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# Determinants and prediction of home nursing utilization among older adults in China: an integration of logistic regression and XGBoost algorithm

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## Abstract

**Objective** To analyze the factors and their interactions influencing home nursing utilization among older adults in China, and to provide a scientific basis for enhancing home nursing services and improving life quality for older adults.

**Methods** We utilized nationally representative data from the 2020 wave of the China Longitudinal Aging Social Survey (CLASS), including a total of 2,723 participants. Logistic regression and XGBoost algorithm were employed to examine the determinants of home nursing utilization. Interactions among determinants were also analyzed to uncover deeper insights into home nursing utilization, with XGBoost further applied to generate individual-level predictions.

**Results** The analysis showed that region type, home visit access, older adults' subsidy, and family support count were significant enabling resources in home nursing utilization. Activities of Daily Living (ADL) score, chronic disease count, recent hospital duration, and life satisfaction, were strong internal motivators. Interactions, including the influence of region type and chronic disease count, life satisfaction and home visit access, self-rated health and region type, home visit access and family support count, further highlighted the complexity of home nursing utilization. The potential role of online access was also recognized as an emerging factor.

**Conclusions** This study emphasizes the critical role of both need-based factors and enabling resources in driving home nursing utilization. Identifying high-need populations is essential for improving home nursing utilization and optimizing resource allocation. Targeted interventions are required to address disparities in the distribution of enabling resources, ensuring effective delivery to underserved areas. Community-based systems should prioritize support for older adults with minimal family support while integrating psychological interventions into care models to better align with individual needs. By developing tailored service strategies, this research provides a scientific foundation for optimizing the design and delivery of home nursing services, ultimately improving the quality of care for older adults.

**Clinical trial number** Not applicable.

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**What is already known**

- The global aging population has significantly increased the demand for home nursing. However, the utilization rate of home nursing remains low.
- Factors influencing home nursing utilization include three aspects: predisposing characteristics, enabling resources, and need-based factors. While traditional statistical methods have examined these factors, most studies assume linear relationships and often overlook complex interactions and non-linear effects.
- The influence of some new emerging factors on the utilization of home nursing remains underexplored in current literature.

**What this study adds?**

- Integration of Logistic regression with XGBoost algorithm to comprehensively examine both linear and non-linear effects, as well as interaction effects.
- Enabling resources and need-based factors are the core determinants of home nursing utilization. Additionally, interactions between factors are identified as key mechanisms shaping utilization patterns.
- The potential but still limited role of online access, suggesting that improving digital literacy could be an emerging strategy to improve home nursing utilization.

**Keywords** Home nursing utilization, Older adults, Age in place, Logistic regression, XGBoost, Influencing factors

## Introduction

The accelerating global aging trend has become a major challenge to healthcare systems [1]. Among various care options, home nursing has gained increasing recognition for aging in place. It provides medical and nursing services directly within the home environment [2]. Home nursing reduces the reliance on hospital-based and institutional care, lowers healthcare costs, and enhances the quality of life for older adults by addressing their health needs in a familiar setting [3–5].

China, as the country with the world's largest aging population, faces immense pressures to meet the growing demand for eldercare. According to the latest governmental statistics, the number of people aged 60 and above in China has reached about 296.97 million, accounting for 21.1% of the total population [6]. The government's "90-7-3" care policy for older adults, promoted by the Ministry of Civil Affairs, aims to establish a tiered care model in which 90% of older adults are supported by home-based nursing care, 7% by community services, and 3% by institutional care. This policy clearly emphasizes the central role of home-based nursing care in China's population aging. Moreover, rapid socioeconomic changes, such as smaller family sizes and an increasing number of older adults living alone, have further amplified the demand for home nursing [7]. This evolving caregiving landscape highlights the urgent need to better understand the utilization of home nursing and its influencing factors.

Previous studies have identified various factors influencing the utilization of home nursing. These researches draw on Andersen's behavioral model of health services use, which categorizes the influencing factors into predisposing, enabling, and need-related dimensions [8, 9]. Predisposing factors, including age, gender, education and so on have been associated with the intensity and patterns of home nursing utilization [10]. Need-related factors primarily reflect health conditions. For instance, patients with more severe chronic illnesses or higher score of activities of daily living (ADL) are more likely to utilize home nursing [11]. Enabling factors involve both micro-level resources and macro-level conditions. At the micro level, the availability, training, and skills of family caregivers and professional caregivers are also critical for home nursing utilization [12]. At the macro level, policy and institutional factors, such as the availability of home nursing resources, government policy support, and financial subsidies, significantly impact access to and utilization of these services [13].

While these studies have provided valuable findings, several gaps still exist. First, some studies rely on small-scale samples or specific regional data, limiting the generalizability of their findings [14, 15]. Second, previous studies employ only traditional medical statistical methods, which assume linear relationships between variables and overlook complex interdependencies and non-linear effects [11, 16]. This oversimplification may obscure critical insights into the factors shaping home nursing utilization. Third, the recent research uses pre-pandemic data, failing to capture the profound shifts in home nursing dynamics brought about by the COVID-19 pandemic [11]. The pandemic increased reliance on home nursing due to hospital restrictions, and accelerated the digital transformation in eldercare. Factors such as online access, which can indicate the extent of individuals' engagement with digitalization, have become critical in shaping healthcare utilization [15]. These emerging factors remain unexplored in current literature.

