Live Life to Your Fullest: Assistive Robot with Theory of Mind to Support Older Adults Aging in Place

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Abstract

This work proposes a design concept for integrating a Theory of Mind (ToM) architecture in a robot to support older adults in aging in place. The robot will continuously assess human capabilities, adapt its assistance to preserve their intrinsic capacity (IC) and functional ability (FA), and directly support Activities of Daily Living (ADLs). While assistive robots exist, assistance is typically limited to either purely social or companionship-oriented interactions, or, in the case of physical assistance, is modeled as a binary decision providing either full assistance or none. Such formulations fail to account for the user's continuously varying IC, FA, preferences, and desire for autonomy. The goal of this project is to (i) integrate assessments of cognitive and physical capabilities into a dynamic, real-time human model, (ii) evaluate ToM-based adaptation, and (iii) validate the system through laboratory testing and long-term user studies. The work addresses research gaps in cognitive monitoring, adaptive assistance, and direct ADL support by socially assistive robots.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; **User models**.

Keywords

Socially Assistive Robot, Aging, Theory of Mind, User Model

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1 Introduction

While the institutionalization of older adults is often framed as a natural progression in later life, the majority of older adults, unsurprisingly, expresses a strong preference to ***age in place*** (i.e., remain in their homes as they grow older). A survey conducted in the United States found that nearly 90% of adults over 65 wish to age in place [2]. This requires the ability to independently and safely perform activities of daily living (ADLs) which are defined as the basic routine activities necessary for daily life that most healthy individuals can perform without assistance. These include personal care tasks such as eating, dressing, bathing, using the toilet, managing continence, and moving from one position to another. The ability to perform ADLs is an essential measure of an individual's functional status and is an increasing challenge for many older adults [16].

The World Health Organization's Integrated Care for Older People (ICOPE) Handbook [54] defines healthy aging as "helping people to develop and maintain the functional ability that enables well-being in older age". Functional ability (FA) refers to the health-related attributes that allow individuals to do and be what they value, reflecting how much a person can act by drawing on their intrinsic capacity (IC) within their environment. IC is "the composite of all the physical and mental capacities that an individual can draw on" and consists of five interrelated domains of locomotion, cognition, vitality, psychological well-being, and sensory function [54]. This concept of healthy aging urges healthcare for older adults towards optimizing IC and FA throughout aging. As IC changes, so do individuals' needs and preferences for clinical, social, and supportive services and care. Therefore, providing integrated and continuous care that aligns with changes in IC and FA is essential for promoting healthy aging and sustaining well-being [54].

Socially assistive robots (SARs) have been widely researched as a support for providing care [4, 10, 19] and literature suggests that increased interaction with SARs can improve mobility [37] and social engagement among older adults [19, 37]. Despite these promising findings, significant gaps remain in deploying SAR systems for sustained cognitive and physical support in real-world home environments. In particular, there is limited research on robots capable of conducting both cognitive and physical monitoring and assessment in domestic settings [3, 32], and continuously track the user's functional status to adapt assistance over time [19, 32]. A direct consequence is that existing works often take on a technosolutionist approach, where assistance is driven more by the robot's technical capabilities than by the user's actual needs, increasing the risk of both over-assistance and under-assistance, thus undermining aging in place. This framing can give rise to robot-mediated paternalism (RMP), where assistive robots provide unwanted assistance or interfere with a user's decisions and actions based on assumptions about their autonomy and care needs [20]. Such interference, whether

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explicit or subtle, can occur even when systems are designed with the intention of benefiting the user, and may ultimately diminish user agency and autonomy [20]. Unfortunately, these risks are often not explicitly considered in existing SAR systems. Finally, most existing SAR applications focus primarily on companionship or mental well-being, with limited work addressing direct support for ADLs [4, 10, 19]. This work explicitly aims to avoid RMP by preserving user agency and autonomy. Rather than deciding actions for the older adult, the robot is designed to support the user by complementing their capabilities and providing assistance only where gaps exist.

The identified research gaps lead to the following research questions.

- **RQ1 - Understanding the older adult's capabilities, intentions & needs:** How could a robot dynamically model an older adult such that it can assess the older adult's intrinsic capacity, functional ability, preferences and needs to inform adaptive assistance?
- **RQ2 - Acting on understanding:** How could a robot provide its assistance to the older adult such that it promotes their agency and autonomy?

