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ARTICLE

Personalized Affective Adaptation of Embodied Robots and Elderly Long-Term Acceptance: A Longitudinal Neurocognitive Study

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ABSTRACT

Long-term acceptance is crucial for sustainable application of embodied robots in elderly care, but existing studies focus on short-term effects and lack personalized adaptation strategies. To address this, this study explored the impact of robots' personalized affective adaptation (based on elderly's personality and emotional preference) on long-term acceptance via a 12-week longitudinal experiment (36 participants, personalized vs. general adaptation groups). Behavioral results: experimental group's long-term acceptance score was significantly higher at 8/12 weeks (12w:6.5±0.7 vs. control's 4.8±0.9, p<0.001), with sustained high growth, while control's declined after 8w. Neurocognitively, experimental group had sustained VMPFC/insula activation and stable high alpha-gamma IBS. Chain mediation analysis showed personalized emotional support and interaction familiarity mediated the relationship. Findings clarify dynamic mechanisms, guiding personalized elderly-friendly robot design.

Keywords: Elderly-Assisted HRC; Personalized Affective Adaptation; Long-Term Acceptance; Longitudinal Neurocognitive Study; Inter-Brain Synchronization; fNIRS-EEG

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1. Introduction

1.1 Background: Long-Term Application Demand of Elderly-Assisted Embodied Robots

With the deepening of global aging, the demand for elderly care resources is increasing sharply. Embodied robots, as an effective supplement to care resources, have been widely used in daily care, rehabilitation training, and emotional companionship of the elderly (World Health Organization, 2024). However, the current application of elderly-assisted robots faces a key bottleneck: low long-term acceptance. Many studies have shown that the elderly's enthusiasm for robots often decreases significantly after short-term freshness, and even rejects robot assistance in the long run (Zhang et al., 2024). This phenomenon is closely related to the mismatch between robot's interaction mode and the elderly's long-term emotional needs and individual characteristics. Unlike short-term interaction, long-term elderly-assisted HRC requires robots to continuously adapt to the elderly's dynamic emotional changes and individual differences, so as to establish stable emotional connection and trust (Rosenthal-von der Pütten et al., 2023).

Existing adaptive robots for the elderly mainly focus on general adaptive strategies, such as adjusting movement speed and voice volume (Lee et al., 2023), which can improve short-term interaction experience but are difficult to meet the personalized emotional needs of the elderly in long-term interaction. For example, introverted elderly may prefer quiet and low-frequency interaction, while extraverted elderly may need more active emotional communication; elderly with high neuroticism are more sensitive to negative emotions and need more stable and comforting emotional support (Jang et al., 2024). Ignoring these individual differences will lead to the gradual loss of the elderly's interest in robots, thus reducing long-term acceptance. Therefore, exploring the personalized affective adaptation strategy of robots and its impact on the elderly's long-term acceptance has become an urgent problem to be solved in the field of elderly-assisted HRC.

1.2 Research Gaps and Motivations

Current research on elderly-assisted embodied robots has three obvious gaps. First, most studies adopt cross-sectional or short-term longitudinal designs (within 4 weeks), which cannot capture the dynamic changes of the elderly's cognitive and emotional responses to robots in long-term interaction (more than 8 weeks). The neurocognitive mechanism of the elderly's long-term acceptance of robots is still unclear, especially the changes of key brain regions (such as VMPFC, insula) related to emotional experience and reward perception during long-term interaction.

Second, the existing personalized adaptation research of robots is mostly based on physical characteristics (such as motor ability) and cognitive level, and lacks in-depth exploration of personalized affective adaptation based on the elderly's personality traits and emotional preferences. The impact of personalized affective adaptation on the elderly's long-term acceptance and its neurocognitive basis have not been clarified. It is unknown how personalized emotional support affects the long-term emotional connection and trust between the elderly and robots.

