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Predicting the growth and key influencing factors of home-visit nursing offices in Japan using machine learning

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Abstract

The distribution of home-visit nursing offices in Japan is uneven, with some municipalities facing shortages. Understanding the factors influencing their growth rate is crucial for policy planning. This study developed a machine learning model to predict the growth rate of home-visit nursing offices using municipality-level time-series data from 2015 to 2022. Demographic indicators, healthcare resources, and economic factors were incorporated as predictors. Extreme Gradient Boosting (XGBoost) was employed, integrating one-year and three-year lag variables and a three-year moving average to capture temporal trends. Model performance was assessed using R^2, and Shapley Additive Explanations (SHAP) analysis was conducted to interpret feature importance. The model demonstrated strong predictive performance, with an average R^2 of 0.87. The past number of home-visit nursing offices had the highest impact on growth, with the three-year moving average contributing positively and the one-year lag variable indicating potential market saturation. Population density was also positively associated with growth. Although the aging rate had a limited overall influence, a higher aging rate tended to be associated with a lower growth rate of home-visit nursing offices. Economic indicators and the number of hospitals had minor influences. These findings suggest that market conditions and supply-side constraints significantly shape the expansion of home-visit nursing offices. Strategic interventions, such as financial support in underserved areas and sustainability measures in saturated regions, are needed to ensure an optimal distribution of services. Future research should explore additional socioeconomic factors and external shocks to refine predictive models and support data-driven policymaking.

Keywords: Home-Visit Nursing; Machine Learning; Healthcare Resource Distribution; Municipality-Level Analysis

1. Introduction

In Japan, the development of a community-based integrated care system has been promoted with the goal of ensuring that individuals can live their final days in a familiar environment while maintaining their preferred lifestyle. This initiative has gained importance in anticipation of 2025, when the baby boomer generation will become late-stage elderly, and the aging rate is expected to exceed 30% [1]. Among various healthcare services, home-visit nursing plays a crucial role in meeting the diverse needs of community-dwelling individuals, including the elderly, pediatric patients, and individuals with physical and mental disabilities. The expansion of home-visit nursing services has been actively encouraged due to their contribution to improving patients' quality of life (QOL) and enabling the continuation of home-based medical care [2].

While the number of home-visit nursing offices has grown substantially across Japan, disparities among municipalities persist. As of 2020, 26% of municipalities did not have a home-visit nursing office [1]. Approximately 60% of these offices are operated by for-profit corporations, making their establishment and continued operation difficult without stable revenue [3]. With the peak of aging and the potential shortage of healthcare and long-term care resources

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projected for 2040, the appropriate distribution and expansion of home-visit nursing offices is an urgent issue [4]. Predicting the future distribution of home-visit nursing offices is essential for policy planning, yet research on this topic remains limited.

Forecasting the regional supply and demand of home-visit nursing services is challenging due to the complexity of influencing factors and limited data availability. Recently, machine learning has gained attention for predicting such complex dynamics [5]. Machine learning has been increasingly applied to forecasting the demand for healthcare services at the regional level [6]. Thus, this study aims to apply machine learning models to predict the trends in the number of home-visit nursing offices and contribute to the design of future policies and medical fee reimbursement structures related to home-visit nursing services.

This study aims to develop a machine learning model trained on municipality-level time-series data to predict the growth rate of home-visit nursing offices and identify key factors contributing to these changes.

2. Materials and Methods

2.1. Data Sources

This study used time-series data from all 1,741 municipalities in Japan. The dataset covered the period from 2015 to 2022 and was obtained from the following publicly available sources:

2.1.1. Medical expenditure data

Municipality-level total medical expenditure under the National Health Insurance and the Late-stage Elderly Medical System [7].

2.1.2. Demographic data

Municipality-level total population, population aged 65 and older, aging rate, and the number of households as of January each year [8,9].

2.1.3. Healthcare resource data

Number of hospitals, number of home-care supporting clinics, and number of home-visit nursing offices as of March each year [10].

2.1.4. Economic indicators

Municipality-level average per capita income tax amount as of July each year [11].

