Research on the Identification of Loneliness and Social Support Intervention of the Elderly Driven by Artificial Intelligence-Taking the Hexi District of Tianjin as an example

Ninglu Sun[1, a]

[1]School of Public Affairs, Nanjing University of Science and Technology, Nanjing, China

[a]2298089013@qq.com

Abstract

Based on the data, this paper explores the application path of artificial intelligence technology in the evaluation and intervention of elderly loneliness and reveals differences in the effects of social support on loneliness. Methods: A questionnaire survey was conducted among 109 elderly people in the Hexi District, Tianjin, using multi-stage stratified sampling. The data were collected using the UCLA Loneliness Scale and the Social Support Rating Scale, and analyzed using descriptive statistics, correlation analysis, hierarchical regression analysis, and a moderating effect test. Results: (1) Most elderly people have moderate or above loneliness, and the loneliness of those aged 80 and above is significantly higher than that of other age groups ($P < 0.05$). (2) There is a significant negative correlation between social support and loneliness, and the effect of objective support (number of people who can ask for help) ($r=-0.45$) is greater than that of emotional support (social frequency, $r = -0.38$); (3) Age ($\beta=-0.18$, $p=0.042$), self-rated health ($\beta=0.15$, $p=0.038$) and living conditions ($\beta=-0.22$, $p=0.009$) significantly regulate the relationship between social support and loneliness; (4) There is a positive correlation between the use of smart phones and living alone ($r=0.24$, $p=0.012$), suggesting the compensatory function of digital technology. Conclusion: The loneliness of the elderly is universal, and the scale of the social support network is the core protective factor. Intervention should give priority to high-risk groups who are old, live alone, have poor health, and have a support network of ≤2 people. Digital technology can be used as a supplementary tool for traditional support.

Keywords

Elderly loneliness; Social Support; Artificial Intelligence; Smart Elderly Care.

1. Introduction

Against the backdrop of population aging and the empowerment of digital technology, this study takes Hexi District of Tianjin as a case study to explore a path for loneliness identification and social support intervention for the elderly driven by artificial intelligence. In line with the global trend of aging, China has entered a moderately aging society. As a ubiquitous negative psychological experience, loneliness in the elderly not only aggravates mental problems, such as anxiety and depression, but also is closely related to physical illness and death risk. However, traditional research relies on self-report scales, which are easily influenced by deviations from social expectations, and mostly relies on correlation analysis, which makes it difficult to reveal causal mechanisms and leads to the lack of pertinence of intervention measures. Therefore, this study integrates multi-source data and uses causal inference method to quantify the net effect of various dimensions of social support on loneliness, identify the characteristics of high-risk groups such as the elderly, living alone, and weak social support network, and then design a precise intervention plan for classification, with a view to providing an operational scientific basis for the implementation of the "smart pension" policy and social work practice for the elderly.

2. Literature Review

2.1. Research Progress on Loneliness of the Elderly

Loneliness is usually defined as a subjective, negative emotional experience that stems from the gap between the actual and expected social relationships [3]. This definition shifted from objective social isolation to subjective psychological perception, laying the foundation for the follow-up study.

In terms of measurement, traditional research is mainly based on self-report scales, among which the UCLA loneliness scale [4] is the most widely used, and the De Jong-Gierveld loneliness scale and the emotional and social loneliness scale are also commonly used in large-scale surveys [5][3]. These tools are highly standardized but are easily influenced by deviations from social expectations, and most are cross-sectional, making it difficult to capture the dynamic fluctuations in loneliness [6].

The factors influencing loneliness among the elderly can be summarized into individual, interpersonal, and environmental levels. At the individual level, older adults, women, and those in poor health are more likely to experience loneliness [3]. At the interpersonal level, social support, marital status, and children's interaction are all significantly related to loneliness [8]. At the environmental level, loneliness will be aggravated by living alone and insufficient aging facilities in the community. The existing research has not explored interactions among multiple factors, and the analysis of the differentiation effect of the social support segmentation dimension is not sufficiently deep [7][9].