Our study aims to address these gaps through following aspects. Using nationally representative data from the China Longitudinal Aging Social Survey (CLASS) 2020, collected during the COVID-19 pandemic, this research explores the factors influencing home nursing utilization, including established determinants and emerging variables. To capture these relationships comprehensively, we integrate traditional medical statistics with modern machine-learning approaches. Logistic regression provides coefficient-based estimation and quantifies the effects of each determinant, whereas XGBoost complements this analysis by identifying non-linear relationships, interaction patterns, and individualized predictions. Such integration follows methodological frameworks for combining explanatory and predictive analytics in health services research [17]. Moreover, individual-level predictions from machine learning can offer a more precise understanding of the factors. The findings can assist policymakers and practitioners to improve home nursing delivery and in responding more effectively to the care needs of an aging population.

## Methods

### Data sources and sample

This study used data from the China Longitudinal Aging Social Survey (CLASS), a nationally representative survey aimed at identifying the challenges and needs of older adults in China. Coordinated by Renmin University of China, CLASS employs a stratified, multistage, and probabilistic sampling method, covering 28 provinces and 462 communities across the country [18]. The survey began in 2014, with subsequent waves in 2016, 2018, and 2020.

The 2020 wave, which provides the most recent data, is particularly noteworthy as it was conducted during the COVID-19 pandemic, capturing the shifts in home nursing utilization driven by increased reliance on home-based care during this critical period. For this study, the focus is on home nursing utilization, using data from the 2020 wave. The initial dataset included 11,398 Chinese citizens aged 60 years and older. Based on missing completely at random (MCAR) test [19, 20], the results did not reject the MCAR assumption. Therefore, 8,675 cases with missing values were excluded, leaving 2,723 complete samples for analysis.

In the remaining dataset, responses to certain variables with values representing "don't know" or "refused to answer" (typically indicated by values starting with 9 and significantly exceeding the expected scale of the variable) were handled using multiple imputation in RStudio 4.4.2 according to Rubin's Rules [21]. This approach can minimize the bias from extreme values, enhance data consistency, and maintain the reliability and academic rigor of the analysis.

### Dependent variable

The dependent variable in this study is home nursing utilization, indicating whether participants used home nursing within the past 12 months. To facilitate later model interpretation, the variable is recoded as "No" = 0 and "Yes" = 1, where 1 represents utilization of home nursing. Furthermore, this binary transformation is essential for both traditional statistical methods such as logistic regression [22] and machine learning algorithm like XGBoost [23].

### Independent variables

The selection of independent variables was guided by Andersen's behavioral model of health service utilization and insights from prior studies, including predisposing characteristics, enabling resources, and need-related factors [9, 24–26].

The predisposing characteristics included in this study are demographic factors such as age, gender, and education. These variables are selected due to their established relevance with health services utilization. The three variables provide a concise yet critical representation of predisposing factors, as the inclusion of additional variables such as marital status negatively impacted model fit.

Enabling resources are included to capture the availability of healthcare support systems that facilitate access to home nursing. Region type can reflect potential disparities in access to health and social services. Personal annual income is a continuous variable that is standardized using the Z-score method during data processing to mitigate potential bias caused by large magnitudes [27]. Older adults' subsidy indicates whether financial assistance tailored for older adults' care is accessible. Home visit access measures the availability of in-home visit services for health or social care. Family support count is the number of family members available to offer help when needed. Online access represents the presence of internet connectivity in the household, a critical resource for accessing digital health information and services. These variables represent the structural and personal resources that can influence older adults' ability to access and utilize services.

Need-based factors reflect participants' health conditions and overall well-being, which directly drive the utilization of health services. Self-rated health is a self-assessment of health status on a five-point scale. Recent hospital duration is the length of the most recent hospitalization, measured in days. The ADL score, which measures basic activities of daily living, was assessed using the Katz Index of Independence in Activities of Daily Living [28], and has been extensively applied in large-scale studies in China, demonstrating good reliability and validity [29]. In our sample, the ADL scale shows good internal consistency with a Cronbach's α value of 0.875. The IADL (Instrumental Activities of Daily Living) scale, developed by Lawton and Brody [30], was initially considered but was excluded from the model due to its high correlation with the ADL score. This exclusion was necessary to mitigate multicollinearity and enhance the model's robustness. The chronic disease count is the total number of chronic diseases, with each disease coded as a binary variable (0 = No, 1 = Yes). The MMSE (Mini-Mental State Examination) score developed by Folstein et al. was adapted in the CLASS survey [31]. This instrument measures the cognitive performance of older adults across domains of orientation (5 points, including questions about residence location, date, zodiac year, the current national leader, and the National Day), memory (3 points, recalling three words), attention and calculation (5 points, consisting of a series of subtraction questions), and recall (3 points, recalling the previously mentioned words). The scale ranges from 0 to 16, and a higher score means better cognitive function. It also shows good reliability with a Cronbach's α value of 0.893. Similarly, the depression score, which evaluates the severity of depressive symptoms, was measured by the short version of the Center for Epidemiologic Studies Depression Scale (CES-D) [32], this scale has been also extensively tested for reliability and validity in older adult populations in China [33]. In our sample, it exhibits excellent internal consistency, reflected in a Cronbach's α value of 0.924. Life satisfaction is assessed on a five-point scale. These variables provide a comprehensive view of participants' health needs and life satisfaction, ensuring that the analysis captures the most critical aspects of home nursing demand.