2.2. Variables and Definitions

2.2.1. Indicators Related to Home-Visit Nursing

Number of home-visit nursing offices and their growth rate (%).

The growth rate was calculated by subtracting the number of offices in the previous year from that of the current year and dividing the difference by the previous year's number. When the number in the previous year was zero, a correction was applied by adding one to the denominator.

2.2.2. Demographic Variables

Aging rate (%), population density (persons/km^2), and population per household (persons/household).

2.2.3. Healthcare Resource Variables

Number of hospitals, number of home-care supporting clinics, and average per capita total medical expenditure (JPY/person) based on National Health Insurance and Late-stage Elderly Medical System data.

2.2.4. Economic Indicators

Municipality-level per capita income tax amount (JPY/person).

3. Analysis Methods

3.1. Model Training

To understand the characteristics and trends of the dataset, descriptive statistics for each variable were calculated for each year, and a correlation matrix was constructed.

The study employed Extreme Gradient Boosting (XGBoost), a machine learning model based on decision trees, for predicting the growth rate of home-visit nursing offices [12]. This model was selected for its ability to achieve high predictive accuracy while simultaneously providing interpretable insights into feature importance. The input variables included the number of home-visit nursing offices, aging rate, population density, number of hospitals, number of home-care supporting clinics, population per household, medical expenditure, and per capita income tax amount [13,14]. To account for temporal changes, one-year and three-year lag variables were created for all features, enabling the model to capture both short-term fluctuations and long-term trends. A three-year moving average was computed using only past data from preceding years in each prediction period. This approach ensured that no future information was incorporated into the feature set, effectively preventing data leakage.

Bayesian optimization was employed to fine-tune hyperparameters, improving predictive accuracy while mitigating overfitting. The optimization process was conducted with 100 iterations to identify the optimal combination of hyperparameters.

3.2. Model Evaluation

The model was validated using a four-fold expanding window cross-validation approach, where training data was gradually expanded while newer years were used as test data. Model performance was assessed using the following evaluation metrics:

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)

These metrics quantitatively measured the difference between predicted and actual values. MSE and RMSE indicated the magnitude of errors, while MAE provided a direct measure of absolute error. R^2 was used to assess the proportion of variance in the target variable explained by the model, with higher values indicating better predictive performance. To interpret the XGBoost model, Shapley Additive Explanations (SHAP) analysis was conducted. SHAP values quantified the contribution of each feature to the prediction, with higher SHAP values indicating greater influence on the model's output. The analysis was conducted using Python (3.11.2) with NumPy (1.26.4) for numerical computations, pandas (2.2.2) for data processing, scikit-learn (1.5.1) for machine learning utilities, XGBoost (2.1.3) for model implementation, and SHAP (0.46.0) for feature importance interpretation.

3.3. Ethical Considerations

This study used only publicly available data and did not include personal information; thus, no specific ethical considerations were required.

Table 1 Summary Statistics of Key Variables for Home-Visit Nursing Office Growth Prediction (2015–2022)

	Home-visit nursing offices		**Growth rate of nursing offices**		**Aging rate**		**Population density (persons/km²)**		**Population per household**	
Year	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2015	5.0	15.5	-	-	30.7	6.8	1292.6	4262.6	2.4	1.0
2016	5.5	16.9	5.3	18.8	31.6	6.9	1293.9	4277.7	2.4	1.0
2017	5.9	18.4	4.7	18.9	32.3	7.0	1294.6	4290.3	2.3	0.3
2018	6.3	19.8	3.6	17.3	33.1	7.1	1294.8	4301.5	2.3	0.3

