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# *Exploration of the Path for Empowering the Elderly Care Service Management of Retired College Staff with Generative Artificial Intelligence*

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***Keywords:*** Elderly Care Services for Retired University Employees; Generative Artificial Intelligence; Smart Education Platform; Health Management; Big Data Analysis

***Abstract:*** With the increasing diversification and personalization of elderly care service needs among retired university employees, existing service models often rely on manual management, resulting in limited service content, delayed responses, and a lack of personalized support. Therefore, this study introduces generative artificial intelligence (AI) to empower elderly care service management. Combining intelligent recommendations with interactive support mechanisms, this study explores detailed improvements in learning engagement, health management, and daily life services to enhance the precision and acceptability of services. A randomized controlled trial design is used, randomly dividing 160 retired university employees into an intervention group and a control group (80 participants in each group). The intervention group receives conventional elderly care services supplemented with generative AI functionality. The intervention group shows significant improvements in learning engagement, self-assessment of health, and platform satisfaction. Learning engagement increases from 4.2 to 4.7; self-assessment of health increases from 3.4 to 3.9; platform satisfaction increases from 4.0 to 4.5. The control group shows significantly smaller increases. Regarding physical health, the intervention group experiences an average decrease in systolic blood pressure of 4 mmHg, and sleep duration increases from 6.8 to 7.2 hours. Qualitative analysis shows that users generally appreciate the platform's trustworthiness and ease of use, but at the same time, they express some concerns about data privacy and reliance on AI for decision-making.

## 1. Introduction

With the accelerated aging of China's population, the elderly care needs of retired university employees are shifting from basic living security to high-quality, multi-level development. Traditional elderly care service models are limited in terms of personalization, precision, and interactivity, making them unable to fully meet the diverse health management, learning participation, and social interaction needs of the elderly. In recent years, the application of intelligent technologies in elderly care services has gradually gained attention, with the integration of artificial intelligence and the Internet of Things offering new possibilities for innovation in elderly care services. However, existing intelligent elderly care services often rely on pre-set programs and limited data processing capabilities, lacking dynamic insights into and personalized responses to the needs of the elderly, making it difficult to achieve continuous optimization and efficient service matching.

In this context, generative artificial intelligence (GAI), with its capabilities for autonomous learning, multimodal data analysis, and content generation, offers a new path to empowering elderly care services for retired university employees. By combining generative AI with smart education platforms, health management systems, and elderly care financial services, personalized learning recommendations, precise health management, and intelligent decision-making support can be achieved, thereby improving the overall elderly care experience and enhancing the efficiency of matching service supply and demand. This study aims to explore the application model and effectiveness of generative AI in the management of elderly care services for retired university employees, providing a theoretical basis and empirical reference for the practice of smart elderly care services.