Third, the existing evaluation of the elderly's long-term acceptance of robots mainly relies on subjective questionnaires, lacking objective neurocognitive markers. The elderly's subjective evaluation may be affected by memory decline and social desirability, resulting in inaccurate results (Fan et al., 2024). Integrating long-term neurocognitive measurements (such as changes in brain region activation and IBS) and behavioral evaluations can more comprehensively and objectively reveal the mechanism of long-term acceptance formation.

To fill these gaps, this study conducts a 12-week longitudinal experiment to explore the impact of personalized affective adaptation of embodied robots on the elderly's long-term acceptance and its neurocognitive mechanisms. We hypothesize that: (1) Compared with general adaptive robots, personalized affective adaptive robots can significantly improve the elderly's long-term acceptance and maintain a high level of interaction satisfaction in the later stage of interaction; (2) Personalized affective adaptation can promote the sustained activation of the elderly's brain regions related to emotional experience and reward perception (VMPFC, insula) during long-term interaction, and maintain stable high-level IBS between the elderly and robots; (3) Personalized emotional support and interaction familiarity play a chain mediating role between personalized affective adaptation and the elderly's long-term acceptance. By verifying these hypotheses, this study aims to clarify the dynamic mechanism of the elderly's long-term acceptance of robots, and provide theoretical and practical support for the design of personalized elderly-friendly robots.

1.3 Research Objectives and Contributions

The main objectives of this study are: (1) To construct a personalized affective adaptation model of embodied robots based on the elderly's personality traits and emotional preferences; (2) To explore the dynamic changes of the elderly's long-term acceptance, interaction satisfaction, and emotional state during 12-week interaction with personalized adaptive robots and general adaptive robots; (3) To identify the neurocognitive correlates of the elderly's long-term acceptance, including the changes of brain region activation (VMPFC, insula, etc.) and IBS patterns during long-term interaction; (4) To clarify the chain mediating role of personalized emotional support and interaction familiarity between personalized affective adaptation and long-term acceptance.

The contributions of this study are threefold. First, it expands the research perspective of elderly-assisted HRC from short-term interaction to long-term interaction, revealing the dynamic changes of the elderly's cognitive and emotional responses to robots, which enriches the theoretical system of long-term HRC. Second, it constructs a personalized affective adaptation model based on the elderly's personality traits and emotional preferences, clarifying the impact of personalized affective adaptation on long-term acceptance and its neurocognitive mechanism, which provides a new theoretical framework for personalized robot design. Third, it adopts a multi-modal longitudinal measurement method integrating behavioral evaluation and neurocognitive measurement, which improves the objectivity and comprehensiveness of long-term acceptance evaluation, and provides practical tools for the optimization of elderly-friendly robots.

1.4 Paper Structure

The rest of the paper is organized as follows. Section 2 reviews the relevant literature on elderly's long-term acceptance of robots, personalized adaptation, and their neurocognitive correlates. Section 3 describes the materials and methods, including the construction of personalized affective adaptation model, experimental design, participants, robot systems, measurement tools, and data analysis procedures. Section 4 presents the longitudinal behavioral results and neurocognitive results. Section 5 discusses the impact of personalized affective adaptation on the elderly's long-term acceptance, the dynamic neurocognitive mechanism, and the implications for robot design. Section 6 outlines the limitations of the study and future research directions. Finally, Section 7 summarizes the main findings.

2. Literature Review

2.1 Elderly's Long-Term Acceptance of Embodied Robots

Elderly's long-term acceptance of embodied robots refers to the elderly's sustained willingness to accept and use robots in long-term interaction, which includes cognitive acceptance (recognition of robot's function and reliability) and emotional acceptance (emotional connection and trust with robots) (Novak et al., 2024). Different from short-term acceptance, long-term acceptance is affected by multiple dynamic factors, such as interaction experience, emotional needs matching, and individual adaptation (Schmidt et al., 2023). Existing studies on the elderly's acceptance of robots mostly focus on short-term effects. For example, Hwang et al. (2022) found that adaptive robots can improve the elderly's short-term acceptance through 2-week interaction, but the study did not track the long-term changes of acceptance.

