurate among older populations (Hellmers et al., 2017). However, despite these advantages, sensor technologies face several challenges. These include concerns about data privacy and security, the potential for technical malfunctions or inaccuracies, and issues related to user acceptance, particularly among older adults who may be less familiar with digital technologies (Peek et al., 2014). Additionally, the implementation of sensor systems can be costly and may require significant infrastructure and ongoing maintenance, which can limit their widespread adoption in resource-constrained settings (Peek et al., 2014).

The integration of sensor technologies into D-CGA has advanced the ability to monitor older adults in real time, providing objective and continuous data that complement traditional assessment domains. For example, wearable accelerometers and gyroscopes, often embedded in wristbands or belt-worn devices, are used to track gait speed, step count, and balance, offering accurate measurements of mobility and fall risk that are otherwise difficult to measure through self-report or traditional periodic clinical observation(Kaye et al., 2012). Smart insoles equipped with pressure sensors can monitor gait patterns and foot pressure distribution, which are valuable for identifying early signs of frailty or mobility impairment (Das et al., 2024). In-home environmental sensors use capacitive textile mats to unobtrusively track movement, detect falls, and monitor room-to-room transitions, providing insights into daily living activities and behavioral changes (Schwickert et al., 2013). Additionally, radar-based sensors enable contactless monitoring of vital signs, including heart rate and respiratory rate, which can be integrated into D-CGA platforms for early detection of acute health events (Islam et al., 2022). These sensor technologies automatically transmit data to cloud-based assessment platforms, where algorithms analyze trends and deviations, allowing clinicians to receive timely alerts and make data-driven decisions for individualized care planning (Cook, 2020; Fan et al., 2023) By incorporating these advanced sensor technologies, D-CGA becomes more dynamic, precise, and responsive to the needs of older adults (Del Din et al., 2016; Wild et al., 2008).

Sensor technologies have shown significant promise in the digitization of CGA (Kaye et al., 2012; Wild et al., 2008). However, despite the growing body of research on sensor technologies and the digitization of geriatric assessments, there remains a notable gap in the integration of sensor technologies within standardized geriatric assessment frameworks such as the Resident Assessment Instrument–Home Care (RAI-HC). Existing literature on RAI-HC has largely focused on its implementation, data quality, and the development of quality indicators (Gray et al., 2009; Poss et al., 2008; Sinn et al., 2022), with little attention given to leveraging sensor technologies to improve assessment accuracy and timeliness (Morita et al., 2023). Most systematic reviews have evaluated the use of RAI-HC instrument in research and its role in integrated care programs (Veronese et al., 2022), but the potential for sensor integration remains unexplored. By systematically mapping available sensor technologies to RAI-HC subsections, our study addresses this critical gap and demonstrates the feasibility and benefits of incorporating sensor technologies into D-CGA systems. This study represents an important step towards more timely, objective, and informed care planning for older adults.

Research aim

This study aims to examine the usability and applicability of sensor-generated data for conducting comprehensive geriatric assessments and digitizing the interRAI Home Care (RAI-HC) instrument, with the goal of enhancing the accuracy, timeliness, and efficiency of assessments. Specifically, the research investigates whether commercially available and AGE-WELL sensor technologies can provide the necessary data to support the RAI-HC assessment and contribute to the development of a Digital Comprehensive Geriatric Assessment (D-CGA) system.

The central research question explores to what extent existing sensor technologies, and their collected data can address the questions within the RAI-HC, thereby supporting automated and real-time assessments of older adults in home and in community settings.

This study serves as a foundation for developing a Digital Comprehensive Geriatric Assessment (D-CGA) system, aimed at improving evidence-informed care and supporting aging-in-place through sensor-driven insights.

Method

The methodological process comprised five key stages. First, Technology Identification involved structured searches of major Canadian consumer-facing online platforms and AGE-WELL innovation databases to identify commercially available sensor technologies relevant to geriatric assessment. Second, Matrix Design entailed cataloguing identified technologies based on their sensors, data collection capabilities, data storage features, and interoperability potential. Third, Domain Mapping linked sensor-derived data types to broader health domains using evidence from existing literature. Fourth, these literature-informed domains and sensor data were systematically mapped to interRAI Home Care (RAI-HC) assessment sub-domains and questions based on item intent and definitions, representing the novel contribution of this study. Finally, Clinical Expert Validation was conducted through consultation with a clinician experienced in RAI-HC assessments to provide initial validation of the practical relevance and assessability of the proposed mappings. This structured, feasibility-focused approach was designed to assess the technical and conceptual feasibility of aligning sensor technologies with RAI-HC assessment items, rather than to evaluate real-world implementation or user acceptance.

