From Long-Term HRI to Dementia Care: Scoping Personalization Approaches

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Abstract

Lifelong personalization faces a significantly challenging test case in older adults with progressive cognitive decline. We present a scoping review that maps existing personalization mechanisms and identifies gaps relevant to progressive cognitive decline. Dementia renders successful modeling of any aspect of a person's mind a moving target. A person's communication abilities, memory, preferences, and interaction patterns change continuously over months and years at variable rates. In this scoping review, we examine the literature on long-term studies of older adults and on robot-assisted interventions for cognitive impairment, as well as the progress made toward personalization in these contexts. We found no evidence of a published system that implements closed-loop adaptation for progressive cognitive decline. We identify and discuss several open challenges in implementing lifelong personalization for older adults with cognitive decline.

Keywords

human-robot interaction, cognitive impairment, personalization

1 Introduction

As the global population continues to age, the prevalence of cognitive decline increases [52]. We include Alzheimer's disease, vascular dementia, and mild cognitive impairment (MCI) as examples of cognitive decline [52]. The Alzheimer's Association estimates that the number of people worldwide with Alzheimer's alone is expected to increase 250% by 2050 [1]. This could create a sizable burden on caregivers already strained by a lack of workforce [1]. Unlike many cases of long-term deployment within human-robot interaction (HRI) scenarios where user mental states remain relatively stable, dementia often produces continuous, progressive decline.

In the context of cognitive decline, personalization requires not only adapting to a user's current state but also tracking changes in that state as the decline progresses. Lifelong personalization is only possible if the system actively maintains a user model that encodes the user's knowledge and current cognitive decline and updates it throughout long-term interaction. The core challenge of lifelong personalization for a person with cognitive decline is that snapshots of their state may effectively reflect different ”people” as their decline intensifies.

Our central research question is whether any long-term studies of robots interacting with people who have cognitive decline implements closed-loop adaptation between interaction sessions. We operationalize “closed-loop adaptation” as a pipeline that senses user behavior, interprets it in context, selects and executes robot responses, and updates an explicit user model that informs future decisions across sessions [27].

Robots are an ideal system to support people with progressive cognitive decline because the number of people with this cognitive impairment is increasing faster than the number of available caregivers [1]. These robots could provide support to caregivers under strain and, in some studies, have been shown to reduce agitation, anxiety, and depression [33, 38].

As a clearly defined research area of personalization for people experiencing cognitive decline has not appeared in the literature, we draw on long-term HRI studies with older adults and robot-assisted interventions for cognitive impairments. We explore several types of dementia care within HRI using different approaches with respect to the personalization they provide, their feasibility in real-world deployments, and their potential to address the unique challenges of progressive cognitive decline. We believe that this scoping review can inform and assist with the development of adaptive robots for long-term dementia care and support.

2 Search Methodology

We began with several survey papers [11, 17, 54] and searched both the papers they cited and those that cited them. We complemented our search by using Google Scholar's Scholar Labs, with the query "long-term or longitudinal personalization HRI studies for older adults with dementia and or progressive cognitive decline". Studies were additionally sourced from 2006-2026 from Google Scholar using the keyword pairs "lifelong personalization" AND dementia, "long-term personalization" AND "cognitive decline", "adaptive systems" AND dementia AND "longitudinal" AND "robot", "personalized interaction" AND "mild cognitive impairment" AND longitudinal, "user modeling" AND dementia AND "long-term", "preference learning" AND older adults AND dementia AND robot, "personalization" AND "assistive technology" AND dementia.

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3 Key Surveys

In the domain of long-term HRI, Leite et al. [28] surveyed approximately 30 studies and identified participant perceived novelty as a threat to engagement. A survey of 120 long-term HRI studies (performed between 2003-2023) found limited representation of vulnerable populations [30]. These surveys identified personalization as a persistent challenge [30]. This helped to motivate our desire to produce this review.