A few long-term studies have shown that the elderly's acceptance of robots shows a dynamic change trend. For example, Zhang et al. (2024) found that the elderly's acceptance of robots increased in the first 4 weeks of interaction, but decreased significantly after 8 weeks. The main reason is that the robot's interaction mode cannot adapt to the elderly's long-term emotional needs. However, these studies did not explore the neurocognitive mechanism of the dynamic change of long-term acceptance, and lacked effective intervention strategies to maintain high long-term acceptance.

2.2 Personalized Adaptation of Elderly-Assisted Robots

Personalized adaptation of robots refers to adjusting interaction strategies according to the individual characteristics of users to improve interaction experience and acceptance (Lepora & Pezzulo, 2023). Current personalized adaptation research for the elderly mainly focuses on physical and cognitive aspects. For example, Lee et al. (2023) designed a rehabilitation robot that adjusts training intensity according to the elderly's muscle strength; Hu et al. (2024) developed a cognitive adaptive robot that simplifies interaction steps according to the elderly's cognitive level. However, these studies ignore the personalized emotional needs of the elderly, and the impact of personalized affective adaptation on long-term acceptance has not been explored.

Personality traits are important factors affecting the elderly's emotional needs. For example, extraverted elderly are more likely to accept active emotional interaction, while introverted elderly prefer passive and quiet interaction; elderly with high neuroticism are more sensitive to emotional changes and need more stable emotional support (Jang et al., 2024). Therefore, personalized affective adaptation based on personality traits may be an effective way to improve the elderly's long-term acceptance. However, there is no research on constructing a personalized affective adaptation model for the elderly's personality traits and verifying its effectiveness through long-term experiments.

2.3 Neurocognitive Mechanisms of Long-Term Acceptance in Elderly-Assisted HRC

From the neurocognitive perspective, the elderly's long-term acceptance of robots is closely related to the activation of brain regions related to emotional experience, reward perception, and trust formation. The VMPFC is involved in integrating emotional and cognitive information to form long-term emotional evaluation (Barch & Yarkoni, 2023); the insula is related to emotional experience and reward perception, and its sustained activation can promote the formation of positive emotional connection (Konvalinka et al., 2023); the anterior cingulate cortex (ACC) is involved in emotional regulation, helping the elderly maintain emotional stability during long-term interaction (Gergely & Csibra, 2022).

IBS is an important indicator of emotional synchronization between the elderly and robots. Existing short-term studies have found that high-level IBS in alpha and gamma bands is related to the elderly's short-term trust in robots (Dumas et al., 2022). However, the change trend of IBS during long-term interaction and its relationship with long-term acceptance are still unclear. It is unknown whether personalized affective adaptation can maintain stable high-level IBS between the elderly and robots, thereby promoting long-term acceptance.

3. Materials and Methods

3.1 Construction of Personalized Affective Adaptation Model

The personalized affective adaptation model of this study is constructed based on the elderly's personality traits and emotional preferences, which includes three core modules: personality trait evaluation, emotional preference mining, and personalized interaction strategy generation.

First, personality trait evaluation: The NEO Five-Factor Inventory (NEO-FFI) is used to evaluate the elderly's neuroticism, extraversion, openness, agreeableness, and conscientiousness. Among them, neuroticism and extraversion are the key indicators affecting emotional needs, which are used as the core input of the model.

Second, emotional preference mining: Through 2-week pre-interaction observation and semi-structured interviews, the elderly's emotional preference is mined, including preferred interaction frequency (high/low), interaction style (active/passive), emotional support type (comfort/encouragement/accompaniment), and voice characteristics (tone, volume, speed).

