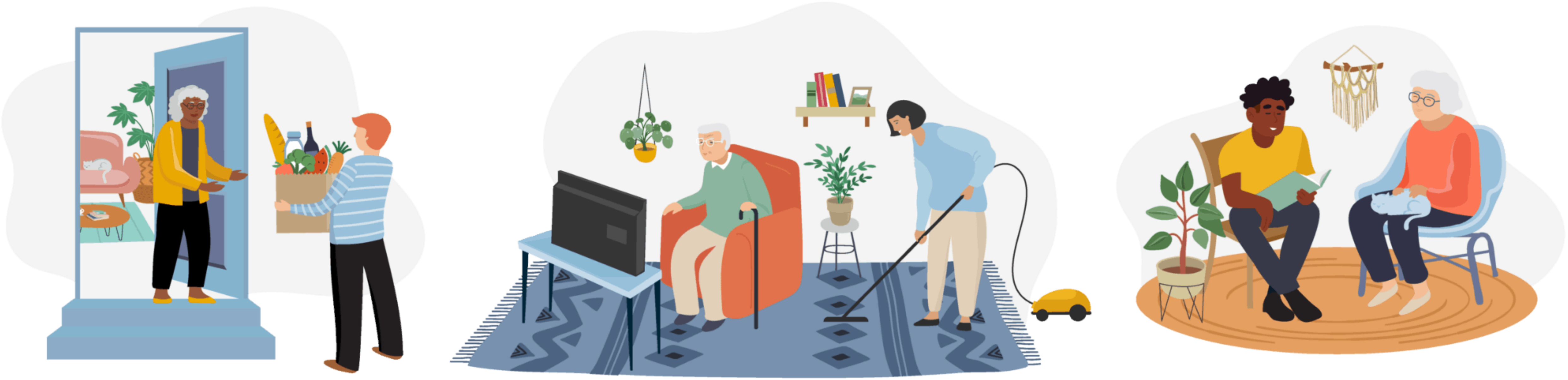
Artificial Intelligence-Enabled System Supporting Older Adults and Their Informal Caregivers



Lu Wang, Drexel University

Motivation: Aging Process

Associated with changes in dynamic biological, physiological, environmental, psychological, behavioral, and social processes.
declines in function of the senses and activities of daily life and increased susceptibility to and frequency of disease, frailty, or disability.

- https://www.nia.nih.gov/about/aging-strategic-directions-research/understanding-dynamics-aging



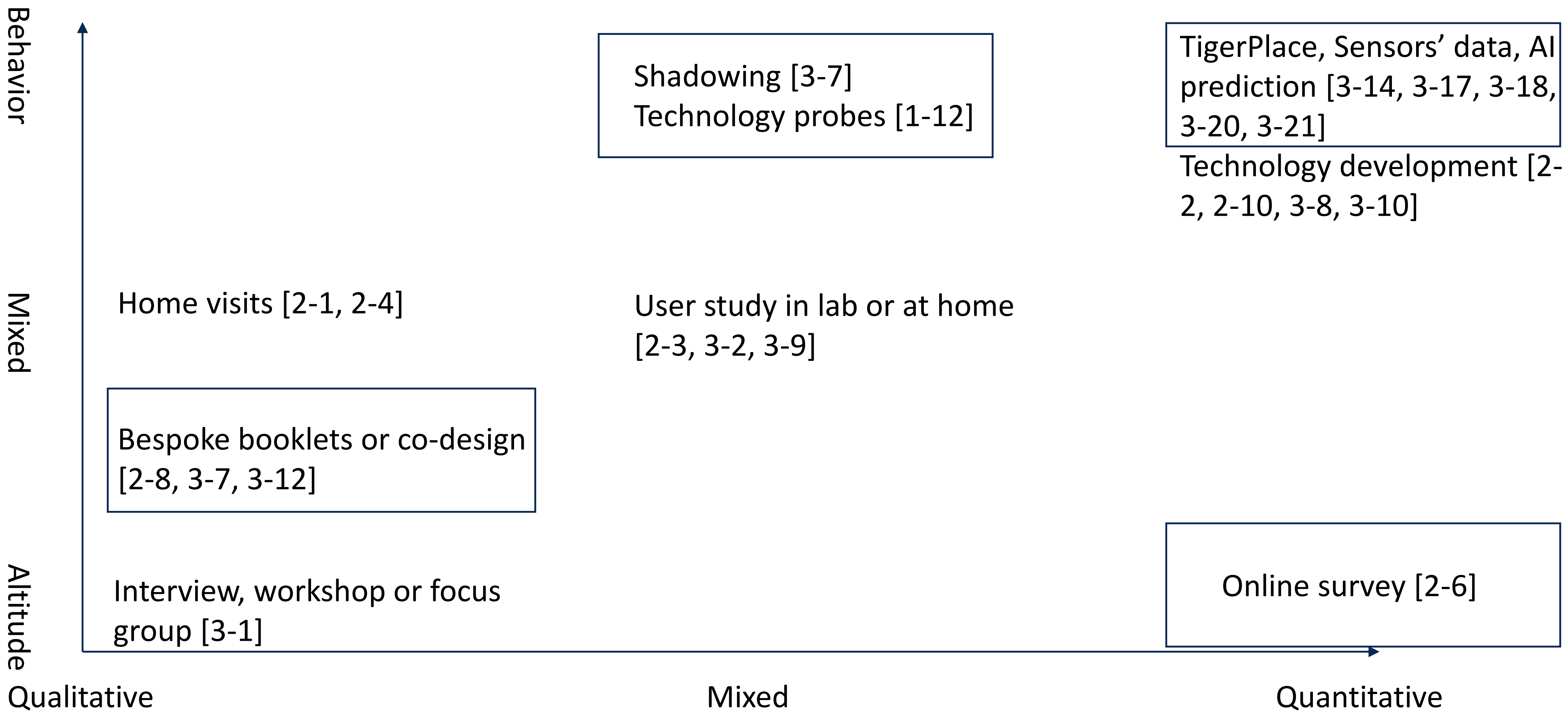

Motivation: Aging-in-place

As a concept proposed to address older adults' needs and expectations of successful aging, describes older adults' desire to remain and live in their own homes without having to transfer to care facilities.




