Mapping Aging in Place Through AI and Robotics: A System Modeling Perspective

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Abstract. This study employs a causal loop diagram (CLD) to model the dynamics of the aging-in-place (AIP) system, using constructivist grounded theory (CGT) to explore latent user needs, product innovation, service offerings, and experience design within the context of AI and robotics. The paper presents a conceptual framework for integrating AI and robotics into AIP services. This framework defines four AI archetypes spanning physical and digital presence and addressing cognitive and functional needs: Advisor AI, Butler Robot AI, Valet Robot AI, and Systems AI. Semi-structured interviews were conducted with four recently retired individuals (mean age 70) in Boston, USA, to gather insights into their perspectives on AI and robotics for independence and well-being. Findings revealed participants' expectations and challenges regarding health monitoring, social well-being, and assistance with daily routines. Key factors such as trust-building, life-stage integration, and service adaptability were emphasized, contributing to the refinement of the proposed framework. The primary contribution lies in raising social awareness regarding housing policy development and technological innovation in AIP. Future research should include pilot testing in real-world scenarios to explore AI- and robot-driven AIP archetypes, expanding the conceptual framework to address ethical considerations, cultural contexts, and adaptive technologies.

Keywords: Aging in Place · Artificial Intelligence · Service Design · System Modeling · Causal Loop Diagram · CLD

1 Introduction

People are living longer and aspiring to maintain a higher quality of life. Aging has become a globally emergent socio-economic and technological challenge for governments, permeating nearly every aspect of life and work. Longevity economy [1, 2] has emerged as a popular concept, mindset, strategy, and action plan to reconsider the multi-generational context of our environment and culture through the lens of transportation, policy, education, healthcare, medical platforms, and other critical social infrastructures.

Housing is a crucial factor in this discourse. This descriptive study specifically addresses the issues of aging in place (AIP), which is conceptualized as a complex

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system involving intersections with artificial intelligence (AI) and robotics. In super-aging societies such as Japan, advanced robotics have been introduced into domestic settings to address the needs of an aging population. For instance, Pepper, an interactive humanoid robot [3], is a technology designed to meet these needs while posing new design, engineering, and business challenges. The ongoing development of AI and robotics to facilitate AIP appears inevitable [4, 5]. However, the perspectives of older adults—whether they are caregivers or care recipients—regarding the role of AI [6, 7] and robotics in their lives and the specific functionalities they envision for these technologies, remain underexplored.

The United States Centers for Disease Control and Prevention (CDC) provides a straightforward definition of AIP: the ability to live safely, independently, and comfortably in one's own home and community, regardless of age, income, or ability level. The notion of AIP has gained significant prominence in various disciplines, including the built environment [8, 9], government policy [10, 11], emerging technologies [12, 13], and service design and innovation [14–16]. Most older adults prefer to remain in their homes as they age, underscoring the importance of independence and familiarity. This preference raises essential questions necessary to support AIP as a system effectively in terms of building suitable conditions and adequate technologies [17–19].

The primary objective of this descriptive study was to employ a causal loop diagram (CLD) to model the dynamics of the AIP system using codes derived from constructivist grounded theory (CGT). This approach explored latent user needs and concerns, product innovation, service offerings, and experience design within the context of AI and robotics.

A conceptual framework was developed and applied to facilitate constructive and meaningful discussions with four Boston-based participants during 35–45-min virtual semi-structured interviews. Specifically, the study explored the following two areas: 1. How can this experimental 2x2 framework be developed to better interpret the relationships between individuals in the early stages of retirement and AI and robotics within AIP? 2. How can CLD be purposefully applied to conduct preliminary qualitative data analysis from a systems modeling perspective and interview insights? These two areas helped bridge the research gap and identify opportunities related to technological innovation in AIP. The findings are also expected to contributed to raising social awareness of policy development and technological innovation in AIP for caregivers and recipients.

2 Related Works

2.1 Aging in Place, Artificial Intelligence, and Service

This study examines systems and service design, alongside the integration of AI and robotics, within the context of AIP. AIP refers to a responsive home environment shaped by innovative products, interconnected services, and dynamic systems. In Japan's super-aging society, the chronic shortage of caregivers for the elderly has become a pressing issue. Domestic robots have emerged as critical solutions within AIP initiatives. Technological advancements now allow AI-embedded robots to communicate naturally with individuals, demonstrating both conversational abilities and complex physical gestures

[20]. Prominent examples include Aibo, a robotic dog introduced in 2018 with cloud-based capabilities to emulate pet-like behaviors, and Paro, a humanoid baby seal robot providing emotional support [3].

