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Cultivating Connection: A Feasibility Study of Robot-Mediated Plant Care and Emotional Support for Older Adults

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Cultivating Connection: A Feasibility Study of Robot-Mediated Plant Care and Emotional Support for Older Adults

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Abstract

This paper presents a pilot study examining how a mobile home robot can support older adults through plant care activities combined with conversational emotional support. The system integrates autonomous navigation, vision-based plant health assessment, and large language model-driven dialogue to address participants' mood, cognitive concerns, and daily living activities over a three-week intervention. Five community-dwelling older adults (aged 65+) participated in weekly sessions at a living lab environment, where the robot guided plant care tasks and engaged in structured conversations across four domains: depression screening, cognitive self-assessment, instrumental activities of daily living, and personal preferences. Standardized questionnaires administered after each of the three sessions measured cognitive function, technology acceptance, daily vitality, and psychological stability. Friedman tests across all three sessions revealed statistically significant improvements in psychological stability ($\chi^2(2) = 7.60$, $p = .022$) and robot acceptance ($\chi^2(2) = 8.40$, $p = .015$). The study demonstrates the technical feasibility and preliminary evidence of deploying such services with older adults and identifies key considerations for scaling the intervention.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; • **Computer systems organization → Robotics**.

Keywords

Social human-robot interaction, robot-mediated plant care, emotional support, older adults

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1 Introduction

Population aging has intensified concerns about depression, social isolation, and cognitive decline among older adults. Social and assistive robots have been explored as companions and service providers in elderly care [1, 2], while horticultural activities promote emotional stability and cognitive engagement in older populations [3]. However, few studies have deployed autonomous robots that coordinate plant care activities while delivering personalized emotional support through natural conversation. Recent advances in large language models enable context-aware, empathic dialogue with clarifying follow-up questions [4].

This work integrates these capabilities by deploying a plant care and emotional support service for older adults using a mobile home robot and compact indoor gardening appliance. The robot autonomously navigates to designated locations, captures plant images for health assessment, and conducts multi-domain conversations covering mood, health concerns, cognitive status, and personal preferences. We further investigated whether a retrieval-augmented memory structure could improve personalization across repeated interactions [5].

The main contributions are: (1) a system architecture that integrates autonomous mobile robot navigation, vision-based plant assessment, and LLM-driven multi-domain dialogue (mood, cognition, daily living, and preferences) for older adults; (2) a privacy-preserving personalization mechanism using on-premises LLM filtering and retrieval-augmented generation to enable history-aware conversations without transmitting raw personal data; (3) preliminary evidence from a three-week pilot study (N = 5) indicating significant improvements in Psychological Stability ($p = .022$) and robot acceptance ($p = .015$); and (4) observations suggesting that grounding interaction in shared plant-care activities can support engagement, though future controlled studies are needed to disentangle activity-based effects from conversational support and novelty.

2 Related Works

Therapeutic robots like Paro have shown effectiveness in reducing loneliness and improving emotional stability in elderly care [1], though systematic reviews note limitations in long-term deployment and integration with daily activities [2]. A co-design study with older adults derived design guidelines for on-body robots, emphasizing safety and familiarity [6]. Our study focuses on a mobile home robot that supports meaningful plant care activities while simultaneously providing emotional support.

Gardening offers well-documented physical and psychological benefits for older adults. HCI research has explored technology-mediated gardening: IDROPO supported novice learning through playful hydroponic interactions [7], and Telegarden demonstrated relationship-building through remote robotic gardening [8]. Building on this prior work, our approach positions a mobile robot

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Figure 1: Q9 robot platform.

as a collaborative partner that visually monitors plants and co-constructs care activities with older adults in their living environment.

Recent advances in large language models enable naturalistic robot conversations, yet long-term personalization remains challenging [4]. Retrieval-augmented memory architectures offer a solution by supporting history-aware interactions [5]; we adopt this approach in our system design. A recent meta-analysis of social robot interventions found significant reductions in depression and loneliness among older adults, with larger effects for structured activities and longer durations [9]. This evidence supports our integration of meaningful plant care activities with sustained conversational engagement.

3 System Design and Implementation

3.1 Hardware Platforms

We utilized Q9 [10], a two-wheeled self-balancing home service robot. Its articulated leg joints enable expressive motion and stable navigation over domestic obstacles such as carpets (Figure 1). Q9 integrates multimodal sensing, including RGB cameras, a microphone array, and environmental sensors, to support voice interaction and visual perception. Built on ROS2, the platform provides standardized interfaces for autonomous navigation, motion control, and multimodal perception. For indoor cultivation, we employed the Tiiun-Mini [11], a compact smart gardening device that supports automated cultivation of two seed kits in an enclosed chamber.

