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Predictive model development for possible sarcopenia in community-dwelling older adults: a cross-sectional machine learning approach using the Korean frailty and aging cohort study

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Abstract

Background Sarcopenia, an age-related decline in muscle mass and physical function, is a major risk factor for frailty, a condition associated with negative health outcomes and increased disease burden in older adults. Providing simple, accurate community-based screening is essential for early prevention and improving the health and quality of life of older adults. Employing screening criteria for possible sarcopenia can broadly identify individuals at risk for sarcopenia and enhance early diagnosis and preventive measures. However, there is a lack of possible sarcopenia prediction models. This study developed and evaluated a model for predicting possible sarcopenia among community-dwelling older adults and identified key predictors.

Methods A supervised machine learning approach was used, with data from the 2022–2023 Korean Frailty and Aging Cohort Study ($n=1,761$). Individuals were classified as having possible or no possible sarcopenia based on the 2019 Asian Working Group for Sarcopenia criteria. Logistic regression, random forest, support vector machine, and extreme gradient boosting machine learning models were developed, and their predictive performance was assessed using accuracy, precision, recall, F1-score, and receiver operating characteristic curve–area under the curve. Feature importance was analysed applying Shapley additive explanations.

Results The final sample comprised 500 individuals with possible sarcopenia (mean age: 83.0 ± 3.76 years; 34.4% men) and 1,261 without possible sarcopenia (mean age: 81.0 ± 3.40 years, 51.6% men). Logistic regression demonstrated the best predictive performance among the four models, with the highest recall of 0.700 and F1-score

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of 0.654. The most influential predictors for possible sarcopenia were lower body mass index, walking aid use, cognitive impairment, older age, and exhaustion.

Conclusions Multidomain geriatric indicators including anthropometric status (body mass index), walking aid use, cognitive function, age, and exhaustion can guide pragmatic, community-based screening for possible sarcopenia. Simple, accessible assessments of these predictors may facilitate earlier identification and referral, and should be considered in sarcopenia screening and prevention strategies.

Clinical trial number Not applicable.

Keywords Aged, Community-dwelling, Machine learning, Cognitive impairment, Body mass index, Possible sarcopenia

Background

Understanding older adults' health and reducing their burden are global priorities. Frailty is associated with various negative health outcomes and an increased disease burden in older adults, including an increased risk of falls, fractures, cardiovascular diseases, depression, and mortality [1, 2]. Sarcopenia is the leading risk factor for frailty [3, 4]. It involves physiological changes in which muscle mass and strength decrease with age [4]. These changes are associated with reduced capacity for physical activity [5], increased risk of falls and fractures [2], the development of metabolic syndrome (including diabetes) [6], dementia or cognitive decline [7]. Managing sarcopenia is becoming increasingly important for preventing frailty.

Since 2010, international consensus statements have recommended screening for physical function, particularly walking speed and handgrip strength, in individuals with suspected physical function decline; if decline is confirmed, sarcopenia should be screened by quantifying muscle mass using dual-energy X-ray absorptiometry (DXA) or bioelectrical impedance analysis (BIA) [8, 9]. In 2019, the Asian Working Group for Sarcopenia (AWGS) introduced a revised diagnostic algorithm: (1) Possible sarcopenia is defined by low muscle strength (handgrip strength) and/or poor physical performance (5-time chair stand test); (2) sarcopenia is diagnosed when low muscle mass coexists with either reduced strength or impaired physical performance; and (3) severe sarcopenia when all three domains are impaired [8]. Because DXA and/or BIA are often unavailable in community and primary care, the possible sarcopenia construct provides a pragmatic pathway for early identification and management and has shown good performance in community screening [10–12].

The estimated global prevalence of sarcopenia varies from 10% to 27% in individuals aged ≥ 60 years in a meta-analysis [13]. A Korean study using 2019 AWGS criteria found that 22.4% of community-dwelling adults aged 70 years and older had possible sarcopenia or sarcopenia [10]. Individuals with possible sarcopenia were more likely to have lower educational attainment, mobility limitations, and cognitive impairment, and they exhibited longer Timed Up and Go times [10]. They also had a lower body mass index (BMI), waist circumference, and systolic blood pressure, along with a higher prevalence of hyperlipidaemia and estimated glomerular filtration rate [11]. The factors associated with possible sarcopenia are diverse, including sociodemographic characteristics and physical and psychological function indicators. Thus, community-based easy risk prediction and the identification of key indicators are needed.