2 Problem Scope

ADLs are widely used as indicators of an individual's physical and cognitive functioning [26]. Within this context, ***hydration*** is a fundamental yet often overlooked component of eating-related ADLs, requiring both sufficient fluid intake and the ability to carry out the actions necessary to obtain and consume fluids. ***Hydration*** is selected as the focus of this work due to its strong physiological, cognitive, and functional relevance in aging populations. Physiologically, aging is associated with reduced kidney efficiency and a diminished thirst sensation, together impairing fluid regulation and increasing risk of dehydration [42]. Older adults therefore may not naturally compensate for fluid loss. A recent systematic review further links dehydration in adults aged 60+ to poorer cognitive performance, particularly among those living independently [17]. From a cognitive perspective, maintaining hydration relies on memory, attention, and executive function. Older adults may forget to drink, fail to recognize early signs of dehydration, or have difficulty maintaining consistent hydration routines. This worsens with cognitive decline, making the initiation and completion of hydration-related actions less reliable. Finally, from a functional perspective, maintaining hydration involves a sequence of coordinated actions requiring multiple cognitive and physical skills. For successful hydration, an individual must (1) perceive internal or external cues related to thirst, (2) recall the need to drink, (3) plan and initiate a sequence of actions for hydration, (4) navigate to a water source, (5) manipulate objects such as cups, bottles, sinks or water dispensers, and (6) successfully consume the water. These steps involve multiple IC domains defined in ICOPE [54], including cognition, mobility, and aspects of vitality related to hydration [31]. Limitations in mobility or coordination can therefore directly impact one's ability to remain hydrated, and thus live independently.

Hydration thus represents a minimally complex yet representative ADL assistive scenario that requires coordination across cognitive, physical, and behavioral domains of IC, and capabilities when considering FA. As such, it provides a suitable starting point for developing and evaluating adaptive assistance, capturing key challenges present in more complex ADLs while remaining manageable for preliminary system design and validation. Supporting hydration also has broader implications for health, well-being, and independence.

As illustrated in Figure 1, our goal is to enable a robot to: **(RQ1)** Regularly and accurately assess the older adult on the cognitive and physical capabilities required for self-hydration, along with daily water intake; and **(RQ2)** adapt its assistance to the person's current IC and FA, which can range from verbal reminders to autonomously fetching and providing water.

3 Related Work

3.1 Measuring Intrinsic Capacity

Standard clinical assessments provide objective and reliable methods for evaluating IC, particularly through measures of cognitive and locomotor (mobility) performance to establish baseline IC levels [8, 54]. Examples of standard geriatric assessments include the Montreal Cognitive Assessment (MoCA) [38] for mild cognitive impairment (MCI), the 4 Mountains Test (4MT) [13] for spatial memory for the diagnosis of pre-dementia Alzheimer's disease, and the Short Physical Performance Battery (SPPB) for mobility [54]. While standard clinical assessments provide scientifically valid measurements, they must be administered by trained professionals and can't be frequently administered due to practical constraints and potential learning effects.

To address this limitation, prior work has inferred cognitive and physical decline from ADLs [5, 14, 15, 52]. For instance, [52] used motion sensors to detect changes in bathroom visits, sleep, and social activity as indicators of early health decline, while [14] correlated ADL features (e.g., activity duration, sensor triggers, transitions) with clinical measures of cognitive and motor health. In addition, Table 3.1 of the ICOPE handbook details a basic assessment for loss of IC that can be done by anyone [54], shown in Figure 2. We postulate that these questions can be administered by a robot to monitor IC of the older adult on a day-to-day basis and detect trends of improvement, decline or stability.

3.2 Assistive Tools for Functional Ability

Cognitive decline, mobility decline, and malnutrition are the major contributors to IC decline [9, 47, 54]. Assistive tools, are considered one of the most effective approaches for sustaining IC and FA [9, 54]. Assistive tools (e.g. wheelchairs, glasses, hearing aids, pill organizers, toilet chairs, fall detection systems, time management software and captioning) maintain or improve FA and independence, and thereby promote well-being.