## 2. Related Works

In recent years, with the increasing diversification of public medical and elderly care service demands, scholars have conducted research on service management from multiple perspectives, such as customer value, artificial intelligence-driven optimization, social capital, and service resilience, providing theoretical and empirical support for improving the quality and efficiency of public services. Komulainen et al. interviewed 17 regional medical service developers and analyzed the interview data using thematic analysis. The results showed that the study proposed five recommendations for public medical service management based on the customer value approach in marketing literature [1]. Ma proposed an innovative artificial intelligence-driven intergenerational community service optimization framework for elderly care communities in Los Angeles. The study integrated advanced machine learning algorithms and dynamic optimization techniques. The model combined demand forecasting based on deep learning, resource allocation based on reinforcement learning, and a comprehensive service quality evaluation mechanism [2]. Raylos et al. explored the impact of social network experience and business innovation on the performance of elderly care institutions in Beijing. Based on social capital theory and resource-based theory, the results of the study revealed the phenomenon of "performance disconnection": business innovation (especially in terms of value proposition) is positively correlated with market responsiveness and organizational vitality [3]. Konishi et al. introduced detailed information on long-term care services covered by public insurance. The Long-term Care Insurance Act divided services into three categories: home care services, nursing home care services, and community long-term care services. Welfare, health, and medical institutions provide nursing home care services for the elderly [4]. Rajala and Jalonen proposed a scenario planning model to apply possible world thinking to public services to test resilience, thereby helping public sector managers understand service resilience and its accompanying critical points. Based on empirical evidence, the scenario planning model shows how service design incorporates assumptions that become inaccurate during the epidemic and how these inaccurate assumptions put pressure on service design and production [5]. Ma et al. proposed a Home Health Care Scheduling and Routing Problem (HHCSRP) that considers multiple care centers, where a group of customers (i.e., patients and the elderly) need to be assigned to care centers. They introduced a brainstorming optimization method (MOBSO) with a specific multi-objective search mechanism based on the characteristics of the HHCSRP studied. The effectiveness of the designed method was tested experimentally [6]. Broms et al. aimed to clarify the existing debate by exploring the differences in service quality between different types of non-public service providers. Based on the theory of dimensional publicness and incomplete contracts, they argued that different forms of non-public ownership are associated with different intensities of profit maximization incentives, which ultimately affect service quality [7]. Based on the perspective of transformative service research, Feng et al. used a mixed method and a sequential quantitative-qualitative design to understand the mutual influence between good employee-customer interaction, social connection, and social well-being. The data confirmed the role of good employee-customer interaction in enhancing the social connection of elderly customers [8]. Folbre et al. believed that paid care service providers in the United States (healthcare, education, and social services industries) have less ability to obtain value-added or collect rents than commercial service providers because limited consumer sovereignty, incomplete quality information, and large positive externalities reduce their relative market power [9]. Jakobsen's empirical narrative was based on personal qualitative research interviews. The results showed that if nurses do not have ethical understanding, they cannot define what factors in the patient's life world may be important and thus cannot identify these needs [10]. Virtanen and Jalonen believed that mainstream public management theory fails to incorporate public services into the basic components of the public administration system. This lack undermines the potential of public services to promote social progress by creating public value, which can strengthen democracy [11]. Although existing research has achieved many results in public medical and elderly care service management, most of them focus on theoretical model construction or local optimization, lack the application of systematic and intelligent tools and integration between different service scenarios, making it difficult to comprehensively improve the accuracy and personalization of services.

## 3. Methods

### 3.1 Big Data-Based Demand Insights and Smart Education Platform Development

Against the backdrop of improved material conditions and shifting retirement concepts, the retirement needs of university retirees are no longer limited to basic security but are evolving towards high-quality, multi-faceted care. To accurately understand the interests and adaptability of this group to information technology, university retirement departments should leverage big data to conduct dynamic surveys to comprehensively understand their preferences and levels in health, art, and information-based learning. On this basis, they should integrate course resources, professional faculty, and technical expertise to build a cross-university shared smart senior education cloud platform. This platform should feature a user-friendly interface and cater to the differentiated needs of both beginners and advanced learners, with a focus on developing courses in health and wellness, culture and art, and information literacy. Generative AI can assist with personalized recommendations and automated generation of learning content, ensuring that educational resources are tailored to their learning interests and consistent with their cognitive and usage habits.

### 3.2 Developing Three-Dimensional Learning and Communication Space that Integrates Online and Offline Learning

To enhance the learning experience of university retirees, a deeply integrated online and offline education service model should be promoted. Online, the smart education cloud platform can provide on-demand courses and interactive live broadcasts, helping employees independently acquire knowledge on health, culture, and information technology. Teachers can also provide online Q&A sessions, enabling real-time communication.

Offline, calligraphy and painting exhibitions and various cultural and sports activities can be organized based on schedules. Experts are invited to hold themed salons, and employees are encouraged to form interest groups. In this process, generative AI can provide personalized learning path planning and recommendations based on learning history and interests, helping to seamlessly connect virtual and real-world scenarios and create a multi-dimensional learning and communication space.

