

Predicting Future Long-Term Care Dependency with Explainable Artificial Intelligence Using Administrative Healthcare Data

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Preventing future long-term care dependency is a major public health challenge in aging societies. We developed an explainable artificial intelligence (AI) model to predict future long-term care dependency among adults aged ≥ 65 years using large-scale administrative healthcare data from Japan's public insurance system. The model demonstrated good discriminative performance in the randomly split internal test cohort (AUC:0.870, sensitivity: 0.790, specificity: 0.800). Age and baseline long-term care certification status were the strongest predictors. Neurological disorders, dementia-related conditions, cerebrovascular diseases, and other chronic diseases also contributed substantially to the predicted risk. Conversely, the model identified factors associated with reduced predicted risk, including hypercholesterolemia, allergic rhinitis, and chronic periodontitis. The model identified both high-risk individuals and disease-specific factors associated with predicted long-term care risk by quantifying feature importance and impact. Unlike conventional black-box models, the proposed model enables transparent interpretation by providing not only predicted risk values but also the factors associated with the predicted risk. This capability may improve the clinical interpretability and practical applicability of AI-based risk prediction for long-term care prevention.

INTRODUCTION

With the rapid progression of population aging worldwide, the growing number of older adults requiring long-term care has become a major societal challenge (1, 2). In Japan, population aging has likewise led to an increase in older adults with chronic diseases, multimorbidity, and functional decline, resulting in an expanding economic and social burden associated with care dependency (3, 4). Consequently, the development of effective strategies to prevent the transition to long-term care dependency among older adults has become an important public health priority. In particular, the early identification of individuals at high risk of future care dependency and the implementation of appropriate health guidance and preventive interventions are essential for extending healthy life expectancy (HLE) and optimizing the use of healthcare and long-term care resources.

Recent advances in the availability of large-scale healthcare data have facilitated the application of machine learning (ML) approaches to the prediction of frailty, functional decline, and other adverse outcomes among older adults (5–7). However, future long-term care needs are determined by a complex interplay of multiple factors that extends beyond frailty alone, including chronic diseases, medication use, health behaviors, and living environments (8, 9). In this context, recent studies have successfully developed machine learning models for prediction of long-term care risk among older adults, leveraging large-scale healthcare administrative data from Japan's public health insurance systems (10, 11). While these models demonstrated high predictive performance, they remained a so-called “black-box” model that could not provide individualized explanations regarding the risk factors underlying their predictions. To address this issue, we developed an explainable AI model that can accurately predict future risk of certification at long-term care level 2 or higher from medical claims data and long-term care certification assessment records, while simultaneously identifying key factors contributing to predicted long-term care risk. The objective of this study was to develop and evaluate a practical decision-support tool that can assist public health nurses, long-term care professionals, and municipal administrators in promoting healthy life expectancy and preventing long-term care dependency.

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MATERIALS AND METHODS

Study population

Among approximately 400,000 residents aged 65 years or older who were eligible for Kobe City's Community-based Integrated Care System (12), a total of 284,660 individuals were included in the analysis after excluding those who had already been certified as requiring Long-Term Care Level 2 or higher during the baseline period (April 2016 to December 2017), as well as those who died or moved out of the city during the study period (April 2016 to December 2019). In Japan's Long-term Care Insurance system, care needs are classified into seven levels based on the type and extent of services required to support daily living: Support Required Levels 1 and 2 and Care Required Levels 1 through 5 (13). Long-term care certification is determined by physicians and long-term care professionals based on assessments across five domains: physical function and mobility, activities of daily living (ADL), cognitive function, mental and behavioral status, and social adaptation. Care Level 2 is defined as a condition in which individuals experience substantial difficulty performing most activities of daily living independently and require continuous care support, and is regarded as an endpoint of healthy life expectancy in Japan (14).

The data used in this study consisted of anonymized linked records provided by the Kobe City Health Bureau, including medical claims data and long-term care certification assessment records derived from the National Health Insurance and Late-Stage Elderly Medical Care systems and long-term care certification assessment records from the Long-Term Care Insurance system.