For assistive robots, recognizing the presence and use of such tools is critical, as they directly affect an individual's functional capabilities. For example, in a hydration task, the robot should account for whether assistive tools are available: if they are, assistance can be adapted based on the user's FA; otherwise, it should rely more heavily on the user's underlying IC to determine appropriate support.

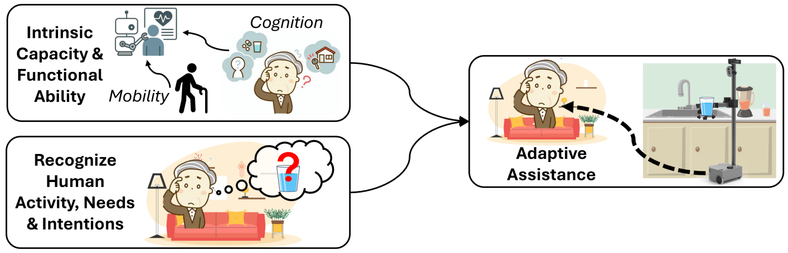


Figure 1: Theory of Mind Model to Adapt Assistance According to Human Capabilities and Intentions.

Table 3.1
Basic assessment for loss of intrinsic capacity

	Filter question If YES, proceed for in-depth assessment (Step 2)	Tests	Assess fully any domain with a checked circle	Pass
5 **Cognitive decline** (Cognition)	**Do you have problems with memory or orientation** (such as not knowing where you are or what day it is)?	1. **Remember three words** (use nouns, for example): flower, door, rice. 2. **Orientation in time and space:** What is the full date today? Where are you now (home, clinic, etc.)? 3. Recalls the three words?	○ Wrong to **either** question or does not know ○ Cannot recall all three words	○ Correct to **both** questions
6 **Limited mobility** (Locomotor capacity)		**Chair rise test** Rise from chair five times without using arms. Did the person complete five chair rises within 14 seconds?	○ No	○ Yes
7 **Undernutrition** (Vitality)		1. **Weight loss** Have you unintentionally lost more than 3 kg over the last 3 months? 2. **Appetite loss** Have you experienced loss of appetite?	○ Yes ○ Yes	○ No to **both** questions
8 **Vision impairment** (Vision) *with spectacles if normally worn	**Do you have any problems with your eyes: difficulties in seeing far or near*, eye pain or discomfort?** **Do you have diabetes, or hypertension, or are currently using steroids or eye medications?**	1. **External eye check** 2. **Visual acuity test** using WHO vision screening chart*: • Distance vision (6/12 for each eye) • Near vision (N6 for both eyes)	○ Fail ○ Fail	○ Pass ○ Pass for **both** distance and near vision
9 **Hearing loss** (Hearing)	**Do you have a hearing problem?** *For those using a hearing aid(s) add, "even when using your hearing aid(s)".*	**Whisper test** or **Screening audiometry** or **Digits-triplet-in-noise test**	○ Fail	○ Pass
10 **Depressive symptoms** (Psychological capacity)		**Over the past 2 weeks, have you been bothered by either of the following:** • Feeling down, depressed or hopeless? • Little interest or pleasure in doing things?	○ Yes ○ Yes	○ No to **both** questions

Figure 2: ICOPE Table 3.1 Basic Assessment for Loss of Intrinsic Capacity.

3.3 Understanding User Intentions and Needs

In addition to estimating IC and FA, assistive systems must infer the older adult's intentions and needs to determine what assistance to provide and when to do so. In other domains, intention recognition approaches have employed recurrent neural networks [35], probabilistic shared-autonomy models [23], and motion-legibility frameworks [27]. Here, we propose that ***Theory of Mind (ToM)*** for robot assistance would be highly suitable in care settings where the robot must prioritize the older adult's condition.