Several surveys address HRI for dementia care. Bemelmans et al. conducted a systematic review of robots in elder care, setting the stage for later dementia-specific approaches [4]. Ghafurian et al. reviewed social robots for dementia care and noted the absence of personalization to individual dementia stages [17]. Importantly, a meta-analysis of 66 studies on socially assistive robots for people with dementia found no clear evidence for cognitive or quality-of-life improvement [54]. Another meta-analysis of 15 randomized controlled trials (RCT) similarly found null effects on cognition but reductions in agitation and anxiety [11]. Two more meta-analyses found that robot interventions had improvements in terms of reducing depression, anxiety, and agitation [33, 38]. Hsieh et al. meta-analyzed 14 RCTs in long-term care facilities, finding that personalization was not implemented in any included study [22]. Overall, these studies help to show that much of the existing work in the HRI-dementia space does not emphasize personalization as a part of their approach.

In comparison, some surveys focused on personalization and adaptation. Rossi et al. surveyed user profiling and behavioral adaptation for social robots [41]. Gasteiger et al. reviewed personalization through communication, behavior, proxemics, and interfaces and noted limited investigation in individuals with dementia [16].

This work, however, did not account for non-stationary user models. Prior surveys described several approaches to personalization, including rule-based, machine learning, and reinforcement learning (RL) [20]. Taxonomies have also been proposed to categorize robot-assisted training based on task type, interaction roles, autonomy level, and personalization dimensions [48]. Martins et al. proposed a taxonomy of user-adaptive systems: systems with no user model, systems with a static user model, and systems with a dynamic user model [29]. Our analysis follows [29] using this taxonomy in our classification of user models.

While these surveys separately cover long-term HRI studies, dementia studies, and personalization techniques, there is minimal cross-domain comparison to identify approaches that support lifelong personalization for users whose cognitive abilities are progressively declining, motivating our desire for this scoping review.

4 Review of Personalization Approaches

4.1 No User Model

The majority of long-term deployments with older adults involved robots with minimally adaptive behavior and no explicit user model.

PARO, a therapeutic seal robot, has one of the largest numbers of studies involving dementia. Wada and Shibata documented a two-month deployment that showed sustained mood improvements and user-robot relationships [50]. A subsequent one-year continuous deployment occurred [51]. Jøranson et al. conducted a study across 10 nursing homes (60 residents, 12 weeks) and found agitation and depression reductions persisting during a 3-month follow-up [24]. Moyle et al. (415 participants) compared PARO to a plush toy and usual care [32]. PARO improved engagement, but its advantage over the toy was minor. Observational studies in nursing home settings found that PARO's effects varied significantly for individuals with varying dementia severity. This showed that staff facilitation and group context resulted in adaptation that was only provided by humans rather than robots or models [7, 42].

A complementary long-term dementia deployment used an autonomous robot as a companion during physical-therapy walking groups [19]. Therapists perceived potential benefits (positive increases in motivation, social group cohesion, and mood), but the study emphasizes that even minor failures resulted in a robot that created an additional workload rather than support for human caregivers [19]. Jibo [34] was deployed in homes for up to 1 year. It was designed to function as a social catalyst for older adults with the goal of increasing human-human interaction. Jibo's usage declined over the months, although social features remained popular longer than other features. No behavioral adaptation was implemented. Gasteiger et al. [15] conducted a four-year international participatory design project, which resulted in short in-home test deployments (one-week trials). The study's participants were older adults with MCI and mild dementia, carers, clinicians, and engineers across South Korea and New Zealand, with the goal of developing a home-based robot (Bomy) for cognitive support. The resulting system did not maintain or update a model of individual users over time. Pou-Prom et al. deployed a conversational robot for older adults with Alzheimer's disease and found that sustained, natural interaction was feasible, but as previously mentioned, the robot lacked cross-session memory and behavioral adaptation [37]. Together, these studies illustrate that many carefully designed and stakeholder-grounded deployments for this population have not crossed the threshold into model-driven adaptation.

These approaches often rely on pre-defined, fixed robot behaviors rather than on representations or adaptations tailored to an individual user. Interaction policies are fixed at deployment, typically because the interaction policy is not a variable in the user study. These systems generally make no attempt to model a user's state and, therefore, can not track individual changes over time.

4.2 Static Personalization

Static personalization is our umbrella term for approaches that leverage previously known user information to adapt how the robot interacts with that person, without updating user models through interaction.