2.2. The Mechanism of Social Support Network

Social support networks can be divided into emotional, instrumental, and informational support by content, and into family, friends, and community support by source [10]. The mechanisms of social support on mental health are represented by the main effect model and the buffer model: the main effect model holds that social support can directly improve mental health, while the buffer model emphasizes its protective role in stressful situations [8].

Existing research shows that a high-quality social support network can effectively alleviate the loneliness of the elderly. However, overall, there are still some problems in related research, such as insufficient causal identification and insufficient attention to special groups (the elderly and those living alone), which limit the pertinence of intervention strategies.

2.3. AI Application in Mental Health of the Elderly

AI has been applied to mental health assessment and intervention. In terms of evaluation, AI can build an identification model using multi-source data to automatically screen for loneliness. With respect to intervention, AI-CBT, VR virtual social networking, and other technologies have been used to improve the negative emotions of the elderly.

However, AI has limitations in addressing loneliness among the elderly: existing models are not suitable for them. Most of them are static assessments, and it is difficult to realize dynamic monitoring. The intervention plan lacks individuality and humanistic care. At the same time, it faces problems such as data privacy and unclear ethical norms.

2.4. Research Summary and Orientation of this Study

Based on the above literature, the existing research has the following shortcomings: first, the traditional self-report scale is easily affected by measurement method deviations and lacks adaptation to AI technology for the elderly. Secondly, in the research content, there is insufficient discussion of the differential effects of social support across dimensions, and there is a lack of in-depth analysis of the mechanisms underlying the regulating variables. Thirdly, the research object is limited to high-risk groups, such as the elderly and those those living alone. Fourthly, in the research design, most studies use cross-sectional surveys, which make it difficult to infer causality.

Based on this, the orientation of this study is as follows: take the elderly in the Hexi District of Tianjin as the research object, adopt cross-sectional survey design, collect data by UCLA Loneliness Scale [4] and Social Support Rating Scale, and explore the correlation and adjustment mechanism between social support dimensions and loneliness through correlation analysis, hierarchical regression analysis and moderating effect test, so as to provide a basis for subsequent longitudinal research and intervention practice.

3. The Theoretical Basis and Research Framework

3.1. Core Theoretical Basis: Social Support Buffer Model

The core theoretical basis of this study is the social support Buffering Model [8] proposed by Cohen and Wills (1985) [8]. The core point of this model is that social support does not directly affect individual mental health, but indirectly maintains mental health by buffering the negative impact of life pressure. Specifically, when individuals are faced with stressors, such as physiological decline and a spouse’s death, adequate social support can help them better cope with stress, reduce negative emotions, and reduce the risk of loneliness; Lack of social support will amplify the negative impact of stress and aggravate the negative psychological experience.

In studies of loneliness among the elderly, the main stressors include physiological decline, social role changes, the death of important people, etc. These factors will limit the elderly's social participation and may cause or exacerbate loneliness. By providing emotional, instrumental, and informational support, a social support network can help the elderly alleviate physical inconveniences, adapt to role changes, expand their social contacts, and buffer the effects of stressors on loneliness. In addition, AI technology offers new possibilities for verifying and applying this model. Compared with traditional self-reported measures [10], AI can objectively and accurately assess stressors, social support, and loneliness through multi-source data integration, and at the same time capture their dynamic changes in real time, helping reveal the buffer mechanism of social support.