Development of training and test datasets

To reduce the risk of re-identification associated with rare conditions, diagnostic variables with fewer than 10 occurrences were excluded from the analysis. After this exclusion, 5,697 ICD-10-based diagnostic variables were included in the analysis. For each diagnosis, a binary explanatory variable was created by assigning a value of 1 if at least one corresponding record was observed during the 21-month baseline period and 0 otherwise. Age, the only continuous variable, was categorized into 5-year age groups and subsequently converted into binary variables.

The dependent variable was defined as the presence or absence of certification for Long-Term Care Level 2 or higher, as recorded in the long-term care certification assessment data. For machine learning analysis, individuals who were newly certified as requiring Long-Term Care Level 2 or higher during the 2-year observation period following the baseline period were coded as 1, whereas all others were coded as 0.

Individual-level explanatory variables measured during the baseline period were linked to the dependent variable to construct datasets for supervised machine learning and model evaluation (Figure 1). Specifically, the 284,660 eligible individuals were randomly divided into a training cohort ($n = 213,495$) and a test cohort ($n = 71,165$). In both cohorts, 5.6% of individuals were certified as requiring Long-Term Care Level 2 or higher during the observation period. For machine learning, 23,888 individuals were randomly selected from the training pool by random under-sampling to achieve an approximately 1:1 ratio of participants with and without long-term care certification at care level 2 or higher.

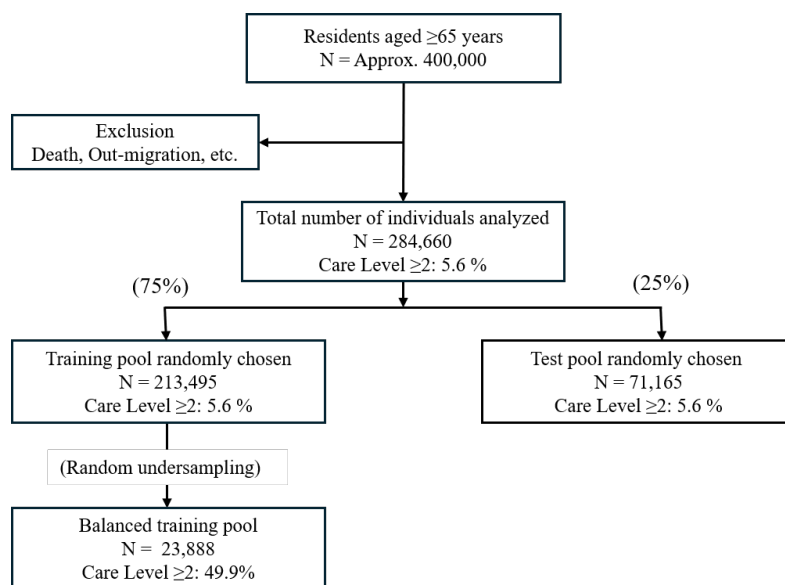


Figure 1.

Patient selection and data distribution. After exclusion from approximately 400,000 subjects whose data were provided by Kobe City, the remaining subjects were randomly allocated to training (75%) and test (25%) datasets. Explanatory variables were obtained during the baseline period (April 2016–December 2017), and outcomes were assessed during the subsequent observation period (January 2018–December 2019). Random under-sampling was applied only to the training dataset to generate a balanced training pool.

Machine learning analysis

Machine learning analysis was performed using the Pointwise Linear Model (B3; Hitachi, Ltd., Tokyo, Japan), an explainable artificial intelligence method with high discriminative performance for large-scale datasets containing numerous explanatory variables (15, 16). B3 was selected because it combines flexible predictive modeling with interpretable, feature-level information for individual predictions. The model generates a sample-specific weight vector, thereby allowing the impact of individual features on each prediction to be evaluated. This property is particularly useful for the present study, which involves high-dimensional healthcare data containing numerous diagnostic variables and aims not only to identify individuals at high risk but also to clarify the factors underlying their predicted risk. Unlike conventional black-box machine learning approaches, for which additional post-hoc methods may be needed to explain individual predictions, B3 provides feature-level impact as part of the model output (15, 16).