2019	6.7	21.1	3.9	17.5	33.7	7.2	1294.5	4312.0	2.3	0.3
2020	7.1	22.5	4.4	16.0	34.3	7.4	1293.4	4321.4	2.5	0.5
2021	7.8	25.1	5.0	18.0	34.9	7.5	1292.1	4327.0	2.3	0.3
2022	8.5	27.8	5.6	18.2	35.4	7.7	1288.2	4320.1	2.2	0.3
	Hospitals		**Home-care clinics**		**Medical expenditure (JPY/person)**		**Income-based tax (JPY/person)**			
Year	Mean	SD	Mean	SD	Mean	SD	Mean	SD		
2015	4.9	12.7	8.3	28.9	553254.5	88232.4	94681.8	27483.8		
2016	4.9	12.6	8.4	29.3	558936.4	87473.3	95172.8	27150.9		
2017	4.8	12.0	8.4	29.2	578290.3	87785.2	95691.7	26478.8		
2018	4.9	12.6	7.8	26.6	589419.9	88732.6	96779.2	27203.3		
2019	4.8	12.5	8.2	27.9	606749.9	89663.6	101058.5	29018.4		
2020	4.8	12.5	8.3	28.3	590387.5	88350.2	101087.1	28094.2		
2021	4.8	12.4	8.5	29.0	611658.8	87553.5	99467.2	27196.4		
2022	4.7	12.3	8.7	29.6	627731.2	88103.5	102603.2	32544.1		
SD: Standard deviation.										

Table 2 Correlation Matrix of Key Variables for Home-Visit Nursing Office Growth Prediction

	Home-visit nursing offices		**Growth rate of nursing offices**		**Aging rate**		**Population density**		**Population per household**		**Hospitals**		**Home-care clinics**		**Medical expenditure**		**Income-based tax**	
Home-visit nursing offices	1.00	[-,-]																
Growth rate of nursing offices	0.24	[0.14, 0.34]	1.00	[-,-]														
Aging rate	-0.15	[-0.25, -0.05]	-0.08	[-0.18, 0.02]	1.00	[-,-]												
Population density	0.33	[0.22, 0.43]	0.45	[0.35, 0.55]	-0.31	[-0.41, -0.21]	1.00	[-,-]										
Population per household	-0.20	[-0.30, -0.09]	-0.25	[-0.35, -0.15]	0.10	[0.00, 0.20]	-0.18	[-0.28, -0.08]	1.00	[-,-]								
Hospitals	0.22	[0.12, 0.32]	0.12	[0.02, 0.22]	-0.05	[-0.15, 0.05]	0.30	[0.20, 0.40]	-0.12	[-0.22, -0.02]	1.00	[-,-]						
Home-care clinics	0.20	[0.10, 0.30]	0.10	[0.00, 0.20]	-0.02	[-0.12, 0.08]	0.25	[0.15, 0.35]	-0.10	[-0.20, 0.00]	0.50	[0.40, 0.60]	1.00	[-,-]				
Medical expenditure	0.10	[0.01, 0.20]	0.06	[-0.04, 0.16]	-0.03	[-0.13, 0.07]	0.14	[0.04, 0.24]	-0.08	[-0.18, 0.02]	0.28	[0.18, 0.38]	0.22	[0.12, 0.32]	1.00	[-,-]		
Income-based tax	0.08	[-0.02, 0.18]	0.04	[-0.06, 0.14]	-0.01	[-0.11, 0.09]	0.10	[0.00, 0.20]	-0.05	[-0.15, 0.05]	0.15	[0.05, 0.25]	0.12	[0.02, 0.22]	0.50	[0.40, 0.60]	1.00	[-,-]
Values represent correlation coefficients with 95% confidence intervals in brackets.																		

4. Results

4.1. Trends in Variables Over the Study Period

The mean and standard deviation of each variable during the study period are presented in Table 1. The correlation between variables is shown in Table 2.

