Trends in Social Sciences and Humanities Research
Print ISSN: 2959-992X
Online ISSN: 2959-9938
DOI: https://doi.org/10.61784/tsshr3242

COMMUNITY ELDERLY-CARE SERVICE DEMAND PREDICTION BASED ON STATE RECURSION AND CONSUMPTION-CONSTRAINED CORRECTION

Yue Zhang
School of Science, Shandong Jianzhu University, Jinan 250101, Shandong, China.

Abstract: This paper develops a demand-prediction framework for embedded community elderly-care service stations by combining state recursion, service-frequency estimation, and consumption-constrained correction. First, a three-state elderly population recursion model is established for self-care, semi-disabled, and disabled residents. Initial community population structures, natural mortality, newly added elderly ratios, and health-state transition probabilities are used to predict the population of each group over a five-year period. Second, the predicted elderly population is converted into theoretical monthly demand for meal assistance, day care, home-based nursing, rehabilitation physiotherapy, bathing assistance, and emergency rescue. Third, income level, available consumption proportion, service price, and free emergency assistance are introduced to revise chargeable demand under affordability constraints. The results indicate that the total elderly population grows steadily, disabled elderly residents increase markedly, communities C and G generate the highest service pressure, and chargeable demand is reduced unevenly across elderly groups after consumption constraints are considered, providing evidence for service-station capacity and resource allocation decisions.
Keywords: State recursion; Markov transition; Elderly-care service demand; Consumption constraint; Community service station

1 INTRODUCTION

Embedded community elderly-care service stations are designed to provide daily assistance, nursing support, rehabilitation-related services, bathing assistance, meal assistance, and emergency help near residents' living areas. As the number and structure of elderly residents change over time, the service station cannot be planned only according to a static population total [1,2]. A community may contain self-care elderly residents, semi-disabled elderly residents, and disabled elderly residents, and the service needs of these groups differ greatly. The selected section of the source document therefore treats demand prediction as the first modeling task before facility location, station-size selection, pricing, subsidy design, and later sensitivity analysis. The problem background is the need to estimate future elderly-care service demand in ten communities, so that subsequent service-station planning has a reliable quantitative basis.
The specific problem raised in this paper is how to predict the number of elderly residents in each health state and how to convert the predicted population into feasible monthly service demand. The original section assumes that the elderly population is not fixed: existing residents may remain in their current state, self-care elderly residents may become semi-disabled, semi-disabled elderly residents may become disabled, some elderly residents may die, and new elderly residents may enter the system. This makes the task a dynamic multi-state recursion problem. After population prediction, demand must be computed across multiple service items. The theoretical demand is determined by the predicted number of people and the average monthly service frequency, but actual demand is also restricted by income, price, and the proportion of income that can be used for elderly-care service consumption [3-5].
The research scheme follows the three-stage modeling logic in the selected section. The first stage constructs a simplified Markov-style state transition model for each community and predicts the numbers of self-care, semi-disabled, and disabled elderly residents over five years. The second stage builds a theoretical monthly demand model by combining the predicted population matrix with the per-capita demand frequency of six services. The third stage introduces consumption constraints: the theoretical monetary demand of each group is compared with the monthly affordable expenditure, and chargeable service demand is compressed proportionally when it exceeds the consumption limit, while emergency assistance is treated as a free service and is not compressed. The paper then analyzes the predicted population trend, service demand patterns, and demand reduction under affordability constraints using the figures and table reported in the source section. The expected outcome is a reproducible demand matrix that can support later decisions on station location, capacity design, service allocation, subsidy estimation, and resource planning across communities effectively and consistently quantified. This organization keeps the original modeling process and results while presenting the content as a compact demand-prediction study for community elderly-care service planning [6].

2 DEMAND PREDICTION FOR COMMUNITY ELDERLY-CARE SERVICES

2.1 Solution Idea

Given the known community population, elderly classifications, transition paths, and transition rates, a state-recursion prediction model is required. A simplified Markov state-transition model is adopted with a three-stage modeling idea. For each community, the numbers of three elderly groups are recursively predicted. The initial elderly structure in year 0 is used as the starting state. Natural mortality, the proportion of newly added elderly residents, and health-state transition probabilities are then combined to predict the numbers of the three elderly groups in each community over five years.