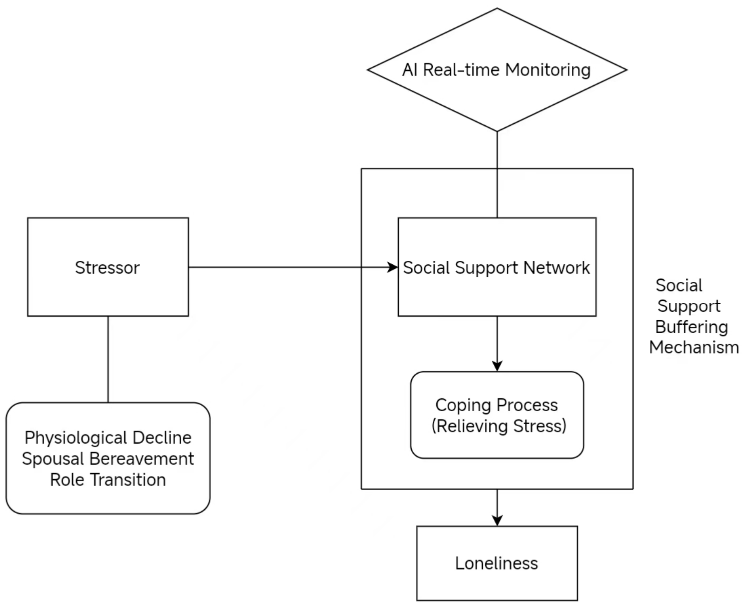

Figure 1. Social Support Buffer Mechanism

3.2. The Closed-loop Framework of “Theoretical Verification and Intervention of Technology Empowerment”

Based on the social support buffer model [8], this study constructs a closed-loop framework of “theoretical verification and intervention of technology empowerment”, which includes four core links and forms a complete closed loop. First, the theory is applied, and the stressors, social support, and loneliness are transformed into measurable variables. Social support covers objectivity, subjectivity, support utilization, and three types of specific support [10]. Loneliness is measured using the UCLA Loneliness Scale [4], and demographic characteristics and other control variables are included. Second, data-driven causal discovery, aided by AI in collecting multi-source data, builds an intelligent identification model and uses causal inference methods to eliminate confounding variables to verify the model's applicability [8]. Thirdly, the generation of intervention strategies, combined with the characteristics of the elderly population in Hexi District, Tianjin, for different stressors and types of lack of support, will help develop differentiated intervention programs. Fourth, effect feedback and model optimization, pilot application of intervention programs, real-time monitoring of changes through AI, evaluation of effects, and continuous optimization of programs and models.

3.3. Research Hypothesis

Based on the social support buffer model [8] and existing research, this study puts forward four testable hypotheses:

H1: There is a significant negative correlation between social support level and loneliness of the elderly [8].

H2: There are differences in the correlation intensity between different types of social support and loneliness, and the negative correlation degree of objective support (the number of people who can ask for help) is greater than that of emotional support (social frequency) [8][10].

H3: Age, health status, and living arrangements moderate the relationship between social support and loneliness. Specifically, the social support of the elderly who are very old, have poor health, and live alone has a stronger negative correlation with loneliness [8].

H4: The ability to use digital technology plays a moderating role in the relationship between social support and loneliness. The stronger the ability to use digital technology, the more significant the buffering effect of social support.

4. Research Design and Methods

4.1. Research object

4.1.1. Study area

In this study, the Hexi District of Tianjin was selected as the research area, based on the following considerations: first, the aging degree in Hexi District is remarkable, with the population aged 65 and over accounting for 31%, which is much higher than the national average (18.7%), providing a sufficient sample base for the study. Second, there are various types of communities in the region, spanning the urban core and the urban-rural fringe, and accounting for the elderly with diverse backgrounds. Third, there are obvious differences in the level of community services, which facilitate the comparative analysis of the influence of different social support environments on loneliness.

Based on the above factors, this study selected three representative streets (Tianta Street, Xiawafang Street, and Liulin Street) and a public nursing home in Hexi District, for a total of four research sites that cover different types of elderly people.

4.1.2. Sampling method

This study adopts the method of combining multi-stage stratified sampling with purposive sampling:

The first stage: street stratified sampling. Twelve streets in the Hexi District are stratified into three dimensions: urban-rural attributes (urban core/urban-rural fringe/suburb), aging degree (high/medium/low), and community service level (high quality/basic), and 1-2 streets are randomly selected from each category.