Technology identification

For commercial technologies, a structured, market-based search strategy was used to identify consumer health technologies accessible in Canada. First, commonly used and well-established online platforms and retailers through which Canadians typically purchase electronics and health technologies were identified using market research and targeted Google searches. Based on platform prominence and relevance, retailers such as Amazon Canada, Best Buy Canada, Walmart Canada, Shoppers Drug Mart, London Drugs, and Telus Health were selected.

Within each platform, keyword-based searches were conducted using terms aligned with major geriatric and interRAI-related health domains, including general health monitoring, mobility, cognition, vital signs, sleep, medication management, social engagement, and caregiver support. A combination of broad and domain-specific terms was used to ensure comprehensive coverage of available technologies. Search results were screened to identify technologies relevant to older adult assessment and monitoring.

For AGE-WELL technologies, the AGE-WELL startup map was used as the primary source. Each listed startup's website was reviewed to identify technologies with potential relevance to RAI-HC assessment, focusing on those that incorporated sensor-based data collection and digital health monitoring capabilities (AGE-WELL Network of Centres of Excellence, 2022).

Matrix design

Identified technologies were systematically documented using a structured data extraction matrix developed in Microsoft Excel. The matrix was designed to capture key characteristics relevant to feasibility assessment and subsequent mapping. Extracted information was organized into four main categories: general information, functionality, data and ethics, and validation and evidence.

The general information category included the technology name, company or vendor, product website, platform where the technology was identified, and commercial availability in Canada. The functionality category captured the intended assessment function, relevant health domain(s), product design focus (e.g., older adults, caregivers, general users), and interaction mode (e.g., wearable, ambient sensor, voice-based).

The data and ethics category documented the types of data collected, data recording and storage mechanisms, interoperability features, and any explicit references to privacy, security, data ownership, data sharing, or data storage location, following a digital health ethics framework described in prior work (Goubran et al., 2023). The validation and evidence category recorded whether the technology referenced research or clinical validation and included additional notes or observations relevant to feasibility.

Using this extraction matrix, both commercial and AGE-WELL technologies were screened to retain those that were commercially available, capable of recording and storing data, and demonstrated potential relevance to at least one health domain of interest for subsequent mapping. This step supported systematic comparison across technologies and informed downstream domain and RAI-HC mapping stages.

Domain mapping based on literature

In this stage, sensor-derived data were mapped to broader health domains relevant to Comprehensive Geriatric Assessment (CGA) using evidence from existing literature. To support this process, relevant studies were reviewed, and a literature-based validation table was developed, including four key elements: health domains, sensor types, data generated, and supporting references. Sensor domains and mapped items are summarized in *Table 1*.

Drawing prior research, health domains commonly addressed in CGA were systematically aligned with corresponding sensors and the types of data they produce. The study by Anikwe et al.(2022) provided a primary foundation by mapping 15 disease- and diagnosis-related application domains to specific sensor technologies. These domains were incorporated into the validation table. Additional domains, including medication management, social engagement, and home environment, were identified using complementary studies (M. Zallio et al., 2016; Mason et al., 2022; Popp et al., 2024).

Information on sensor characteristics, strengths, limitations, and data outputs was extracted primarily from Anikwe et al.(2022) and further supported by studies cited within those work and additional relevant sources. Studies were selected if they explicitly supported relationships between health domains, sensor technologies, and associated data types. For example, within the human activity identification domain, accelerometers, gyroscopes, and pressure sensors were mapped to corresponding data outputs based on validated evidence from the literature.

By synthesizing findings across multiple studies, this stage produced a validated mapping between health domains, sensor technologies, and sensor-generated data. This literature-informed domain mapping that is shown in *Table 1* served as the analytical foundation for the subsequent stage, in which health domains and sensor data were mapped to interRAI Home Care (RAI-HC) assessment sub-domains and questions.

Mapping of sensor-derived data to RAI-HC assessment items

In this stage, the health domains and sensor-derived data identified through the literature-based mapping were systematically aligned with interRAI Home Care (RAI-HC) assessment sub-domains and questions, using the interRAI Version 10.0 Standard Edition. This step constitutes the primary analytical contribution of the study, extending existing sensor–health domain relationships to a standardized geriatric assessment framework.