The second stage establishes a theoretical service-demand model. The number of each elderly group in each community at the end of year 5 is multiplied by the per-capita monthly demand frequency for six service items to obtain theoretical monthly service demand without considering affordability. The third stage establishes a consumption-constrained correction model. According to elderly residents' monthly income, available consumption proportion for elderly-care services, and service prices, the consumption upper limit is calculated. Chargeable service demand is compressed according to the consumption constraint ratio, while emergency assistance is treated as a free service and is not compressed [7,8].

2.2 Data Visualization Analysis

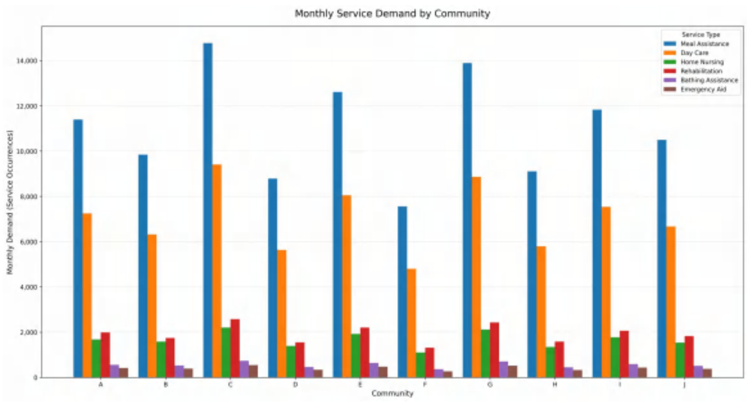

Figure 1 Comparison of Average Monthly Demand for Service Items in Ten Communities

Figure 1 shows that meal assistance has the largest monthly demand in all communities, while emergency assistance has the smallest monthly demand. Comparing service demand among communities indicates that communities C and G have higher demand, whereas community F has lower demand [9,10].

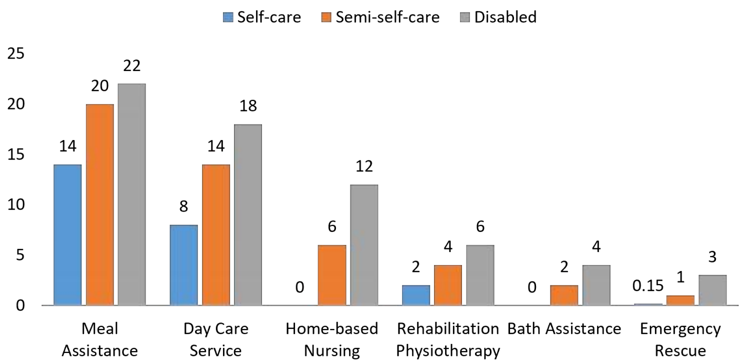

Figure 2 Comparison of Average Monthly Service Demand by Elderly Self-Care Ability

Figure 2 shows that meal assistance has the highest monthly demand among service types, while emergency assistance has the lowest. The groups with the highest demand for each service are mainly disabled elderly residents, whereas the lowest demand is mainly from self-care elderly residents. Self-care elderly residents have no demand for home nursing and bathing assistance in the reported data.

2.3 Model Establishment

2.3.1 Elderly population recursive prediction model

Let the community set be:

$$I=\{A,B,C,D,E,F,G,H,I,J\} \tag{1}$$

Let the elderly-type set be:

$$K=\{S,H,D\} \tag{2}$$

Here, S denotes self-care elderly residents, H denotes semi-disabled elderly residents, and D denotes disabled elderly residents. Let the service-item set be:

$$R=mealassistance,daytimecare,\mathrm{h}omenursing,re\mathrm{h}abilitationt\mathrm{h}erapy,bat\mathrm{h}ingassistance, \tag{3}$$

emergency assistance}

For any community i, the total elderly population at the end of year t is:

$$N_i(t)=S_i(t)+H_i(t)+D_i(t) \tag{4}$$

The recursive prediction equations for the three elderly groups are:

$$S_i(t+1)=(1-d)(1-a)S_i(t)+gN_i(t) \tag{5}$$

$$H_i(t+1)=(1-d)aS_i(t)+(1-d)(1-b)H_i(t) \tag{6}$$

$$D_i(t+1)=(1-d)bH_i(t)+(1-d)D_i(t) \tag{7}$$

Here, $d = 0.05$ is the annual natural mortality rate of elderly residents, $g = 0.07$ is the proportion of newly added elderly residents, $a = 0.045$ is the probability that self-care elderly residents become semi-disabled, and $b = 0.10$ is the probability that semi-disabled elderly residents become disabled.