### 3.3 Building Smart Elderly Care Platform and Precision Health Services

To meet the health and elderly care needs of retired university graduates, an integrated smart elderly care service platform should be established, forming a complete "technology layer - platform layer - service layer" structure. Wearable devices and environmental sensors can be used to collect real-time data on the elderly's daily activities and physiological indicators, and the data can be uploaded to the cloud for processing and storage. This data can then be combined with generative AI models for multi-dimensional analysis to achieve personalized health management and risk warnings. The platform not only provides a visual display of health monitoring data but also feeds information back to service management departments, enabling professionals to promptly implement health interventions, medical consultations, and nursing guidance. This reduces the need for seniors to make multiple trips, enabling precise matching of supply and demand and efficient coordination.

Furthermore, compared to traditional smart elderly care devices that rely on pre-programmed routines, health management systems powered by general artificial intelligence (AGI) can proactively integrate multi-dimensional physiological indicators such as heart rate, blood pressure, and sleep quality to generate dynamic health prediction models. These models integrate with interdisciplinary knowledge bases to develop personalized plans for diet, exercise, and medication management. Its adaptive and continuous optimization capabilities are enabling it to gradually evolve into a personalized "smart health companion," injecting new vitality and value into university elderly care services.

### 3.4 Compliance Management and Intelligent Application of Pension Finance Data

As a crucial pillar for safeguarding the interests of retired university employees, pension finance data collection, transmission, and application must be strictly controlled. During the collection process, raw data should be desensitized and encrypted to prevent privacy leaks. At the application level, large-scale models and machine learning technologies should be leveraged for pension insurance asset management, claims risk warnings, and fraud detection. Generative AI can build on this foundation by generating risk analysis summaries, providing personalized financial management tips, and continuously monitoring and analyzing financial data in real time, thereby enhancing the security and foresight of pension financial services. At the same time, strict hierarchical authorization and authority control are essential in the circulation and sharing of information, along with the establishment of robust data management systems and backup mechanisms to ensure the legal and compliant use of information and support the optimization of financial services and risk control.

## 4. Results and Discussion

### 4.1 Overall Design and Grouping

Design Type: Quasi-experimental + Mixed Methods (Quantitative + Qualified).

Intervention Group: Utilized the "Smart Elderly Care/Education Platform" integrated with generative AI capabilities (including: automated generation/recommendations of personalized learning materials, AI-generated health reports and risk warnings, and financial risk summaries/warnings).

Control Group: Utilized a traditional version with identical functionality but without generative AI-generated/automated text output (only general recommendations or manually edited materials). Other support (sensor acquisition, basic visualization) remained the same.

Allocation Method: Random assignment (randomly assigning individuals or groups across multiple universities/institutions) is used if conditions permitted. If complete randomization is not possible, paired assignment (matching by age, gender, health status, and digital literacy) is used to reduce confounding bias.

Sample size: Based on a two-sample t-test with a medium effect size (Cohen's $d = 0.5$), $\alpha = 0.05$, and power of 0.80, a conventional two-sided design is used for both one-sided and two-sided studies. Approximately 63 participants are required per group, with a rounding up recommendation of 64 participants per group (total sample size 128). To account for dropout and stratified analysis, a budget of 80–100 participants per group is budgeted.

### 4.2 Sample and Recruitment

Subjects: Retired university employees (including those of varying age groups, years of retirement, and professional backgrounds).

Inclusion Criteria: Retired employees registered with the university system, physically or cognitively capable of using a smart device, and willing to sign an informed consent form.

Exclusion Criteria: Individuals with severe cognitive impairment unable to complete the questionnaire or use the platform; individuals without basic internet access.

Recruitment Methods: Notices from the Retirement Affairs Office/Trade Union, posters, and phone/WeChat group invitations.

### 4.3 Results

This experimental indicator aims to comprehensively measure multiple aspects of retired university employees' performance before and after the intervention, including learning participation, health self-assessment, changes in key physiological indicators, sleep quality, financial understanding, and platform satisfaction. These indicators reflect the intervention's improvement in learning and cognitive abilities, assess improvements in health management and lifestyle habits, and examine user acceptance and user experience of the smart elderly care service platform, providing a comprehensive basis for quantitative and qualitative analysis of the intervention's effectiveness.