Machine learning has been widely used to develop predictive models in health-related fields [14, 15]. Recent studies have applied machine learning techniques to sarcopenia by discriminating between possible sarcopenia and metabolic syndrome using arterial waveforms [16], detecting cases from electronic health records [17], predicting sarcopenia from ocular examinations [18], and comparing sex-stratified risks [19]. However, models targeting possible sarcopenia, which may capture individuals overlooked by diagnostic criteria, remain limited. Machine learning can prioritise simply collected predictors, thereby guiding scalable screening workflows in community and primary care settings. Accordingly, this study aimed to develop a machine learning–based model to predict possible sarcopenia and to determine the most informative predictors to guide early identification and referral.

Methods

Design

We conducted a secondary data analysis using data from the Korean Frailty and Aging Cohort Study (KFACS). Additionally, we adopted a supervised machine learning-based approach to predict possible sarcopenia.

Primary data source

The KFACS is a longitudinal, population-based study involving community-dwelling adults aged 70 years and older in Korea. The KFACS was designed to investigate frailty status and the transitions between frailty states over time [20]. We selected 2022–2023 data (the fourth

wave), reflecting the most recent KFACS dataset available for public use, to examine the latest trends.

The baseline KFACS cohort profile was initiated from May 2016 to November 2017, and follow-ups were conducted biennially by trained interviewers. A total of 3,014 community-dwelling adults aged 70–84 years were recruited from 10 hospitals and health centres in Korea at baseline using an age- and sex-stratified allocation method. The KFACS repeatedly measured participants' demographic characteristics; health status; behaviours; physical, cognitive, and social functions; and anthropometry at two-year intervals [20]. The KFACS dataset was ideal for the present study because of its inclusion of various factors related to frailty characteristics in the older Korean population. In addition, the data contained components of the AWGS 2019 criteria for possible sarcopenia, such as calf circumference (CC) measurement; a screening questionnaire to identify risk for sarcopenia, including strength, assistance with walking, rising from a chair, climbing stairs, and falls (SARC-F); handgrip strength; the five times sit-to-stand test; and walking speed. This allowed screening for possible sarcopenia. The data were provided by the KFACS at the request of the researchers after anonymising the data.

Participants

Figure 1 illustrates the selection of study participants and the group classification process. The basic inclusion criteria of the KFACS were community-dwelling adults aged 70–84 years who had no history of dementia or communication difficulties and did not plan to relocate outside the three neighboring towns within two years. In total, 2,886 individuals who participated in the 2022 and 2023 KFACS were initially considered in this study. We excluded 1,125 participants who did not attend either the centre-based or home-visit assessments and therefore