ToM refers to the ability of an agent to "...impute(s) mental states to (themselves) and others. A system of inferences of this kind is properly viewed as a theory because such states are not directly observable, and the system can be used to make predictions about the behavior of others" [44]. In robotics, ToM has been explored to enhance assistive communication in cooperative tasks [12], foster trust between humans and robots [48, 49], and influence perceptions of social and task attractiveness [11]. These approaches vary from reinforcement learning [12] to Wizard-of-Oz (i.e., robot behavior is triggered by an experimenter remotely) and pre-programmed behavioral models [11, 48, 49]. More recently, [6] proposed and evaluated a two-layer ToM-enabled architecture for socially adaptive robot assistance tailored to the user's capabilities in a card memory game. This two-layer architecture combines the learning layer for simulation and policy optimization (i.e., game strategy advice to suggest), and the ToM layer for estimating the user's strategy and beliefs about the card choice. While this demonstrates how ToM reasoning can be used, this implementation is still limited to social interactions. Overall, ToM can allow robots to reason about an older adult's intentions and needs in relation to their IC and FA to plan assistive actions accordingly. This work extends prior work by extending ToM reasoning to embodied, task-oriented contexts for providing both social and physical adaptive assistance.

3.4 Human Activity Recognition and ADL Classification

Automated human activity recognition and ADL classification have been studied across multiple application domains using vision-based, wearable, and multimodal sensing approaches [39, 43, 55]. Applications include general activity classification [34, 43, 55, 56], ADL recognition for individuals with disorders [39], and activity recognition tailored to older adults [46, 51].

In care settings, human activity recognition systems are primarily used for monitoring, including general activity tracking [36], detection of activities that precede hazardous events such as falls [40], and recognition of activities performed in real-world environments [7]. While showing feasibility of activity recognition in real-world settings, they are focused on observation and detection rather than on enabling adaptive, task-level assistance.

One recent robot-centric framework has incorporated a multimodal deep-learning-based ADL classifier with a user state estimation module capable of identifying seen, unseen, and atypically performed ADLs [46]. Atypically performed ADLs are those done different to how the seen ADLs were performed by a user. This represents a step toward richer user state modeling and significantly improving activity recognition in realistic settings. However, the resulting assistance remains binary, providing either full assistance or none, and without considering varying IC, FA, preferences, or desire for autonomy in the decision making. This limits the robot's ability to deliver nuanced support. Nevertheless, the proposed multimodal user-state estimation approach provides a strong foundation for activity recognition in adaptive assistive robotic systems.

It is also important to note that many existing activity recognition and ADL classification models are trained on datasets that under-represent older adults. As a result, these models may exhibit bias or reduced performance (i.e., reduced reliability of inferred activities) when applied to older adults, whose movement patterns, speeds, and interaction behaviors can differ significantly from younger or able-bodied populations. To mitigate this bias, this work will prioritize using datasets that include older adult participants and anticipates collecting additional data where necessary.

3.5 Adaptive Robotic Assistance

Research on adaptive robotic assistance for physical care remains limited. In [45], a framework was proposed which combined motion anticipation for predicting human movement and utility inference for estimating user preferences over physical task execution parameters (e.g., speed and force), evaluated on tasks such as feeding. While the adaptive assistance is based on estimating some aspect of the user state, the total level of assistance for each set of user preferences remains fixed. As such, this form of adaptation tunes how assistance is delivered rather than how much assistance is provided, and therefore does not align with the notion of adaptive assistance targeted in our work.

In [28], a Reinforcement Learning Assist-as-Needed (RL-AAN) controller for robot-assisted upper-limb rehabilitation was proposed, which dynamically balances user performance, effort, and task difficulty to promote active participation. Although evaluated only with healthy participants, the controller achieved comparable movement accuracy to state-of-the-art methods while providing substantially less assistance and led to improved retention of target movements. However, the approach is also limited to short-term, task-specific rehabilitation scenarios and does not model or track user IC or FA over time. In [25], an adaptive robotic system was proposed for assisting paralyzed users by modulating autonomy levels based on cognitive fatigue, switching between fully controlled, semi-autonomous, and fully autonomous modes. While this work incorporates one aspect of the user's internal state, adaptation only occurs primarily at the level of autonomy selection, still with binary assistance.

While these approaches introduce sophisticated mechanisms for adapting assistance, whether through motion prediction, reinforcement learning, or autonomy switching, they do not consider the context of the user's lived experience, including changes in IC, FA, and personal intentions and goals. They primarily frame adaptation as a control or policy problem rather than a holistic, temporally extended process of supporting autonomy and well-being. This overlooks the socio-cognitive and clinical dimensions essential for sustained assistive care, thereby limiting the applicability of such systems in real-world, long-term deployment scenarios.