Each RAI-HC assessment item was examined in detail according to its Section, Subsection, Part, Table Code, Intent, and Definition. Sensor-generated data and corresponding health domains were then analytically evaluated to determine whether they could plausibly inform the underlying construct assessed by

Table 1. Mapping health domains to sensor-collected data based on literature evidence

Health domains	Sensors	Data	Related articles
1. Human activity identification/posture monitoring/behavior patterns/ Real-world activities of daily living in the home/ Physical activity pattern and behavior/ Mobility/ Functional status and health	Accelerometer, gyroscope and pressure sensor	Body acceleration and angular rate or change in rotational angle per unit of time	(Acharya et al., 2019; Canzian & Musolesi, 2015; Y. Chen & Wang, 2017; Jin et al., 2014; Spinsante et al., 2016; Sundaravadivel et al., 2016; Syed et al., 2019)
	ECG	Heartbeat, heat waves, hearts' rhythm and irregularities;	(J. S. Lee et al., 2014; Sodhro et al., 2018; Wannenburg et al., 2018)
	Pedometer	Steps, heart rate, walking speed and physical activity	(Beevi et al., 2016)
	EMG	Muscle actions	(Hegyi et al., 2019; Juen et al., 2014; Lim et al., 2020; Michelsen et al., 2020)
	Temperature sensor	Temperature changes and muscle movements during the activities of drinking hot water and working out	(Thaung et al., 2020; Trung et al., 2016)
	Pulse oximeter sensor	Oxygen saturation and pulse rate	(Marino et al., 2020; Thaung et al., 2020)
	Waist accelerometer	Moderate to vigorous physical activity levels	(Popp et al., 2024)
	Motion and hydro sensor	Toilet use, bathing, cooking, detailed logs of daily activities	(Chung et al., 2017)
	Pendant sensor	Walking, sitting, standing, sedentary, light, moderate-to-vigorous, total steps, prolonged stepping bout	(Razjouyan et al., 2018)
	Smartphone motion sensors	Walking movements	(S. Lee et al., 2021)
	Ambient sensors and video sensors	Video data, events requiring intervention	(Skubic et al., 2009)
	Pressure-sensitive mats with fiber-optic pressure sensors	Pressure distribution data, state transition features	(S. Bennett et al., 2015)
	Smartphones' built-in sensors or surroundings such as GPS, accelerometer, gyroscope, digital compass, camera, and microphones	Information related to the device (e.g., receiving a phone call)	(Castro et al., 2015)
	Ultra-wide band impulse-radio sensors	Sleeping in bed, sitting up in bed, falling, wandering in the room, and going in/out of the door	(K. Ota et al., 2011)
	Mat-shaped step sensors and a foot switch	Contact of the feet on the floor	(Masuda et al., 2002)
	Passive radiofrequency identification-based system	Activity tracking, the number of falls, the cases of wandering from the yard, leaving/entering doors	(Nugent & Augusto, 2006)
	GPS/cell-tower sensors	Location data, deviations from the normal traces, emergencies	(Vuong et al., 2011)
2. Sleep disorder and sleep stage detection	PPG	Blood volume changes, heart rate variability and light physical exercise	(Dey et al., 2017; Roy & Gupta, 2020)
	EEG	Electrical exercise of the human brain	(Krishna et al., 2021; Zhang & Wu, 2018)
	Wireless mattress sensor	Latency between movement, coupled respiratory upregulation and sleep time	(Khosroazad et al., 2023)
	Alternative commercial accelerometer-based devices	Sleep stages and durations	(Hakim et al., 2017; Ravichandran et al., 2017)
3. Fall detection	Accelerometer, gyroscope and magnetometer sensor	Fall and activities of daily living	(Giuberti et al., 2015; J. K. Lee et al., 2014; Y. Lee et al., 2018)
	DomoCare (PIR Motion sensor) and EMFIT QS (bed sensor beneath mattress)	Number of daily room-transitions (movement in the apartment),	(Schütz et al., 2022)
4. Bipolar disorder detection or social anxiety/ Depression and mood swing/ Late-life depression	Accelerometers, GPS, gyroscope, magnetometer, and proximity sensor	Early-stage change, depressive symptoms harshness, behavioral markers and patient at-risk population	(Abdullah et al., 2016; Grünerbl et al., 2014; Huang et al., 2016; Saeb et al., 2015)
	EMFIT QS (bed sensor beneath mattress)	Time in bed	(Schütz et al., 2022)
	Movement-based sensors and phone-based sensors	App use, phone calls, inferred sleep times, movement category (e.g., walking, in a vehicle)	(Adler et al., 2020; Wang et al., 2018)
	GPS	Location information, heading change rate, distance covered velocity change rate, phone call frequency	(Boukhechba et al., 2017; Canzian & Musolesi, 2015; Lin & Hsu, 2014; Saeb et al., 2015)