- Choi, Y. K., Thompson, H. J., & Demiris, G. (2020). Use of an Internet-of-Things Smart Home System for Healthy Aging in Older Adults in Residential Settings: Pilot Feasibility Study. *JMIR Aging, 3*(2), e21964. doi:10.2196/21964
- Choi, Y. K., et al. (2021). "Internet-of-Things Smart Home Technology to Support Aging-in-Place: Older Adults' Perceptions and Attitudes." J Gerontol Nurs **47**(4): 15-21.

Methods: Overview

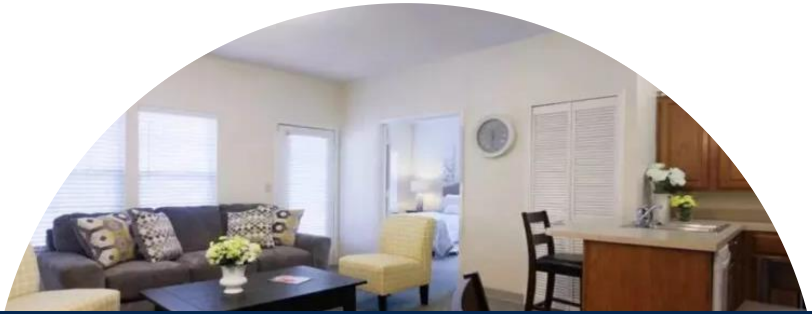


Methods: TigerPlace, Behavior Modeling

Lead Researchers

Marilyn Rantz, PhD, RN, FAAN

Marjorie Skubic, PhD



- https://agingmo.com/research-projects/aging-in-place/tigerplace/

Methods: TigerPlace, Behavior Modeling

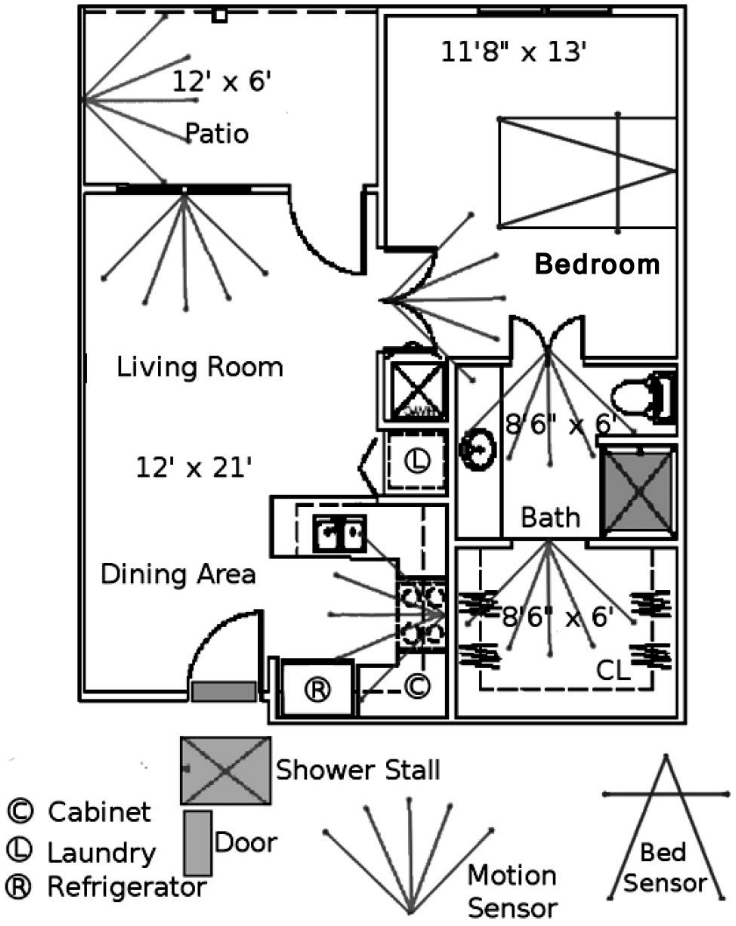


FIGURE 2. **A typical one bedroom apartment with embedded sensors, as used in this study.**