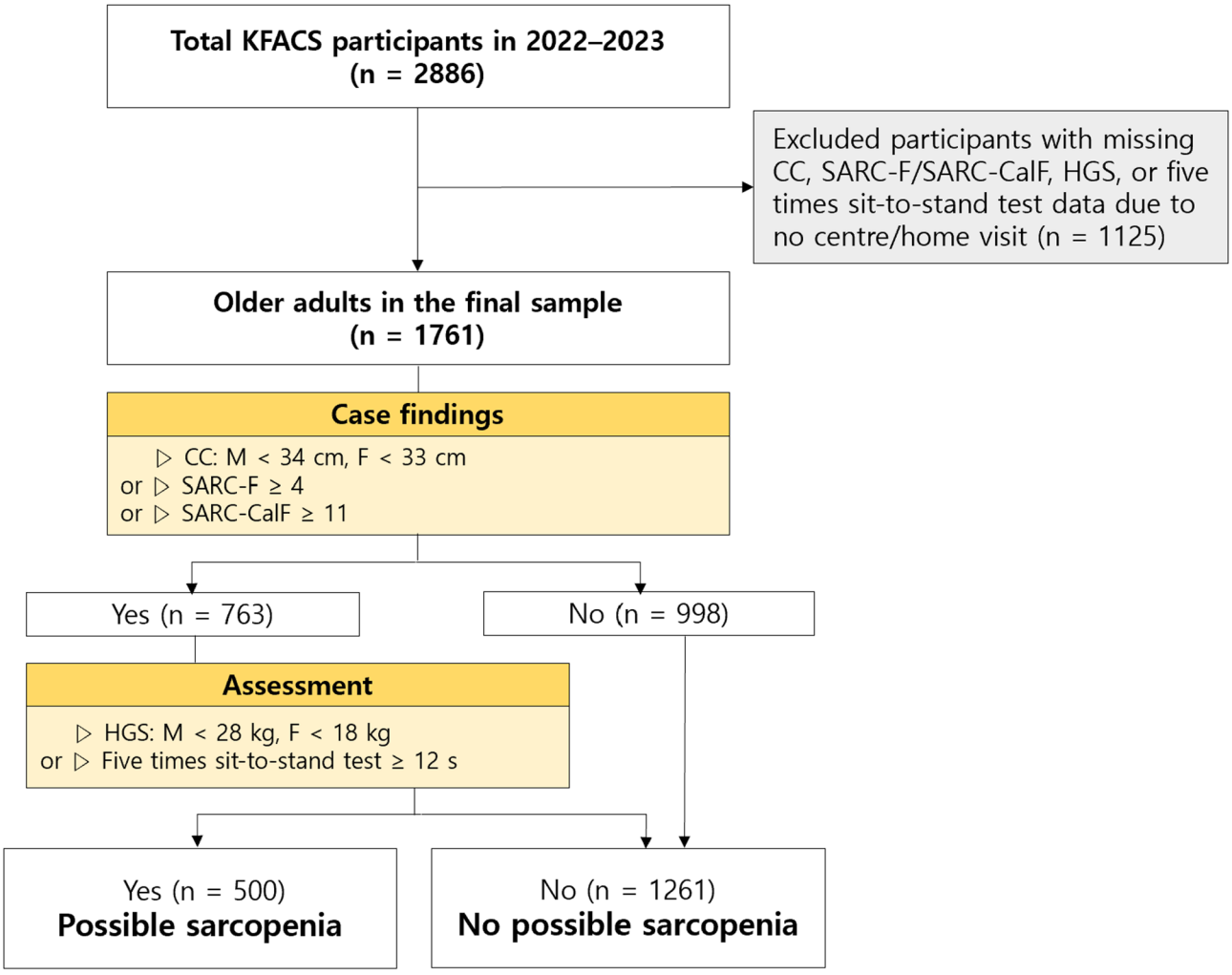

Fig. 1 Flowchart of participant classification into possible sarcopenia and no possible sarcopenia groups. Abbreviations: KFACS, Korean Frailty and Aging Cohort Study; CC, calf circumference; SARC-F, Strength, Assistance in walking, Rising from a chair, Climbing stairs, and Falls; SARC-CalF, SARC-F combined with calf circumference measurement; HGS, handgrip strength

lacked data required for determining possible sarcopenia (i.e. CC, SARC-F, SARC-CalF, handgrip strength, or the five-times sit-to-stand test). Case finding and assessment of possible sarcopenia were conducted based on the 2019 AWGS criteria. A total of 1,761 participants were classified into a possible sarcopenia group ($n = 500$) and a no possible sarcopenia group ($n = 1,261$).

Procedures

This study was approved by the Institutional Review Board of Kyung Hee University (approval no. 2024-05-035). Written informed consent was obtained from all KFACS participants prior to the interviews. We obtained anonymised and de-identified data from KFACS and handled them with caution to maintain privacy and confidentiality.

Variables

This study developed a predictive model of possible sarcopenia that did not require hospital visits or specialised equipment. Therefore, we included only self-reported questions and simple assessments of physical function and anthropometric measurements that could easily assess possible sarcopenia in a community setting, based on previous studies related to sarcopenia [10, 11] and available data from KFACS [20].

Possible sarcopenia

The primary outcome variable was the presence of possible sarcopenia. We defined possible sarcopenia according to the 2019 AWGS criteria using CC, SARC-F, and SARC-CalF for case finding, and handgrip strength and the five-times sit-to-stand test for the final group classification [8]. AWGS 2019 recommends either a CC < 34 cm for men or < 33 cm for women, or SARC-F ≥ 4, or SARC-CalF ≥ 11 as criteria for identifying sarcopenia case finding [8]. CC was measured bilaterally with participants standing upright; two measurements per side were obtained using a non-stretchable tape at the point of maximal girth, and the largest value across sides was used for analysis [8, 21]. SARC-F consisted of five items—strength, assistance with walking, rising from a chair, climbing stairs, and falls— with each item scored from 0 to 2 (range: 0–10) [22]. SARC-CalF is a combined criterion of CC measurement (10 points) and SARC-F (range: 0–10) [8]. Handgrip strength < 28 kg for men and < 18 kg for women or five times sit-to-stand test time ≥ 12 s were criteria for possible sarcopenia assessment [8]. Handgrip strength was measured using a digital handgrip dynamometer (T.K.K.5401; Takei Scientific Instruments Co., Ltd., Tokyo, Japan) [20]. Participants were instructed to stand straight with their shoulders in a neutral position, arms to the sides with elbows fully extended, and squeeze the handle with one hand as hard as possible for three seconds [20]. Each hand was measured twice and expressed in kilograms. The highest measurement from any hand was used as the handgrip strength for this study [8]. The five-times sit-to-stand test measures the time required to stand up five times from a sitting position without using the arms in a straight-backed armchair. Participants were asked to stand up and sit down five times as quickly as possible. The time taken from the first sitting position, when the examiner said 'Go', to a fully upright position at the end of the fifth stand was measured to the nearest 0.01 s [23].