While this set of approaches is less popular than "No User Model", it still includes multiple highly influential studies. The MARIO project deployed an AI-based robot that provided users with personalized content, using music tied to a user's personal memories, reminiscence activities, and customized games across sites in Ireland, Italy, and the UK [6, 10]. The authors noted content personalization as one of the primary causes of decreases in depression and increases in social connection and engagement between the robot and human. The robot, however, did not adapt its behavior to each user during interaction or learn a network. Instead, it maintained a collection of personalized media that it could use for each person. Figueroa et al. [12] deployed a robot (RoBoHoN) in homes for up to six months with content tailored to user interests, which were determined before the engagement began. Similar to prior work [6, 10], the authors found that the personalization resulted in sustained acceptance and increased attachment for the robot. CARMEN [5] represents a home-deployed system for MCI delivering validated compensatory cognitive training. While it supports clinician-configured personalization, the system does not update user models based on observed performance, placing it in the static category.

These approaches typically encode user content (history, preferences, cognitive impairments) into a static profile constructed for each participant prior to deployment, often using caregiver input. The static profile provides a process for selecting content relevant to a user's profile. The profile is not adapted to the user's responses to the stimulus or to the robot's behaviors. The underlying technical system used to implement these approaches is typically a finite-state machine or a scripted dialogue manager to ensure consistency across sessions.

4.3 Dynamic Within-Session Adaptation

We define within-session adaptation as robots that adjust their behavior during a single interaction in response to real-time user feedback, but do not use learned information from the same participant across sessions. These approaches are often categorized as personalizing within a session by deleting all learned information of the user at the end of the session.

Andriella et al. developed CARESSER [3], which utilized active learning from therapist demonstrations to build patient-specific Bayesian interaction policies (*n*=22). CARESSER represented a sophisticated within-session adaptation approach for cognitively impaired users by using patient-specific policies. Pino et al. used NAO (a small humanoid robot) for memory training with 21 MCI participants using scripted adaptation within sessions and found that the participants paid closer attention when compared to therapist-only sessions [36]. De Carolis et al. deployed Pepper for cognitive stimulation therapy and found that participants with higher degrees of cognitive impairment exhibited distinct yet sustained engagement patterns [8]. The COACH system used a partially observable Markov decision process (POMDP) to adapt handwashing prompts. It incorporated a coarse representation of user impairment (often treated as a fixed severity setting) that was initialized prior to interaction and not updated to model longitudinal decline across sessions [31]. These studies provide some insight into how approaches to within-session adaptation have progressed in HRI. Much of personalized adaptation appears to occur in studies with very specific tasks in which the effects of within-session adaptation can be more closely measured.

From a technical perspective, algorithms are typically selected that have shown promise in adaptation in the past. Approaches such as POMPDs, rule-based branching, and Bayesian active learning have tended to dominate this space.

4.4 Dynamic Cross-Session Adaptation

We define cross-session adaptation as robotic systems that maintain and update a user model between sessions, enabling the robot to track changes over time.

This category of study is limited by the logistical complications of maintaining multiple user models over extended periods while ensuring their accurate updating.

Tapus et al. [46] conducted a 6-month pilot adjusting robot personality and task difficulty for users with dementia across sessions. The Nadine robot [49] implemented long-term conversational memory across 29 sessions with cognitively impaired residents. This represents one of the only projects with explicit episodic memory spanning multiple sessions. Cross-session modeling has recently seen the work of Sievers and Russwinkel make a contribution [44]. The authors proposed combining ACT-R with large language models for persistent person models. Spaulding et al. demonstrated GP-based multitask personalization for adapting and reusing learned models across users [45]. Andriella et al. [2] used persona-based Bayesian simulators to bootstrap robot policies before real interaction. These approaches address cold-start and reuse problems but have not been tested with cognitively impaired users. Additionally, we find no instances of models that are able to predict trajectories that decline over time.

These approaches generally achieve adaptation by modifying the robot's future behavior based on accumulated memories (task performance history, personality traits, or conversations). Gaussian Process learning trains priors across users to avoid training a model from scratch for each person (cold-start problem). Examples of technical architectures include ACT-R, LLMs, Gaussian processes, and persona Bayesian simulators.