FakhrHosseini et al. [21] proposed a taxonomy framework to classify homes into five levels of automation: electric, customized, proactive, supportive, and companion homes. Their research emphasizes the transformation of living spaces into interconnected ecosystems of services, smart devices, and robots. Their research highlighted the need for harmonized terminology and concepts within AIP, focusing on smart homes, AI, and robotics to meet user needs, enhance engagement, and promote technology adoption.

Given the absence of a universally accepted definition of AI, this study investigated AI and robot applications in home environments considering digital technologies, the Internet of Things (IoT), and information and communication technologies (ICT). We concentrated on AI's taxonomies and applications concerning human needs [22] and the values and challenges associated with AIP. For example, Wang et al. [23] discussed three types of AI: artificial narrow intelligence (ANI), which is designed for specific tasks; artificial general intelligence (AGI), capable of performing general intellectual tasks; and artificial super intelligence (ASI), a hypothetical form of AI that surpasses human capabilities.

Czaja and Ceruso [7] highlighted the potential contributions of AI in supporting aging adults by fostering independent and dignified living, improving quality of life, and facilitating meaningful connections with family, close friends, and the local community. Atluri et al. [4] emphasized the value of AI-enabled smart homes in addressing challenges related to home security, daily life routines, household maintenance, and social engagement. Additionally, Canham et al. [14] proposed the Aging in the Right Place (AIRP) conceptual framework for older adults experiencing homelessness. This framework comprises eight key categories: 1. built and natural environment, 2. housing access and home modification, 3. resources, transportation, technology, safety, 4. physical/mental health and functional abilities, 5. finances, 6. emotional place attachment, 7. meaningful recreation and exercise, and 8. social support, participation, and inclusion.

AIRP has incorporated the concept of service design within the AIP paradigm. Suppipat et al. [15] investigated intercultural and accessible co-living service models as a potential strategy to support AIP based on applying and evaluating seven design methods, including persona, user journey mapping, PEST analysis, and business model canvas. Their findings indicate that service-oriented strategies have the potential to support AIP, foster new capabilities, and drive financial growth. Similarly, Yang et al. [24] introduced service concepts, identified enabling digital technologies, and analyzed unique service attributes to propose an implementation framework for AIP innovation. Scharlach et al. [25] also adopted a human-centered design (HCD) approach, emphasizing service design and its role in improving health, well-being, and life quality through the "Village" model, which aims to support older adults within the AIP framework.

The literature review identifies significant opportunities to explore service innovation, AI, and robotics integration in the AIP context. Future research should focus on enhancing cognitive and physical functions through digital and physical interventions, positioning AIP as a dynamic, interconnected system.

2.2 System Dynamic and System Thinking

As complexity grows in socioeconomic-technological challenges, systems thinking becomes crucial for success. Systems thinking does not merely involve thinking systematically; it entails understanding phenomena as interconnected systems [25, 26]. This perspective emphasizes the existence of distinct entities, including the components, elements, and parts, and the relationships that connect them.

In the era of complex dynamic systems, traditional approaches often fail due to time limitations and the broad scope of systems [28]. Systems thinking is essential for studying the dynamic behavior of complex systems through a holistic approach. System dynamics, as a field of knowledge, provides tools to understand the evolution of complexity over time [29]. It utilizes feedback systems, addressing non-linear behaviors, time delays, and multi-loop structures [28]. Sterman [30] described modeling as an inherently creative yet disciplined process comprising four iterative stages: 1. problem articulation, 2. dynamic hypothesis formulation, 3. testing, and 4. policy formulation and evaluation. The simplicity of CLDs supports the early conceptualization of models [31]. de Weck [26] noted that CLDs are effective for interpreting system dynamics, as they help formulate, communicate, and validate dynamic hypotheses related to causal structures.

CLDs describe the hypothesized mechanisms underlying system behavior over time [28]. The dynamic hypothesis examines whether the system's feedback can explain the observed behavior. This hypothesis is provisional, evolving with the evidence from the reference mode [30]. CLDs identify principal feedback loops by developing a dynamic hypothesis through a systematic six-step process: 1. defining the problem, 2. identifying critical elements, 3. recognizing secondary and tertiary elements, 4. defining cause-effect relationships, 5. identifying closed loops, and 6. identifying balancing and reinforcing loops [28].