3.6 Human-Centered Adaptive Robotic Assistance

To provide effective and adaptive assistance, robot behavior should not only maximize task success chances and usage of the older adult's IC and FA, but also preserve sense of agency, autonomy, and preferences.

Regarding agency and autonomy, [18, 24] points out that while SARs have strong potential to enhance human autonomy, they could also inhibit and disrespect it, such as by focusing exclusively on therapeutic goals and neglecting user autonomy. One way to mitigate this is by using user-centered principles [18, 24, 53]. In [53], the authors showed that a robot that always provides different options to the user (in this case children learning a second language) is one way to maintain autonomy. [24] also noted that reliance on extrinsic rewards was found to be detrimental. Hence, it may be better to provide emotional rewards such as positive feedback or compliments, as they inspire positive emotions and fortify users' enjoyment [24]. Aligning with the goals of this work, [18, 24] concluded that SARs should empower users toward meaningful goals and support their competencies, rather than restricting their choices or offering superficial options without genuine consideration of their autonomy.

In [29, 50], the authors found that for older adults without cognitive disorders, a social robot can use a combination of multimodal behaviors to help maintain engagement and prolong social interactions. For those with Mild Cognitive Impairment (MCI), a robot's behaviors can be designed to (1) include repetition of instructions, (2) minimize distractive behaviors by using pointing gestures for visual focus of attention, (3) provide more time for each step of an activity, and (4) give positive reinforcement when completing an activity step. These findings are useful to employ in this work for the behavior design of when the robot is providing assistance.

Continuous robot monitoring in home environments also raises important concerns regarding privacy and dignity. Recent work has shown that users' perceptions of comfort and acceptability are also influenced by how it is physically present in the environment—for example, whether the robot remains in close proximity at all times or maintains a respectful distance within shared spaces [22]. These findings suggest that intrusive or persistent monitoring behaviors may negatively impact users' sense of privacy and dignity, even when the robot's intentions are assistive. Another important design consideration is ensuring that monitoring and IC/FA assessment are conducted in an unobtrusive manner or only on a voluntary basis. In this work, the robot relies primarily on directly observable data (e.g., general physical movements, ADL completion behaviors) to infer the user's state, rather than requiring explicit user input or interrupting ongoing activities. For example, functional indicators such as sit-to-stand performance can be assessed passively during natural daily activities without requiring the user to perform dedicated tests. We address these considerations by designing robot behaviors that are minimally intrusive, context-aware, and responsive to user preferences. To ensure the resulting behavior design achieves this, co-design sessions must be conducted with geriatric professionals and older adults.

4 Concept

4.1 Robot Platform

For this work, we use the Stretch 3 [1] robot (Hello Robot, USA). It is a mobile manipulator consisting of a mobile base and a manipulator arm that can move vertically and extend and retract horizontally. The arm has a gripper at the end with a payload of 2 kg, capable of carrying a variety of household objects and open doors. We chose Stretch 3 because its hardware and built-in manipulation capabilities match our scenario, and its simple appearance does not over-promise capabilities, which is a phenomenon observed in social robotics and human-robot interaction research [30]. The Stretch 3 robot has also been evaluated with older adults, which confirms that its capabilities and use-cases are suitable and accepted by older adults [41].

4.2 First Minimal Implementation

The current implementation utilizes a minimal finite state machine, designed as a concept for the proposed interaction paradigm in which an assistive robot supports ADLs by adapting its assistance strategy to the older adult's IC, FA, preferences, identified needs and intentions. State machines are a way to model the behavior of a system that can only exist in one of a few "states" at any given time. Specific triggers called "transitions" allow the system to change from one state to another. Transitions are often certain conditions that have been fulfilled or commands that the system received. Our state machine was created using Yet Another State Machine (YASMIN) [21], a library for state machine development specifically designed for use within the Robot Operating System 2 (ROS2) [33],the de-facto standard in middleware for robotics, also used by the Stretch 3 robot.

4.3 Finite State Machine

The state machine illustrated in Figure 3 consists of three operational states: 1) Idle, 2) Assess, and 3) Assist. The robot will always operate in one of these states.

4.3.1 *Baseline Intrinsic Capacity and Functional Ability.*

The robot will first establish a baseline for IC by conducting the basic assessments from ICOPE discussed in Section 3.1. This is then used as the baseline for the Assess State, which is updated with data acquired from the robot sensors. To establish a baseline for FA, the usage of assistive tools based on documentation from care records can be input into the robot before deployment.