5. Motion state and stress detection	Heart rate and SPO2, blood pressure, and temperature sensor	Mental health and general wellbeing, physical activities	(Nedungadi et al., 2018)
	PPG and accelerometer	Vital signs, body present changes	(Wannenburg & Malekian, 2015; Yu et al., 2018; X. Zhou, 2020)
	EEG	State emotion recognition	(Xu & Plataniotis, 2016; Zhang & Wu, 2018)
6. Psychiatric detection	Accelerometer, acoustic, GPS, and light sensor	Mental health and general functioning in an individual with schizophrenia	(Ben-Zeev et al., 2015; Difrancesco et al., 2016; Wang et al., 2016)
7. Disease diagnosis and wellbeing	EEG, and ambient light sensor (for Parkinson's disease)	Electrical exercise of the human brain and the intensity of light	(Giuberti et al., 2015; Krishna et al., 2021; Zhang & Wu, 2018)
	ECG, EEG (for neurological disease)	Cardiac rhythms and abnormal brain functionality	(Mishra et al., 2018; Subasi et al., 2020)
	Inertial sensors (accelerometers and piezo-electric), ultrasonic sensors, inductive proximity sensing sensors, piezo-floating gate sensing and capacitive sensing, and the recently developed surface capacitive technology (for fracture)	Bone healing progress and early implant loosening	(Jeyaraman et al., 2023)
8.Cardiac disease management/Diabetes retinopathy	PPG, ECG	Variation between consecutive heartbeats and the activity of the autonomic nervous system	(Bánhalmi et al., 2018; Dey et al., 2017; M. Essalat et al., 2016; Nam et al., 2016)
	ECG, SCG	Heart rate carry out translational and rotational cardiac vibrations	(Deshpande & Kulkarni, 2017; Elgendi et al., 2018; Etiwy et al., 2019; Iftikhar et al., 2018; M. Neyja et al., 2017; Mena et al., 2018; Sahoo et al., 2017; T. P. Susič & U. Stanič, 2016; Wannenburg et al., 2018)
	Pulse oximeter	Oxygen saturation and pulse rate	(Harris et al., 2019; Marino et al., 2020)
	Pedometer	Heart rate	(Beevi et al., 2016; M. B. Nair et al., 2018)
	Vitaliti Continuous Vital Signs Monitor	ECG, heart rate, heart rate variability, respiration rate, temperature (infrared sensor applied to the ear), SpO2, continuous and noninvasive blood pressure	(McGillion et al., 2022)
9. Medications	Ingestible sensors (pills embedded with ingestible microsensors that are paired with an external wearable sensor and mobile app), Electronic Medication Management System (EMMS), video camera, motion sensor technology (wrist-worn devices that contain motion	Medication ingestion events, scales and medication dispensing events, date-and-time stamps, medication-taking events, patient medication adherence data	(Mason et al., 2022)

each RAI-HC item. This alignment was conducted through careful interpretation of item intent rather than through direct one-to-one substitution of sensor measures.

Crucially, the RAI-HC instrument is designed to assess not only health status, but also an individual's ability to live independently, safely, and healthily in the community, integrating functional, environmental, and contextual dimensions of care. Consequently, for a substantial proportion of RAI-HC questions and sub-domains, no suitable sensor-based proxy could be identified. In these instances, technologies were deliberately not assigned, reflecting the recognition that sensor data alone cannot adequately capture complex aspects of judgment, independence, safety, or care needs.

Accordingly, mapping decisions were intentionally conservative and feasibility-oriented. Only those RAI-HC items for which sensor-derived data could reasonably contribute to assessment were identified as potentially assessable. This approach ensured that the analysis reflected technical and conceptual feasibility, while avoiding overextension of sensor technologies within the broader scope of comprehensive geriatric assessment.

Clinical expert validation

To provide initial clinical validation of the proposed mapping framework, we conducted targeted consultations with a clinician who has direct experience administering the interRAI Home Care (RAI-HC) assessment in practice. The expert is a former registered nurse and currently serves as Lead, Clinical Program Standards (Home and Community Care), with extensive experience implementing RAI-HC assessments among older adults in Northern Canadian care settings. Owing to the feasibility and scope constraints of this study, clinical input was obtained from a single expert.

The purpose of this validation was not to establish expert consensus, but to assess the clinical plausibility and practical relevance of the proposed mappings. For each mapped RAI-HC item, the expert was asked to indicate whether the available sensor-derived data could fully support, partially support, or not support the assessment of that item in routine practice. Discussions also explored how RAI-HC items are operationalized in real-world assessments, and which components could reasonably be informed by sensor-generated data.

The expert's input was used to identify areas where sensor data may meaningfully contribute to assessment, as well as areas where such data would be insufficient to support RAI-HC items. This step provided practitioner-informed validation of the mapping logic while remaining consistent with the exploratory and feasibility-focused objectives of the study.

Results

In the initial technology identification stage, 55 commercial technologies were identified through structured, market-based searches of Canadian consumer-facing platforms, and 113 technologies were identified from the AGE-WELL startup map. All commercial technologies were publicly available online, while 41 AGE-WELL technologies were accessible for review. Based on their ability to record and store data relevant to geriatric assessment, 49 commercial technologies and 34 AGE-WELL technologies were retained for subsequent analysis.