3.2 Architecture

The system adopts a distributed robot-server architecture (Figure 2). The robot handles autonomous navigation, on-board perception, and real-time interaction, while the server performs dialogue generation, plant image analysis, and user memory management. Server components include a conversational engine for intent understanding and response generation; a plant analysis module that assesses overall plant health (leaf condition, color, wilting), soil status (dry/moist), and recommends appropriate care actions (watering, light adjustment) based on sunlight adequacy; and a user memory manager maintaining structured information on each participant's health, mood trends, and preferences.

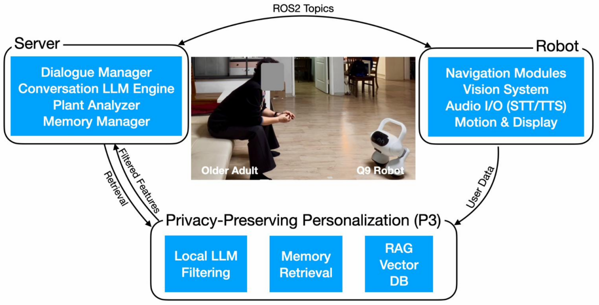

Figure 2: System architecture.

3.3 Privacy-Preserving Personalization

To address the inherent privacy vulnerabilities of cloud-based Large Language Models (LLMs), we designed a Privacy-Preserving Personalization (P3) module. This architecture effectively decouples sensitive user data from cloud inference by implementing a local Retrieval-Augmented Generation pipeline. Initially, the system performs on-premises sanitization, where a local LLM processes raw user utterances to extract relevant conversational features while filtering Personally Identifiable Information. These anonymized features are then transformed into vector embeddings and stored within a local vector database, enabling long-term memory and user-specific personalization without transmitting raw conversational logs to external providers. During interaction, the module executes k-nearest neighbor (k-NN) retrieval to inject relevant historical context into the inference prompt. By grounding external LLM requests in locally-retrieved, sanitized context, the P3 architecture ensures that raw sensitive data never leaves the local server while enabling personalized, history-aware interactions.

3.4 Interaction Scenario

Each session consisted of five steps. (1) The robot navigated to the participant, greeted them, and proposed plant care. (2) The robot guided the participant to prepare water. (3) The robot captured plant images for analysis. (4) The robot explained the analysis results and jointly planned care actions. (5) The robot conducted a conversation covering four domains: depression/emotional state [12], cognitive concerns [13], daily living and health [14], and personal preferences. Each session lasted approximately 30–40 minutes. Conversation prompts were based on validated assessment scales. Depression-related items were adapted from the Geriatric Depression Scale (GDS-15) [12]. Cognitive items were derived from the Mini-Mental State Examination (MMSE) [13]. Daily living questions followed the Instrumental Activities of Daily Living (IADL) scale [14]. Preference questions assessed interaction comfort and pacing (e.g., speech rate, movement speed, and activity timing) to support personalized service delivery.

4 Study Design and Methodology

4.1 Participants and Setting

Five older adults (three men, two women; mean age = 72.4 years, range = 65–79) were recruited from a local senior welfare center.

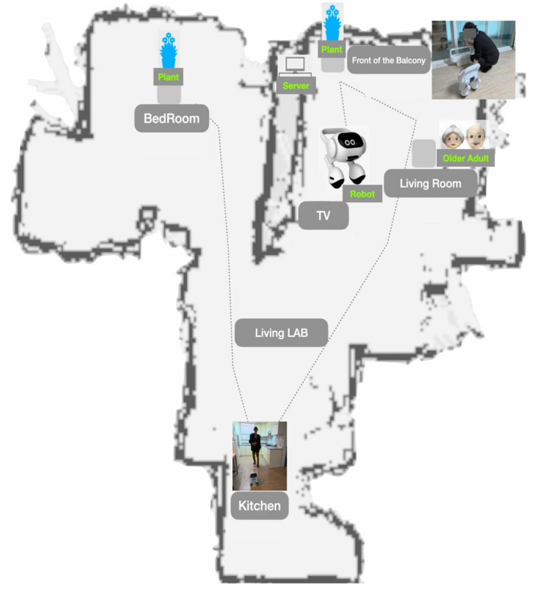

Figure 3: Layout of the residential living lab environment.

Inclusion criteria required participants to be 65+, living independently, and possessing adequate sensory and language abilities without cognitive impairment (e.g., dementia). The study was approved by the Institutional Review Board of the Electronics and Telecommunications Research Institute (ETRI IRB; approval no. N01-202510-01-011). The study was conducted in a residential living lab consisting of a bedroom, living room, kitchen, and balcony. Indoor gardening appliances were placed in the living room adjacent to the balcony and in the bedroom (Figure 3). Q9, an autonomous mobile robot, navigated the environment under the coordination of a central server that managed dialogue generation and plant health analysis. Participants followed Q9 to specific plant locations for care tasks, while social interactions were primarily centered in the living room.

