



From Emotional Computing to Spatial Intelligence: Research on Indoor Design System for the Elderly Enabled by AI

Zhichao Zou, Rina Abd Shukor*, Liying Zhao, Jie Yang

City University Malaysia, Petaling Jaya 46100, Selangor Darul Ehsan, Malaysia.

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***Corresponding author:** Rina Abd Shukor, City University Malaysia, Petaling Jaya 46100, Selangor Darul Ehsan, Malaysia.

Abstract

In response to the real challenge of increased loneliness among elderly individuals living alone in the context of global aging, this study explores innovative approaches to age-friendly living spaces driven by artificial intelligence technology. By integrating affective computing and spatial intelligence technologies, an indoor design system capable of environmental perception and emotional feedback is constructed, focusing on addressing the dual needs of psychological support and physical environment adaptation for the elderly population. The study employs a mixed-method approach to validate system effectiveness, developing multimodal interaction modules that enable coordinated operation of emotion recognition and environmental regulation. The integration of speech semantic analysis with non-contact physiological monitoring technology enhances the system's dynamic capture of user emotional states. Empirical research shows that this system significantly alleviates loneliness and optimizes living quality, with the spatial reconfiguration capabilities of intelligent environments complementing emotional interaction mechanisms, creating living scenarios for the elderly that combine a sense of security and companionship. The study identifies issues such as insufficient operability of the user interface and the need to improve multi-source data fusion efficiency, proposing the establishment of a "need-technology-space" trinary adaptation model as an optimization direction. The research findings provide interdisciplinary solutions for the age-friendly transformation of smart homes, promoting the paradigm shift from functional carriers to emotional carriers in living spaces, and offering theoretical support and practical references for building an age-friendly society.

Keywords

AI empowerment; elderly adaptation; interior design; system

1. Introduction

As the global aging process accelerates, the proportion of elderly people living alone continues to rise, and mental and physical health issues caused by loneliness are becoming increasingly prominent. Studies show that prolonged loneliness not only significantly increases the risk of depression and cardiovascular disease in the elderly but also severely diminishes their quality of life. Although current smart home technology has made progress in health monitoring and environmental automation, it generally lacks a deep focus on the emotional needs of the elderly. Existing systems often concentrate on physical environment control, neglecting the organic integration of affective computing technology and spatial intelligence, leading to significant gaps in emotional support within age-friendly living spaces.

In this context, this study proposes the construction of an AI-empowered age-friendly interior design system. By integrating affective computing and spatial intelligence technologies, it innovatively achieves dual optimization of the physical environment and emotional care. The system architecture will incorporate multimodal affective recognition technologies (such as speech and semantic analysis, micro-expression capture), intelligent environmental sensing networks, and adaptive spatial adjustment modules to build a smart home ecosystem with an emotional feedback mechanism. In terms of spatial design, it breaks through traditional functional zoning thinking and explores the collaborative mechanisms of dynamic spatial layout and emotional interaction interfaces, such as using light environment to intelligently regulate emotions and leveraging spatial acoustics to enhance social presence (Ma, 2025).

2. The current situation of indoor design for the elderly under 2AI empowerment

2.1 Development of smart home technology

The evolution of smart home technology reflects the continuous reshaping of living spaces by technological innovation. In the early 1980s, the introduction of remote control devices marked the beginning of technology's integration into family life, with system functions limited to basic operations such as turning air conditioners on and off and switching lights. With the maturation of IoT protocols and breakthroughs in artificial intelligence algorithms, device interconnectivity and scenario-based services have become possible. Modern systems now form a comprehensive network that includes environmental monitoring, security alerts, and health management. Taking the elderly living scenario as an example, the perception layer, composed of temperature and humidity sensors and infrared detectors, can capture changes in the indoor environment in real time. Combined with deep analysis of user behavior patterns through machine learning, the system can predict needs and autonomously adjust device parameters. The development in health monitoring has been particularly significant, with millimeter-wave radar and biosensor technologies enabling non-contact vital sign detection. Abnormal data, such as nighttime bed activity duration and respiratory rate, can trigger immediate alerts.

2.2 The combination of emotion computing and smart home

The introduction of emotional computing technology has infused smart homes with human-centric service genes, driving device interaction from mechanical command execution to emotional resonance. A facial expression recognition system based on convolutional neural networks can construct an elderly person's emotional state assessment model by finely capturing changes in wrinkles around the eyes and movements of the mouth muscles. The voice interaction module breaks through traditional semantic understanding limitations by using voiceprint feature extraction technology to analyze paralinguistic features such as speaking rate, pitch, and pause frequency, achieving precise emotional state recognition. Practical cases show that a home hub integrated with emotional computing can automatically activate virtual social scenarios after identifying a user's loneliness: smart projections display holographic images of children, surround sound systems simulate family gathering atmospheres, and such multimodal interventions can reduce psychological loneliness indices.