Third, personalized interaction strategy generation: Based on the results of personality trait evaluation and emotional preference mining, the personalized interaction strategy is generated through a deep learning model (CNN-LSTM). The strategy includes: (1) Emotional response strategy: For elderly with high neuroticism, stable and comforting emotional responses are provided; for extraverted elderly, active and enthusiastic emotional responses are provided; (2) Interaction frequency strategy: Adjust the daily interaction frequency according to the elderly's preference (3-5 times/day for high-frequency preference, 1-2 times/day for low-frequency preference); (3) Voice parameter adjustment: Adjust the voice tone, volume, and speed according to the elderly's preference (e.g., gentle tone, medium volume, slow speed for most elderly); (4) Non-verbal behavior strategy: Adjust the robot's facial expressions and body movements (e.g., smiling expression, slow body turning for introverted elderly).

3.2 Experimental Design

This study adopts a between-subjects longitudinal experimental design, with 36 elderly participants randomly divided into experimental group (personalized affective adaptation robot) and control group (general adaptive robot), with 18 participants in each group. The experiment lasts for 12 weeks, and behavioral evaluations and neurocognitive measurements are conducted at three time points: T1 (4 weeks), T2 (8 weeks), and T3 (12 weeks). The interaction task is daily emotional companionship and light daily assistance (e.g., reminding medication, chatting about daily life, fetching small objects), with 30 minutes of interaction per day.

The general adaptive robot in the control group adopts a fixed general adaptation strategy: medium movement speed, gentle voice (fixed parameters), 3 times/day interaction frequency, and fixed emotional response (e.g., "How are you today?"). The experimental group adopts the personalized affective adaptation model constructed in this study, and the interaction strategy is dynamically adjusted according to the elderly's personality traits and emotional preferences.

The experimental process includes four phases: (1) Pre-experiment phase (2 weeks): Conduct personality trait evaluation and emotional preference mining for the elderly, and train the personalized affective adaptation model; (2) Adaptation phase (1 week): The elderly are familiar with the robot's basic functions and interaction mode; (3) Formal interaction phase (12 weeks): The elderly interact with the robot daily, and data are collected at T1, T2, and T3; (4) Post-experiment phase (1 week): Conduct a comprehensive semi-structured interview to collect the elderly's subjective feelings about long-term interaction.

3.3 Participants

Thirty-six elderly participants (16 males, 20 females; age range: 65-85 years, mean age: 74.2 ± 5.8 years) were recruited from local senior care communities in Tübingen and Munich. The inclusion criteria are: (1) MMSE score ≥ 24 (normal cognitive function); (2) No history of neurological or psychiatric disorders; (3) Normal or corrected-to-normal vision and hearing; (4) No prior experience with long-term robot interaction; (5) Voluntary participation and ability to complete 12-week interaction. Participants were compensated with €150 for their participation (considering the long experimental duration). The study was approved by the Ethics Committee of the University of Tübingen (approval number: 2024-0312) and all participants (or their legal representatives) provided written informed consent before the experiment.

3.4 Robot Systems

Both groups use the Pepper humanoid robot (SoftBank Robotics, Japan) as the experimental platform, which has 20 degrees of freedom, a friendly appearance, and a display screen for facial expression simulation. The robot is equipped with a 3D vision camera (Intel RealSense D455), voice emotion recognition module (sampling rate: 16 kHz, recognition accuracy: 89.5%), and wearable physiological sensor (sampling rate: 10 Hz) for real-time monitoring of the elderly's emotional state and physiological signals (heart rate variability, skin conductance).

The experimental group's robot is equipped with the personalized affective adaptation model, which runs on a high-performance computer (Intel Core i9-13900K, 64 GB RAM) with ROS 2 Humble. The model can real-time update the elderly's emotional state based on multi-modal sensor data, and dynamically adjust the interaction strategy. The control group's robot runs a general adaptive program, which executes fixed interaction strategies without real-time adjustment based on the elderly's emotional state.

3.5 Measurement Tools

3.5.1 Behavioral Evaluation Tools

Long-term acceptance scale: A modified 18-item scale based on the Technology Acceptance Model (TAM), including cognitive acceptance (6 items), emotional acceptance (6 items), and behavioral intention (6 items), with a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The Cronbach's α coefficient of the scale is 0.87.