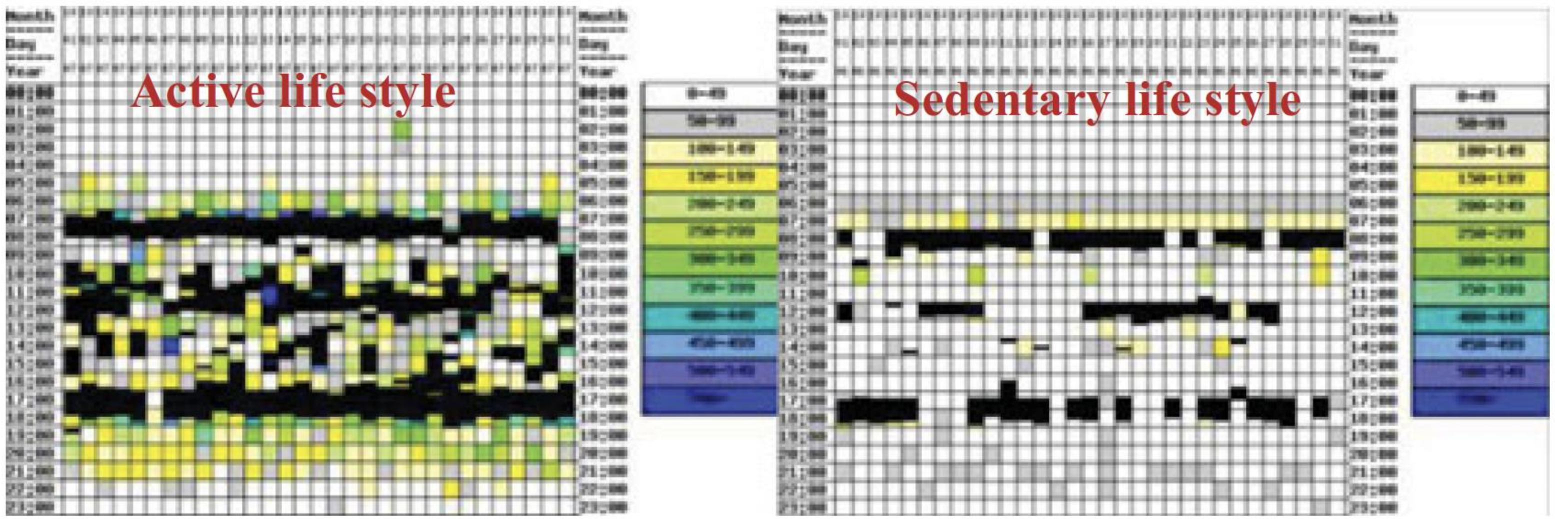


Fig. 2. Examples of activity density maps.

- Skubic, M., Guevara, R. D., & Rantz, M. (2015). Automated health alerts using in-home sensor data for embedded health assessment. IEEE journal of translational engineering in health and medicine, 3, 1-11.
- Wang, S., Skubic, M., & Zhu, Y. (2012). Activity density map visualization and dissimilarity comparison for eldercare monitoring. IEEE Transactions on Information Technology in Biomedicine, 16(4), 607-614.

Methods: Technology Probes

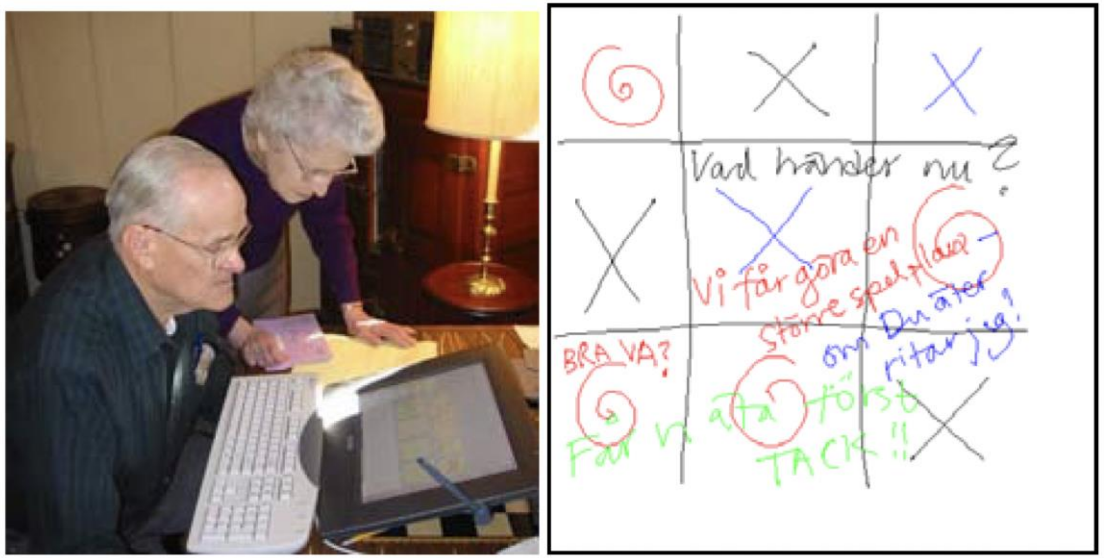


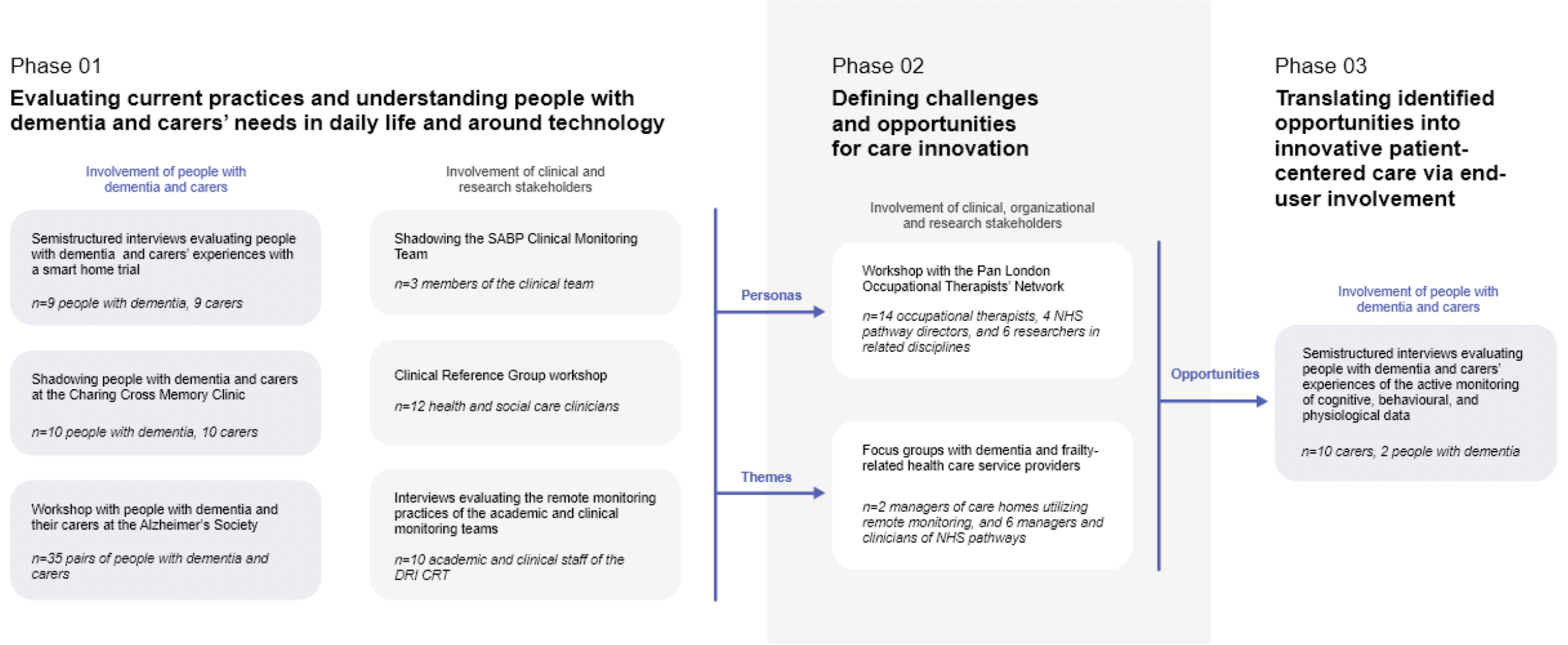
Figure 2. U.S. messageProbe (left) and Swedish message (right). (Note that the keyboard was not used for the messageProbe.)