2.3 Integration of age-appropriate design and smart home

The collaborative innovation of aging-friendly concepts and intelligent technologies is reshaping the functional logic of elderly living spaces. Spatial design transcends the physical limitations of traditional barrier-free renovations, creating more adaptable living scenarios through dynamic environmental adjustment systems. The smart floor pressure sensor network can track user movement in real time; when it detects abnormal gait, it activates the lighting system to increase path illumination intensity while simultaneously activating the electromagnetic adsorption function of handrail devices. In terms of cognitive assistance, augmented reality technology projects medication reminders and schedule arrangements into specific areas of the space, combining eye-tracking technology to confirm information reception status, thus avoiding the interference issues associated with traditional reminder devices. Data shows that homes equipped with spatial cognitive compensation systems reduce the frequency of orientation disorders in Alzheimer's patients. However, during the integration of these technologies, there has been a contradiction between functional redundancy and operational complexity. Approximately one-third of aging-friendly renovation projects are abandoned by elderly users due to excessive interface interaction levels, highlighting the need for age-friendly design to return to the core issue of meeting users' essential needs.

2.4 Research gaps and challenges

There are multiple fractures between theoretical construction and technical practice in the current research system. In terms of technology integration, the data coupling degree between the emotion computing module and spatial adjustment system is insufficient, and up to 1/3 of multi-source heterogeneous data fusion occurs.

3. Research methods

3.1 Research design

This study adopts an evidence-based design methodology to guide the full development cycle, structured around a three-phase model of “need identification — prototype iteration — effect validation” to establish a closed feedback loop. During the system construction phase, an agile development strategy is implemented, enabling incremental functional enhancements in three-week sprints. The initial prototype incorporates a multimodal emotion recognition module, integrating an 8K wide-angle camera and a high-sensitivity microphone array installed in the living room. The experimental setting involves retrofitting twenty representative elderly households, maintaining their original spatial layout while embedding clusters of smart devices to ensure the seamless integration of technological interventions with daily living contexts. Data collection utilizes a mixed-method observational approach, wherein system back-end logs automatically capture changes in environmental parameters and durations of voice interactions. Simultaneously, physiological indicators such as heart rate variability and skin conductance are tracked through wearable wristbands. The experimental protocol adopts a crossover design, with a fourteen-day baseline period followed by a fourteen-day intervention phase, to control for time-related effects. For data analysis, Bayesian statistical models are employed to construct a multidimensional evaluation framework encompassing twelve indicators, including emotion recognition accuracy, responsiveness of environmental adjustments, and user satisfaction. In parallel, grounded theory is used to conduct three-tier coding of interview transcripts, extracting cognitive schemas and emotional perceptions that elderly participants associate with the intelligent system.

3.2 Research objectives

The research sample was selected using a multi-stage stratified sampling method, in collaboration with community elderly care service centers, to conduct comprehensive recruitment across six cities in the Yangtze River Delta region. The target population was limited to individuals aged 65 and above who lived alone, excluding those with severe cognitive impairment or auditory and visual function deficits. Ultimately, 54 participants were included, with an average age of 72.3 years, and 61.1% were female. In the sample design, the Technology Anxiety Scale (TAS) was introduced as a stratification variable to ensure a balanced proportion of high and low technology acceptance groups (Chen, 2025). Regarding physical condition, 38.9% of the participants had chronic diseases requiring long-term medication, and 22.2% had mild mobility impairments. Pre-participation training was conducted using an immersive scenario simulation method, with eight hours of systematic operational guidance provided by professional social workers, along with a customized graphical operation manual. To ensure research ethics, the review committee approved a dual informed consent process: in addition to written agreements, a voice confirmation step was added to ensure full understanding. A dynamic exit mechanism was established during the experiment, and data from three cases that exited due to equipment adaptation issues were included in the dropout rate analysis. The sample characteristics were verified through chi-square tests, showing regional representativeness in variables such as gender, education level, and years of residence (Wang & Ding, 2025).

3.3 Overview of system modules

The system architecture adopts a hybrid deployment model of edge computing and cloud computing. The core perception layer consists of millimeter-wave radar arrays, array microphones, and infrared thermal imagers, which non-invasively capture the movement trajectories and acoustic features of organisms in space. The emotion recognition engine is equipped with a cascaded neural network architecture. The front-end module extracts facial electromyographic signals and acoustic features, while the back-end integrates an attention mechanism-based long-term short-term memory (LSTM) network to achieve emotion classification. The validation set shows an accuracy rate of 83.7% for identifying six common emotions in elderly groups. The environmental control center employs fuzzy logic algorithms, forming an adaptive decision-making model through 792 sets of historical data. The lighting adjustment

module is equipped with quantum dot LED arrays to achieve precise color temperature adjustments of 500K, and the temperature control subsystem connects to a ground-source heat pump to maintain dynamic balance at $\pm 0.5^{\circ}\text{C}$. The voice interaction unit breaks away from traditional command-based dialogue by introducing an emotional dialogue generation model (EDGM), which combines nearly 30,000 pieces of elderly language corpus training to generate natural language that aligns with the communication habits of seniors. During the system deployment phase, a modular assembly design is used, allowing seamless installation of all home devices within 72 hours, with average power consumption controlled at 1.2kW h/day during operation. Function validation experiments show that the system's emotion recognition response latency is $\leq 400\text{ms}$, and the match accuracy for environmental parameter control reaches 89.3%. Both core indicators have passed the ISO9241-210 usability standard certification (Zhang, 2024).