Sociodemographic characteristics

Sociodemographic characteristics were assessed based on participants' age, sex, educational levels, living arrangements, and living security recipients. Educational levels were classified as elementary school graduation or lower, middle school, and high school or higher. Living arrangements were dichotomised as living alone or living with someone. We categorised either National Basic Living Security or National Medical Aid beneficiaries as living security recipients and those who were not beneficiaries as non-recipients.

Health status characteristics

Health status variables included diagnosed diseases, vision problems, hearing aid use, walking aid use, fall experiences, fear of falling, and hospitalisation or long-term care facility (LTCF) admission during the past year. Diagnosed diseases were assessed to determine whether participants had been diagnosed with diabetes, hypertension, dyslipidaemia, any type of cancer, chronic diseases (e.g. cardiovascular diseases, cerebrovascular diseases, gastroenteric diseases, osteoarthritis, rheumatoid arthritis, chronic obstructive pulmonary disease, and asthma), or mental illness (depression, anxiety). All variables were reported as 'yes' or 'no'. Fear of falling was assessed by the question, 'Are you afraid of falling?' with four response options: never, occasionally, often, and very often. Responses were dichotomised as 0 = never and 1 = occasionally/often/very often [24].

Health behavioural and physical characteristics

Smoking, alcohol drinking, unintentional weight loss, nutritional status, activities of daily living (ADLs), instrumental activities of daily living (IADLs), and physical activity were assessed for health behavioural and physical characteristics. Smoking, alcohol drinking, and unintentional weight loss of 4.5 kg or more over the past year were recorded as binary responses (yes/no). Nutritional status was evaluated using the Mini-Nutritional Assessment-Short Form (MNA-SF), a widely used and validated screening tool for identifying nutritional risk in older adults [20]. According to the MNA-SF scoring system

(6 items; score range: 0–14), a score of 12–14 indicates normal nutritional status, 8–11 indicates a risk of malnutrition, and 0–7 indicates malnutrition [25]. ADLs and IADLs were assessed using the Korean Activities of Daily Living (K-ADL) and Korean Instrumental Activities of Daily Living (K-IADL) scales, respectively [26]. Physical activity was assessed using the International Physical Activity Questionnaire (IPAQ), a widely recognised standard instrument for evaluating physical activity levels such as vigorous, moderate, and walking activity. Physical activity levels were calculated according to the IPAQ scoring protocol and expressed in metabolic equivalent minutes per week, reflecting energy expenditure [27].

Psychological and cognitive characteristics

Exhaustion, cognitive function, overall health status, and depressive symptoms were included for psychological and cognitive characteristics. Exhaustion captures perceived fatigue or low energy and reflects reduced physiological reserve [1]. Exhaustion was defined based on a 'yes' response to one of the following items from the Centre for Epidemiologic Studies Depression Scale (CES-D) on three or more days per week: 'I felt that everything I did was an effort' and 'I could not get going' [1, 20]. Cognitive function was assessed using the Mini-Mental State Examination in the Korean version of the Consortium to Establish a Registry for Alzheimer's Disease (CERAD) assessment packet (MMSE-KC), with a total score ranging from 0 to 30 and lower scores indicating a decline in cognitive function [28]. Overall health status was measured using the EuroQol visual analogue scale (EQ-VAS), with values between 0 (worst imaginable health) and 100 (best imaginable health) [29]. Depressive symptoms were assessed using the Korean version of the Geriatric Depression Scale–Short Form (SGDS-K) [20]. The SGDS-K consists of 15 dichotomous (yes/no) items designed to screen for depressive symptoms in older adults, with a total score ranging from 0 to 15. Higher scores indicate more depressive symptoms [30].

Anthropometric measurements and physical performance

BMI was calculated as the weight in kilograms divided by the height in meters squared (kg/m^2) and was used as a continuous variable in the analysis. In the KFACS, body weight was measured using a calibrated digital scale and height with a stadiometer, both assessed by trained staff following standardised protocols [20]. Physical performance was assessed based on walking speed over four meters, and the average of two trials was used for analysis, following the KFACS protocol [20].