Using the training dataset, a supervised machine learning model was implemented to generate individualized probability of future long-term care certification. The developed model was then applied to the test cohort. Individuals with predicted risk probabilities of 0.5 or greater were classified as high risk, whereas those with probabilities below 0.5 were classified as low risk. These predictions were compared with the actual long-term care certification outcomes to evaluate model performance. The primary performance metric was the area under the receiver operating characteristic curve (AUC). Secondary performance metrics included sensitivity, specificity, accuracy, F1 score, and the average precision (AP).

Evaluation of variable importance and impact

To quantitatively assess the contribution of explanatory variables to risk prediction, score and weight values were calculated for all variables using the B3 model. The score represents the relative importance of each feature in the model, with a maximum value of 1.00. The weight represents the impact, i.e., the direction and magnitude of the feature's contribution to the predicted risk, with positive and negative values indicating increased and decreased predicted risk, respectively.

All analyses were conducted using Python version 3.8.10 and B3 (Hitachi AI Technology/Explainable AI; Hitachi, Ltd., Tokyo, Japan; <https://www.hitachi.com/products/it/ai/index.html>).

Ethics

The Kobe City Health Bureau provided record-linked anonymized data. This study was conducted on an opt-out basis after approval by the Medical Ethics Committee of Kobe University (Approval Number: B200234; September 19, 2020), the Kobe City Health Project Research Ethics Committee (March 22, 2021), and the Ethics Review Committee of the Hitachi Group (December 28, 2021). According to the ethical guidelines of the Hitachi Group, its members are permitted to participate in data analysis only when a given feature is present in at least 10 individuals to minimize the risk of personal identification.

Access to the dataset is restricted to the Kobe University laboratory to ensure data security and confidentiality.

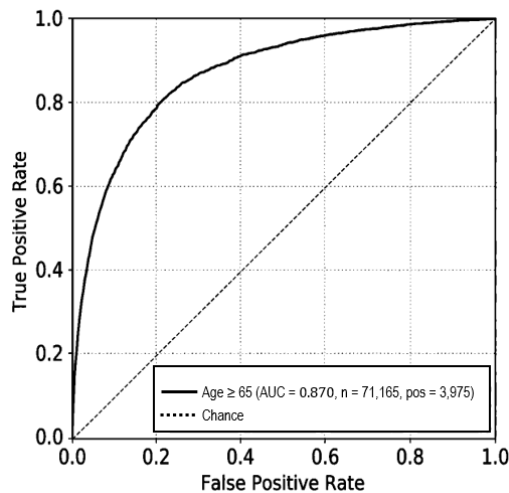
RESULTS

Predictive performance of the machine learning model

The predictive performance of the supervised machine learning model using B3 for predicting certification of long-term care level 2 or higher was evaluated using an independent test dataset. As shown in Figure 2 and Table I, the model demonstrated good discriminative performance.

Table I. The performance metrics of the developed machine learning model

AUC-ROC	Accuracy	Sensitivity	Specificity	F1 Score	Average Precision
0.870	0.791	0.790	0.800	0.299	0.339

**Figure 2.**

Receiver operating characteristic (ROC) curve of the prediction model for future certification of long-term care level 2 or higher among individuals aged ≥ 65 years. The gray dashed line indicates the performance expected by chance.

Evaluation of feature importance and feature impact

Among the 5,697 disease variables included as features in this study, 1,348 had a Score of >0 . The Score is an index generated by B3 that represents the importance of each feature. Figure 3 shows the feature impact of functional independence level and age. The impact increased with increasing levels of care dependency, reaching approximately 15% for individuals certified as requiring long-term care level 1. Regarding age, the feature impact became positive from 75 years onward and exceeded 10% among individuals aged ≥ 85 years.