### Statistical analysis and machine learning algorithm

Descriptive statistics were reported as means (standard deviations) for continuous variables and as frequencies (percentages) for categorical or ordinal variables. Before conducting regression analysis, we tested correlation coefficients and variance inflation factor (VIF) values to check the potential multicollinearity. VIFs were calculated based on ordinary least squares (OLS) auxiliary regressions among the independent variables, in line with established practice in the literature. The highest correlation coefficient is 0.510, between the ADL score and MMSE score, which is within an acceptable range. The maximum VIF value is 1.80 for Self-rated health status, which is well below the commonly accepted threshold of 10, confirming that severe multicollinearity is not present.

Logistic regression was used to analyze the relationship between home nursing utilization and independent variables. The ordinal variables in the model, including region type, self-rated health, and life satisfaction, were treated as continuous ordinal predictors. This treatment preserves the meaningful ranking structure of the variables while allowing for a parsimonious model specification. However, logistic regression typically imposes a linear and additive functional form, which limits its ability to identify complex non-linear relationships and interaction patterns. The XGBoost algorithm was therefore applied to evaluate feature importance, capture non-linear effects, explore potential interactions among predictors, and generate individual predictions [23]. All predictors were included in XGBoost, and only features with non-zero SHAP value variance are displayed in the SHAP importance plot due to the intrinsic feature selection of the algorithm. SHAP interaction values were computed using the shapviz package, and the variable pairs with the highest interaction contributions were selected for visualization. To ensure reproducibility, a random seed of 123 was set, and the model was trained on 70% of the dataset, with the remaining 30% used for testing.

The logistic regression model was conducted in Stata MP18.0, and the XGBoost algorithm was implemented in RStudio 4.4.2.

### Ethical considerations

All participants in the CLASS study provided informed consent, and ethical approval was obtained from the National Survey Research Center at Renmin University of China. The original CLASS consent process included provisions for the use of its data in secondary research. This study utilizes secondary data from CLASS, which is fully anonymized and publicly accessible through the Institute of Gerontology at Renmin University of China. Data access was granted in accordance with CLASS's policies for secondary usage. The dataset is anonymized to ensure participant confidentiality, with no potential for individual identification.

## Results

### Description of the sample

Table 1 shows the descriptive statistics of the sample. The sample included 2,723 older adults, and the mean age is 71.52 years. Among the participants, 52.59% were male. In terms of residential location, 34.46% lived in central urban areas of cities or counties, while 44.97% resided in rural areas. 6.02% of the participants received home-based older adults' care subsidies, and 27.84% reported the availability of home visit services in their community. Additionally, 47.37% of participants had access to internet (wired or wireless) in their current residence, and 7.24% of participants had used home nursing services.

### Result of logistic regression

Table 2 Presents the results from four logistic regression models with Stepwise inclusion of control variables. Result (1) serves as a baseline model and does not include any control variables. Result (2) introduces region type as a control variable. Result (3) adds gender as an additional control variable alongside region type. Result (4) represents the fully adjusted model, incorporating all control variables and independent variables. For robustness,

**Table 1** Description of the sample

| Variable | Explanation of variable | Mean (S.D) | *N* (%) |
|---|---|---|---|
| **Dependent Variable** | | | |
| Home nursing utilization | Usage of home nursing services in the past 12 months | | |
| | 0 = No | | 2526(92.76%) |
| | 1 = Yes | | 197(7.24%) |
| **Independent Variable** | | | |
| Age | Age(years) | 71.520 (5.532) | |
| Gender | | | |
| | 0 = Male | | 1432(52.59%) |
| | 1 = Female | | 1291(47.41) |
| Education | Educational level | | |
| | 1 = Illiterate | | 638(23.43%) |
| | 2 = Literacy Class/Private School | | 115(4.23%) |
| | 3 = Primary School | | 1002(36.78%) |
| | 4 = Middle School | | 674(24.74%) |
| | 5 = High School/Vocational School | | 230(8.45%) |
| | 6 = College | | 53(1.96%) |
| | 7 = Bachelor's Degree or Above | | 11(0.42%) |
| Region type | Type of residential area | | |
| | 1 = Central Urban Area of City/County | | 938(34.46%) |
| | 2 = Peripheral Urban Area of City/County | | 278(10.19%) |
| | 3 = Urban-Rural Fringe of City/County | | 166(6.10%) |
| | 4 = Town Outside City/County | | 116(4.27%) |
| | 5 = Rural Area | | 1225(44.97%) |
| Personal income | Total personal income in the past 12 months (in Chinese Yuan) | 11207.355 (15642.003) | |
| Personal income Z | Z-score standardized total personal income in the past 12 months | 0 (1) | |
| Older adults' subsidy | Receiving home-based care subsidy for older adults | | |
| | 0 = No | | 2559(93.98%) |
| | 1 = Yes | | 164(6.02%) |
| Home visit access | Availability of home visit services in the community | | |
| | 0 = No | | 1965(72.16%) |
| | 1 = Yes | | 758(27.84%) |
| Family support count | Number of family members/relatives providing help when needed | | |
| | 0 = None | | 88(3.22%) |
| | 1 = 1 Person | | 373(13.70%) |
| | 2 = 2 People | | 862(31.65%) |
| | 3 = 3–4 People | | 929(34.13%) |
| | 4 = 5–8 People | | 355(13.05%) |
| | 5 = 9 People or More | | 116(4.24%) |
| Online access | Availability of Internet signal (wired or wireless) in current residence | | |
| | 0 = No | | 1433(52.63%) |
| | 1 = Yes | | 1290(47.37%) |
| Self-rated health | Self-rated health status | | |
| | 1 = Very Healthy | | 220(8.06%) |
| | 2 = Relatively Healthy | | 1060(38.94%) |
| | 3 = Average | | 1007(36.99%) |
| | 4 = Relatively Unhealthy | | 364(13.37%) |
| | 5 = Very Unhealthy | | 72(2.64%) |
| Recent hospital duration | Duration of most recent hospitalization (Days) | 6.222 (19.900) | |
| ADL score | Basic activities of daily living assessment (Scale Score) | 7.086 (2.610) | |
| Chronic disease count | Chronic disease score based on total number of chronic diseases (for each disease, 0 = No, 1 = Yes) | 1.898 (1.560) | |
| MMSE score | Mini-mental state examination score (Scale Score) | 13.102 (3.079) | |
| Depression score | Depression assessment score (Scale Score) | 12.917 (3.866) | |