4.3.2 *Idle State.*

In the *Idle* state the robot is on standby and passively observes the older adult and the environment. The actions taken by the robot during this state can yield three possible outcomes, two of which result in transitions to a different state. The transitions are as follows:

1) Assessment Trigger / Timer: Robot transitions from the *Idle* state to the *Assess* state either when a periodic timer elapses (scheduled assessment) or when detected user (in)activity triggers an on-demand assessment (event-driven assessment of the user's current state).

2) Assistance Need Detected / Timer: Robot transitions from the *Idle* state to the *Assist* state when a need for assistance is detected, or a periodic timer elapses without the older adult drinking water. A need for assistance may trigger through an explicit request or observed behavioral cues indicating the intention to drink water.

3) Observing: If neither an assessment trigger nor an assistance-related event occurs, the robot remains in the *Idle* state and continues passive observation of the user and environment.

4.3.3 *Assess State.*

In the *Assess* state, the robot actively tracks user behavior to infer and update the older adult's internal state and capabilities. Two transitions are possible, described as follows.

1) Assessing: Here, the robot uses its sensors to gather the older adult's activity data which are used for assessments of the older adult's IC (IC) and FA as well as for observing preferences of the older adult. Assessment data are logged and aggregated to produce assessment results, which update the IC/FA and human preferences model within the ToM framework. The robot remains in this state until sufficient evidence is collected to reach a confident assessment.

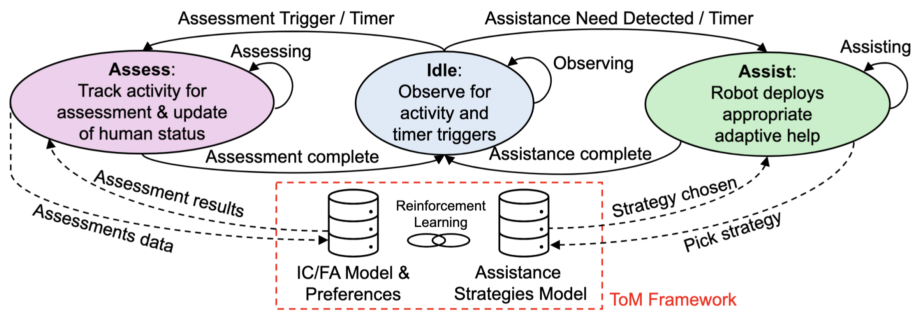


Figure 3: Concept of a State Machine for Hydration Task Considering both the Current Activity and Capabilities of the Older Adult.

Upon assessment completion, it transitions back to the *Idle* state. In the case of unobtrusive assessments (triggered by older adult activity), the robot opportunistically leverages spontaneous user activities when the observed interaction or sensor data are sufficient to instantiate one or more of the basic assessment items shown in Fig. 2. In contrast, scheduled assessments are initiated when a predefined time interval has elapsed, prompting the robot to actively administer any basic assessment tests from Fig. 2 that have not been completed within the specified monitoring window. For scheduled assessments, the robot will always first gain consent from the older adult.

2) Assessment Complete: Robot transitions back to the *Idle* state upon assessment completion.

4.3.4 Assist State. In the *Assist* state, the robot deploys adaptive assistance strategies tailored to the user's current estimated IC, FA, and preferences. Based on the updated human model maintained within the ToM framework, the system selects an appropriate assistance strategy (e.g., verbal prompting, step-by-step guidance, or physical assistance) from the assistance strategies model, and refines its selection criteria via reinforcement learning. The robot delivers and dynamically adapts the selected support in response to the user's ongoing behavior and interaction signals. The robot remains in this state while it is providing assistance for the hydration task and transitions back to the *Idle* state once the assistance is complete, i.e. when the robot detects that the older adult has successfully consumed water. The transitions are as follows:

1) Assisting: Robot delivers and dynamically adapts the selected support in response to the user's ongoing behavior and interaction signals.

2) Assistance Complete: Robot transitions back to the *Idle* state upon assistance completion.

4.4 Example Scenarios

In this section we provide hypothetical scenarios of two different older adults with different impairments to demonstrate how the current state machine works and what that implies for the real robot and older adult.