4.2. Implementation and Evaluation of Machine Learning Model

4.2.1. The results of Bayesian optimization identified the following optimal hyperparameters:

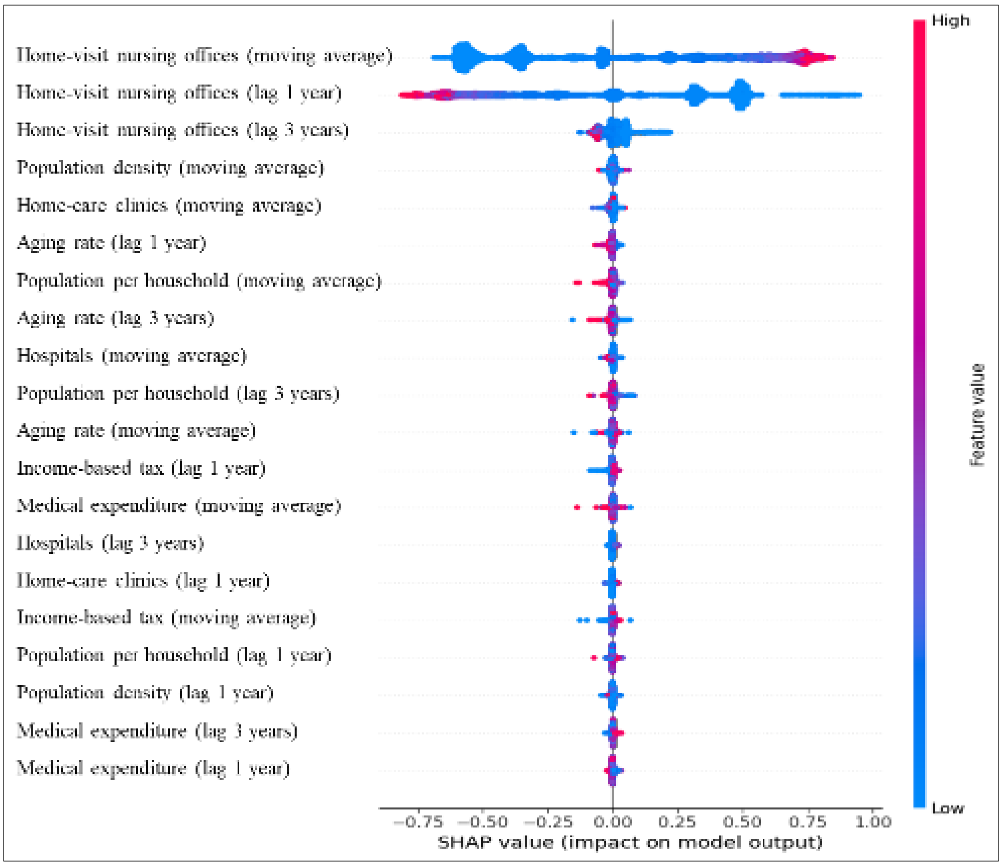
- Learning rate: 0.0499
- Maximum depth: 6
- Number of estimators: 250
- Subsampling ratio: 0.8
- Feature sampling ratio: 0.9867
- L1 regularization: 0.0
- L2 regularization: 0.5

The performance metrics for model evaluation are summarized in Table 3. The feature importance and SHAP analysis results are presented in Table 4, and the SHAP summary plot is shown in Figure 1.

Table 3 Performance Evaluation of the Machine Learning Model

Test data (year)	MSE	RMSE (%)	MAE (%)	R^2
2019	0.003	5.2	3.0	0.91
2020	0.003	5.3	2.9	0.89
2021	0.003	5.2	2.9	0.92
2022	0.008	9.1	4.7	0.75
mean	0.004	6.2	3.4	0.87
SD	0.002	1.7	0.8	0.07

MSE: Mean Squared Error; RMSE: Root Mean Squared Error; MAE: Mean Absolute Error; R^2: Coefficient of Determination; SD: Standard deviation.



This SHAP summary plot visualizes the impact of each feature on the model's predictions. The x-axis represents the SHAP values, which indicate the contribution of each feature to the predicted growth rate of home-visit nursing offices. A positive SHAP value suggests a higher predicted growth rate, while a negative SHAP value indicates a lower predicted growth rate. Each point represents an instance (observation) in the dataset. The color gradient represents the feature value, where red indicates a high value and blue indicates a low value. Features at the top have the highest importance, meaning they contribute the most to model predictions. Features with a wider distribution of SHAP values have a more variable impact on predictions. This plot helps interpret the model's decision-making process by illustrating how different features contribute to the prediction of home-visit nursing office growth.