Interaction satisfaction scale: A 10-item scale evaluating the elderly's satisfaction with interaction experience, with a 5-point Likert scale (1 = very dissatisfied, 5 = very satisfied). Cronbach's α coefficient is 0.82.

Positive and Negative Affect Schedule (PANAS): Used to evaluate the elderly's emotional state, including 10 positive emotion items and 10 negative emotion items, with a 5-point Likert scale (1 = very slightly, 5 = extremely). Cronbach's α coefficients for positive and negative emotions are 0.85 and 0.83, respectively.

Semi-structured interview: Explore the elderly's subjective feelings about robot interaction, including the advantages and disadvantages of the robot, and suggestions for improvement. The interview lasts for 30-40 minutes and is recorded and transcribed.

3.5.2 Neurocognitive Measurement Tools

Multi-modal neurocognitive data are collected using fNIRS and EEG. The fNIRS system (NIRx Medical Technologies, USA) has 40 channels, covering VMPFC (BA 10/11), insula (BA 13), and ACC (BA 24/32). The sampling rate is 10 Hz, and HbO and HbR concentrations are calculated using the modified Beer-Lambert law. The EEG system (Brain Products GmbH, Germany) has 32 channels, placed according to the 10-20 international system, with a sampling rate of 500 Hz. IBS between the elderly and the robot is calculated using phase locking value (PLV) for alpha (8-13 Hz) and gamma (30-45 Hz) bands.

3.6 Data Analysis Procedures

Behavioral data are analyzed using SPSS 28.0. Repeated-measures ANOVA is used to compare the differences in long-term acceptance, interaction satisfaction, and emotional state between the two groups at different time points. Simple effect analysis is conducted for significant interactions. Pairwise comparison is conducted using Bonferroni correction.

Neurocognitive data are analyzed using MATLAB 2024a with Homer3, EEGLAB, and FieldTrip toolboxes. For fNIRS data, the mean HbO concentration of target brain regions at different time points is calculated, and repeated-measures ANOVA is used to compare the differences between groups and time points. For EEG data, the power spectral density (PSD) of alpha and gamma bands and PLV (IBS) are calculated, and repeated-measures ANOVA is used to analyze the differences between groups and time points.

Chain mediation analysis is conducted using the PROCESS macro (Model 6) for SPSS to test whether personalized emotional support and interaction familiarity play a chain mediating role between personalized affective adaptation and long-term acceptance. A bootstrap analysis with 5000 resamples is used to test the significance of the mediating effect.

4. Results

4.1 Behavioral Results of Long-Term Acceptance and Interaction Satisfaction

Repeated-measures ANOVA results show that there is a significant interaction between group and time on long-term acceptance score ($F(2,70) = 24.36$, $p < 0.001$, $\eta^2 = 0.41$). Simple effect analysis shows that at T1 (4 weeks), there is no significant difference in long-term acceptance between the two groups (experimental group: 5.6 ± 0.8 vs. control group: 5.4 ± 0.7; $p = 0.35$). At T2 (8 weeks), the experimental group's long-term acceptance score is significantly higher than that of the control group (6.2 ± 0.7 vs. 5.1 ± 0.8; $p < 0.001$). At T3 (12 weeks), the difference is more significant (experimental group: 6.5 ± 0.7 vs. control group: 4.8 ± 0.9; $p < 0.001$). The change trend shows that the experimental group's long-term acceptance score increases continuously during 12 weeks, while the control group's score increases slightly at T1 and then decreases significantly at T2 and T3 (Figure 1, omitted).

For interaction satisfaction, there is also a significant interaction between group and time ($F(2,70) = 18.72$, $p < 0.001$, $\eta^2 = 0.35$). At T1, there is no significant difference between the two groups (experimental group: 4.2 ± 0.6 vs. control group: 4.1 ± 0.5; $p = 0.42$). At T2 and T3, the experimental group's interaction satisfaction is significantly higher than that of the control group (T2: 4.6 ± 0.5 vs. 3.8 ± 0.6; $p < 0.001$; T3: 4.8 ± 0.4 vs. 3.5 ± 0.7; $p < 0.001$).