2.3.2 Theoretical monthly service demand model

After the numbers of the three elderly groups at the end of year 5 are obtained, the theoretical monthly demand frequency for service item s in community i and elderly type k is:

$$Q_{i,k,s}=P_{i,k}\times r_{k,s} \tag{8}$$

The total theoretical monthly demand frequency for service item s in the whole region is:

$$Q_s=\sum_{i\in I}\sum_{k\in K}Q_{i,k,s} \tag{9}$$

2.3.3 Service demand model under consumption constraints

The theoretical consumption amount for different communities, elderly types, and service items is:

$$C_{i,k,s}=Q_{i,k,s}\times p_s \tag{10}$$

The total theoretical consumption of chargeable services for community i and elderly type k is:

$$C^{charge}{}_{i,k}=\sum_{s:p_s>0}C_{i,k,s} \tag{11}$$

Emergency assistance is free, so it is not included in the chargeable-service consumption calculation. The maximum monthly amount available for purchasing elderly-care services is:

$$M_{i,k}=Y_i\times\eta_k\times P_{i,k} \tag{12}$$

If the total theoretical consumption of chargeable services does not exceed the consumption limit, theoretical demand can be fully realized. Otherwise, chargeable service demand is compressed proportionally. The consumption constraint ratio is:

$$\lambda_{i,k}=\min\left(1,\frac{M_{i,k}}{C^{charge}{}_{i,k}}\right) \tag{13}$$

The constrained monthly demand frequency of chargeable services is:

$$Q_{i,k,s}{}'=\mathrm{round}(Q_{i,k,s}\times\lambda_{i,k}),p_s>0 \tag{14}$$

To evaluate reduction, the reduction ratio is defined as:

$$\rho_{i,k,s}=1-\frac{Q_{i,k,s}{}'}{Q_{i,k,s}} \tag{15}$$

When $Q_{i,k,s} = 0$, $P_{i,k,s}$ is set to 0, indicating that the service currently has no demand and is not reduced.

2.4 Model Result Analysis

2.4.1 Number of elderly residents in each community

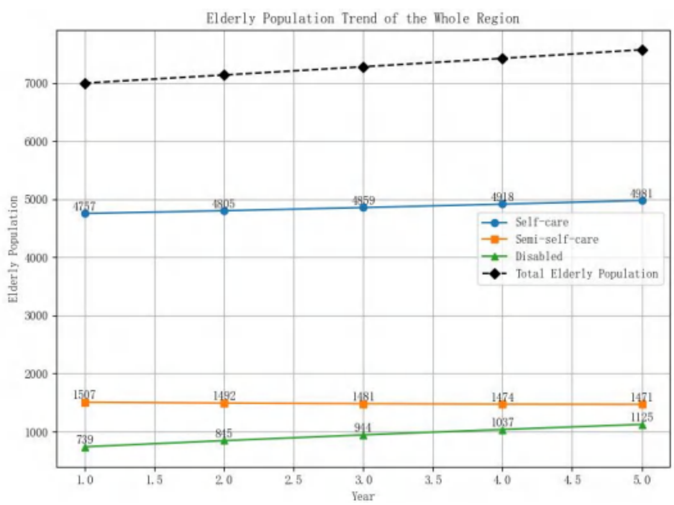

Figure 3 Line Chart of Elderly Population Changes in the Whole Region

Figure 3 shows that the total elderly population increases steadily over the five-year period. Compared with the initial 7000 people, the total number of elderly residents rises. The number of semi-disabled elderly residents decreases from 1507 to 1471, while self-care elderly residents increase from 4757 to 4981 and disabled elderly residents increase from 739 to 1125.