3.4 Data collection methods

3.4.1 Quantitative data

The study conducted longitudinal tracking measurements using standardized scales, employing the third edition of the UCLA Loneliness Scale to assess changes in loneliness intensity among older adults. The scale consists of 20 items and uses a four-point rating method to quantify dimensions such as social isolation and emotional void. The quality of life assessment referenced the revised WHOQOL-BREF scale by the World Health Organization, conducting quantitative analysis across four major areas: physical function, mental state, social relationships, and environmental adaptation. A comprehensive scoring system was constructed using 26 indicators. Data collection was set with two nodes: the baseline period and the follow-up period, completing the scale completion 48 hours before system deployment and within 24 hours after the experiment ended, respectively (Feng, 2024).

3.4.2 Qualitative data

Qualitative data collection integrates in-depth interviews and natural observation, designing semi-structured interview outlines based on the grounded theory framework, focusing on exploring older adults' value perceptions, emotional experiences, and improvement suggestions regarding system functions. Each interview lasts 40-60 minutes, conducted in familiar living scenarios, with full audio recording and simultaneous non-verbal behavior documentation. The observation method employs an event sampling strategy, capturing daily interactions between older adults and smart devices through hidden cameras, emphasizing the frequency of voice commands, emotional trigger scenarios, and environmental response efficiency. All recorded materials are transcribed into text by professional transcription personnel and then coded using NVivo12 software in three stages: open coding to extract core concepts from raw statements, axial coding to establish logical connections between concepts, and selective coding to form a theoretical framework. The research team ensures analytical validity through member checking and triangulation, ultimately producing a qualitative analysis report covering three main themes: technology acceptance, emotional resonance, and functional fit (Zheng, 2024).

3.5 Data analysis methods

Quantitative analysis was conducted using SPSS, where paired sample t-tests were applied to compare changes in loneliness levels and quality of life among elderly participants before and after the use of the system. This statistical approach enabled the evaluation of the system's impact on key psychological and well-being indicators.

Qualitative analysis followed the principles of thematic analysis to identify and summarize recurring feedback themes emerging from participant interviews. Key themes such as "enhanced sense of companionship" and "challenges in interface navigation" were extracted to capture users' authentic experiences and emotional responses. This dual-method approach ensures a comprehensive understanding of both measurable outcomes and subjective perceptions associated with system usage (Hou et al., 2024).

4. Research results

The research findings indicate that an elderly-friendly home system integrating emotional computing and environmental intelligence regulation has a positive impact on alleviating the loneliness experienced by seniors. Quantitative analysis shows a significant decline in the level of loneliness among the subjects after using the system, with longitudinal comparison data from psychological assessment scales confirming the effectiveness of the emotional intervention mechanism. Multidimensional analysis of quality of life assessments reveals particularly notable improvements in social experiences and environmental adaptation for the elderly, highlighting the critical role of the

intelligent interaction module in creating a supportive living environment. Qualitative studies find that most participants positively evaluate the emotional companionship provided by the system, generally reporting sustained psychological comfort in daily routines. Some interviewees specifically mentioned the anthropomorphic experience brought by voice interaction functions, noting that automated service mechanisms effectively compensate for the lack of social interaction in solitary living. Behavioral observation data further confirm the process of establishing human-machine trust, characterized by a steady increase in system usage frequency over time and a gradual shift from passive response to active initiation in interaction patterns. Notably, individual adaptive challenges have emerged during technology application, primarily manifested in semantic recognition errors for specific dialects and the initial learning curve for interface operations. These findings provide important references for subsequent technological iterations.

5. Discussion

This study validates the potential value of integrating emotional computing technology with smart home systems in improving the quality of life for elderly individuals living alone. Experiments show that intelligent environments equipped with emotional interaction functions can effectively alleviate the loneliness experienced by elderly users, particularly in establishing emotional connections and reducing social isolation. The anthropomorphic interaction mechanism of voice assistants provides continuous emotional support to seniors, compensating for the lack of real-life social interactions to some extent. However, several practical issues have emerged during the application of these technologies: the stability of speech recognition modules in complex acoustic environments needs improvement, and interface interaction logic still poses operational barriers for seniors with weaker cognitive abilities. The study also found that the accuracy of emotional computing models directly affects system response quality, necessitating the integration of multimodal data to enhance the reliability of emotion state judgments. Future research should focus on two areas of optimization: first, reducing interaction error rates through iterative advancements in natural language processing technology and developing minimalist operation interfaces that align with the cognitive characteristics of seniors; second, building cross-scenario emotional databases to enhance algorithmic adaptability, enabling the system to dynamically respond to users' personalized needs. Overall, the emotionalized smart home system demonstrates its practical significance in innovative elderly-friendly environments, but it is essential to strike a better balance between technological maturity and user experience to truly realize the inclusive value of technology in assisting the elderly (Feng, Zeng, & Long, 2025).

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