4.2 Procedure

All participants provided informed consent following a detailed explanation of study objectives, procedures, and potential risks. The study followed a structured protocol consisting of four phases: (1) informed consent and baseline data collection, including demographic information and pre-intervention questionnaires; (2) robot introduction and familiarization; (3) the main intervention involving scenario-based plant care over three weekly sessions; and (4) post-session questionnaires assessing interaction satisfaction and perceived effectiveness. The intervention comprised weekly sessions with progressively expanding complexity. In Session 1, the robot assessed plant status and engaged participants in brief, turn-limited conversations. Session 2 introduced plant watering activities; the memory function was enabled to reference prior interactions, and conversation length was unrestricted. In Session 3, the robot acknowledged successful plant growth, provided encouragement, and conducted in-depth conversations drawing on accumulated memory. Questionnaires were administered immediately following each session.

4.3 Measures

We designed a questionnaire packet consisting of four scales using five-point Likert responses: Cognitive Self-Assessment (6 items, $\alpha = .78$) adapted from everyday memory assessment [13]; Robot-Assisted Plant Care and Satisfaction (10 items, $\alpha = .85$) assessing perceived clarity, appropriateness, ease of use, and intention to reuse; Daily Living Vitality (6 items, $\alpha = .81$) measuring perceived energy and willingness to engage in activities [14]; and Psychological Stability (6 items, $\alpha = .83$) evaluating emotional comfort, anxiety, and loneliness [12]. Semi-structured interviews were conducted after the final session.

4.4 Data Analysis

Given the small sample size (N = 5) and repeated measures across three time points, non-parametric tests were employed. We applied Friedman tests to examine overall session effects, followed by Wilcoxon signed-rank tests for pairwise comparisons where significant main effects were observed. Effect sizes (r) for pairwise comparisons were calculated using the formula: $r = Z/\sqrt{2N}$, where N represents the number of participants. Effect sizes of .10, .30, and .50 were interpreted as small, medium, and large effects, respectively [15]. Statistical significance was set at $\alpha = 0.05$. We report p-values to provide preliminary evidence, acknowledging that these findings require replication with larger samples.

5 Preliminary Results

5.1 Participant Characteristics

All participants rated their overall health as good with no major vision or hearing problems when using corrective devices. Most lived with a spouse; one lived alone. Plant care experience ranged from none to more than five years. Prior experience with robots or AI speakers was limited.

5.2 Cognitive Function and Daily Living

Cognitive self-assessment scores were generally high across sessions, with most responses indicating agreement with positive statements about task memory. This suggests participants perceived themselves as cognitively capable at baseline, leaving limited room for improvement. Daily living vitality scores were also relatively high, with some participants reporting feeling slightly more energetic and motivated after sessions. Due to small sample size and ceiling effects, we interpret these trends cautiously.

5.3 Psychological Stability

Friedman test revealed a statistically significant improvement in psychological stability across the three sessions ($\chi^2(2) = 7.60$, $p = .022$). Participants initially showed room for improvement on items related to loneliness and worry, with several reporting neutral or negative responses after Session 1. By Session 3, responses shifted toward more positive categories, indicating more stable mood and reduced loneliness. Participants also reported that discussing daily concerns with the robot helped them feel listened to

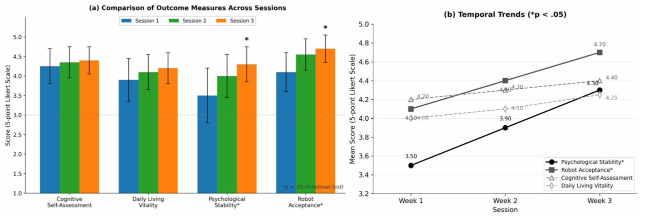

Figure 4: Comparison of outcome measures across three sessions. (a) Mean scores with error bars (±1 SD). (b) Temporal trends for measures with significant improvements. $^*p < .05$ (Friedman test).

and emotionally supported, particularly when the robot referenced prior conversations.

5.4 Robot Acceptance and Interaction Quality

Robot acceptance significantly improved across sessions ($\chi^2(2) = 8.40$, $p = .015$). Satisfaction scores also increased, with most items rated in the top two categories by Session 3. Participants reported that they could perform plant care behaviors by following the robot's guidance and that the advice was appropriate to the plants' conditions; all participants expressed willingness to use the service again. Figure 4 summarizes outcome measures across sessions. (a) Bar plots show mean scores with standard deviation error bars; asterisks indicate significant effects in the Friedman test ($p < .05$). (b) Line plots depict session-wise trends for the two measures showing significant improvements: Psychological Stability increased from 3.50 to 4.30 (+0.80), and Robot Acceptance increased from 4.10 to 4.70 (+0.60). Conversely, Cognitive Self-Assessment and Daily Living Vitality showed non-significant gains, consistent with baseline ceiling effects.