A total of 34 diseases showed a positive feature impact of ≥ 0.01 (Figure 4). Alzheimer's disease exhibited the highest impact, followed by Parkinson's disease, dementia, constipation, and cerebral infarction. In addition, various respiratory, cardiovascular, neuropsychiatric, dermatological, gastrointestinal, traumatic, bladder storage disorders, including overactive bladder, and ophthalmological diseases showed positive feature impacts of >0.01 . Among musculoskeletal disorders, lumbar vertebral compression fracture, chronic low back pain, and lumbar spondylosis showed relatively high feature impacts. Although below the threshold of 0.01, Osteoporosis (weight, 0.0092) and thoracic vertebral fracture (weight, 0.0087) were also identified as important predictors. Furthermore, gait disorder (weight, 0.0092) and difficulty walking (weight, 0.0090), which reflect impaired gait and mobility, were identified as important predictors.

Conversely, 16 diseases, including hypercholesterolemia, allergic rhinitis, and chronic periodontitis, exhibited a negative feature impact of $\leq -1\%$ (Figure 5). The feature importance of all these diseases exceeded 0.80.

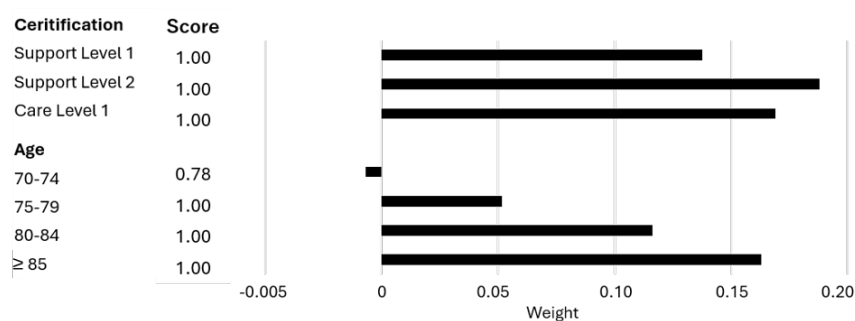


Figure 3. Feature importance (score) and feature impact (weight) of certification status and age group. Bars indicate the corresponding weight values. Positive and negative weights indicate increased and decreased predicted risk of future long-term care certification, respectively. Scores indicate the relative importance of each feature in the model, with a maximum value of 1.00.

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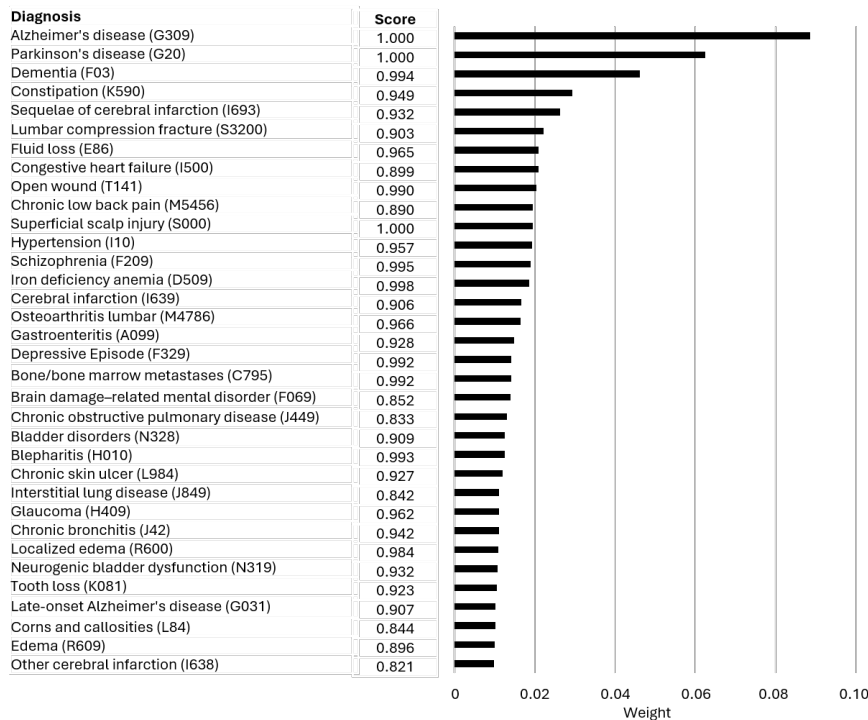


Figure 4.