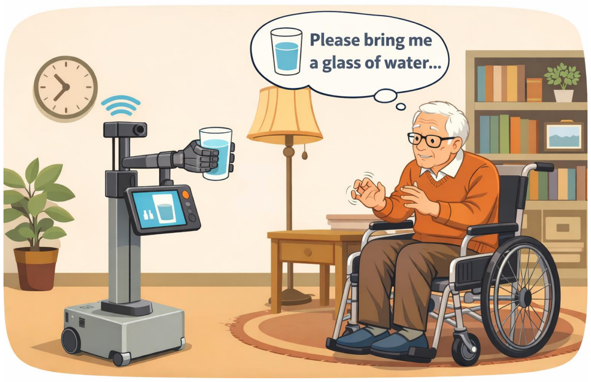
4.4.1 Example Scenario A. Consider an older adult with significant physical impairment (i.e., reduced IC in mobility and dexterity), including wheelchair use and temporary hand tremors, but largely preserved cognitive IC. While the older adult is cognitively able to recognize hydration needs, physical limitations make independent fetching and handling a cup of water difficult. Although such impairments are directly observable, relying solely on preconfigured parameters (e.g., assuming a fixed level of assistance based on wheelchair use) can lead to misaligned assistance. FA can vary both across days and within a single interaction depending on factors such as fatigue, pain, or temporary fluctuations in motor control (e.g., severity of hand tremors). Dynamic FA inference enables the robot to move beyond static assumptions by continuously estimating the user's capabilities in real time. This allows the robot to determine not only whether assistance is needed, but also which type of assistance is appropriate, for example distinguishing between situations where the user can independently grasp a cup versus when physical support or full assistance is required. Table 1 walks through how the state machine operates step by step in this scenario.

4.4.2 Example Scenario B. Consider an older adult with mild cognitive impairment (i.e., reduced IC in cognition) but largely preserved physical IC and FA. The older adult is physically capable of fetching and drinking water independently but may forget to hydrate without external prompting. Table 2 walks through how the state machine operates step by step in this scenario.

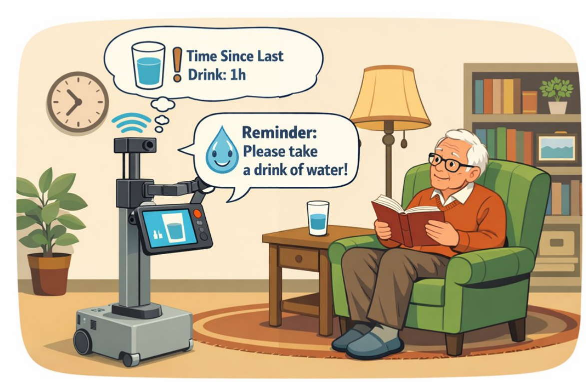
5 Conclusion and Future Work

This work presented a design concept and preliminary architecture for a ToM–based assistive robot designed to support aging in place by regularly and accurately modeling an older adult's IC and adapting assistance accordingly. Using the hydration task as an illustrative scenario, we present a first concept of how adaptive assistance can be created using a basic state-machine that, informed by the user's IC/FA and preferences and assistive strategies models, dynamically selects between cognitive and physical assistance strategies depending on the user's estimated functional abilities.

Future work will focus on the following. First, robot-administered cognitive and physical geriatric assessments, multimodal sensing and activity-recognition pipelines will be integrated



(a) Scenario A: Robot brings water to older adult with physical impairment (wheelchair & temporary hand tremors) and little to no cognitive decline



(b) Scenario B: Robot gives reminder to older adult with mild cognitive decline (MCI) and little to no physical decline

Figure 4: Illustration of Example Scenarios of Older Adults with Different Impairments

Images generated using GPT Image 1.5.