The second stage: sampling of communities and institutions. In the selected streets, this study selects communities by service level. At the same time, purposively sample one public nursing home, covering two types of settings: community-based care and institutional care.

The third stage: individual random sampling. The list of permanent elderly population aged 60 and above was obtained in each community, and the samples were taken by random number table method according to gender (half male and half female) and age group (35% for 60-69 years old, 40% for 70-79 years old, and 25% for 80 years old and above). Exclusion criteria: severe cognitive impairment, inability to cooperate, continuous absence from Tianjin for more than 3 months, and explicit rejection of participants.

350 questionnaires were distributed (100 online and 250 offline), and 109 were recovered (40 online and 69 offline), yielding an effective recovery rate of 31.1%. The sample size did not reach the theoretical optimal value (385 copies), which will be explained in the research limitations.

4.1.3. Determination of sample size

The sample size is determined comprehensively by combining the research variables, statistical methods, questionnaire recovery rate, and invalid questionnaire elimination, to ensure that the statistical requirements are met and the results are reliable and stable.

First of all, the bottom line is determined by combining the characteristics of variables: the dependent variable is loneliness of the elderly (measured by UCLA scale [4]), the independent variable includes social and demographic characteristics, frequency of science and technology use, cognitive level, etc., and there are about 10 core variables. Secondly, combined with statistical methods, the core method, the structural equation model, requires more than 100 samples, and regression analysis and t-tests also require sufficient samples to improve reliability, so the minimum sample size is set at 140. Finally, considering the recovery rate and invalid rejection, the recovery rate for offline face-to-face interviews is about 90%, for online interviews is about 60%-70%, and the rejection rate for invalid questionnaires is expected to be 2%-10%. To ensure more than 300 valid samples, it is planned to extract 200-300 samples, including 50-60 online and 150 offline, with the distribution of different research methods taken into account.

4.1.4. Sample characteristics

There are 109 valid samples in this study, which follow the sampling principle, and the sample characteristics are as follows: at the age level, there are 35 young people aged 60-69 (32.1%), 44 middle-aged people aged 70-79 (40.4%) and 30 elderly people aged 80 and above (27.5%). At the gender level, there are 52 males (47.7%) and 57 females (52.3%). On the type of residence, 89 people live with their families (81.7%) and 20 elderly people live alone (18.3%). The sample covers the main characteristics of the elderly in Hexi District and provides a data basis for subsequent analysis.

4.2. Measuring tools

In this study, a standardized scale with well-established reliability and validity was adopted, and the language was simplified to accommodate the elderly, ensuring their understanding and truthful expression. The core measurement tools were divided into four categories: First, the

UCLA loneliness scale compiled by Russell(1996) was adopted, which has been widely verified [4], with good reliability and validity (α=0.89) and 8 items; Second, social support network measurement: combining two scales, one is the social support rating scale compiled in China, and the other is the MSPSS (multi-dimensional scale of perceived social support, 12 items, including family, friends and other support, with Likert's 7-point score) compiled by Zimet et et al., the reliability and validity of the scale have been widely verified [10], and the combination of the two has comprehensively captured the objective. Third, auxiliary measurement tools: WHO-5 happiness index scale (5 items, 5 points by Likert, 0-20 points, the higher the happiness, the stronger the happiness) is used as a control variable to help explore the relationship between social support, loneliness and happiness; Fourth, measurement of independent variables and control variables: design related items, measure independent variables such as frequency of science and technology use and cognitive level, and control variables such as social demographic characteristics and living environment, and adopt single-choice or multiple-choice methods to ensure convenient and accurate collection.