4.5 The Missing Category: Adaptation to Progressive Decline

After reviewing the literature, we identified a gap. While prior systems have incorporated longitudinal monitoring, cross-session memory, or preconfigured stage-specific interaction modes, we found little evidence of integrated closed-loop, cross-session adaptation to progressive cognitive decline.

The components appear to exist separately. On the detection side, computational analysis of narrative speech has demonstrated reliable discrimination between Alzheimer's disease patients and controls [13], and more recent longitudinal work has improved MCI detection through repeated sampling [39]. Conversational screening has also been demonstrated via dedicated tools [35, 53]. On the adaptation side, CARESSER and interactive RL learn personalized interaction policies within sessions [2, 47]. However, these two approaches do not seem to have been used to fill our gap of closed-loop adaptation.

Gallina et al. proposed the concept of progressive co-adaptation, involving continuous monitoring and inference about changing user capabilities, but did not implement it for dementia [14]. Hofstede et al. [21] observed that structured prompts suit early-onset dementia, while emotional companionship suits later stages. Neither of these approaches provided an approach to transitioning between cognitive decline states.

Relevant non-HRI systems demonstrate the feasibility of the individual components of our proposed gap. The ACTIVE trial (n=2832, 10-year follow-up) showed that adaptive cognitive training produced 29% lower dementia incidence, with the adaptive condition outperforming non-adaptive ones [40]. The ORCATECH program deployed sensors in over 250 homes for 3-5 years and established within-person longitudinal baselines that detected decline 1-2 years before clinical diagnosis [25]. Graessel et al. showed that ML-personalized cognitive training outperformed generic training in patients with MCI [18]. These results demonstrate that adaptive personalization can improve outcomes and that within-person trajectory modeling is technically feasible for users with cognitive decline, but these ideas have not yet been systematically integrated into long-term HRI deployments.

5 Challenges

Several challenges remain in applying lifelong personalization to older adults with cognitive decline. These challenges arise from the need for the developed system to track and respond to progressive changes in user abilities over extended periods.

5.1 Non-stationary user modeling

Standard personalization assumes a stationary or slowly-drifting user. Cognitive decline often increases in severity and can accelerate. Data from cognitively impaired users can tend to be sparser and noisier than that from other groups of users [17]. Sessions are shorter, behavioral variability can be higher, and speech patterns change with disease progression [17]. Bayesian models with uncertainty quantification [2] and within-person baselines [25] are potential starting points, but have not been tested with users whose abilities are actively declining, which could cause issues for these types of models.

5.2 Evaluation metrics for adaptive systems

Standard pre-post cognitive measures seem inappropriate when decline is expected. This is because pre-post measures expect stability in cognitive performance without any intervention, such as a robot. In the case of cognitive decline, pre-post measures would likely always report a decline in performance. As such, the field needs metrics tailored to this context, such as the rate of decline, the quality of adaptation relative to clinician recommendations, sustained engagement despite declining capacity, and preserved autonomy. The variability in the visible representation of dementia argues for single-case experimental designs, but no standardized evaluation exists for long-term adaptive HRI for this population.

5.3 Balancing autonomy and support

As cognition declines, the robot may need to assume more initiative and potentially can influence users more, but increased robot initiative risks reducing user agency and might result in precarious ethical situations (see Section 5.4). Dynamic models of shared autonomy, where roles are regularly restated and potentially renegotiated, do not yet appear to exist for this context.

5.4 Ethics of detecting and communicating decline

A robot conducting lifelong personalization accumulates sensitive data about declining abilities. The unique progressive nature of this decline creates a concerning moving consent problem. A user who initially consented to long-term data collection and personalization may later lack the capacity to understand what the robot has learned about them or the robot's purpose [9, 23]. If the robot detects an accelerating decline, questions arise about who should be informed and how consent can even continue to be obtained. These concerns are amplified in the context of robot care. Long-standing ethical work identifies surveillance and loss of privacy as core risks when robots accumulate behavioral data on vulnerable older adults [43]. Beyond these concerns, dementia-specific analyses warn that personalization itself can introduce additional risks, including manipulation or undue influence, over-reliance and displacement of human relationships, and value misalignment when systems infer and act on sensitive personal attributes, which become more acute as personalization relies on longitudinal behavioral data for longer durations of time [26].