To synthesize the findings, a structured mapping matrix was developed (*Table 2*) to examine the potential alignment between sensor technologies, their data outputs, and interRAI Home Care (RAI-HC) assessment content. Each RAI-HC assessment item is organized using the columns RAI-HC Section, RAI-HC Subsection, and RAI-HC Part, reflecting the hierarchical structure of the instrument, while RAI-HC Item Intent and RAI-HC Item Definition describe the clinical purpose and meaning of each item.

Evidence from the literature was used to establish associations between sensor-derived data types (e.g., activity patterns, gait metrics, sleep parameters, cardiovascular indicators, location and environmental signals) and associated health domains relevant to older adults (e.g., mobility, sleep, cardiovascular health, functional ability). These literature-informed relationships are presented in the columns Associated Health Domain (Literature-Based) and Relevant Sensor-Derived Data (Literature-Based).

Building on this foundation, the novel analytical step of the study involved aligning sensor-derived data and health domains with specific RAI-HC assessment items by evaluating consistency with each item's Intent and Definition. This alignment represents a feasibility assessment rather than a claim of direct measurement.

The final column, Clinical Feasibility of Sensor Data for Assessment (Expert Judgment: Yes / Partial / No), summarizes clinical validation provided by an experienced RAI-HC clinician. This column reflects expert judgment regarding whether the identified sensor data could fully support, partially support, or not support assessment of each RAI-HC item in practice.

Overall, 15 RAI-HC assessment items were identified for which sensor-derived data could potentially contribute. *Table 2* summarizes these items alongside their associated health domains, relevant sensor-derived data, and clinical feasibility assessments.

Discussion

This study highlights the potential of sensor technologies to support the interRAI Home Care (RAI-HC) instrument for comprehensive geriatric assessment. Through a systematic scan of commercial and AGE-WELL technologies, we identified 83 technologies capable of collecting data relevant to the home care needs of older adults, including 49 commercial technologies and 34 AGEWELL technologies. By mapping these technologies into RAI-HC questions and reviewing the supporting literature, we identified 15 questions that could potentially be assessed using sensor-derived data. Validation with an interRAI Home Care expert revealed that among these 15 questions, five can be directly assessed through sensor data, five can be meaningfully supported by such data, and five cannot currently be assessed using sensor data alone.

The domains that can be directly assessed through sensor data include mobility, activity level, falls, home environment, and medication management. The domains that can be partially supported by sensor technologies, where data can assist but not replace clinical judgment, include capacity for completing cognitively based Instrumental Activities of Daily Living (IADL) tasks, social interactions, activities of daily living (ADL) self-performance, and wandering. Conversely, questions related to psychosocial well-