As shown in Table 1, this study includes 80 retired employees in both the intervention and control groups. There are no statistically significant differences between the two groups in baseline demographics and key study indicators (all $p>0.05$), indicating comparability between the two groups. Specifically, the mean age in the intervention and control groups is $67.5\pm4.2$ years and $68.0\pm4.5$ years, respectively ($p=0.42$), and the gender distribution is similar (male employees accounted for 52.5% and 50.0%, respectively, $p=0.72$). The two groups are generally comparable in terms of years of retirement and educational level ($p=0.61$, $p=0.74$). In terms of key indicators directly relevant to the study, no significant differences are found between the intervention and control groups in digital literacy scores ($3.1\pm0.8$ vs. $3.0\pm0.9$, $p=0.51$), self-rated health ($3.4\pm0.7$ vs. $3.3\pm0.8$, $p=0.38$), willingness to participate in learning ($4.2\pm0.6$ vs. $4.1\pm0.7$, $p=0.45$), and self-rated financial understanding ($3.0\pm0.9$ vs. $3.1\pm0.8$, $p=0.57$). This suggests that the overall characteristics of the two groups are balanced before the experiment begins, laying a good foundation for subsequent comparison of the intervention's effectiveness.

*Table 1. Baseline demographics and key indicators of retired university employees*

| Variable | Intervention Group (n=80) Mean ± SD / n (%) | Control Group (n=80) Mean ± SD / n (%) | p-value |
|---|---|---|---|
| Age (years) | 67.5 ± 4.2 | 68.0 ± 4.5 | 0.42 |
| Gender (Male) | 42 (52.5%) | 40 (50.0%) | 0.72 |
| Years of Retirement (years) | 8.2 ± 3.1 | 8.5 ± 3.4 | 0.61 |
| Education Level (Bachelor or above) | 50 (62.5%) | 48 (60.0%) | 0.74 |
| Digital Literacy (1–5 points) | 3.1 ± 0.8 | 3.0 ± 0.9 | 0.51 |
| Self-rated Health (1–5 points) | 3.4 ± 0.7 | 3.3 ± 0.8 | 0.38 |
| Learning Participation Willingness (1–5 points) | 4.2 ± 0.6 | 4.1 ± 0.7 | 0.45 |
| Self-rated Financial Understanding (1–5 points) | 3.0 ± 0.9 | 3.1 ± 0.8 | 0.57 |