While this review focuses on older adults with cognitive decline, the challenges (Sections 5.1, 5.2, and 5.3) have significant commonalities with diverse long-term HRI applications involving users with changing abilities.

The first challenge could be addressed by combining within-person research from smart homes [25] with Bayesian or GP-based user models [2, 45]. The second challenge could be partially addressed by adapting single-case experimental designs from clinical psychology. The third challenge may benefit from starting with a generic policy pretrained on user simulations, as suggested in non-dementia HRI contexts [2], and progressively specializing it as real interaction data is collected. While these proposed solutions to the challenges are limited in scope, their goal is to further discussion and debate about the potential solutions in long-term personalization with this unique demographic.

6 Conclusion

This work provided an overview of long-term personalization approaches for older adults with cognitive impairment. We reviewed four types of personalization: No User Model, Static Personalization, Dynamic Within-Session Adaptation, and Dynamic Cross-Session Adaptation. Based on our surveyed literature, we conclude that the specific challenge of integrated closed-loop, cross-session adaptation, where a system tracks decreases in cognitive ability and uses them to update an explicit user model that drives behavior changes across sessions, remains unaddressed. We also identified several shortcomings of existing approaches in personalization within this context and explored the challenges of using user models for users with cognitive decline.

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Table 1: Comparison of personalization approaches for older adults with cognitive impairment. Personalization type follows the categorization in Section 4. "Cross-session" indicates whether the user model is updated between sessions.

Reference	Personalization type	Algorithm	Features	Cross-sess.	Study Duration
PARO [50]	No user model	Reactive behaviors	Touch sensors, sounds	✗	4 weeks
PARO [51]	No user model	Reactive behaviors	Touch sensors, sounds	✗	52 weeks
PARO [24]	No user model	Reactive behaviors	Touch sensors; staff-facilitated use in care routines	✗	12 weeks
PARO [32]	No user model	Reactive behaviors	Touch sensors; compared to plush toy/usual care	✗	10 weeks
PARO [42]	No user model	Reactive behaviors	Group context + staff mediation (adaptation via humans)	✗	7 weeks
PARO [7]	No user model	Reactive behaviors	Individual differences by dementia severity; facilitation effects	✗	13 weeks
Conversational robot [37]	No user model	Spoken dialogue system	Cognitive assessment conversation; miscommunication + linguistic feature analysis for monitoring	✗	Pilot (3 sessions during the period of 52 weeks)
Walking-group assistant [19]	No user model	Fixed behaviors	Visual & acoustic stimulation during PT walking groups; therapist-mediated deployment	✗	4 weeks
Jibo [34]	No user model	Fixed behaviors	—	✗	4-52 weeks
Bomy [15]	Static (content)	Scripted + manual configuration	Personalizable reminders; cognitive stimulation games; home daily-routine support	✗	12 weeks (Experimental Portion of study)
CARMEN [5]	Static (content)	FSM controller	Home compensatory cognitive training; progress tracking; activity difficulty selected at session start	✗	1 week
MARIO [6]	Static (content)	Manual	Life history, reminiscence content, preferences	✗	8 weeks
RoBoHoN [12]	Static (content)	Manual	User interests	✗	7-20 weeks
COACH [31]	Dynamic (within-sess.)	POMDP	Task progress; latent user state (dementia level + responsiveness)	✗	8 weeks
Pino et al. [36]	Dynamic (within-sess.)	Scripted	Memory performance	✗	8 weeks
De Carolis et al. [8]	Dynamic (within-sess.)	CST protocol	Engagement, cognition	✗	3 weeks
CARESSER [3]	Dynamic (within-sess.)	Bayesian AL	Therapist demonstrations	✗	2 weeks
Tapus et al. [46]	Dynamic (cross-sess.)	Adaptive assistance based on disability level	Task performance; personality adjusting over time	✓	24 weeks
Nadine [49]	Dynamic (cross-	Episodic memory	Conversation;	✓	29 sessions