Table 1: Example Walkthrough Scenario A. Older adult with physical impairment and little to no cognitive decline

	Scenario	Sensor Information Output	State Machine
A0	Robot initializes baseline IC (IC) and FA from ICOPE screening [54]. Baseline: low physical IC/FA (wheelchair use, hand tremors), preserved cognitive IC.		
A1	Older adult is sitting and watching TV	No explicit hydration-related cues detected	Idle (Observing)
A2	Older adult maneuvers wheelchair to reach the TV remote and change channels	Vision and motion cues indicate limited reach range, slow wheelchair maneuvering, and reduced fine motor stability	Idle ⟶ Assess (Triggered assessment)
A3	Robot passively observes user's activity without interrupting the user	Multimodal activity data logged to infer FA in mobility and dexterity (wheelchair control, reach, grasp stability)	Assess (Assessing)
A4	Assessment is completed and IC/FA model is updated	Confidence threshold reached; FA (mobility/dexterity) updated in ToM model	Assess ⟶ Idle (Assessment complete)
A5	Prolonged sedentary activity without drinking for an extended period	Time since last drink exceeds hydration threshold	Idle ⟶ Assist (Assistance need detected)
A6	Robot selects assistance strategy based on updated IC/FA (physical impairment, preserved cognition)	Low physical FA inferred; user cognitively capable of following instructions	Assist (strategy selection)
A7	Robot verbally reminds the older adult to drink water and suggests a low-effort option (e.g., straw, bottle within reach)	Audio/vision sensors detect user attention and compliance attempt	Assist (Assisting)
A8	Older adult attempts to drink; hand tremors cause difficulty stabilizing the cup	Visual cues indicate unstable grasp and spillage risk	Assist (Assisting; adaptive assistance refinement)
A9	Robot asks whether the older adult would like help with drinking the water	Speech interaction indicates need for assistance; user consents to help	Assist (Assisting; user-in-the-loop adaptation)
A10	Robot provides physical assistance (e.g., stabilizes cup or repositions it closer)	Successful drinking detected; hydration status updated	Assist ⟶ Idle (Assistance complete)
A11	Older adult resumes watching TV	No hydration need detected; passive monitoring continues	Idle (Observing)

Table 2: Example Walkthrough Scenario B. Older adult with MCI and little to no physical decline

	Scenario	Sensor Information Output	State Machine
B0	Robot initializes baseline IC (IC) and FA from ICOPE screening [54]. Baseline: mild cognitive decline, preserved physical IC and FA.		
B1	Older adult is reading in the living room	No explicit hydration-related cues detected	Idle (Observing)
B2	Scheduled periodic assessment is triggered by timer	Robot gained consent and prompts the older adult to perform short ICOPE-based assessment actions (e.g., simple recall, short walk)	Idle → Assess (Scheduled assessment)
B3	Older adult performs prompted ICOPE assessment actions	Multimodal sensor data (vision/audio/activity) logged to update IC/FA and preferences	Assess (Assessing)
B4	Assessment is completed and IC/FA model is updated	Assessment confidence threshold reached; IC/FA estimates updated in ToM model	Assess → Idle (Assessment complete)
B5	Prolonged sedentary activity without drinking for an extended period	Time since last drink exceeds hydration threshold	Idle → Assist (Assistance need detected)
B6	Robot selects assistance strategy based on updated IC/FA (preserved physical ability, mild cognitive decline)	Human capable of physical mobility; no gait instability detected	Assist (strategy selection)
B7	Robot verbally reminds the older adult to drink water and suggests walking to the kitchen to get a glass of water, explaining that the short walk can also help maintain physical activity	Audio/vision sensors detect user attention and acknowledgment of the reminder and suggestion	Assist (Assisting)
B8	Older adult stands up, walks to the kitchen, fetches water, and drinks	Vision-based activity recognition indicates successful sit-to-stand, walking, grasping, and drinking	Assist → Idle (Assistance complete; hydration status updated)
B9	Older adult resumes reading	No hydration need detected; passive monitoring continues	Idle (Observing)

to provide intrinsic-capacity estimates measurements. Particular attention will be given to the representativeness of training data by prioritizing use of datasets including older adults or creating new datasets with older adult participants. Second, this first concept will be extended into a ToM-enabled adaptive decision architecture capable of reasoning over longer temporal horizons, modeling user preferences, and providing graded levels of assistance rather than discrete intervention strategies. Third, the robot assistive behaviors will be designed through co-design sessions with geriatric doctors, care experts and older adults. To this end, we are currently establishing contact with geriatric doctors and care workers. Fourth, the system will be evaluated through user studies to assess usability, acceptance, and long-term effects on FA and autonomy.

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