**Table 1** (continued)

| Variable | Explanation of variable | Mean (S.D) | *N* (%) |
|---|---|---|---|
| Life satisfaction | Overall life satisfaction | | |
| | 1 = Very Satisfied | | 473(17.36%) |
| | 2 = Relatively Satisfied | | 1293(47.49%) |
| | 3 = Average | | 696(25.57%) |
| | 4 = Relatively Unsatisfied | | 192(7.05%) |
| | 5 = Very Unsatisfied | | 69(2.53%) |

**Table 2** Results of logistic regression

| Variables | OR (95% CI) (1) | OR (95% CI) (2) | OR (95% CI) (3) | OR (95% CI) (4) |
|---|---|---|---|---|
| Age | | | | 0.985 (0.924–1.050) |
| Gender | | | 1.011 (0.990–1.031) | 1.010 (0.990–1.032) |
| Region type | | 0.691*** (0.552–0.864) | 0.696*** (0.558–0.868) | 0.695*** (0.557–0.868) |
| Personal income Z | 1.325** (1.093–1.601) | 1.369* (1.124–1.668) | 1.260* (0.975–1.628) | 1.260* (0.976–1.626) |
| Education | 1.349 (0.917–2.015) | 1.193 (0.953–2.255) | 1.766 (0.710–2.826) | 1.771 (0.904–2.268) |
| Older adults' subsidy | 16.056 ** (1.173–57.701) | 16.830** (1.954–59.797) | 6.562* (1.148–20.587) | 6.691* (1.140-20.978) |
| Home visit access | 3.770*** (1.910–7.563) | 2.578*** (1.261–6.397) | 2.540*** (1.248–5.449) | 2.565*** (1.268–5.402) |
| Family support count | 1.223* (0.941–1.691) | 1.369* (0.979–1.818) | 1.359* (1.090–2.023) | 1.355* (1.096–2.018) |
| Online access | 2.216** (1.089–4.502) | 1.733 (0.850–3.617) | 1.429 (0.668–3.055) | 1.410 (0.650–3.030) |
| Self-rated health | 0.492*** (0.342–0.710) | 0.737* (0.475–1.230) | 0.829 (0.513–1.341) | 0.827 (0.511–1.338) |
| Recent hospital duration | 1.067 (0.991–1.150) | 1.070* (0.996–1.153) | 1.066* (0.996–1.149) | 1.065* (0.997–1.147) |
| ADL score | 1.083*** (1.006–1.181) | 1.087*** (1.009–1.170) | 1.117*** (1.014–1.227) | 1.119*** (1.016–1.233) |
| Chronic disease count | 1.219** (1.118–1.484) | 1.133** (1.097–1.379) | 1.176** (1.006–1.430) | 1.178** (1.029–1.430) |
| MMSE score | 0.993 (0.972–1.029) | 0.998 (0.987–1.008) | 0.935 (0.829–1.054) | 0.931 (0.824–1.041) |
| Depression score | 1.002 (0.972–1.039) | 1.003 (0.972–1.035) | 1.004 (0.970–1.033) | 1.003 (0.968–1.035) |
| Life satisfaction | 0.563** (0.370–0.854) | 0.581** (0.383–0.883) | 0.663* (0.428–1.027) | 0.665* (0.431–1.038) |
| cons | 0.022** (0.003–0.178) | 0.059** (0.007–0.582) | 0.014 ** (0.001–0.438) | 0.043 (0.000-17.631) |
| N | 2723 | 2723 | 2723 | 2723 |
| Log likelihood | -166.113 | -159.761 | -154.484 | -154.374 |
| LR $\chi^2$ | 934.42 | 947.12 | 957.68 | 957.89 |
| Prob > chi$^2$ $\chi^2$ | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ |
| Pseudo $R^2$ | 0.738 | 0.748 | 0.756 | 0.756 |

Note: Values in parentheses indicate 95% confidence intervals. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

logistic regression was also performed after multiple imputation for missing data, and the results presented in the appendix table A1 remained consistent in both coefficients' direction and significance.

The logistic regression reveals several significant variables influencing home nursing utilization. They are region type, personal income (standardized), older adults' subsidy, home visit access, family support count, ADL score, chronic disease count, life satisfaction and recent hospital duration.