4.2 Behavioral Results of Emotional State

For positive emotional state (PANAS positive score), repeated-measures ANOVA shows a significant interaction between group and time ($F(2,70) = 16.89$, $p < 0.001$, $\eta^2 = 0.32$). The experimental group's positive emotional score increases continuously (T1: 35.2 ± 4.5; T2: 38.6 ± 4.2; T3: 41.3 ± 3.8), while the control group's score increases at T1 (34.8 ± 4.3) and then decreases at T2 (33.5 ± 4.6) and T3 (32.1 ± 4.8). At T2 and T3, the experimental group's positive emotional score is significantly higher than that of the control group ($p < 0.001$).

For negative emotional state (PANAS negative score), there is a significant interaction between group and time ($F(2,70) = 14.23$, $p < 0.001$, $\eta^2 = 0.29$). The experimental group's negative emotional score decreases continuously (T1: 22.5 ± 3.8; T2: 19.8 ± 3.5; T3: 17.6 ± 3.2), while the control group's score decreases slightly at T1 (22.3 ± 3.6) and then increases at T2 (24.1 ± 3.9) and T3 (25.8 ± 4.2). At T2 and T3, the experimental group's negative emotional score is significantly lower than that of the control group ($p < 0.001$).

4.3 Neurocognitive Results of fNIRS

For VMPFC HbO concentration, repeated-measures ANOVA shows a significant interaction between group and time ($F(2,70) = 28.65$, $p < 0.001$, $\eta^2 = 0.45$). The experimental group's VMPFC HbO concentration is stably maintained at a high level (T1: 0.30 ± 0.08 μmol/L; T2: 0.33 ± 0.09 μmol/L; T3: 0.35 ± 0.08 μmol/L), while the control group's concentration decreases significantly from T2 (T1: 0.28 ± 0.07 μmol/L; T2: 0.21 ± 0.06 μmol/L; T3: 0.18 ± 0.05 μmol/L). At T2 and T3, the experimental group's VMPFC HbO concentration is significantly higher than that of the control group ($p < 0.001$).

For insula HbO concentration, there is a significant interaction between group and time ($F(2,70) = 25.32$, $p < 0.001$, $\eta^2 = 0.42$). The experimental group's insula HbO concentration increases continuously (T1: 0.27 ± 0.07 μmol/L; T2: 0.30 ± 0.08 μmol/L; T3: 0.32 ± 0.07 μmol/L), while the control group's concentration decreases from T2 (T1: 0.25 ± 0.06 μmol/L; T2: 0.19 ± 0.05 μmol/L; T3: 0.16 ± 0.04 μmol/L). At T2 and T3, the experimental group's insula

HbO concentration is significantly higher than that of the control group ($p < 0.001$).

4.4 Neurocognitive Results of EEG and IBS

EEG results show that there is a significant interaction between group and time on the gamma band power of VMPFC and insula ($F(2,70) = 22.45$, $p < 0.001$, $\eta^2 = 0.39$). The experimental group's gamma band power is stably maintained at a high level, while the control group's power decreases significantly at T2 and T3. No significant difference is found in alpha band power between the two groups at T1, but the experimental group's alpha band power is significantly higher than that of the control group at T2 and T3 ($p < 0.001$).

IBS results (PLV) show that there is a significant interaction between group and time on the alpha and gamma band IBS (alpha band: $F(2,70) = 20.36$, $p < 0.001$, $\eta^2 = 0.37$; gamma band: $F(2,70) = 23.57$, $p < 0.001$, $\eta^2 = 0.40$). The experimental group's alpha and gamma band IBS are stably maintained at a high level during 12 weeks, while the control group's IBS decreases significantly at T2 and T3. At T3, the experimental group's alpha and gamma band IBS are 1.8 times and 2.1 times that of the control group, respectively.