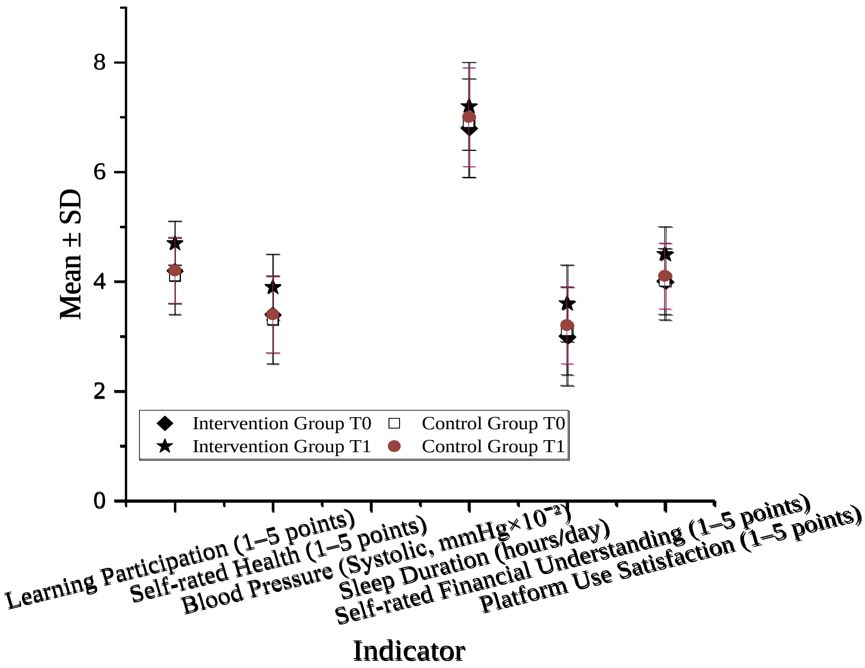


*Figure 1. Comparison of intervention effects*

The experimental results show that the intervention group of retired university employees performs better than the control group on all indicators. Specifically, the intervention group shows significant improvements in learning engagement, self-rated health, and platform user satisfaction. Learning engagement increases from 4.2 to 4.7, self-rated health from 3.4 to 3.9, and platform user satisfaction from 4.0 to 4.5, while the control group has significantly smaller increases. Regarding physical health, the intervention group's systolic blood pressure decreases by an average of 4 mmHg, and sleep duration increases from 6.8 hours to 7.2 hours, while the control group has more modest changes. Self-rated financial understanding increases from 3.0 to 3.6 in the intervention group, demonstrating the positive impact of the intervention on elderly workers' understanding of financial knowledge (see Figure 1). Overall, the intervention group demonstrates significant improvements in learning, health, financial understanding, and platform user experience, demonstrating that the intervention effectively enhances the multi-dimensional elderly care service experience for retired university employees.

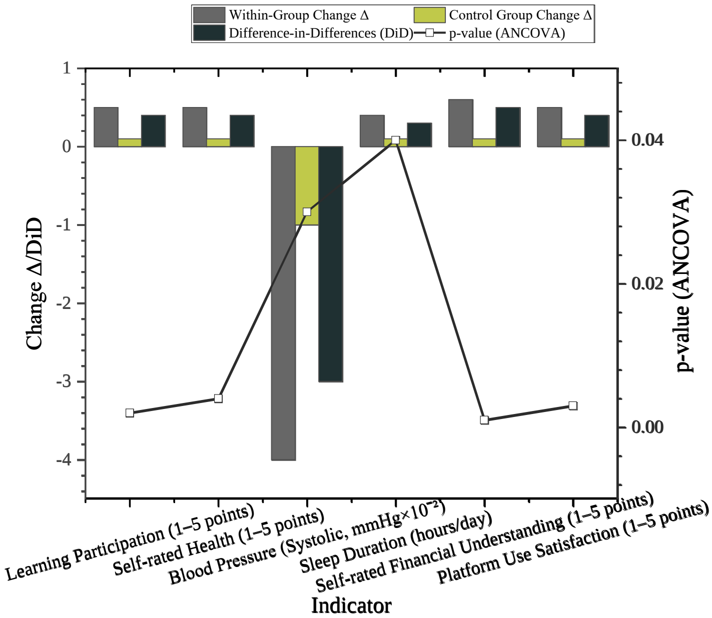


*Figure 2. Intervention effect analysis results (difference-in-differences, ANCOVA)*

The intervention effect analysis results in Figure 2 show that the intervention group significantly outperforms the control group in all indicators. Specifically, the intervention group shows a 0.5-point increase in both learning engagement and self-rated health, while the control group has only a 0.1-point increase. Difference-in-differences (DiD) analysis reveals statistically significant differences of 0.4, respectively (p=0.002 and 0.004). Regarding physical health, systolic blood pressure decreases by 4 mmHg in the intervention group and by 1 mmHg in the control group, with a DiD of -3 mmHg (p=0.03). Sleep duration increases by 0.4 hours, while the control group has an increase of only 0.1 hours, with a DiD of 0.3 hours (p=0.04). Self-rated financial understanding increases by 0.6 points, while the control group has a 0.1-point increase, reaching a DiD of 0.5 (p=0.001). Platform user satisfaction increases by 0.5 points, while the control group has an increase of 0.1 points, with a DiD of 0.4 (p=0.003). These results demonstrate that the intervention has a significant effect on promoting learning engagement, health management, financial understanding, and platform experience.