Region type is significant at the 1% level (OR = 0.695, 95% CI = 0.557–0.868 in fully adjusted model), indicating that areas farther from city centers are associated with lower home nursing utilization. Higher personal income (OR = 1.260, 95% CI = 0.976–1.626) and older adults' subsidy (OR = 6.691, 95% CI = 1.140-20.978) both increase the likelihood of using home nursing. Home visit access, highly significant at 1% (OR = 2.565, 95% CI = 1.268–5.402), strongly promotes home nursing utilization. Family support count (significant at 10%, OR = 1.355, 95% CI = 1.096–2.018) slightly increases usage probability, while higher ADL and chronic disease count (significant at 1%, OR = 1.119, 95% CI = 1.016–1.233 and 5% OR = 1.178, 95% CI = 1.029–1.430, respectively) are positively associated with home nursing use. The life satisfaction score, significant at the 10% level (OR = 0.665, 95% CI = 0.431–1.038), shows a negative association: as life satisfaction scores increase (indicating lower satisfaction), the likelihood of utilizing home nursing services decreases. Finally, recent hospital duration shows a positive relation with home nursing utilization, which means long hospital duration with more likely to use home nursing.

### Result of XGBoost algorithm

Figure 1 illustrates the SHAP (Shapley Additive Explanations) values derived from the XGBoost algorithm, showing the contributions of different features to the likelihood of home nursing utilization. These results further support the finding from logistic regression.

Features such as home visit access, chronic disease score, recent hospital duration, family support count, older adults' subsidy and ADL score show consistent positive contributions to the likelihood of home nursing utilization, where higher feature values (represented by yellow points) generally associated with larger positive SHAP values. Conversely, region type and life satisfaction score exhibit a negative association, where higher feature values drive SHAP values further into the negative range. Additionally, although online access contributes positively to home nursing utilization, its importance is limited. The distribution of SHAP values for personal income is wide, suggesting that income influences vary among individuals.

Figure 2 presents SHAP interaction plots that illustrate the non-linear relationships and interactions influencing home nursing utilization.

In the first subplot, a higher chronic disease score consistently increases the likelihood of home nursing utilization and the moderating role of region type is evident. In central urban areas (region type = 1), even older adults with relatively low chronic disease scores of 0–2 tend to use home nursing. By contrast, in other areas (region type = 2, 3, 4, 5), usage remains limited when chronic disease scores are low, but once the chronic disease score reaches three or above, the probability of home nursing

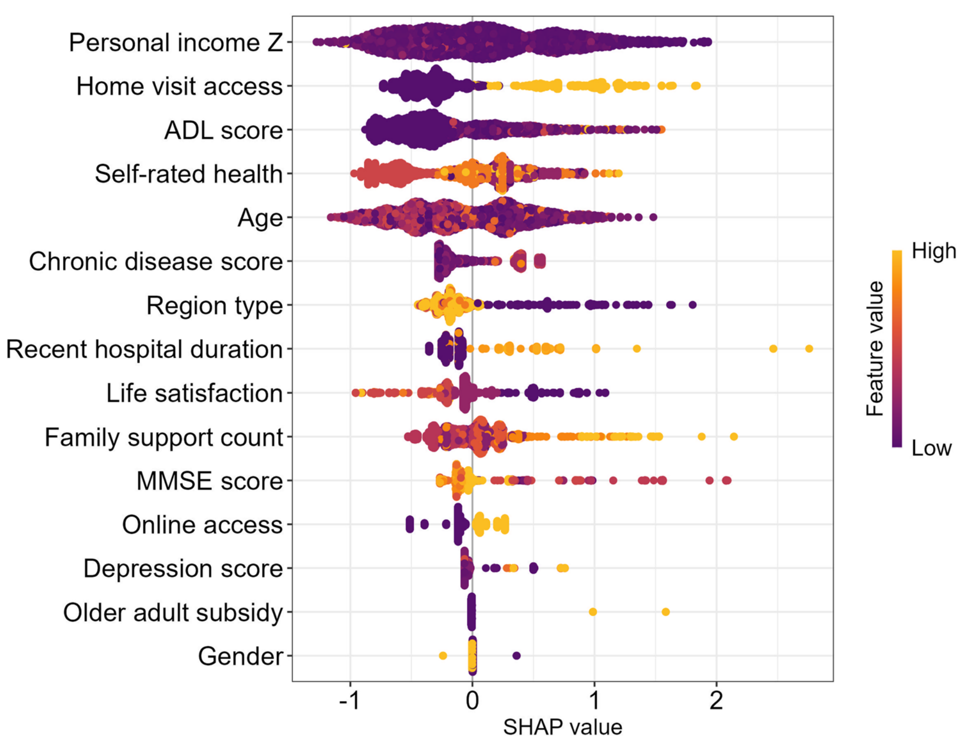


**Fig. 1** SHAP importance plot from XGBoost


**Fig. 2** SHAP interaction plot between chronic disease score, home visit access, region type, and family support count

adoption rises markedly. This suggests that region type modifies the threshold at which chronic illness translates into actual home nursing utilization.

In the second subplot, home visit access emerges as the primary driver, exerting a significant positive influence on home nursing utilization. When home visit access is available (home visit access = 1), lower values of life satisfaction (indicating greater life satisfaction, represented by darker colors) further enhance the likelihood of home nursing utilization. This suggests that when home visit is accessible, individuals with greater life satisfaction are more inclined to use home nursing.

In the third subplot, self-rated health status interacts significantly with region type in urban areas (region type = 1). Individuals with higher self-rated health scores (indicating poorer health) in urban areas are more likely to use home nursing services, as reflected by higher SHAP values. However, in other regions (region type = 2, 3, 4, 5), this interaction becomes negligible.