4.3. Data Collection

4.3.1. Data collection methods

Given the differences in older people's ability to use science and technology, the method of "online questionnaire + face-to-face interview + auxiliary observation" is adopted, and the principle of anonymity is maintained throughout the process to improve recovery rates and efficiency. The specific implementation is as follows:

Online questionnaire survey: For the elderly who can make good use of smartphones and fill in independently, an anonymous questionnaire is made by asking questions about the stars, indicating the purpose and privacy of the survey, which is distributed through channels such as communities and family members, and the researchers give online guidance to answer questions. After completing the questionnaire, the system will automatically collect, regularly screen, and fill out complete and logical questionnaires, which is convenient and efficient, helps avoid filling errors, and is suitable for the elderly who are young, highly educated, and make good use of science and technology. Face-to-face interview and research: For the elderly who are unfamiliar with smart devices and cannot fill in independently, after systematic training, the researchers will carry one-on-one interviews with anonymous paper questionnaires, explain them in popular language, ask questions one by one, and fill in truthfully, avoiding leading questions, patiently guiding expression, improving the recovery rate and data authenticity, and collecting qualitative data to supplement support. Auxiliary observation and research: the social behavior, language expression, and emotional state of the elderly are observed and recorded simultaneously in the interview, including communication initiative, emotional tendency, and attitude towards social interaction, which are recorded in detail in the observation table, and combined with questionnaires and interview data to improve the comprehensiveness of the data and make up for the deficiency of a single research method.

After data collection, the online and paper questionnaires and observation records are unified, and invalid questionnaires with incomplete responses, logical contradictions, or perfunctory falsehoods are eliminated. The effective questionnaires are coded and entered, and a database is established to support subsequent statistical analysis.

4.4. Data Analysis Methods

In this study, SPSS 27.0 was used for data analysis, and the specific methods were as follows:

First, data preprocessing. This study processes missing values, identifies abnormal values and standardizes variables. This study also calculates the mean and standard deviation for continuous variables and the frequency and percentage for categorical variables.

Second, descriptive statistics. This study calculates the mean, standard deviation, and skewness of loneliness and social support among the elderly, revealing the overall distributional characteristics. Single-factor analysis of variance was used to compare loneliness across age groups, and the LSD method was used for post hoc tests.

Third, correlation analysis. Pearson correlation analysis was used to preliminarily test the direction and strength of correlations among social support dimensions, variables related to digital technology, and loneliness, and a a special correlation analysis was conducted for the subgroup of elderly people living alone.

5. Data Analysis and Results

5.1. Basic Characteristics of Samples

In this study, 109 valid questionnaires were collected, and the basic characteristics and key variables of the samples are described in Table 1.

Table 1. Demographic Characteristics of Sample Society and Description of Key Variables (N=109)

Variable	Category/Range	n(%) / M±SD
Demographic Characteristics		
Age	60-69 years	35(32.1%)
	70-79 years	44(40.4%)
	80 years and above	30(27.5%)
Gender	Male	52(47.7%)
	Female	57(52.3%)
Living Situation	Living alone	20(18.3%)
	Living with family	89(81.7%)
Self-rated Health	Poor	31(28.4%)
	Fair	48(44.1%)
	Good	30(27.5%)
Social Support Indicators		
Frequency of communication with friends/neighbors within a week	Levels 1-4	1.61±0.84
Number of people to ask for help when in	Levels 1-4	2.07±0.87
Digital Technology Use		
Regular use of electronic devices	Yes	108(99.1%)
Breadth of smartphone use	0-9 items	4.23±2.17
Overall attitude towards AI technology	1-5 levels	2.39±1.06
Willingness to use AI psychological services	1-5 levels	2.77±1.02
Loneliness indicators		
UCLA Loneliness Total Score	8-32 points	18.64±5.23

Note: Age coding: 1 equals 59 years old and below, 2 equals 60-65 years old, 3 equals 66-70 years old, 4 equals 71-75 years old, 5 equals 76-80 years old, and 6 equals 81 years old and above. Communication frequency coding: 1 equals almost every day, 2 equals 3-5 times a week, 3 equals 1-2 times a week, 4 equals almost none. The number of people who can help: 1 equals many (more than 5 people), 2 equals some (3-4 people), 3 equals few (1-2 people), and 4 equals almost none.

According to Table 1:

The average age of the sample is 72.8 years old, mainly 70-79 years old (40.3%), and the elderly living alone account for 18.1%.