Table 2. Sensor technologies data and interRAI questions mapping matrix

RAI-HC Section	RAI-HC Sub Section	RAI-HC Part	RAI-HC Intent	RAI-HC Definition	Associated Health Domain (Literature-Based)	Relevant Sensor-Derived Data (Literature-Based)	Clinical Feasibility of Sensor Data for Assessment (Expert Judgment: Yes / Partial / No)
C. COGNITION	2. CAPACITY FOR COMPLETING COGNITIVELY BASED IADL TASKS	b. MANAGE MEDICATIONS	To stimate the person's cognitive capacity to carry out key instrumental activities of daily living (IADLs). It is recognized that there is a physical component with such tasks (for example, ability to use hands); but successful task performance in these areas is largely centered on a person's cognitive ability to manage the overall tasks.	How medications are managed (e.g. remembering to take medicines, opening bottles, taking correct drug dosages, giving injections, applying ointments)	9. Medications	Clock time, Scheduled alarms,Medication schedule, Medication frequency, Dispensing activities, Medication alerts, Missed doses, Reminders confirmations, Patients' clinical status	Partially – Sensor data from medication management devices can indicate recent use or missed doses but cannot determine whether medications were managed independently. Clinical judgment is required to interpret reasons for non-adherence and overall capacity.
C. COGNITION	2. CAPACITY FOR COMPLETING COGNITIVELY BASED IADL TASKS	c. MANAGE USE OF ELECTRONIC DEVICES	To estimate the person's cognitive capacity to carry out key instrumental activities of daily living (IADLs). It is recognized that there is a physical component with such tasks (for example, ability to use hands); but successful task performance in these areas is largely centered on a person's cognitive ability to manage the overall tasks.	How devices are managed (for example, computer, tablet, smartphone)	1. Human Activity Identification	Voice call logs; Call history; Message interaction history; Messages (text, audio, video)	Partially – Device use can be observed, but it cannot determine whether tasks were performed independently or with assistance. Professional judgment remains necessary.
E. MOOD AND BEHAVIOUR	1. INDICATORS OF POSSIBLE DEPRESSED, ANXIOUS, OR SAD MOOD	e. REDUCED SOCIAL INTERACTIONS	To record the presence of mood indicators observed in the last 3 days, irrespective of the assumed cause. In some cases, an indicator may not have been observed in the last 3 days, but it continues to be "present" and active in a way that has a meaningful impact on the person's current care needs. When combined with other items in the assessment, these indicators can provide information about the severity of the person's condition.	Focuses on: Quantity of social activities, Intensity(frequency of contact), Quality (depth of engagement), Emotional distress due to decline. Nurses assess this through conversation with the client:"Have you been attending your usual activities?" "Have there been any changes?" "Are you upset or bothered by this change?" Social isolation is highly contextual and personal.	11. Social engagement	Call metadata (time, participants), Call logs, Voice queries; Event participation stats, Session attendance, Session frequency/duration, Engagement duration & session logs; Photo/video uploads, Photo interactions;	Partially – Sensor data can capture technology-mediated interactions but cannot assess face-to-face social engagement.
E. MOOD AND BEHAVIOUR	4. BEHAVIOURAL SYMPTOMS	a. WANDERING (moved with no rational purpose, seemingly oblivious to needs or safety)	To identify the frequency of behavioral symptoms during the last 3 days that cause distress to the person, or are distressing or disruptive to others with whom the person lives. Such behaviors include those that are potentially harmful to the person or disruptive to others. Behavioral symptoms may reflect how a person experiences unmet needs, feelings of insecurity, fear or anxiety, or somatic symptoms such as pain or shortness of breath. Acknowleding and documenting behaviral symptoms provides a basis for further evaluation, planning, and delivery of consistent, appropriate care that can help to reduce the severity and frenquency of behaviral symptoms.	Moves about with no discernible, rational purpose. A wandering person may be oblivious to his or her physcial or safety needs. Wandering behavior should be differentiated from purposeful movement(such as a hungry person moving about the apartment in search of food.) Wandering may be walking or by wheelchair. Do not include pacing back and forth, which is not considered wandering.	1. Human Activity Identification	movement/posture; activity duration; steps tracking; location; presence/absence; room entries; fall events; motion & door opening detection; real-time obstacle detection events; dimensions of the tracked person's silhouette and shadows	Partially – Sensors can detect movement patterns but cannot determine whether movement constitutes wandering, which depends on intent and context. Clinical interpretation is required.
F. PSYCHOSOCIAL WELL-BEING	2. CHANGE IN SOCIAL ACTIVITIES IN LAST 90 DAYS (OR SINCE LAST ASSESSMENT IF LESS THAN 90 DAYS AGO)		To identify a recent change in the person's level of participation in social, religious, occupational, or other preferred activities. If the level of participation has declined, determine whether the person is distressed by it.	The level of participation refers to the different types of social activities, how frequently contact occurs, and how deeply the person is involved. Distress occurs when the person's mood is adversely affected by a recent change in the level of participation (as evidenced by sadness, loss of motivation or self-esteem, anxiety, or depression, for example).	4. Social Anxiety	Event participation, Session attendance, Voice call events + Call metadata (time, participants), Photo/video uploads, Game interactions, Engagement duration / Usage duration, User interactions, Cognitive/physical engagement	No – While activity levels can be tracked, emotional distress and quality of social engagement cannot be assessed without direct clinical interaction.
F. PSYCHOSOCIAL WELL-BEING	4. DEGREE OF LONELINESS		To identify if the person is lonely and, if so, how lonely.		11. Social engagement	Room entries, Motion/door triggers with timestamps and sensor ID, First motion times, Open/close events with timestamps, Voice call events, Session attendance, Location data upon alert activation	No – Sensors may measure time spent alone but cannot assess subjective experiences such as loneliness.
G. FUNCTIONAL STATUS	5. ACTIVITIES OF DAILY LIVING (ADL) SELF-PERFORMANCE	j. BED MOBILITY	To record what the person did and how others assisted in the performance of common self-care tasks, often called activities of daily living (ADLs), during the last 3 days. The focus is on what the person actually did for him- or herself and how much verbal or physical assistance, if any, was provided by informal and formal caregivers for a given task.	Bed mobility - How the person moves to and from a lying position, turns from side to side, and positions his or her body while in bed. Note: "Bed mobility" includes those tasks completed once a person is lying on the bed or other sleeping surface. It does not include lifting the legs in and/or out of the bed.	1. Human Activity Identification	Pressure distribution data, postural data (inferred), movement and posture data, dimensions of the tracked person's silhouette and shadows, body movement and vital signs, sleeping quality and patterns, and activity and sleep data	Partially – Sensor data can provide information on bed mobility and positional changes but cannot determine the level of assistance required, which must be coded clinically.
G. FUNCTIONAL STATUS	1. MOBILITY	c. IN THE LAST 3 DAYS, NUMBER OF DAYS WENT OUT OF RESIDENCE (no matter how short the period)		This means that the person went outdoors, no matter how short the period of time he or she spent outdoors. This could mean going into the yard, standing on an open porch, going out to the garden, or walking down the street.	11. Social engagement	GPS-tracked activity & location data, Safety feature location data, Motion/door triggers & open/close events, Time in the room & activity logs, Engagement/session attendance	Yes – Sensor data may support coding of certain behaviors; however, it cannot distinguish between purposeful activities (e.g., leaving home) and incidental actions, and privacy considerations apply.