A CLD consists of variables (exogenous, endogenous, and excluded), causal links, feedback loops (reinforcing or balancing), and archetypes (Fig. 1). Exogenous variables act as constant drivers, influencing other variables but not being influenced. Endogenous variables interact dynamically with different variables, while excluded variables are not linked causally to the system. Causal links are unidirectional, with positive (+) or negative (-) valence, connecting variables to form feedback loops. Positive valence implies that variables change in the same direction, whereas negative valence indicates opposite changes. Feedback loops are fundamental elements of system dynamics. Reinforcing (R) and balancing (B) feedback loops indicate growth or equilibrium dynamics, respectively, and links with line markers denote delays. Archetypes represent recurring configurations that illustrate common system structures and behaviors [31].

Though testing CLDs poses challenges, they remain valuable for making system dynamics accessible. This study employed CLDs to model systems related to AI, robotics, and AIP based on 14 codes using CGT.

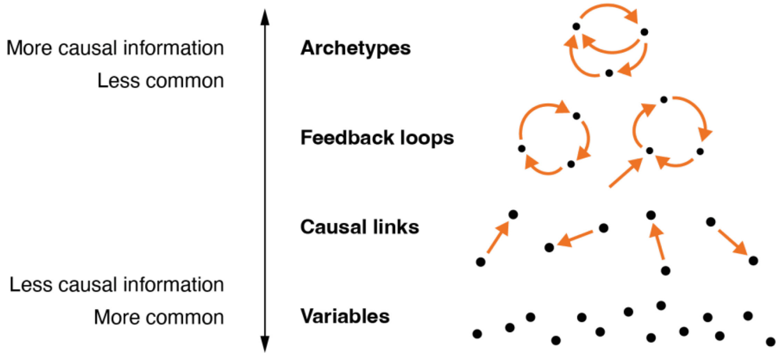

Fig. 1. Hierarchical causal structure among variables, causal links, feedback loops, and archetypes, adapted from Kenzie et al. (2024).

3 Research Method

3.1 Overview of Research Flow and Participant Recruitment

The descriptive study comprised six phases: 1. participant recruitment, 2. conceptual framework testing, 3. qualitative data collection, documentation, and analysis, 4. system modeling, 5. synthesis of insights, and 6. refinement (Fig. 2). The primary objective was to refine the conceptual framework through CGT qualitative analysis and CLD system modeling, highlighting key design considerations for AIP concerning AI and robotics.

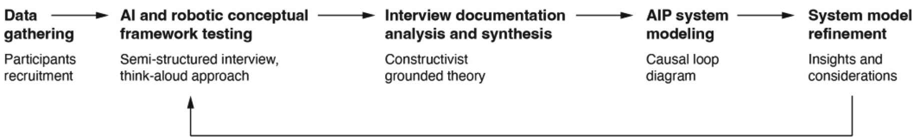

Fig. 2. Research flow overview

The authors interviewed four Boston-based participants (2 men and 2 women), averaging 70 years of age, in the early stages of retirement, with experience in long-term pension and financial planning. Three participants had professional backgrounds in research institutes or universities with expertise in technology and entrepreneurship, and one retired from the financial industry. All were in good health, held at least a bachelor's degree, and had substantial financial resources, with an average pre-tax household income of US $150,000 or more and investable assets exceeding US $100,000. The small sample recruited from the MIT AgeLab's research volunteer database was purposively selected to provide valuable insights and personal stories for this descriptive study.

3.2 Conceptual Framework of Artificial Intelligence, Robotics, and Aging in Place

The conceptual 2 × 2 framework (Fig. 3) was developed through a literature review on AI, robotics, and AIP, supplemented by expert discussions from academia and industry.

The x-axis represents AI forms (digital and physical), while the y-axis differentiates cognitive functions ("head" or auxiliary brain) from physical functions ("hands" or auxiliary muscle).

The framework defines four archetypes: 1. Advisor AI, implemented as voice user interfaces (VUIs) like Amazon Alexa or Siri, offers solutions, identifies opportunities, and provides task reminders. 2. Butler Robot AI is a physical system addressing dynamic needs, such as deliveries, health tracking, or home monitoring [8], as seen in Serve Robotics' delivery service. 3. Valet Robot AI supports routine tasks, including cleaning, dressing, and grooming, akin to the iRobot Roomba. 4. Systems AI operates digital, interconnected modules and services for tasks such as wheeled porters and object lifters [14]. While not all examples are currently AI-driven, AI integration for AIP is expected soon. This study aims to develop a conceptual framework to understand the role of AI and robotics in AIP and systematically identify key design considerations.