Figure 4. videoProbes in the French families' homes

- Hutchinson, H., Mackay, W., Westerlund, B., Bederson, B. B., Druin, A., Plaisant, C., ... & Eiderbäck, B. (2003, April). Technology probes: inspiring design for and with families. In Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 17-24).

Methods: Shadowing, Workshop and Focus Group

Figure 2. Purpose and activities of each of the three phases of this study. CR&T: Care Research and Technology Centre; DRI: Dementia Research Institute; NHS: National Health Service; SABP: Surrey and Borders Partnership.



- Tiersen, F., Batey, P., Harrison, M. J., Naar, L., Serban, A. I., Daniels, S. J., & Calvo, R. A. (2021). Smart home sensing and monitoring in households with dementia: User-centered design approach. JMIR aging, 4(3), e27047.

Methods: Co-design

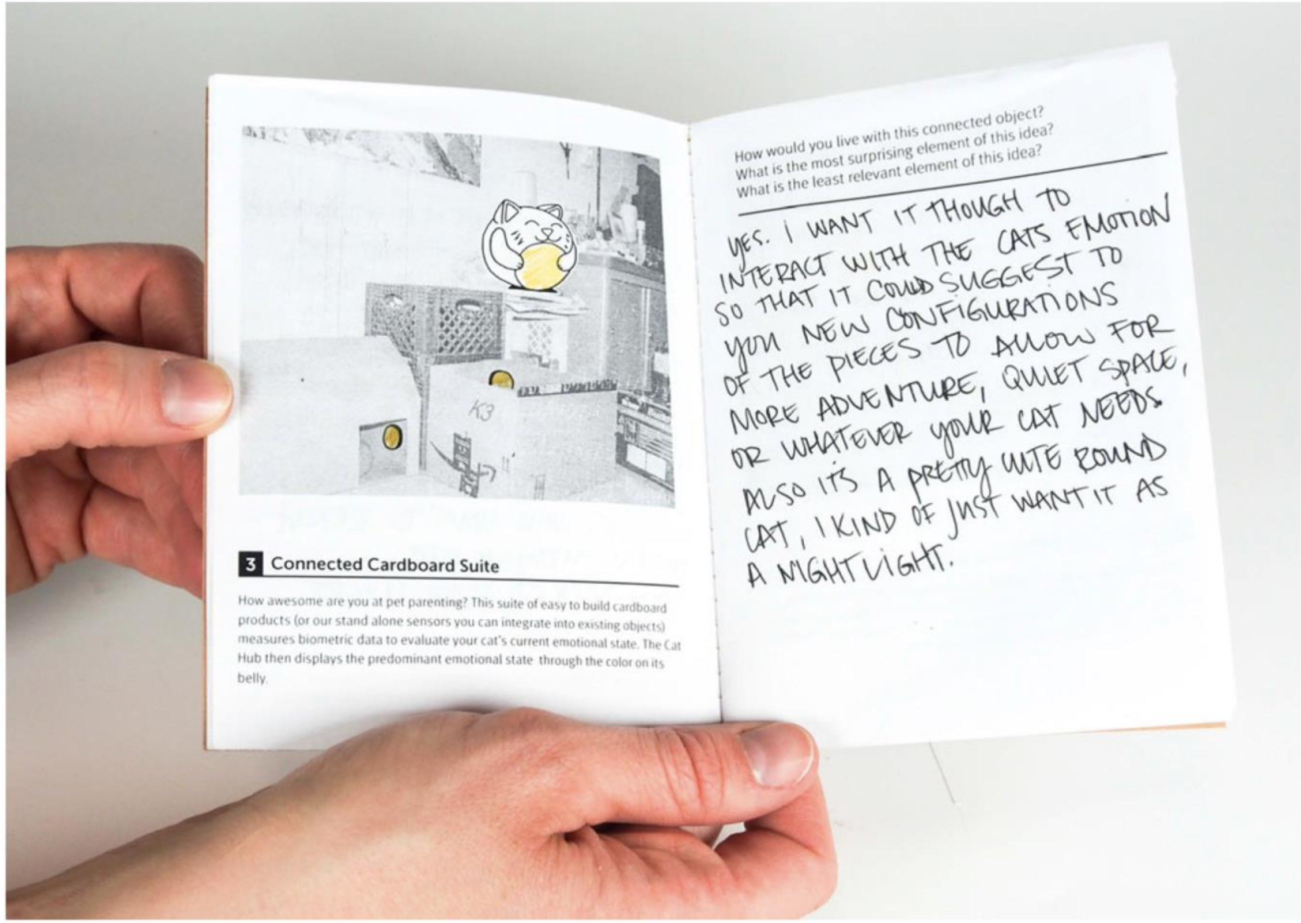


Figure 2. Bespoke Booklet: Left pages included photos of the home, right pages allowed space for comments.