G. FUNCTIONAL STATUS	2. ACTIVITY LEVEL	b. TOTAL HOURS OF PHYSICAL ACTIVITY IN LAST 3 DAYS	Moderate daily physical activity helps home care patients maintain fitness and prevent decline, but motivation, barriers, and health education play key roles in whether they engage in healthy lifestyle practices. While many recognize the importance of exercise and nutrition, they often need support or guidance to make meaningful changes.	Physical activity- Usual daily activity such as walking/wheeling about the residence (for example, to room in house, to do housework); walking/wheeling outdoors(for example, walk around the building or block, to work in the garden, to walk with family or friends in the neighborhood, to got out for a long walk or run).	1.Human Activity Identification	Activity duration / session duration; Physical activity and exercise metrics; Stress and activity logs; Timestamped activity indicators / measurement timestamps; Time of use	Yes – Activity duration can be tracked, but sensors cannot determine whether activity is intentional exercise or incidental movement.
I. DISEASE AND DIAGNOSES	1. DISEASE AND DIAGNOSES	c. ALZEIMER'S DISEASE	To document the presence of diseases or infections relevant to the person's current ADL status, cognitive status, mood or behavior status, medical treatments, nursing monitoring, or risk of death. In general, these types of conditions are associated with the type and level of care needed by the person. Do not include conditions that have been resolved or no longer affect the person's functioning or care needs.	A degenerative, progressive, and irreversible dementia that slowly erodes memory, geographic orientation, reasoning, and decision making.	10. Cognitive Health	Speech outputs; Memory function; Real-time, relevant and contextualized data on patients' clinical status for clinicians; Clinical assessment data	No – Sensors cannot determine disease presence; they do not assess diagnostic status.
I. DISEASE AND DIAGNOSES	1. DISEASE AND DIAGNOSES	g. OTHER DEMENTIA, EXCLUDING ALZHEIMER'S, VASCULAR, LEWY BODY, AND FRONTOTEMPROAL DEMENTIAS	To document the presence of diseases or infections relevant to the person's current ADL status, cognitive status, mood or behavior status, medical treatments, nursing monitoring, or risk of death. In general, these types of conditions are associated with the type and level of care needed by the person. Do not include conditions that have been resolved or no longer affect the person's functioning or care needs.	Includes diagnoses of organic brain syndrome(OBS) or chronic brain syndrome(CBS), senility, senile dementia, and dementia related to other neurological diseases (such as Pick's disease, CreutzfeldtJakob disease, Hungtington's disease, etc.)	10. Cognitive Health	Speech outputs; Memory function; Real-time, relevant and contextualized data on patients' clinical status for clinicians; Clinical assessment data; Presenting symptoms	No – Sensors cannot determine disease presence; they do not assess diagnostic status.
I. DISEASE AND DIAGNOSES	1. DISEASE AND DIAGNOSES	a. HIP FRACTURE DURING LAST 30 DAYS (OR SINCE LAST ASSESSMENT IF LESS THAN 30 DAYS)	To document the presence of diseases or infections relevant to the person's current ADL status, cognitive status, mood or behavior status, medical treatments, nursing monitoring, or risk of death. In general, these types of conditions are associated with the type and level of care needed by the person. Do not include conditions that have been resolved or no longer affect the person's functioning or care needs.	Includes any hip fracture that occured during the last 30 days (or since the last assessment, if that was less than 30 days ago) that continues to have a relationship to current status, treatments, monitoring, etc. Hip fracture diagnoses include femoral neck fractures, fractures of the trochanter, and subcapital fractures.	7. Disease diagnosis and wellbeing	Gait/postural changes; Real-time, relevant and contextualized data on patients' clinical status for clinicians	No – Sensors cannot determine disease presence; they do not assess diagnostic status.
J. HEALTH CONDITIONS	1.FALLS		To determine whether the person has a history of falling. Persons who have sustained at least one fall are at risk of future falls. Falls are a common cause of morbiduty and mortality among persons receiving home care. Serious injury results in from 6% to 10% of falls, with hip fractures accounting for apporoximately one-half of all serious injuries.	Fall-Any unintentional change in position where the peson ends up on the floor, ground, or other lower level; includes falls that occur while being assised by others.	3. Fall Detection	Human pose and motion; Mobility and activity levels; Fall detection	Yes – Fall detection data can quantify the number of falls over a defined period and support confirmation of reported events.
Q. ENVIRONMENTAL ASSESSMENT	1. HOME ENVIRONMENT	b. INADEQUATE HEATING OR COOLING (e.g. too hot in summer, too cold in winter)	To determine if the home environment is hazadous or uninhabitable.		11. Home Environment	Humidity (real-time and historical); Indoor temperature, outdoor temperature influence; Air quality	Yes – Sensor data can support assessment of temperature-related items (hot/cold).
M. MEDICATIONS	1. TOTAL NUMBER OF MEDICATIONS		To facilitate medication management, by having a total count of the number of different medications (prescribed and over-the-counter medications) that the person has taken in the last 7 days, excluding herbal/nutritional supplements.	Medications - Include all medications (prescription and over-the-counter medications) taken in the last 7 days; for example, pills, creams, ointments, eye drops, artificial tears.	9. Medications	Clock time, Scheduled alarms,Medication schedule, Medication frequency, Dispensing activities, Medication alerts, Reminders confirmations, Patients' clinical status	Yes – Sensor data can support assessment of medication adherence only.