In the fourth subplot, family support count demonstrates a general positive relationship with the likelihood of using home nursing, as higher support counts correspond to higher SHAP values. Importantly, this effect is moderated by home visit access in a non-linear way. When only one family member provides support (family support count = 1), home visit access substantially increases the likelihood of home nursing utilization. A similar effect is observed when the number of supporting family members exceeds five (family support count = 4, 5). However, among older adults with two to four family supporting members (family support count = 2, 3), the effect of home visit access appears to be reversed, with individuals without visit access exhibiting slightly higher SHAP values. This pattern suggests that the interaction between family support and home visit access is context-dependent, varying across the number of family supporting members.

XGBoost also demonstrated excellent predictive performance except effectively capturing feature importance, non-linear relationships, and interactions. The model achieved an AUC of 99.2% on the training set and 96.3% on the testing set, indicating strong predictive power, as illustrated by the ROC curve in Fig. 3(a). To further illustrate its predictive ability, Fig. 3(b) presents the SHAP waterfall plot for the prediction of a randomly selected individual (row = 237). Key features such as recent hospital duration, ADL score, age, and self-rated health positively influenced the prediction, while personal income, life satisfaction, region type, chronic disease count and online access contributed negatively. The

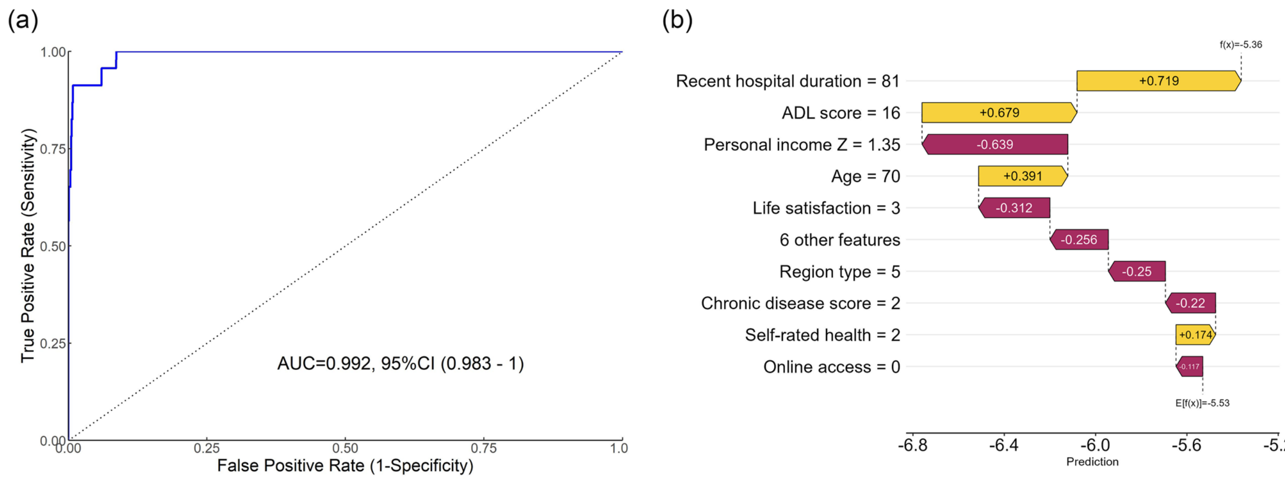


**Fig. 3** Model performance and individual prediction interpretation using XGBoost

negative contributions collectively outweighed the positive factors, resulting in a final prediction of non-utilization of home nursing (output f(x) = -5.36). These results show the model's good performance in prediction and its capacity for detailed interpretability.

## Discussion

This study analyzes the factors influencing home nursing utilization. The findings offer new insights into various influential factors and interactions under home nursing utilization, through the lens of predisposing characteristics, enabling resources, and need-based factors [8, 9]. The results indicate that predisposing characteristics did not have a significant impact on home nursing utilization, whereas enabling resources and need-based factors demonstrated strong associations with its utilization. In light of these findings, the discussion centers on determinants that show consistent influence across both logistic regression and the XGBoost algorithm.

### Predisposing characteristics: not significant

Unlike many prior studies that have identified age and gender as significant predictors of healthcare utilization [34, 35], evidence has shown that higher age is associated with both the utilization of and transition to long-term care in community, and that notable gender differences exist in the average amount of informal and formal care. Another study further indicates that age is significantly related to home care utilization [34], and that female elderly patients are more likely to use mobile internet-based home nursing [15]. However, this study finds that neither variable has a significant impact on home nursing utilization, that may stem from limited age variation of the study sample, which exclusively includes individuals aged 60 and above. In our sample, the mean age was 71.52 years (SD = 5.532), the median was 70 [IQR: 67–76], and the range was from 60 to 98. Such a restricted age distribution reduces its explanatory power in differentiating service utilization patterns. In contrast, the significant effect of age reported by Jarling et al. may be partly due to their small sample size (317 participants) and the restricted older age groups (75, 80, 85, and 90 years) [34]. Our result is in line with Hasanusta et al., who found that individuals aged 60 and above have stronger age-related consistency, and differ significantly from younger age groups [36].

Additionally, gender disparities in home nursing utilization appear to diminish in older populations, this is consistent with previous research on long-term care usage in Germany, where no significant differences in the demand for long-term care were observed between men and women aged 65 and above in community settings [35]. This may be due to equalized caregiving needs at older age and policy interventions aimed at reducing gender-based inequities [37].

### Enabling resources: strong external drivers

Enabling resources, including region type, home visit access, older adults' subsidy, family support count, emerged as critical drivers of home nursing utilization.