Figure 4. Needs map ranking worksheet.

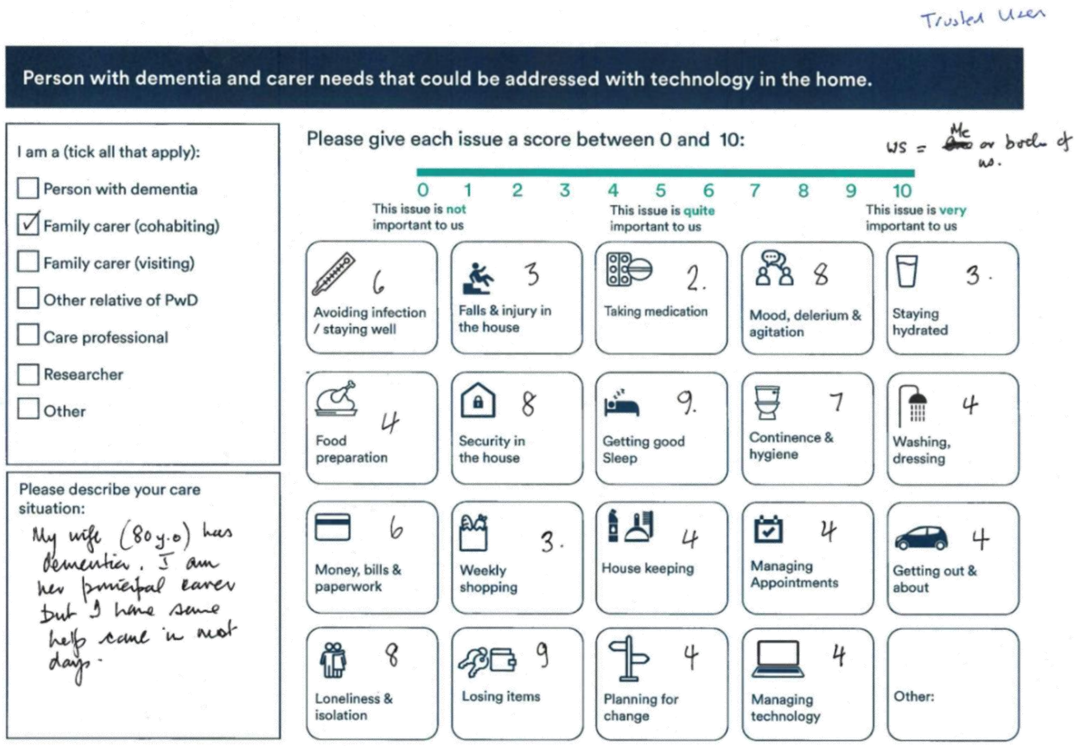


Figure 1: (L) The Un-Kit IoT elements and (R) the in-home co-design using the IoT Un-Kit Experience.

- Desjardins, A., Viny, J. E., Key, C., & Johnston, N. (2019, May). Alternative avenues for IoT: Designing with non-stereotypical homes. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1-13).
- Ambe, A. H., Brereton, M., Soro, A., Chai, M. Z., Buys, L., & Roe, P. (2019, May). Older people inventing their personal internet of things with the IoT un-kit experience. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

Methods: Online Survey, Scenarios

Factors	Components
Motivation	Intrinsic motivation, goals, utility
Difficulty	Social skills, creativity, effort required, expertise required, human ability
Risk	Accountability, uncertainty, impact
Trust	Machine ability, interpretability, value alignment

Table 1: An overview of the four factors in our AI task delegability framework.

We created scenarios in the form of vignettes, where we explored all combinations of data attributes, recipients, and transmission principles

CI Parameter	Value	# Description
Sender	The SPA	*The SPA being used, e.g. Amazon Echo/Alexa, Google Home/Assistant.*
Subject	The SPA User	*The User speaking to the SPA.*
Attribute	The 15 attributes in Table 2	*Represents a variety of information types flowing across the SPA ecosystem.*
Recipients	- Users - SPA provider - Skill provider - External Parties	*Partners, children, housemates, neighbors, house keeper, visitors, etc..* *The company that provides the SPA service, e.g., Amazon, Google, etc..* *The provider of third-party Skills. See Table 2 for Skill categories.* *Advertising Agencies, Law Enforcement Agencies.*
Transmission Principles	- No purpose, No condition - Purpose, No Condition - Purpose, Condition	Purpose: *the purpose for which data is collected was stated.* Condition: *1) If you are notified; 2) If the data is anonymous; 3) If the data is kept confidential, not shared with others; 4) If the data is stored as long as necessary for the purpose; 5) If you can review or delete the data.*