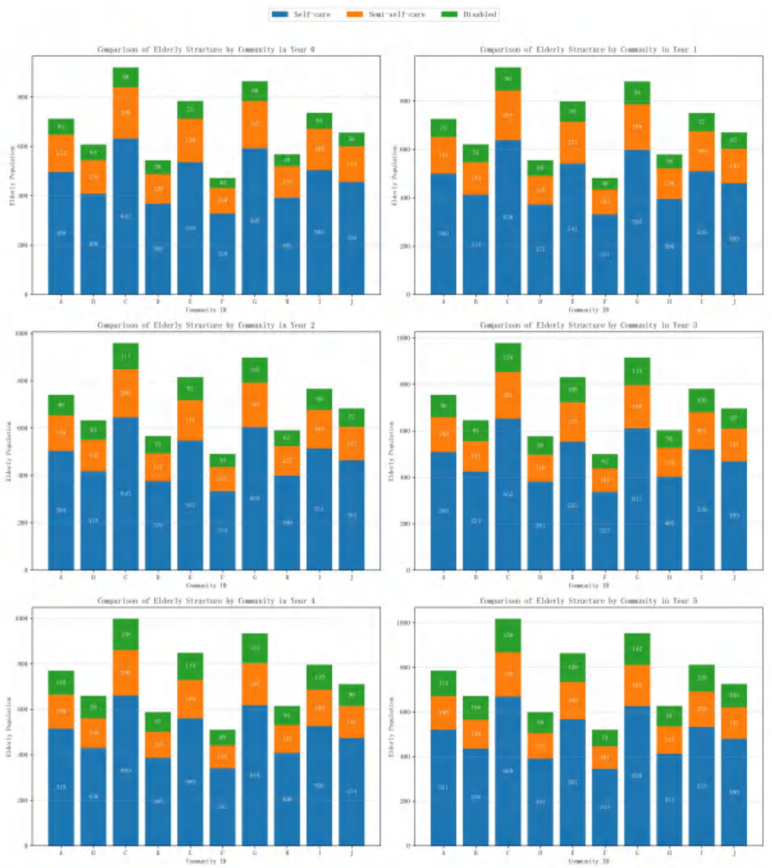

Figure 4 Elderly Structure Comparison across Communities from Year 0 to Year 5

Figure 4 shows that elderly structures in each community change only slightly and remain relatively stable. Self-care elderly residents are the largest group in each community. In year 5, community C has 669 self-care elderly residents, while community F has 345. Disabled elderly residents are fewer than the other two groups; community C has 150 disabled elderly residents, while community F has 74.

2.4.2 Theoretical monthly demand frequency

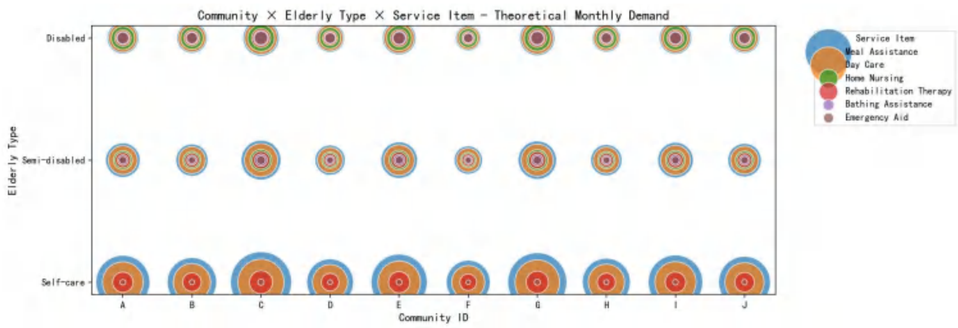

Figure 5 Bubble Chart of Theoretical Monthly Demand by Community, Elderly Type, and Service Item

Figure 5 shows that total theoretical demand follows the order disabled elderly residents > semi-disabled elderly residents > self-care elderly residents. Communities C and G have the largest bubbles for all elderly types, indicating the highest regional demand, while communities F and D have smaller bubbles and lower demand intensity.

Figure 6 Theoretical Monthly Service Demand in Communities A to E

Figure 7 Theoretical Monthly Service Demand in Communities F to J

Figures 6 and 7 present the theoretical monthly demand frequency of each community for each service item at the end of year 5. The distributions are similar across communities and elderly groups, which is consistent with the previous results and supports the reliability of the output.