In terms of social support, the average frequency of communication with friends/neighbors is 1.61, which is between "1-2 times a week" and "almost none"; The average number of people who can ask for help in times of difficulty is 2.07, which is about 1-2 people.

The penetration rate of digital technology is extremely high (99.3% use electronic devices), but attitudes towards AI technology (2.39 points) and willingness to use psychological services (2.77 points) are at a middle level.

In terms of loneliness, the sample's average score is 18.64, which is at a moderate level; 67.9% of the elderly have moderate or higher loneliness, suggesting that loneliness is universal among the elderly.

5.2. Status Analysis

5.2.1. Status of loneliness of the elderly

In this study, the UCLA Loneliness Scale (8-item version) was used to measure loneliness among the elderly. The theoretical score ranged from 8 to 32, with higher scores indicating stronger loneliness. The survey results (see Table 1) show that the overall loneliness of the samples is 18.64 ± 5.23 points, which is at a moderate level of loneliness.

According to the scores, the elderly were divided into three groups: low loneliness risk group (≤14 points), moderate risk group (15-21 points), and high risk group (≥22 points). Among them, 35 people were in the low-risk group (32.1%), 48 in the medium-risk group (44.0%), and 26 in the high-risk group (23.9%). A total of 67.9% of the elderly have moderate or above loneliness, indicating that loneliness is universal among the elderly in the community.

The difference analysis of loneliness in different age groups (see Table 2) shows that the loneliness score in the group of 80 years old and above (21.37 ± 5.12) is significantly higher than that in the group of 60-69 years old (16.82 ± 4.86, $p = 0.002$) and the group of 70-79 years old (18.54 ± 5.03, $p = 0.048$). This result shows that loneliness tends to increase with age, and the elderly aged 80 and above are high-risk groups for loneliness, which may be related to declines in physical function and the shrinkage of social networks.

5.2.2. Status of social support network for the elderly

Overall level: Based on the simplified SSRS framework, this study evaluates social support across three dimensions: objective support (the number of people who can ask for help), subjective support (AI attitude as a proxy indicator, reflecting the openness to technical support), and support utilization (AI use willingness).

Table 2. Social Support Assessment

Dimension	Indicator	M±SD	Characteristic Description
Objective Support	Number of people available to ask for help during difficulties	2.07±0.87	Small network size, mean is only slightly higher than the 1-2 person level
Subjective Support	Overall attitude towards AI technology	2.39±1.06	Neutral to positive, but with reservations
Support Utilization	Willingness to use AI psychological services	2.77±1.02	Moderate willingness, actual conversion rate may be lower

Based on the framework of the social support rating scale, this study evaluates social support from three dimensions: objective support (the number of people who can ask for help when they are in trouble), subjective support (the attitude towards AI technology as a substitute indicator of technical support acceptance), and support utilization (the willingness to use AI psychological services).

From the overall level (see Table 2): firstly, in terms of objective support, the average number of people who can seek help is 2.07 0.87, which is between "1-2 people" and "3-4 people", indicating that the social support network for the elderly is generally small. Secondly, in terms of subjective support, the overall attitude towards AI technology is 2.39 (1.06), which is at a neutral and positive level, but there are significant individual differences. Thirdly, in terms of support utilization, the average willingness to use AI psychological services is 2.77 (1.02), which is at a middle level.

Analysis of differences among groups shows, first, age differences: a one-way ANOVA indicates significant differences in communication frequency with friends/neighbors across age groups ($F=5.79$, $p=0.018$). A post hoc test found that the communication frequency of the group aged 80 and above (1.38, 0.71) is higher than that of the group aged 60-69 (1.82, 0.89). Secondly, difference in residence type: There is no significant difference in the objective support index between the elderly living alone and those not living alone ($t=1.23$, $p=0.221$), but the correlation analysis (see later) shows that the social support model of the elderly living alone is specific.