Table 2: Sensitivity of Data Attributes

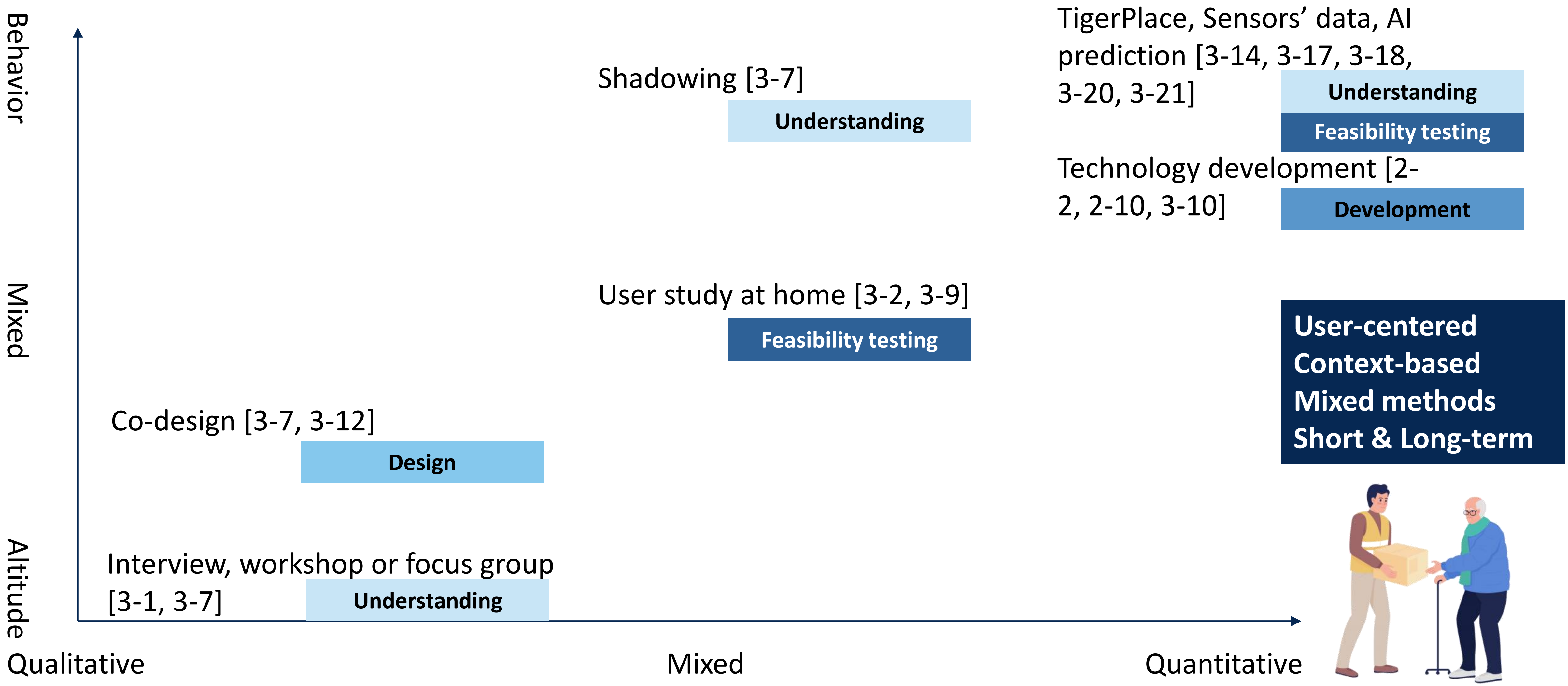
Skill Category	DataType	Data Collected	Sensitivity Mean	Sensitivity SD
Smart Home	**Smart Door Locker**	*Door lock state*	4.0	1.2
	Smart Thermostat	*History log*	2.8	1.1
	Smart Camera	*Home surveillance*	4.4	1.0
Business & Finance	**Banking**	*Bank account details*	3.8	1.2
Social & Communication	**Email**	*Email content*	4.0	1.0
	Call Assistant	*Contacts*	3.5	1.0
	Video calls	*Video calls data*	3.7	1.0
Health & Fitness	**Healthcare**	*Diagnosis results*	4.1	1.0
	Sleep Aid	*Sleeping hours*	2.6	1.0
Music & Audio	**Playlists**	*Frequently played music*	2.3	1.3
Shopping	**Online Shopping**	*Shopping history*	2.8	1.2
Productivity	**To do lists**	*Reminders*	3.0	1.4
Weather	**Weather forecast**	*Weather updates*	1.8	1.1
Travel & Transportation	**Ride services i.e. Uber**	*User location*	3.0	1.0
Non-skill SPA data	**Voice recordings**	*Command history*	3.7	1.5

We choose 100 tasks drawn from academic conferences, popular discussions in the media, well known occupations, and mundane tasks people encounter in their everyday lives. These tasks are generally relevant to current AI research and discussion, and present challenging delegability decisions with which to evaluate our framework. To additionally balance the variety of tasks chosen, we categorize them as art, creative, business, civic, entertainment, health, living, and social, and keep a minimum of 7 tasks of each.

- *Personal survey. We include all the four factors in Table 1 and ask participants "If you were to do the given (above) task, what level of AI/machine assistance would you prefer?"*
- *Expert survey. We include only difficulty, risk, and trust, and ask participants "If you were to ask someone to complete the given (above) task, what level of AI/machine assistance would you prefer?"*

- Abdi, N., Zhan, X., Ramokapane, K. M., & Such, J. (2021, May). Privacy norms for smart home personal assistants. In Proceedings of the 2021 CHI conference on human factors in computing systems (pp. 1-14).
- Lubars, B., & Tan, C. (2019). Ask not what AI can do, but what AI should do: Towards a framework of task delegability. Advances in Neural Information Processing Systems, 32.