2.4.3 Monthly demand frequency under consumption constraints

Under consumption-capacity constraints, monthly demand frequency is shown in Table 1.

Table 1 Monthly Demand Frequency under Consumption Constraints

Community	Semi-disabled elderly	Disabled elderly	Self-care elderly	Total
A	7050	6311	12582	25943
B	5767	5377	10529	21673
C	9353	9226	16156	34735
D	4782	4479	9443	18704
E	7896	7340	13693	28929
F	3917	3298	8332	15547

G	8695	8297	15118	32110
H	5285	4477	9974	19736
I	7473	6457	12872	26802
J	6453	5489	11592	23534
Total	66671	60751	120291	247713

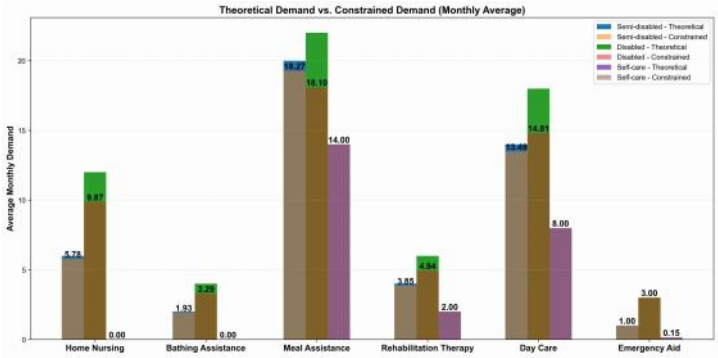

Figure 8 Theoretical Demand versus Constrained Demand

Figure 8 shows that all average demand frequencies decrease after applying constraints. Semi-disabled elderly residents experience the largest decrease, disabled elderly residents rank second, and self-care elderly residents have the smallest decrease.

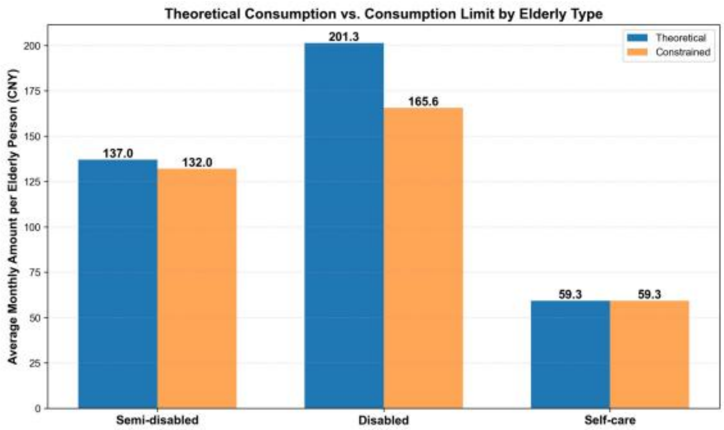

Figure 9 Theoretical Consumption Amount versus Consumption Limit by Elderly Type

Figure 9 shows that the theoretical consumption amount of self-care elderly residents is close to the actual constrained amount. The difference is about 5 yuan for semi-disabled elderly residents, whereas the difference for disabled elderly residents is 35.7 yuan, about seven times that of semi-disabled elderly residents.