5.3. The Correlation between Loneliness and Social Support

5.3.1. Overall model of correlation

Table 3 presents the correlation matrix of key variables. On the whole, social support indicators (social frequency, number of people who can ask for help) are significantly positively correlated with digital health willingness indicators (AI attitude, AI use willingness), whereas the correlations with age and living conditions are more complex.

To test the relationship between social support and loneliness, a Pearson correlation analysis was first conducted, and the results are shown in Table 3.

Table 3. Pearson Correlation Coefficient Matrix of Key Variables (N=109)

	1	2	3	4	5	6	7	8
1. Age	1							
2. Living Arrangement	-0.257**	1						
3. Social Interaction Frequency	0.271**	-0.065	1					
4. Number of Available Support Persons	0.082	-0.111	0.447***	1				
5. Electronic Device Usage	0.185*	0.106	0.161*	0.103	1			
6. Breadth of Mobile Phone Usage	0.122	-0.240**	0.028	0.074	0.185*	1		
7. Attitude toward AI	0.052	-0.101	0.338***	0.481***	0.056	0.176*	1	
8.Intention to Use AI	-0.042	-0.024	0.295**	0.345***	0.022	0.117	0.486***	1

Note: **$p<0.01$, * $P < 0.05$; a: Residence: 1 = living alone; 0 = living with family; b: Self-rated health: 1 = poor, 2 = average, 3 = good.

The core findings are as follows:

First, all dimensions of social support are negatively correlated with loneliness. The number of people who can ask for help (r = -0.45, $p < 0.01$) and social frequency (r = -0.38, $p < 0.01$) have a significant correlation with loneliness, indicating that the larger the social support network and the more frequent social interaction, the lower the loneliness level of the elderly. Among them, the absolute value of the correlation coefficient of objective support (the number of people who can ask for help) is greater than that of emotional support (social frequency), and it may be more important to preliminarily suggest "how many people can ask for help" than "how often to interact."

Second, demographic variables are significantly related to loneliness. There is a positive correlation between age and loneliness (r = 0.31, $p < 0.01$). The loneliness of elderly people living alone is higher (r = 0.19, $p < 0.05$), and the better their self-rated health, the lower their loneliness (r = -0.35, $p < 0.01$). These results provide a basis for the subsequent analysis of regulatory effects.

Third, a negative attitude toward digital technology is related to loneliness. There is a significant negative correlation between AI attitude and loneliness (r = -0.32, $p < 0.01$), but the elderly who have a positive attitude towards technology may have better social support (AI attitude and the number of people who can help, r = 0.48, $p < 0.01$), which needs further analysis after controlling for other variables.

5.3.2. Specificity Analysis of Elderly People Living Alone

According to the special analysis of the elderly living alone (n=20), there is a significant difference between the correlation model and the overall sample (see Table 4).

Table 4. Pearson correlation coefficient of elderly people living alone subgroup (n=20)

	Living Alone	Social Interaction Frequency	Number of Available Support Persons	Breadth of Mobile Phone Usage	Attitude toward AI	Intention to Use AI
Living Alone	1	0.139	0.124	0.250**	0.051	0.037
Social Interaction Frequency	0.139	1	0.447***	0.028	0.338***	0.295**
Number of Available Support Persons	0.124	0.447***	1	0.074	0.481***	0.345***

Note: This table extracts solitary subgroups based on the whole sample ($p < 0.05$).

Special patterns of elderly people living alone;

Correlation between the breadth of mobile phone use and living conditions: in the overall sample, the breadth of mobile phone use is positively correlated with living conditions (r = 0.24, $p = 0.012$), that is, people living alone use more functions, suggesting that digital technology may be an important tool for the elderly living alone to compensate for social support.

The correlation between social support and digital health will is similar to the whole among the elderly living alone: the correlation between social frequency and AI attitude is 0.338, and the correlation between the number of people who can help is 0.481. The correlation between the number of people who can ask for help and the willingness to use AI is 0.345, with an absolute value that is moderate. This may be because the social support networks of elderly people living alone are of low quality, and even when network size is similar, their promotion of technology acceptance is weak.