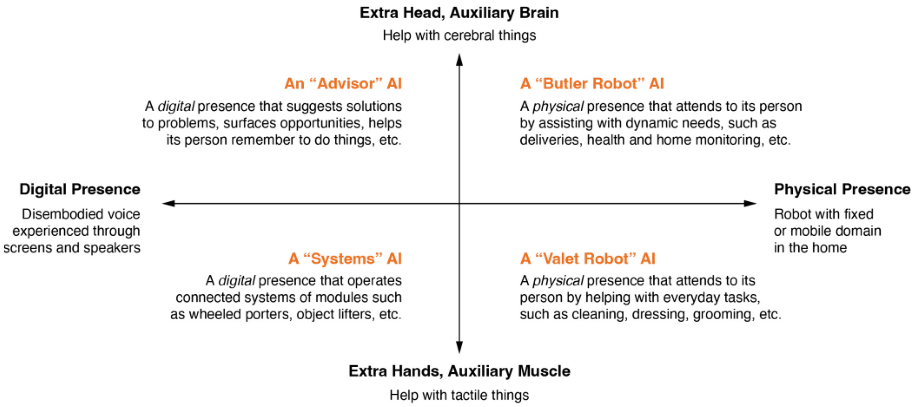

Fig. 3. A conceptual framework for investigating AI and robotics within an AIP context, co-designed and developed in collaboration with Devin Liddell.

3.3 Qualitative Data and System Modeling

The research aimed to understand participants' perceptions of the conceptual framework, focusing on their preferences for AIP assistance types and areas where they sought support. A think-aloud method [31, 32] was employed, involving four virtual semi-structured interviews of 35 to 45 min each. The authors analyzed four interview video transcripts using Charmaz's [34] constructivist grounded theory (CGT) through four coding stages: initial, focused, axial, and theoretical coding. Initial coding captured raw data, while focused coding grouped similar initial codes to identify central themes, incorporating axial codes as connectors. Theoretical coding then encapsulated the core themes. The iterative, line-by-line comparison in CGT enabled the systematic synthesis of interview content, fostering a comprehensive understanding of the data and generating key insights.

Based on CGT, the authors selected 13 codes (excluding one theoretical code) for CLD system modeling variables (Table 1). Synthesizing the interviews and team discussions, we first identified causal links by determining their direction and positive (+) or negative (−) valence between the two axial codes and three focused codes. Eight initial codes were then added to iterate this process, forming or removing meaningful causal links. Next, we examined potential reinforcing or balancing feedback loops among these causal links. Finally, all feedback loops were analyzed to identify any emerging archetypes. This CLD modeling provided a dynamic perspective on the system behavior of the AIP, intersecting AI, robotics, and participants' latent needs over time.

Table 1. The overview of CGT theoretical sampling with selected participants quotes.

Initial code (n = 8)	Focused code (n = 3)	Axial code (n = 2)	Theoretical code
I1. Human-AI interaction	F1. Product (I1, I5)	A1. Lifestyle (F1, F3)	T1. Transformation
I2. Daily routine	F2. Service (I2, I3, I4, I7)	A2. Life transition (F2)	
I3. Sustainability	F3. Experience (I4, I6, I8)		
I4. System			
I5. Health monitoring			
I6. Family			
I7. Social well-being			
I8. Smart home			

4 Research Result

4.1 Theoretical Sampling and Synthesizing by Constructivist Grounded Theory

Charmaz's [34] CGT was the primary qualitative data analysis method, employing constant comparison and line-by-line coding of four 35–45-min video transcripts. Table 1 presents eight initial codes (I1 to I8), which were subsequently clustered into three focused codes representing distinct design expressions: product (F1), service (F2), and experience (F3). Lifestyle (A1) and life transition (A2), representative of two axial codes, shaped the one core code, transformation (T1), which encapsulates the emergent theme of the study.

4.2 System Modeling Using Causal Loop Diagram

According to the procedure outlined in Sect. 3.3, the system modeling results in Fig. 4 present the CLD derived from 13 codes, excluding the theoretical code "transformation," as identified through CGT.