Figure 1 SHAP Summary Plot of Feature Contributions to the Model's Predictions

Table 4 Feature Importance and SHAP Analysis of the Machine Learning Model

Feature variable		Value	Rank	SHAP value (mean)	SD	Rank
Home-visit nursing offices	Lag (1 year)	0.288	1	0.404	0.198	2
	Lag (3 years)	0.062	3	0.034	0.026	3
	Moving average (3 years)	0.126	2	0.441	0.212	1
Aging rate	Lag (1 year)	0.027	8	0.005	0.005	6
	Lag (3 years)	0.024	11	0.004	0.006	8
	Moving average (3 years)	0.023	12	0.004	0.004	11
Population density	Lag (1 year)	0.061	4	0.003	0.003	18
	Lag (3 years)	0.022	18	0.002	0.003	21
	Moving average (3 years)	0.026	9	0.006	0.005	4
Population per household	Lag (1 year)	0.020	20	0.003	0.003	17
	Lag (3 years)	0.028	6	0.004	0.004	10

	Moving average (3 years)	0.022	16	0.005	0.005	7
Hospitals	Lag (1 year)	0.023	13	0.000	0.000	24
	Lag (3 years)	0.018	23	0.003	0.003	14
	Moving average (3 years)	0.019	22	0.004	0.004	9
Home-care clinics	Lag (1 year)	0.037	5	0.001	0.001	15
	Lag (3 years)	0.015	24	0.003	0.003	23
	Moving average (3 years)	0.028	7	0.005	0.005	5
Medical expenditure	Lag (1 year)	0.023	14	0.002	0.003	20
	Lag (3 years)	0.019	21	0.003	0.003	19
	Moving average (3 years)	0.022	17	0.003	0.004	13
Income-based tax	Lag (1 year)	0.024	10	0.003	0.004	12
	Lag (3 years)	0.022	19	0.002	0.002	22
	Moving average (3 years)	0.019	15	0.003	0.004	16
Lag: Lagged variable; SHAP: Shapley Additive Explanations; SD: Standard deviation.						

5. Discussion

This study developed a machine learning model to predict the growth rate of home-visit nursing offices using municipality-level time-series data and analyzed the factors influencing these changes. The results demonstrated that past numbers of home-visit nursing offices had the greatest influence on growth trends. While the relative impact of population density, home-care clinics, and aging rate was lower, these factors still contributed to variations in growth. The influence of economic indicators was relatively minor. These findings suggest that the expansion of home-visit nursing services is shaped by both demand-side and supply-side factors, with market saturation and regional disparities playing a key role in service distribution.

5.1. Predictive Performance of the Model

The developed model demonstrated high predictive accuracy, with RMSE and MAE values lower than the standard deviation of the target variable, indicating that the model's errors were within an acceptable range [15]. The overall explanatory power was also high, as shown by the R^2 value, suggesting that the model effectively captured the relationships between the input variables and the growth rate of home-visit nursing offices. However, when tested on 2022 data, the model’s predictive performance declined, likely due to the effects of the COVID-19 pandemic, which disrupted historical trends in healthcare service demand and supply [16]. The pandemic introduced sudden shifts in resource allocation and operational constraints, making it difficult for the model to accurately capture short-term fluctuations. This suggests that future predictive models should incorporate external shocks to improve robustness.

5.2. Key Factors Influencing the Growth of Home-Visit Nursing Offices

Among the influencing factors, past numbers of home-visit nursing offices consistently showed the strongest impact on growth trends. However, the direction of this effect varied depending on the timeframe considered. The three-year moving average had a positive effect, suggesting that regions with a stable and sustained number of offices over multiple years were more likely to experience continued expansion. Conversely, the one-year lag variable had a negative impact, indicating that in areas where the number of offices had increased in the previous year, growth tended to slow down in the following year. This pattern suggests the presence of market saturation effects, where areas that have recently experienced growth may reach a threshold limiting further expansion.

Population density was another important factor, showing a positive correlation with growth. This is consistent with previous findings that home-visit nursing offices are more concentrated in urban areas [17]. However, while population density contributed to the model’s predictions, its effect was weaker than that of past office numbers, suggesting that urbanization alone does not fully explain service expansion. Instead, economic sustainability and regional healthcare infrastructure are likely to play a role in shaping market dynamics.