Feature importance (score) and feature impact (weight) of diagnoses with positive weights for future long-term care certification. Only diagnoses with weight values ≥ 0.01 are shown. Bars indicate the corresponding weight values. Scores indicate the relative importance of each feature in the model, with a maximum value of 1.00.

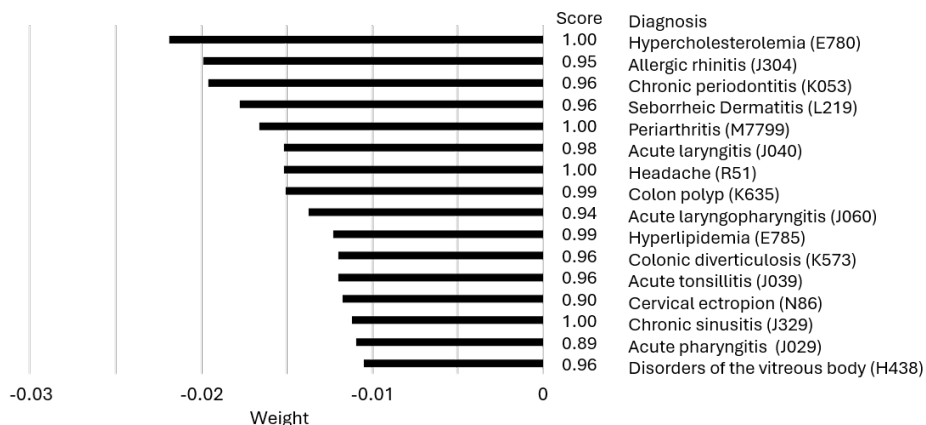


Figure 5.

Feature importance (score) and feature impact (weight) of diagnoses with negative weights for future long-term care certification. Only diagnoses with weight values ≤ -0.01 are shown. Bars indicate the corresponding weight values. Scores indicate the relative importance of each feature in the model, with a maximum value of 1.00.

DISCUSSION

In this study, we developed an explainable artificial intelligence (AI) model for predicting future certification of Long-Term Care Level 2 or higher using medical claims data and long-term care certification records. The model achieved an AUC of 0.870, exceeding the commonly accepted benchmark of 0.80 for good discriminative performance (17). Furthermore, the model was capable not only of predicting the future risk of long-term care dependency at the individual level but also of simultaneously identifying major explanatory variables (disease diagnoses) associated with predicted long-term care risk and quantitatively evaluating their respective contributions. These findings suggest that the present model may serve as a practical decision-support tool for extending healthy life expectancy and promoting long-term care prevention.

Previous studies using Japanese administrative healthcare data reduced the dimensionality of claims-based variables before model development. Sato et al. applied ANOVA-based filtering to select 150 representative codes, while our previous study reduced and consolidated the original variables before applying XGBoost (10, 11). In contrast, the present study incorporated 5,697 ICD-10-based diagnostic variables without disease grouping or prediction-oriented feature selection, except for the exclusion of rare variables for privacy protection. Despite this high-dimensional input, the B3 model achieved good discrimination (AUC, 0.870) while enabling the importance

and impact of individual diagnostic features to be evaluated. These findings suggest that routinely collected claims-based diagnostic information can be used for long-term care risk prediction with limited feature engineering, supporting the potential utility of administrative healthcare data for practical risk prediction.

Feature impact analysis revealed that reduced functional independence and advanced age were the strongest contributors to future long-term care dependency, consistent with our previous machine learning study. These findings are in agreement with previous epidemiological studies demonstrating that functional decline and aging are strongly associated with the transition to long-term care dependency, and that the present model appropriately reflects the characteristics of long-term care risk among older adults (18, 19).

With respect to disease-specific variables, neurodegenerative diseases and cerebrovascular diseases, including Alzheimer's disease, Parkinson's disease, dementia, and cerebral infarction, exhibited high feature impacts. These conditions are well recognized as major causes of the transition to long-term care dependency because they directly impair cognitive and physical function, leading to declines in activities of daily living (20, 21).