Methods: Aging related



Findings: Overview

Needs of Aging Process

Solutions of Supporting Aging

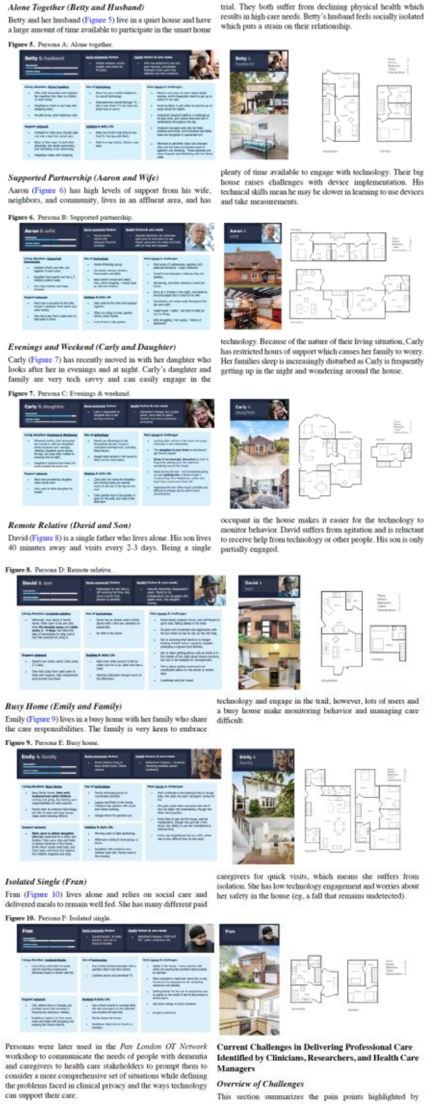
AIoT: An acronym combining Artificial Intelligence (AI) and the Internet of Things (IoT)

Findings: Needs of Aging Process: Complex Conditions

Detect needs through assessments and provide timely support considering the context of living and stakeholders disregarding the capabilities of users

Table 2. Technology and service development opportunities identified in a workshop with clinicians, researchers, and service managers and 2 focus groups with health care service providers.

Technology and service development opportunity	Mentions
Efficient, accurate remote cognitive assessments which are validated against standard tests despite learning, language, education, and cultural variations in patients	23
Objective covert behavioral and physiological data (eg, falls risk)	22
Measuring and managing caregiver strain through peer and professional support regarding dealing with situations, knowing what to expect, and planning for emergencies	16
Improving access to the wider network of casual and professional care and social services	15
Alternating between continuous and episodic measurements for optimal use of resources	8
Increased on-demand communication for practical, clinical, and emotional support	7
Informal monitoring products (eg, trackers) for caregivers	7
Educating patients and caregivers to use proposed technologies	6
Proactive medical interventions (eg, UTI prediction) to prevent further deterioration	6
Identifying and treating causes of psychological disturbances (eg, surveillance paranoia) before implementing intervention	5
Automated reminders and interventions supporting activities of daily living	5
Providing reliable clinical oversight to manage false alarms and prevent anxiety	5
Dynamic adjustment of medication administration enabled by granular monitoring of its effects	3



Alone Together (Betty and Husband)

Betty and her husband (Figure 5) live in a quiet house and have a large amount of time available to participate in the smart home trial. They both suffer from declining physical health which results in high care needs. Betty's husband feels socially isolated which puts a strain on their relationship.

Figure 5. Persona A: Alone together.

Supported Partnership (Aaron and Wife)

Aaron (Figure 6) has high levels of support from his wife, neighbors, and community, lives in an affluent area, and has plenty of time available to engage with technology. Their big house raises challenges with device implementation. His technical skills mean he may be slower in learning to use devices and take measurements.

Figure 6. Persona B: Supported partnership.

Evenings and Weekend (Carly and Daughter)

Carly (Figure 7) has recently moved in with her daughter who looks after her in evenings and at night. Carly's daughter and family are very tech savvy and can easily engage in the technology. Because of the nature of their living situation, Carly has restricted hours of support which causes her family to worry. Her families sleep is increasingly disturbed as Carly is frequently getting up in the night and wondering around the house.

Figure 7. Persona C: Evenings & weekend.

Remote Relative (David and Son)

David (Figure 8) is a single father who lives alone. His son lives 40 minutes away and visits every 2-3 days. Being a single occupant in the house makes it easier for the technology to monitor behavior. David suffers from agitation and is reluctant to receive help from technology or other people. His son is only partially engaged.

Figure 8. Persona D: Remote relative.

Busy Home (Emily and Family)

Emily (Figure 9) lives in a busy home with her family who share the care responsibilities. The family is very keen to embrace technology and engage in the trail; however, lots of users and a busy house make monitoring behavior and managing care difficult.

Figure 9. Persona E: Busy home.

Isolated Single (Fran)

Fran (Figure 10) lives alone and relies on social care and delivered meals to remain well fed. She has many different paid caregivers for quick visits, which means she suffers from isolation. She has low technology engagement and worries about her safety in the house (eg, a fall that remains undetected).

Figure 10. Persona F: Isolated single.

Personas were later used in the *Pan London OT Network* workshop to communicate the needs of people with dementia and caregivers to health care stakeholders to prompt them to consider a more comprehensive set of situations while defining the problems faced in clinical privacy and the ways technology can support their care.

Current Challenges in Delivering Professional Care Identified by Clinicians, Researchers, and Health Care Managers

Overview of Challenges

This section summarizes the pain points highlighted by

- Tiersen, F., Batey, P., Harrison, M. J., Naar, L., Serban, A. I., Daniels, S. J., & Calvo, R. A. (2021). Smart home sensing and monitoring in households with dementia: User-centered design approach. JMIR aging, 4(3), e27047.

Findings: Solutions of Supporting Aging-Fall

6-month fall risk prediction in older adults using geriatric assessments, GAITRite measurements, and fall history.

- The geriatric assessments included were Activities of Daily Living (ADL), Instrumental Activities of Daily Living (IADL), Mini-Mental State Examination (MMSE), Geriatric Depression Scale (GDS), and Short Form 12 (SF12). These geriatric assessments are collected by staff nurses regularly in senior care facilities.

- From the GAITRite assessments on the residents, we included the Functional Ambulatory Profile (FAP) scores and gait speed to predict fall risk.