In-depth interviews with retired employees further reveal key themes in their user experiences with generative AI-enabled elderly care services. As shown in Figure 3, trust and understandability are core elements repeatedly emphasized by users. "Trust in the platform and AI system" is the most frequently mentioned criterion (n=25), indicating that trust is a prerequisite for long-term user acceptance and continued use of the service. "Easy interface" (n=20) and "easy to understand AI recommendations" (n=18) highlight the importance of understandability in reducing learning costs. On an ethical level, some respondents express concerns about "data privacy concerns" (n=15) and "reliance on AI decisions" (n=12), suggesting the need to strengthen data security and the design of human-machine collaboration mechanisms in their promotion and application. Furthermore, personalized experiences and social interaction emerge as key drivers of satisfaction, with "highly compatible recommendations with interests" (n=22) and "group activities fostering communication" (n=17) being frequently mentioned. Overall, the data in Figure 3 shows that the theme of "satisfaction with overall elderly care services" appears most frequently among respondents (n=28), consistent with the significant increase in platform satisfaction shown in the quantitative results. This suggests that the intervention not only improves health and learning indicators but also generates high levels of user appreciation in terms of subjective experience.

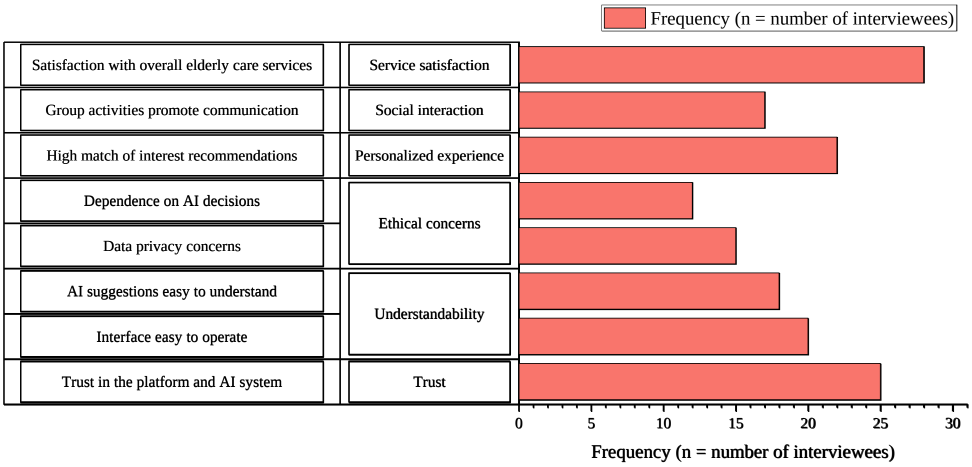


*Figure 3. Example of thematic analysis of interviews on the experience of retired university employees with elderly care services*

## 5. Conclusions

This study, targeting retired university employees, explores the application of generative artificial intelligence in elderly care service management. By constructing a big data-based smart education platform, a three-dimensional online and offline learning space, and an integrated smart health and elderly care service platform, personalized learning recommendations, precise health management, and intelligent financial services are achieved. The experimental results show that the intervention group significantly outperforms the control group in learning engagement, health self-assessment, blood pressure control, sleep duration, financial understanding, and platform satisfaction. The differences are statistically significant ($p<0.05$). The adoption rate and user usability ratings of generative AI-generated content meet acceptable standards, demonstrating its effective empowerment of elderly care services. Qualitative interviews further demonstrate that employees express high trust in the platform and AI system, high evaluation of the interface understandability, and personalized experience, while also experiencing improvements in social interaction and service satisfaction. Overall, generative AI can provide dynamic, intelligent, and sustainably optimized service support in university-based elderly care services, providing empirical evidence for improving retired employees' learning engagement, health management, and overall elderly care experience. However, this study also has certain limitations, such as a limited sample size, a relatively short intervention period, and the need for further verification of the adaptability of generative AI in different elderly care scenarios. Future research can be expanded through larger-scale, multi-center pilots, incorporating more intelligent devices and multimodal data, to continuously optimize the effectiveness and scalability of personalized elderly care services.

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