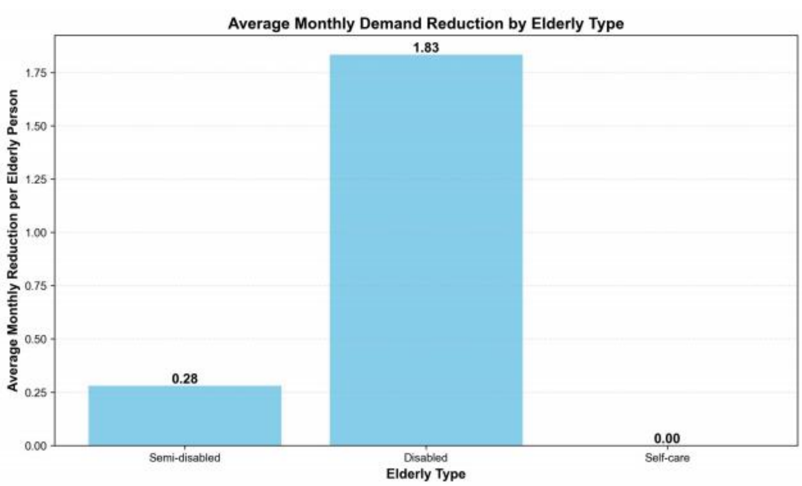

Figure 10 Average Monthly Demand Reduction by Elderly Type

Figure 10 shows that the average monthly reduction for self-care elderly residents is almost 0, the average reduction for semi-disabled elderly residents is 0.38, and the highest average reduction is 1.83 for disabled elderly residents.

3 CONCLUSION

The proposed state-recursion and consumption-constrained correction framework provides a quantitative basis for predicting community elderly-care service demand. By distinguishing self-care, semi-disabled, and disabled elderly residents, the model describes how population aging, mortality, new elderly inflow, and health-state deterioration jointly reshape future service needs. The results show that the total elderly population increases steadily over five years, disabled elderly residents grow more rapidly than the other groups, and communities C and G become the main demand-pressure areas. The comparison between theoretical demand and constrained demand further shows that affordability does not affect all services equally: disabled elderly residents face the strongest demand compression, semi-disabled elderly residents are moderately affected, and self-care elderly residents are only slightly constrained. Therefore, service-station planning should not rely only on total population size, but should also consider health-state structure, service type, payment capacity, and community-level spatial differences. In practical application, the model can support station capacity design, staff allocation, subsidy estimation, priority-service arrangement, and dynamic adjustment of service packages. Future research can improve the framework in several directions. First, transition probabilities can be updated dynamically by using longer-term health records, medical utilization data, and community follow-up surveys. Second, household income, family support, insurance reimbursement, and government subsidies can be incorporated to build a more realistic affordability module. Third, service preferences, waiting-time tolerance, distance accessibility, and caregiver availability can be added to distinguish potential demand from actually realized demand. Finally, the model can be combined with facility-location optimization and scenario simulation so that community elderly-care stations can be planned under different aging-speed, price, subsidy, and capacity-expansion assumptions.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Shehadeh A, Malak Z M, Ayed A, et al. Physical environment in nursing homes and the psychological adaptation of healthcare providers in Palestine. Workplace health & safety, 2025, 74(2): 67-78.

[2] Zhou F, Hu S, Du X, et al. Anston attentional network for structured data based stroke risk prediction in smart aging. Scientific Reports, 2025, 15(1): 34926.

[3] Shao L, Wang Z, Qi X, et al. Validation and comparison of 4 fall risk assessment tools for older adults in Chinese nursing homes: a prospective cohort study. Journal of the American Medical Directors Association, 2025, 26(12): 105882.

[4] Ren Y, Ding J, Luo J, et al. Development and comparative validation of multiple models for cognitive frailty in older adults residing in nursing homes. Frontiers in Public Health, 2025, 13: 1661298.

[5] Rasilainen S, Aden M, Kivelä J A, et al. Using wearable sensors to measure and predict personal circadian lighting exposure in nursing home residents: model development and validation. JMIR aging, 2025, 8: e72338.

[6] Beiglary S, Feng Y, Wang N, et al. Using wearable sensors to measure and predict personal circadian lighting exposure in nursing home residents: model development and validation. BJS open, 2025, 9(5).

[7] Abul Y, Mcconeghy K, Devone F, et al. Analyzing SARS-CoV-2 case numbers and clustering to predict a nursing home outbreak. Aging Clinical and Experimental Research, 2025, 37(1): 265.

[8] Segelman M, Rowan N, Mukamel B D, et al. Changes in nursing home staffing instability throughout the COVID-19 pandemic. Journal of the American Medical Directors Association, 2025, 26(11): 105837.

[9] Cui C, Zhou B, Gao L, et al. Physical health and cognitive ability factors in predicting retirement adjustment based on machine learning approach: results from the China Health and Retirement Longitudinal Study. Frontiers in Psychology, 2025, 16: 1601723.

[10] Sun Q. A dynamic early warning model based on LSTM-AM for property-based elderly care resource shortages in urban-rural integrated counties in China. Scientific Reports, 2025, 15(1): 29502.