Region type highlights the significant urban-rural disparities in health care utilization, consistent with prior research on healthcare inequities [38, 39]. Urban residents use home nursing services more frequently, even at lower levels of health demands. Whereas older adults in rural areas have limited resources, such as geographic isolation, inadequate service availability, and insufficient financial support systems, resulting in challenges for older people to access home care and support [40, 41]. This finding still emphasizes the barriers faced by rural populations and highlights the urgent need for targeted investments and interventions in rural areas.

Home visit access plays a critical role in home nursing utilization, serving as both a necessary factor and a key interaction with family support. These results align with prior studies emphasizing the importance of accessible health service delivery frameworks in promoting healthcare utilization within communities, such frameworks have been shown to be particularly beneficial for older individuals with poor health in the healthcare systems of Western countries [42–45]. What's more, researchers have emphasized the need to address limitations in home visit access within communities' conditions. One promising strategy is to leverage the potential of community convenience stores as hubs to expand home nursing access. With their proximity, multifunctionality, and social significance, these stores can serve as accessible points for coordinating healthcare services, disseminating health information, and facilitating telehealth consultations [46]. Although this strategy was proposed in Japan, the underlying concept is also relevant in China. Community convenience stores, service stations, and emerging 15-minute living circles began to support basic public services and primary healthcare functions, providing a practical foundation for exploring similar community-based approaches to improving home visit access [47].

Older adults' subsidy also showed a significant positive association, reflecting the critical role of financial incentives in reducing economic barriers to care. This finding is consistent with evidence from subsidy programs in U. S., which demonstrate that financial assistance is essential for satisfying older people's increasing desire to age in place and promoting equitable access to healthcare services [48]. However, subsidies alone may not be sufficient, the findings suggest that their impact is amplified when coupled with robust enabling resources, such as home visit access.

Family support count, which is the number of family members available to help older individuals, also showed a positive relationship with home nursing utilization. This finding is consistent with studies highlighting the importance of family support in complementing formal healthcare services, older people with sufficient support from children and social support are more likely to utilize home nursing [49]. Notably, the SHAP interaction analysis revealed that the impact of family support count is amplified by home visit access. In cases where home visit services are available, family members may feel more confident and supported in their caregiving roles, which in turn encourages the utilization of home nursing.

However, this interaction also raises important considerations. For older individuals without robust family networks, the lack of family support may further exacerbate barriers to accessing home nursing utilization, particularly in regions with limited home visit availability. The findings suggest a pressing need of comprehensive care models that integrate formal services with community-based support systems, thereby reducing reliance on family caregiving, especially for vulnerable populations without adequate family networks.

Finally, online access is found to be a weaker predictor, which aligns with previous findings that older adults often face barriers in using information and communication technology (ICT) for social interaction, primarily due to limited digital skills. These limitations hinder the effective use of ICT in various contexts [50]. However, other studies suggest that integrating digital tools into healthcare systems can enhance older adults' usage on home-based eldercare by facilitating access to services [51]. While the inclusion of digital tools has the potential to provide tangible benefits in real-world [52], the weak influence observed in this study may be due to limited digital literacy among old population [53, 54]. Additionally, as questionnaire was collected in 2020, it may not fully capture the evolving role of digital tools in healthcare system, which could represent an emerging but not yet mature factor influencing home nursing utilization.

#### Need-based factors: initial and strong internal drivers

As expected, need-based factors are among the strongest predictors of home nursing utilization. ADL score and chronic disease score demonstrated robust positive associations, confirming the importance of functional impairments and chronic health conditions as primary drivers of home nursing demand [55]. These findings are consistent with prior studies highlighting that individuals with greater physical and health-related limitations are more likely to rely on formal caregiving services [56]. The SHAP analysis provides additional insights, revealing that these need-based factors not only act independently but also interact significantly with enabling resources, such as region type, to shape utilization patterns. Smaller region type values (indicating more centralized areas) amplify the effect of chronic disease score, suggesting that communities in centralized areas may better address the challenges faced by individuals with a higher burden of chronic diseases.

Recent hospital duration also is a significant factor of home nursing utilization, consistent with studies about the critical role in post-hospitalization care. Research has shown that individuals with recent hospitalizations are more likely to use home nursing services due to their heightened healthcare needs and the necessity of continuous monitoring during the recovery phase [57]. Patients discharged from prolonged hospital stays are particularly vulnerable to physical decline, including the risk of rehospitalization, delayed recovery, and diminished functional independence [58]. Effective discharge planning that incorporates home nursing can mitigate these risks by providing timely and structured post-hospital care. These services are essential for maintaining care continuity, addressing medical needs, and promoting rehabilitation.

The life satisfaction score, which negatively correlated with home nursing utilization, provides a psychosocial perspective. Individuals with higher life satisfaction (lower scores) are more inclined to utilize caregiving services, aligning with studies that positive well-being will increase self-care ability and healthcare engagement [59]. Furthermore, this study reveals the moderating role of life satisfaction between home visit access and home nursing utilization. These findings suggest that interventions aimed at improving overall well-being could further encourage the utilization of home nursing, particularly when combined with accessible healthcare options.