In addition to these diseases, constipation also showed a high feature impact. Constipation is recognized as a geriatric syndrome that is closely associated with reduced physical activity, malnutrition, dehydration, polypharmacy, and neurodegenerative diseases in older adults (22). More recently, chronic constipation has also been reported to be closely associated with frailty and physical functional decline (23). Therefore, the present findings suggest that constipation itself does not directly cause long-term care dependency but may instead serve as a comprehensive marker reflecting overall health status and physical functional decline in older adults.

Among musculoskeletal disorders, lumbar vertebral compression fracture, chronic low back pain, and lumbar spondylosis exhibited high feature impacts. Osteoporosis and thoracic vertebral compression fracture also showed relatively high impacts close to the threshold used in Figure 4. Furthermore, disease diagnoses reflecting impaired gait and mobility, such as gait disorder and difficulty walking, were identified as important features. The feature importance (Score) of all these conditions exceeded 0.80. Osteoporotic fractures and spinal disorders are known to contribute to the progression of frailty and sarcopenia through chronic pain, impaired mobility, and reduced physical activity (24, 25). In addition, gait disorder and difficulty walking represent major clinical manifestations of physical frailty and functional decline and are regarded as important indicators of future long-term care dependency (10, 26, 27). The identification of these diseases and conditions as important features suggests that the present model comprehensively captures not only musculoskeletal disorders but also impairments in gait and mobility when assessing the future risk of long-term care dependency.

On the other hand, a broad spectrum of diseases, including respiratory diseases, cardiovascular diseases, neuropsychiatric disorders, dermatological diseases, gastrointestinal diseases, bladder storage disorders such as overactive bladder, and ophthalmological diseases, showed positive feature impacts. These findings indicate that the transition to long-term care dependency is influenced not only by a single major disease, such as stroke or dementia, but also by the cumulative effects of multimorbidity and age-related functional decline, as has been widely acknowledged (18, 28). By utilizing comprehensive medical claims data, the present model may provide a multidimensional assessment of the health status of older adults and more comprehensively capture the future risk of long-term care dependency.

Conversely, hypercholesterolemia, allergic rhinitis, and chronic periodontitis showed negative feature impacts. In older adults, hypocholesterolemia is associated with frailty, malnutrition, and poor overall health status, a phenomenon commonly referred to as reverse epidemiology in geriatric medicine (29, 30). Likewise, allergic rhinitis and chronic periodontitis are more likely to be diagnosed in relatively healthy older adults who are able to maintain regular outpatient visits and appropriate self-care. Importantly, these negative feature impacts should not be interpreted as evidence that these conditions have a causal protective effect against long-term care dependency. Rather, they may represent surrogate markers reflecting relatively preserved functional status, greater engagement with healthcare services, or other unmeasured characteristics. Therefore, these associations should be interpreted cautiously, and further studies are required to clarify the mechanisms underlying these negative feature impacts.

The present study has several limitations. First, because the study population was limited to beneficiaries of the National Health Insurance and the Late-Stage Elderly Medical Care System in Kobe City, caution is required when generalizing the findings. Regional differences in population demographics, disease prevalence, healthcare utilization, and long-term care service availability may affect both model performance and the relative importance of individual predictors. Therefore, external validation and, if necessary, model recalibration using data from municipalities with different demographic and healthcare characteristics will be required before broader application. Nevertheless, because medical claims and long-term care certification data are collected under standardized national insurance systems in Japan, the data framework used in this study may facilitate application to other municipalities and, ultimately, larger-scale implementation across Japan. Second, information on lifestyle factors, socioeconomic status, family structure, and physical function was unavailable for analysis. Incorporating these variables may further improve the predictive performance of the model.

In conclusion, the explainable AI model using the B3 algorithm accurately predicted future long-term care dependency while simultaneously identifying important factors associated with predicted long-term care risk. The present model has the potential to serve as a practical AI tool for the early identification of older adults at high risk of future long-term care dependency and to support individualized long-term care prevention strategies aimed at extending healthy life expectancy. Furthermore, the longitudinal administrative healthcare database used in this study is expected to provide a valuable platform for developing AI models for predicting long-term care risk and other applications in geriatric medicine and long-term care research.

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