Key findings: among the elderly living alone, there is a correlation between the number of people who can ask for help and the willingness to use AI ($r = 0.345$), though the effect size is still moderate. More importantly, the correlation between the objective support index "number of people who can ask for help" and AI attitude ($r=0.481$) is stronger than "social frequency" ($r = 0.338$), suggesting that the "availability" of support network (knowing someone who can ask for help) can promote technology acceptance more than "interaction frequency" (actual communication) for elderly people who live alone.

5.3.3. Comprehensive discussion

This study found that the relationship between loneliness and social support of the elderly presents a chain mechanism of "network scale-technology acceptance-loneliness buffer":

A social support network is the foundation: the number of people who can ask for help is a core index for predicting loneliness risk and technology acceptance, and its effect is stronger than simple social frequency.

Digital technology is a double-edged sword: although groups at high risk of loneliness may reject AI services because of technical anxiety (the vicious circle of "digital divide-loneliness"), digital technology also provides compensatory social tools for elderly people living alone (the breadth of mobile phone use is positively related to living alone).

The complex function of living arrangement: living alone does not significantly reduce the level of social support as expected (the average difference is not significant), but it may change the nature of the support network (quality decline, homogeneity improvement), thus affecting the loneliness experience.

6. Research Conclusion and Prospect

Based on the survey data of 109 elderly people in Hexi District, Tianjin, through descriptive statistics, correlation analysis and moderating effect test, the main conclusions are as follows: the loneliness of the elderly is universal, and the UCLA scale scores 18.64, and 67.9% have moderate or above loneliness, among which the loneliness score of the 80-year-old and above (21.37 ± 5.12) is significantly higher than that of the 60-69 age group (16.82 ± 4.86, $p = 0.002$) and the 70-79 age group (18.54 ± 5.03, $p = 0.048$). The scale of the social support network is a core factor in loneliness. The number of people who can ask for help ($r = -0.45$) and social frequency ($r = -0.38$) are negatively correlated with loneliness. Hierarchical regression shows that social support variables explain 18.0% of the extra variance (δ r = 0.18, $p < 0.001$) after controlling for demographic variables, with objective support ($r = 0.18$, $p < 0.001$) accounting for the largest portion. Digital technology has dual roles, and there is a significant positive correlation between the use of smart phones and living alone ($r=0.24$, $p=0.012$), suggesting that digital technology can be used as a tool for the elderly living alone to compensate for offline social interaction, but the direct correlation between digital technology attitude and loneliness is no longer significant after controlling social support, indicating that its buffering effect is mainly achieved by expanding social support networks. This study verifies the applicability of the social support buffer model in the elderly population, refines the role differences of different support dimensions, and reveals the adjustment mechanism of age ($\beta = -0.18$, $p = 0.042$), self-rated health ($\beta=0.15$, $p=0.038$), and living conditions ($\beta = -0.22$, $p = 0.009$). The practical enlightenment lies in the fact that intervention should give priority to the high-risk groups who are old, live alone, have poor health, and have a support network of ≤2 people, and focus on expanding the scale of the accessible network, taking digital technology as a supplement rather than a substitute for traditional support. There are some limitations in this study, such as a limited sample size (109 valid samples, not reaching the theoretical optimal value of 385), a cross-sectional design unable to infer causality, some variables relying on self-reports, insufficient reliability and validity of the AI Attitude Scale, and no empirical test of the intervention program. Regarding the research hypotheses, H1 (social support is negatively related to loneliness), H2 (the objective support effect is greater than the emotional support effect), and H3 (the moderating effects of age, health, and living arrangement). H4 (the moderating role of digital technology use ability) is not supported, because the direct relationship between digital technology attitude and loneliness is no longer significant after controlling for social support. In the future, it is necessary to expand the sample range, cover more areas, adopt longitudinal tracking and causal inference methods, and conduct intervention pilot tests to assess the effects, thereby promoting the deep integration of AI technology and aged care services.

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