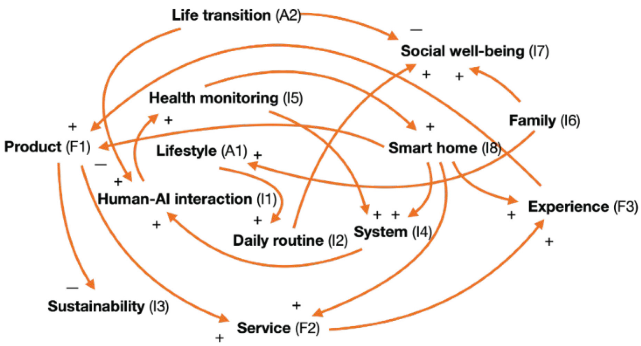

Fig. 4. The CLD overview derived from the coding results obtained through CGT.

The CLD was analyzed by examining its causal structure across four layers (Table 2). The first layer consisted of 13 variables, which formed 18 unidirectional causal links as the second layer—15 with positive (+) valence and three with negative (-) valence. The third layer generated three reinforcing feedback loops. The author modeled and identified one distinct archetype. This archetype consisted of four interconnected variables arranged in a clockwise sequence: I1, I5, I8, and I4. Additionally, A2 and I6 were identified as endogenous variables, considered system "drivers," as they influenced 11 exogenous variables without being affected by any other variables in the model [35].

Table 2. Characteristics of the CLD across four layers of causal structure.

# of **variables** (n = 13)	The CLD comprised 13 variables, including 11 exogenous variables, two endogenous variables (A2 and I6), and no excluded variables
# of **links** (n = 18)	The CLD comprised 18 unidirectional causal links, of which 15 exhibited positive (+) valence and three exhibited negative (-) valence, interconnecting 13 variables
# of **loops** (n = 3)	The CLD comprised three reinforcing (R) feedback loops: R1, consisting of F3, F1, and F2 (counter-clockwise); R2, composed of I1, I5, I8, and I4 (clockwise); and R3, involving I1, I5, and I4 (clockwise)
# of **archetypes** (n = 1)	An archetype was established, consisting of four interconnected variables arranged in a clockwise sequence: I1, I5, I8, and I4

5 Discussion

5.1 Causal Structure Between Variables and Links

The CLD (Fig. 5) revealed the intricate interconnections among variables, causal links, feedback loops, and archetypes. In the discussion, six exogenous variables and their associated causal links were selected to explore their relationships with AIP, AI, and robotics. Participants emphasized the integration of smart devices into smartphones, suggesting a negative valence in the link between smart home (I8) and product (F1), as they preferred fewer distinct physical or digital products in favor of a more integrated service experience for AIP (Fig. 5-1). As more AI and robotics features are integrated into AIP, demand for service-oriented features will increase (positive valence), consequently fostering the development of more experience-driven products (positive valence), as illustrated in Fig. 5-2, 5-3, and 5-6.

All four participants highlighted the importance of their physical health, particularly the role of AI and robotics in health monitoring (I5). Echoing their desire, Fig. 5-4 illustrates the positive valence in the relationship between the system (I4) and the design of the smart home (I8), focusing on human-AI interaction (I1). Additionally, participants underscored critical aspects of their social well-being (I7), considering the availability of family members as primary caregivers and the maintenance of daily routines, such as volunteering or engaging with local or virtual communities, as a means of self-motivation. They also sought stability, reliability, and safety during their life stage transition from retirement to post-retirement (Fig. 5-5).

5.2 Collective System Modeling to Incorporate Implicit User Needs

This study employs CLDs as a system modeling tool for collaborative efforts involving modelers (e.g., designers, researchers) and participants. This co-creative approach facilitates the exploration of potential causal structures, including variables, links, feedback loops (reinforcing and balancing), and system archetypes, by incorporating insights from diverse stakeholders. The formation, modification, or removal of causal structures was conducted through a collective decision-making process, enabling researchers to better describe dynamic hypotheses and system behavior over time.

From a systems dynamics perspective, methodologies are provided to analyze complex system behaviors, often non-linear, over time, particularly for topics involving AIP, AI, and robotics. CLDs, in particular, are instrumental in delineating the boundaries of complex systems by identifying endogenous, exogenous, and excluded variables using constructivist grounded theory (Fig. 6). Identifying the variables within the system's scope facilitated a deeper understanding of underlying participants' latent needs for AIP, AI, and robotics that are implicit and challenging to articulate or observe.

Regarding implicit user needs, during the four semi-structured interviews, participants highlighted the ethical and practical challenges of integrating AI and robotics into AIP, including privacy concerns and data storage—issues that were underexplored and difficult to address comprehensively during brief virtual interviews. Future research should investigate how AIP systems can more effectively mitigate adoption barriers of trust, address ethical considerations, and develop strategies to enhance the reliability of AI and robotic technologies for older adults, whether as caregivers or recipients.