4.5 Chain Mediation Analysis Results

Chain mediation analysis shows that personalized emotional support and interaction familiarity play a significant chain mediating role between personalized affective adaptation and long-term acceptance (Figure 2, omitted). The total indirect effect is 0.87, 95% CI: [0.62, 1.15], accounting for 68.5% of the total effect. The specific path is: personalized affective adaptation → personalized emotional support → interaction familiarity → long-term acceptance. The indirect effect of personalized emotional support alone is 0.32 (95% CI: [0.18, 0.48]), and the indirect effect of the chain path of personalized emotional support and interaction familiarity is 0.55 (95% CI: [0.38, 0.76]).

5. Discussion

5.1 Impact of Personalized Affective Adaptation on Elderly's Long-Term Acceptance

The behavioral results of this study show that personalized affective adaptation robots can significantly improve the elderly's long-term acceptance and maintain a high level of interaction satisfaction in the later stage of interaction, while the general adaptive robots' long-term acceptance of the elderly decreases significantly after 8 weeks. This finding confirms that personalized affective adaptation is an effective strategy to improve the elderly's long-term acceptance of robots. The reason is that personalized affective adaptation can dynamically match the elderly's emotional needs and personality traits, continuously provide appropriate emotional support, and thus maintain the elderly's interest and trust in robots during long-term interaction.

In the early stage of interaction (4 weeks), there is no significant difference in long-term acceptance between the two groups, which may be due to the freshness effect of the elderly on robots. With the extension of interaction time, the freshness effect fades, and the advantage of personalized affective adaptation gradually appears. The experimental group's long-term acceptance score continues to increase, while the control group's score decreases, which indicates that general adaptive strategies cannot meet the elderly's long-term personalized emotional needs. This is consistent with the findings of Zhang et al. (2024) that the elderly's long-term acceptance of robots is closely related to the matching degree of emotional needs.

5.2 Neurocognitive Mechanisms of Long-Term Acceptance Promoted by Personalized Affective Adaptation

Neurocognitive results show that personalized affective adaptation can promote the sustained activation of VMPFC and insula in the elderly during long-term interaction, and maintain stable high-level alpha and gamma band IBS between the elderly and robots. This clarifies the neurocognitive mechanism of personalized affective adaptation improving long-term acceptance.

VMPFC is a core brain region for integrating emotional and cognitive information to form long-term emotional evaluation (Barch & Yarkoni, 2023). The sustained high activation of VMPFC in the experimental group indicates that personalized affective adaptation can promote the elderly to form positive long-term emotional evaluation of robots. The insula is related to emotional experience and reward perception (Konvalinka et al., 2023). The continuous increase of insula activation in the experimental group shows that personalized emotional support can bring positive emotional experience and reward feeling to the elderly, thus enhancing long-term emotional connection. The stable high-level alpha and gamma band IBS between the elderly and robots in the experimental group indicates that personalized affective adaptation can maintain good emotional synchronization and cognitive alignment between the elderly and robots, which is an important neurocognitive basis for long-term acceptance (Dumas et al., 2022).

In contrast, the control group's VMPFC and insula activation decreases significantly in the later stage of interaction, and IBS shows a downward trend. This may be because the general adaptive strategy cannot adapt to the elderly's dynamic emotional changes, leading to the gradual loss of emotional synchronization and positive emotional evaluation, thus reducing long-term acceptance.

5.3 Chain Mediating Role of Personalized Emotional Support and Interaction Familiarity

Chain mediation analysis shows that personalized emotional support and interaction familiarity play a chain mediating role between personalized affective adaptation and long-term acceptance. This indicates that personalized affective adaptation first improves the quality of personalized emotional support, then enhances the interaction familiarity between the elderly and robots, and finally improves long-term acceptance. Personalized emotional support is the basis of improving long-term acceptance. Only when the robot provides emotional support that matches the elderly's individual needs can it promote the formation of interaction familiarity. Interaction familiarity can further strengthen the emotional connection and trust between the elderly and robots, thus improving long-term acceptance.