Audio, Video, Sensors: 80%-100% Accuracy

- Mishra, A.K., Skubic, M., Despins, L.A., Popescu, M., Keller, J., Rantz, M., Abbott, C., Enayati, M., Shalini, S., & Miller, S. (2022). Explainable fall risk prediction in older adults using gait and geriatric assessments. Frontiers in digital health, 80.
- Qian, K., Zhang, Z., Yamamoto, Y., & Schuller, B. W. (2021). Artificial intelligence internet of things for the elderly: from assisted living to health-care monitoring. IEEE Signal Processing Magazine, 38(4), 78-88.

Findings: Solutions of Supporting Aging-Daily Activities

TABLE 1. **Results of the forward feature selection process.**

Features tested	Best features by order	
	Case #1	Case #2
Day time motion density		
Number of bathroom visits	8	
Total time in bathroom	7	4
Bedroom events		
Living room events		
Number of times away from home	6	
Total time away from home		
Number of visitor events	3	
Total time of visitor activity	4	1
Night time motion density	1	
Number of times in bed		
Total time in bed	5	
Bed restlessness 1 events < 3 sec		
Bed restlessness 2 events 3-6 sec		
Bed restlessness 3 events 6-9 sec	9	
Bed restlessness 4 events > 9 sec		
Low pulse events < 30/min	2	
Normal pulse events		3
High pulse events > 100/min		
Low breathing events < 6/min		
Normal breathing events		
High breathing events > 30/min		2
Area under the ROC for best set	**0.90**	**0.94**

TABLE 2. **Alert parameters and sensor data monitored for the alerts.**

Alert parameter	Sensors
Bathroom Activity	Sum of motion sensor events in the bathroom (bathroom, shower)
Bed Restlessness	Number of all bed restlessness events
Bed Breathing Low/Normal/High	Number of bed breathing low/normal/high events
Bed Pulse Low/Normal/High	Number of bed pulse low/normal/high events
Kitchen Activity	Sum of kitchen motion sensor (kitchen, fridge, etc.) events and stove/oven temperature high
Living Room Activity	Number of living room motion sensor events

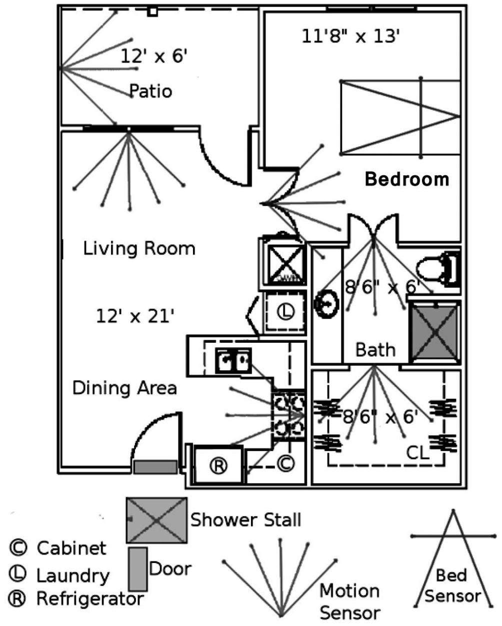


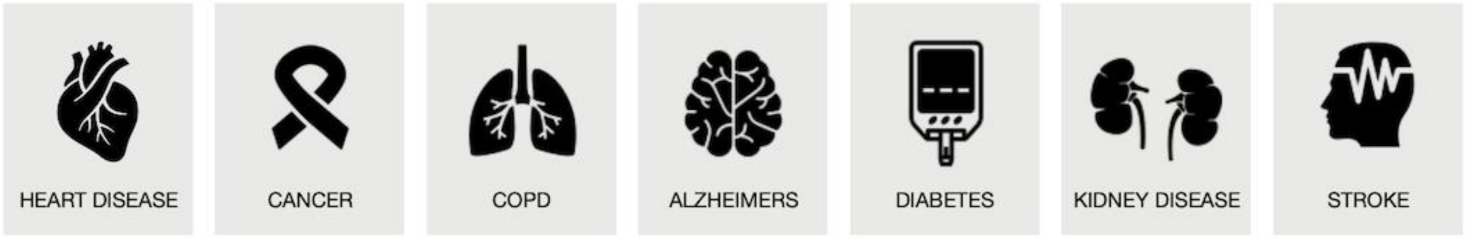
FIGURE 2. **A typical one bedroom apartment with embedded sensors, as used in this study.**

IoT collects data while AI recognizes and classifies activities.

Video, Sensors: 70%-100% Accuracy

- Skubic M., Guevara, R. D., & Rantz, M. (2015). Automated health alerts using in-home sensor data for embedded health assessment. IEEE journal of translational engineering in health and medicine, 3, 1-11.
- Qian, K., Zhang, Z., Yamamoto, Y., & Schuller, B. W. (2021). Artificial intelligence internet of things for the elderly: from assisted living to health-care monitoring. IEEE Signal Processing Magazine, 38(4), 78-88.

Findings: Solutions of Supporting Aging-Healthcare



Chronic disease: diabetes mellitus and heart disease

Mental health

Audio, Sensors, Text: 60%-90% Accuracy

- Tun, S. Y. Y., Madanian, S., & Mirza, F. (2021). Internet of things (IoT) applications for elderly care: a reflective review. Aging clinical and experimental research, 33, 855-867.
- Qian, K., Zhang, Z., Yamamoto, Y., & Schuller, B. W. (2021). Artificial intelligence internet of things for the elderly: from assisted living to health-care monitoring. IEEE Signal Processing Magazine, 38(4), 78-88.

Findings: Gaps

Health management:

- Extracting and processing health information from collected data
- The capture, store, and access of data from and by users.

Interaction: Natural interactions for aging activities and timing of the interventions

Personalized:

- Needs tailored by various conditions of aging in various habiting environments with multi-stakeholders
- Technology solutions’ roles and designs influenced by dynamic needs

Privacy norms and design for fairness based on technology mechanisms (AI and IoT)

Sep 9th, 2023