6 Discussion

This pilot study demonstrates the feasibility of a robot-mediated service integrating plant care with emotional and cognitive support for older adults. A notable observation was the shift in participant behavior from passive instruction-following to proactive engagement, such as inquiring about plant health. This suggests that anchoring robot interactions in meaningful shared activities, rather than abstract dialogue, is more effective for enhancing engagement in elderly care. Furthermore, the memory-based personalization module fostered a sense of continuity and relationship [5], though it highlights the necessity for robust privacy-by-design frameworks for long-term data management. Despite these promising results, the study is limited by its small sample size (N=5) and short intervention duration. Future work will include larger samples (15–20 participants), longer interventions (8–12 weeks), more diverse plant species and care activities, and home deployments using validated measures.

7 Conclusion

We presented a pilot implementation and evaluation of a robot-based plant care and emotional support service for older adults. The proposed system combines autonomous navigation, vision-based plant assessment, conversational AI, and memory-based personalization. In a three-week study with five older adults, the service was well accepted, with statistically significant improvements in psychological stability and robot acceptance. These findings provide preliminary empirical evidence and design insights to inform the future development of robot-mediated plant care and emotional support services for aging societies.

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References

[1] Kazuyoshi Wada and Takanori Shibata. Living with seal robots—its sociopsychological and physiological influences on the elderly at a care house. *IEEE Transactions on Robotics*, 23(5):972–980, 2007.
[2] Roger Bemelmans, Gert Jan Gelderblom, Pieter Jonker, and Luc de Witte. Socially assistive robots in elderly care: A systematic review into effects and effectiveness. *Journal of the American Medical Directors Association*, 13(2):114–120, 2012.
[3] Masashi Soga, Kevin J. Gaston, and Yuichi Yamaura. Gardening is beneficial for health: A meta-analysis. *Preventive Medicine Reports*, 5:92–99, 2017.
[4] Tom B. Brown et al. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901, 2020.
[5] Patrick Lewis et al. Retrieval-augmented generation for knowledge-intensive NLP tasks. In *Advances in Neural Information Processing Systems*, volume 33, pages 9459–9474, 2020.
[6] Victor Nikhil Antony, Chanjung Jin, Jeeheon Lee, Chengzhi Han, Antti Oulasvirta, Hao Peng, and Ge Gao. The design of on-body robots for older adults. In *Proceedings of the 2025 ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*, Melbourne, Australia, 2025. ACM.
[7] Federica Carrozzo, Ruben Faccini, Angelo Falci, Beatrice Redaelli, Mirko Gelsomini, Giacomo Zannoni, and Franca Garzotto. IDROPO, a hydroponic planting system to teach gardening through play. In *Proceedings of the Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–4. ACM, 2018. doi: 10.1145/3170427.3186489.
[8] Peter H. Kahn, Batya Friedman, Irene S. Alexander, Nathan G. Freier, and Stephanie L. Collett. The distant gardener: what conversations in the Telegarden reveal about human-telerobotic interaction. In *ROMAN 2005. IEEE International Workshop on Robot and Human Interactive Communication, 2005*, pages 13–18. IEEE, 2005.
[9] Hsin-Yen Yen, Chih Wei Huang, Huei-Ling Chiu, and Grace Jin. The effect of social robots on depression and loneliness for older residents in long-term care facilities: A meta-analysis of randomized controlled trials. *Journal of the American Medical Directors Association*, 25(6):104979, 2024.
[10] LG Electronics. LG Q9, home robot developer platform. https://q9.developer.lge.com/, 2024.
[11] LG Electronics. LG Tiiun Mini, a compact smart indoor garden device. https://www.lge.co.kr/lg-tiiun/l023m1, 2024.
[12] Jerome I. Sheikh and Jerome A. Yesavage. Geriatric depression scale (GDS): Recent evidence and development of a shorter version. *Clinical Gerontologist*, 5 (1-2):165–173, 1986.
[13] Marshal F. Folstein, Susan E. Folstein, and Paul R. McHugh. Mini-mental state: A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research*, 12(3):189–198, 1975.
[14] M. Powell Lawton and Elaine M. Brody. Assessment of older people: Self-maintaining and instrumental activities of daily living. *Gerontologist*, 9(3):179–186, 1969.
[15] Jacob Cohen. *Statistical Power Analysis for the Behavioral Sciences*. Lawrence Erlbaum Associates, Hillsdale, NJ, 2nd edition, 1988.

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