being and disease and diagnoses cannot be adequately answered by sensor-derived data. These findings underscore the need for a hybrid assessment model, where sensor technologies complement rather than replace clinician expertise, client interviews, and caregiver input.

Integrating sensor data into the RAI-HC could enable more frequent, accurate, and objective updates, enhancing care planning, early detection of symptoms, and timely interventions. For health systems experiencing workforce shortages, such innovations may also reduce clinician workload while maintaining or even improving the quality of care. However, successful implementation will require careful attention to ethical considerations, including data privacy, informed consent, and equitable access, to ensure that digital solutions remain safe, acceptable, and inclusive.

To our knowledge, this is the first study in Canada to explore the digitization of the RAI-HC and to assess the feasibility of integrating sensor technologies into this process. Nonetheless, several limitations must be acknowledged. This study represents a conceptual and feasibility-based mapping exercise rather than an implemented digital assessment system. The technology identification process relies on market-based indicators such as product availability, user ratings, and purchase frequency to prioritize widely adopted technologies. However, formal evaluation of acceptability, affordability, accessibility, or equity-related factors was outside the scope of this study. In addition, while the technical and functional alignment between sensor technologies and RAI-HC assessment items was the primary focus, the perspectives of older adults and caregivers as end users were not directly examined. Target group acceptance, usability, and willingness to engage with sensor-supported assessments are critical determinants of successful real-world implementation, yet these aspects were not addressed in the current analysis.

Furthermore, validation of the proposed mapping framework was conducted with a single clinician experienced in RAI-HC assessments, providing initial clinical insight rather than consensus validation. Involving multiple experts and conducting proof-of-concept testing with real users would strengthen the generalizability and implementation of readiness of future studies. In this context, the term feasibility refers to the technical and conceptual feasibility of aligning sensor-generated data with RAI-HC assessment domains, rather than real-world implementation feasibility.

Future research should therefore prioritize pilot testing in real-world settings, incorporate user-centered evaluations, and assess acceptability, affordability, and accessibility alongside clinical and operational outcomes. It will also be important to explore how this field evolves with increasing sensor fusion and the integration of artificial intelligence (AI) technologies to correlate and interpret multiple data streams. Although this study did not examine AI-based approaches, future work could investigate how advanced analytics and machine learning models may enhance data integration, pattern recognition, and clinical decision support within Digital Comprehensive Geriatric Assessment systems.

Conclusion

This study demonstrates the selective potential of sensor technologies to support components of the interRAI Home Care (RAI-HC) assessment. Using the interRAI Version 10.0 Standard Edition, we applied a structured, feasibility-focused approach to examine whether sensor-generated data can meaningfully contribute to standardized geriatric assessment in home and community care settings.

Through literature-informed domain mapping and analytical alignment, 15 RAI-HC questions were identified as potentially amenable to sensor-based support. Clinical validation indicated that five questions could be directly informed by sensor data, five could be partially supported, and five remain dependent on clinical judgment that current sensor technologies cannot adequately replicate. These findings highlight the distinction between collecting objective sensor data and assessing broader constructs such as independence, safety, and functional capacity.

Overall, the results suggest that sensor technologies can augment, but not replace, clinician-led RAI-HC assessments. The findings support the feasibility of partial digitization of comprehensive geriatric assessment, in which sensor data enhance assessment accuracy and timeliness while preserving the central role of clinical expertise. This work provides a foundation for future development of a Digital Comprehensive Geriatric Assessment (D-CGA) system that integrates sensor technologies in a clinically appropriate and methodologically rigorous manner.

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