Fig. 5. The six exogenous variables (highlighted in orange) and their associated causal relationships.

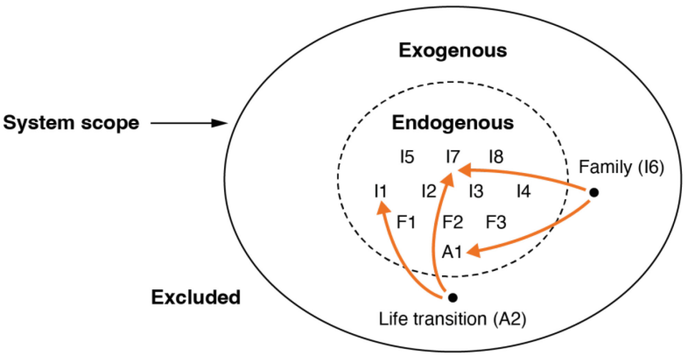

Fig. 6. The CLD, consisting of 11 endogenous and two exogenous variables (A2, I6), defined the system scope for analysis, adapted from Ford (2010).

5.3 Directions for Future Research

CLD is a subjective system modeling approach used in qualitative data analysis. It involves identifying and defining selected variables, establishing meaningful interrelationships, characterizing reinforcing or balancing feedback loops, and constructing critical system archetypes. Given the inherent subjectivity of CLD, future research could focus on developing evaluation frameworks or methodologies to validate the quality, reliability, and feasibility of CLDs. To mitigate bias, one approach is to triangulate CLD results with quantitative methods during the validation phase or involve additional experts in the AIP system modeling process to enhance the credibility of the outcomes.

Furthermore, increasing the sample size in CLD-based studies could provide broader perspectives. Expanding the participant pool to include diverse demographics, mainly varying socioeconomic backgrounds, geographic locations, and levels of technological literacy, could enhance the depth and accuracy of the analysis and the comprehensiveness, representativeness, and reliability of the system model. Future research could include pilot tests in real-world scenarios to explore meaningful AI- and robot-driven AIP archetypes derived from CLD while expanding the conceptual framework to address ethical considerations, various cultural contexts, and adaptive technologies.

6 Conclusion

Population aging has become a global concern, posing challenges for governments to adapt health and social infrastructures to demographic shifts. The pace of population aging is accelerating; between 2015 and 2050, the proportion of individuals over 60 is projected to rise from 12% to 22% [36]. Consequently, aging in place (AIP) has emerged as a significant trend. The American Association of Retired Persons (AARP) defines AIP as the ability to live safely, independently, and comfortably in one's home and community as one ages. Older adults value the quality of life, aim to maintain daily routines and motivation, fear losing community ties, and hold strong emotional attachments to their homes and neighborhoods [35, 36]. This study proposes and evaluates a conceptual framework for exploring AI and robotics within the context of AIP, employing semi-structured interviews, constructivist grounded theory (CGT), and system modeling. The primary contribution of this research is to enhance social awareness regarding policy development and technological innovation in AIP.

Through CGT analysis, 14 codes were identified (eight initial, three focused, two axial, and one theoretical), capturing participants' primary insights (Table 1). A causal loop diagram (CLD) was then applied to model causal structure among the codes (Fig. 4). The CLD consisted of 13 variables—11 exogenous and two endogenous, including life transition (A2) and family (I6). Synthesized with the CGT result, A2 and I6 were primary drivers for other variables and feedback loops. This might indicate latent participant needs related to trust building, life-stage integration, and service adaptability for AI and robotics in AIP.

The CLD also revealed three reinforcing (R) feedback loops: counter-clockwise R1, involving experience (F3), product (F1), and service (F2); clockwise R2, centered on human-AI interaction (I1), health monitoring (I5), smart home (I8), and system (I4); and clockwise R3, which included I1, I5, and I4. R1 highlighted the need for integrating products, services, and experiences into an AI and robotic ecosystem for AIP. R2 underscored health monitoring through AI to foster social well-being, while R3 stressed the importance of AI interfaces for supporting daily routines.

The integrated analysis of CGT and CLD elucidated participants' expectations and challenges in health monitoring, social well-being, and daily routine support. Furthermore, the findings underscored pivotal elements such as trust development, life-stage integration, and service adaptability in applying AI and robotics for AIP, thereby refining the proposed conceptual framework.

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