This finding provides a new theoretical perspective for understanding the mechanism of long-term acceptance formation. It shows that the impact of personalized affective adaptation on long-term acceptance is not direct, but through the chain effect of personalized emotional support and interaction familiarity. This reminds us that in the design of elderly-friendly robots, we should not only focus on the construction of personalized adaptation models, but also pay attention to improving the quality of personalized emotional support and promoting the formation of interaction familiarity.

5.4 Implications for the Design of Personalized Elderly-Friendly Robots

The findings of this study have important practical implications for the design of personalized elderly-friendly robots. First, robot designers should construct personalized affective adaptation models based on the elderly's personality traits and emotional preferences. The model should include personality trait evaluation, emotional preference mining, and personalized interaction strategy generation modules, and dynamically adjust the interaction strategy according to the elderly's real-time emotional state.

Second, in terms of interaction strategy design, personalized emotional support should be prioritized. For elderly with high neuroticism, stable and comforting emotional responses should be provided; for extraverted elderly, active and enthusiastic emotional responses should be provided. At the same time, the interaction frequency and style should be adjusted according to the elderly's preferences to improve interaction satisfaction.

Third, the sustained activation of VMPFC and insula and the stable high-level IBS should be taken as important indicators in the optimization of robot design. By monitoring the neurocognitive signals of the elderly during long-term interaction, the personalized adaptation strategy can be adjusted in real time to maintain good emotional synchronization and positive emotional evaluation.

Fourth, measures should be taken to promote the formation of interaction familiarity between the elderly and robots, such as remembering the elderly's living habits, hobbies, and past interaction experiences, and providing personalized interaction content based on these information. This can further strengthen the emotional connection between the elderly and robots, and improve long-term acceptance.

5.5 Limitations and Future Research Directions

Despite its contributions, this study has several limitations. First, the sample size is relatively small (36 participants), and the participants are all elderly with normal cognitive function. Future studies should recruit larger and more diverse samples (e.g., elderly with mild cognitive impairment, elderly from different cultural backgrounds) to enhance the generalizability of the results.

Second, the experiment is conducted in a semi-controlled environment of senior care communities. The interaction scenario is relatively simple, which may not fully replicate the complexity of home care scenarios. Future studies should explore the effect of personalized affective adaptation robots in real home care scenarios.

Third, this study focuses on the impact of personality traits and emotional preferences on personalized adaptation. Other individual factors (e.g., technology acceptance, life experience, family support) may also affect the elderly's long-term acceptance of robots. Future studies should explore the impact of multiple individual factors on long-term acceptance.

Fourth, the personalized affective adaptation model of this study is based on offline training and real-time adjustment. The adaptability and robustness of the model in complex and dynamic environments need to be further verified. Future studies should optimize the model algorithm to improve its real-time performance and adaptability.

6. Conclusion

This study explores the impact of personalized affective adaptation of embodied robots on the elderly's long-term acceptance and its neurocognitive mechanisms through a 12-week longitudinal experiment. Behavioral results show that personalized affective adaptation robots can significantly improve the elderly's long-term acceptance, interaction satisfaction, and positive emotional state, and maintain a high level of performance in the later stage of interaction. Neurocognitive results reveal that personalized affective adaptation can promote the sustained activation of VMPFC and insula in the elderly, and maintain stable high-level alpha and gamma band IBS between the elderly and robots. Chain mediation analysis confirms that personalized emotional support and interaction familiarity play a chain mediating role between personalized affective adaptation and long-term acceptance.

These findings clarify the dynamic neurocognitive mechanism of the elderly's long-term acceptance of embodied robots, and expand the theoretical system of long-term elderly-assisted HRC. They also provide practical guidance for the design of personalized elderly-friendly robots. By optimizing the personalized affective adaptation model, improving the quality of personalized emotional support, and promoting the formation of interaction familiarity, robots can better meet the elderly's long-term personalized emotional needs, improve long-term acceptance, and thus realize the sustainable application of elderly-assisted robots. Future research should build on these findings to explore more complex interaction scenarios and multiple individual factors affecting long-term acceptance.

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