Although the aging rate had a relatively limited influence, it was still a contributing factor to the growth of home-visit nursing offices. While aging populations increase the demand for home-based healthcare services, the establishment of home-visit nursing offices appears to be influenced by supply-side constraints, including operational costs, workforce availability, and market feasibility. Furthermore, both the one-year and three-year lagged aging rates exhibited negative associations with growth, suggesting that regions with higher aging rates in previous years were less likely to experience an increase in office numbers. This suggests that while demand may be high in aging regions, economic and logistical challenges hinder service expansion [18]. Given the negative correlation between aging rate and population density, it is likely that many aging regions are located in suburban or rural areas, where lower population concentrations and higher transportation costs make service provision less feasible [19].

5.3. Relationship Between Healthcare Resources and Home-Visit Nursing Office Growth

The presence of home-care supporting clinics was positively associated with the growth rate of home-visit nursing offices, as these clinics help coordinate patient referrals and facilitate service expansion [20]. However, their impact was relatively smaller than that of past office numbers and population density, indicating that while healthcare resources contribute to growth, they are not the primary drivers. In contrast, the number of hospitals had little influence, suggesting that the presence of large medical institutions does not necessarily promote the expansion of home-visit nursing offices.

Other variables, such as population per household, medical expenditure, and per capita income tax amount, exhibited relatively minor effects on the model's predictions. This suggests that while socioeconomic conditions may indirectly influence healthcare service distribution, they do not play a dominant role in determining the rate at which new home-visit nursing offices are established. Instead, the expansion of these services appears to be more strongly influenced by the existing market structure and operational feasibility.

5.4. Limitations and Future Directions

While this study successfully developed a machine learning model for home-visit nursing office growth, several limitations should be noted. First, the machine learning model identified associations between variables and the growth rate but did not explicitly analyze causal relationships. Although SHAP analysis provided insights into feature importance, the results do not establish direct causality. External factors such as policy changes, financial incentives, and workforce availability may have influenced trends but were not explicitly accounted for in the model.

Second, while demographic, healthcare, and economic indicators were considered, other critical factors influencing home-visit nursing office growth were not included. Factors such as government subsidies, reimbursement policies, and local healthcare network structures could significantly impact market dynamics [21,22]. Future research should incorporate these elements to provide a more comprehensive understanding of service expansion mechanisms. Additionally, while time-series data was used, the model did not explicitly incorporate external shocks such as pandemics or major policy shifts. The impact of the COVID-19 pandemic on home-visit nursing services suggests that sudden disruptions can introduce significant variations in service trends [16]. Future models should incorporate exogenous variables to better capture the effects of such events on healthcare service distribution.

Despite these limitations, this study provides valuable insights into the expansion of home-visit nursing offices. The results highlight the importance of considering both demand and supply-side constraints when predicting service growth. Future research should further investigate the balance between market expansion and saturation while integrating additional factors, such as regulatory policies and financial incentives, to enhance machine learning models and guide healthcare planning.

6. Conclusion

This study developed a machine learning model trained on municipality-level time-series data to predict the growth rate of home-visit nursing offices in Japan. The XGBoost model exhibited high predictive performance, and SHAP analysis identified the past number of offices as the most influential factor, with the three-year moving average positively associated with growth and the one-year lag variable indicating potential market saturation. While the direct impact of the aging rate was limited, its lagged values were negatively correlated with office growth, suggesting that supply-side constraints play a significant role. These findings highlight the need for targeted policy interventions; in areas with insufficient office numbers, financial support and enhanced collaboration with medical institutions may support the establishment of new offices, whereas in regions approaching saturation, maintaining existing services should be prioritized. Further research incorporating socioeconomic factors such as financial incentives and workforce availability is necessary to refine predictive models and inform evidence-based strategies for optimizing the distribution of home-visit nursing services.

Compliance with ethical standards

Statement of informed consent

This study used only publicly available data and did not involve human participants; therefore, informed consent was not required.

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