### Methodological contributions

In addition to the empirical findings, this study also makes methodological contributions. First, we combine logistic regression and XGBoost algorithm. This dual-model approach not only examine the stability of the results but also strengthened the credibility of the analysis. Second, the use of XGBoost, combined with SHAP interpretation can uncover interaction effects and non-linear relationships that traditional regression models typically fail to capture, thereby deepening the understanding of how different factors jointly influence older adults' home nursing utilization. Finally, the predictive capability of XGBoost provides individual-level prediction. Such prediction extends the practical value of the study, offering a tool for identifying vulnerable groups and informing targeted policy interventions.

### Limitations of the work

This study possesses external validity as it draws on data from a large and diverse sample of older Chinese adults. The findings provide valuable insights into the influencing factors of home nursing utilization, which may inform similar aging populations and healthcare systems in comparable contexts worldwide. However, certain limitations should be acknowledged. Firstly, although there is no evidence against the MCAR hypothesis, the exclusion of incomplete cases may increase sampling variance and reduce statistical power. To ensure unbiased results and better model reliability, the analysis in this paper was based on complete cases, while the results from multiple imputation for missing data were also provided in the appendix. Secondly, as this study used a cross-sectional dataset, it captures the relationships among variables only in a single year. While associations can be identified, longitudinal studies are required to examine the temporal dynamics underlying home nursing utilization. Thirdly, the data were collected in 2020, which, although the most recent at the time, may not fully reflect the latest context of home nursing demand and utilization, particularly in light of post-pandemic shifts in healthcare systems. Surveys incorporating 2024 data would offer a more comprehensive understanding of how evolving societal and healthcare dynamics shape the utilization of home nursing.

## Conclusion

This study provides a comprehensive analysis of the factors influencing home nursing utilization among older adults, combining logistic regression and XGBoost algorithm to uncover both linear and non-linear relationships. Enabling resources, including region type, home visit access, older adults' subsidy, and family support count, as well as need-based factors, including ADL score, chronic disease count, and recent hospital duration, significantly affect the use of home nursing. Our study also finds significant interactions between enabling resources and need-based factors, indicating the need for targeted interventions to reduce urban-rural disparities and to enhance service accessibility. In addition, psychosocial factors, particularly life satisfaction, play an important role in shaping healthcare decisions, this can offer new perspectives on integrating well-being factors into home nursing utilization. By addressing the limitations and leveraging the insights presented, this research contributes to the growing body of knowledge on eldercare and offers actionable guidance for policymakers and practitioners seeking to improve home nursing utilization.

## Implications for practice and policy

The findings of this study offer actionable insights for healthcare practice and policy aimed at improving home nursing utilization among older adults within communities. First, the strong influence of enabling resources, such as home visit access and older adults' subsidies, indicates the need for targeted policy interventions to address structural and financial barriers. Governments should expand the coverage of older adults' care subsidies so that low-income seniors can afford essential nursing services. The distribution of subsidies should be optimized by adopting electronic payments or direct subsidies to service providers, reducing complexity in the application and utilization process. Second, the interaction between need-based factors and enabling resources highlights the importance of integrated care models that prioritize continuity of care, especially for patients recently discharged from hospitals or those with chronic conditions, policymakers should consider strengthening hospital-to-home transition programs, expanding multidisciplinary care teams, and implementing digital health records for seamless information sharing to enhance long-term care outcomes. Third, for older people with limited family support, barriers to home nursing may arise, necessitating care framework that integrate home nursing services with community-based support systems.

Fourth, enhancing overall well-being, such as social engagement programs, mental health counseling, and personalized care strategies can indirectly promote home nursing utilization among older adults. Lastly, although digital access showed limited effects in this study, it represents an emerging pathway for strengthening care delivery. Future efforts should prioritize digital literacy, telehealth expansion, and optimization of digital platforms to improve access to home nursing. These implications collectively advocate for a comprehensive approach that addresses both social barriers and individual needs to optimize the utilization of home nursing.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12912-026-04371-y.

Supplementary Material 1

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Not applicable.

**Author contributions**

Jing Zhao contributed to conceptualization, methodology, visualization, and writing of the original draft. Xiaofei Du contributed to conceptualization, data curation, and data interpretation. Jun Lin and Weiwei Guo contributed to methodology; Shaopeng Wang and Fan Yang contributed to review and editing, validation, and supervision. All authors reviewed and approved the final manuscript.

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**Data availability**

The datasets used in this study were provided by the Institute of Gerontology at Renmin University of China. Access to the China Longitudinal Aging Social Survey datasets can be granted upon request at: http://jkzgyjy.ruc.edu.cn/sjzy/CLASSsjsq/.

## Declarations

**Ethics approval**

All procedures involving human participants were conducted in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. This study was conducted using secondary data from the China Longitudinal Aging Social Survey (CLASS). According to Articles 38, 39, and 40 of the Constitution of the People's Republic of China, and Chapter I, Article 9 of the Statistics Law of the People's Republic of China, the study was exempt from formal ethics committee review. Formal ethical approval was not required as per the national regulations, and no Institutional Review Board (IRB) approval was obtained. The data provider (Institute of Gerontology and National Survey Research Center at Renmin University of China) confirmed that data collection complied with national ethical guidelines.

**Consent to participate**

Informed consent was obtained from all participants prior to data collection. Interviewers recorded participants' consent status, including their agreement to participate, the time of consent, and reasons for refusal when applicable. Documentation of consent is stored at the Institute of Gerontology and National Survey Research Center, Renmin University of China. Additional consent was not required for secondary analysis.

**Consent for publication**

The study used secondary data and did not contain any identifiable individual data. Therefore, consent for publication is not applicable.

**Competing interests**

The authors declare no competing interests.

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