Data analysis

To explore participants' characteristics and compare the possible sarcopenia and no possible sarcopenia subgroups, descriptive and frequency analyses, independent t-tests, and chi-squared tests were performed using Jeffrey's Amazing Statistics Program (JASP), an open-source software package. We assessed distributional assumptions using the Shapiro–Wilk test and Q–Q plots, and evaluated homogeneity of variance using Levene's test, where applicable. Although the Shapiro–Wilk tests indicated deviations from normality (p <.05), the large sample sizes (n = 500 and n = 1,261) justified the use of parametric tests under the central limit theorem [31, 32]. Continuous variables were summarised as median with interquartile range (IQR). Group comparisons in participant characteristics were performed using independent t-tests for continuous variables and chi-squared tests for categorical variables, as appropriate. Analyses were conducted with available data; missing values ranged from 0.0 to 3.8% across variables. All tests were two-sided tests with a significance level of 0.05. We implemented predictive model development based on machine learning algorithms using the open-source service Google Colaboratory and the Python programming language.

Development of predictive models using machine learning algorithms

We used machine learning methods and documented the procedures and findings in accordance with established guidelines for biomedical research involving machine learning, as outlined by a consortium of multidisciplinary experts [33].

Splitting the training and test datasets

The dataset was partitioned into training (n = 1,408) and test (n = 353) sets at an 8:2 ratio to facilitate the development and evaluation of the machine learning models. We employed a stratified split to maintain class allocation in both the training and test sets, consistent with the original dataset, and address the class imbalance between the no possible sarcopenia (n = 1,261) and possible sarcopenia (n = 500) groups. Stratified splitting is essential for handling imbalanced datasets, as it enhances model performance on minority classes and ensures the reliability of performance evaluation [34]. Supplementary Table S1 provides a detailed comparison of the baseline characteristics between the training and test sets.

Data preprocessing

Data preprocessing involved data cleaning and transformation. First, we explored the selected data and handled missing values by imputing the most frequent values for categorical variables using SimpleImputer and replacing the mean values for continuous variables due to missing data, less than 3.8% in this study [35]. Subsequently, one-hot encoding was applied to the categorical variables, and standardisation using StandardScaler (mean = 0,

standard deviation = ± 1) was performed on continuous variables to convert the data into a format suitable for machine learning modelling.

Feature selection

During the initial model-building phase, we utilised 32 features as independent variables selected based on domain knowledge and statistical significance identified through the analysis of participants' characteristics. Next, we used recursive feature elimination (RFE) with a random forest classifier to select the optimal features from the training set. RFE is an effective feature selection approach that iteratively removes the least significant variables until models are built with the desired number of variables [36]. The following top 15 features were selected: BMI, cognitive function, age, overall health status, walking physical activity, depressive symptoms, moderate physical activity, IADL, walking aid use, fear of fall, educational level, exhaustion, nutritional status, ADL, and sex.

Model development

We employed machine learning algorithms for classification, comprising logistic regression, random forest, support vector machine (SVM), and extreme gradient boosting (XGBoost), to develop a predictive model for possible sarcopenia using the training dataset. The synthetic minority oversampling technique (SMOTE) was employed during the training phase to address the class imbalance between individuals without and with possible sarcopenia (2.5:1 ratio). SMOTE enhances the representation of minority classes by generating synthetic samples through interpolation between existing minority instances in the feature space. This approach mitigates the risk of model bias toward the majority class, which is a common issue in imbalanced datasets [37]. By improving the representativeness of the minority class, SMOTE contributes to the development of more robust and generalisable predictive models, particularly by ensuring adequate sensitivity to the underrepresented class [37]. Before applying SMOTE, the training set comprised 400 cases of possible sarcopenia (class 1) and 1,008 cases of no possible sarcopenia (class 0). After applying SMOTE, the class distribution was balanced, resulting in 1,008 cases under both classes.

Evaluation of model performance

We evaluated model performance using accuracy, precision, recall, F1-score, and receiver operating characteristic curve area–under the curve (ROC AUC) score. Accuracy reflects the proportions of all observations, regardless of class, that are correctly identified by the model, whereas precision represents the proportion of predicted positive instances that are true positives [38]. Recall, also known as sensitivity in psychological research, measures the proportion of true positive cases that are accurately predicted as positive. The F1-score, representing the harmonic average of precision and recall, is especially valuable in imbalanced classification tasks where accuracy alone may be misleading [39]. For the intended use of screening for possible sarcopenia in this study, recall and F1-score were mainly assessed to ensure both high sensitivity and overall discriminative ability. Recall is prioritised as a key evaluation metric, reflecting the critical importance of detecting all true-positive cases in healthcare settings, while the F1-score provides a balanced view of model performance by addressing both false positives and false negatives [39]. The ROC AUC score was also assessed as a global measure of diagnostic accuracy, ranging from 0.5 (no discrimination) to 1.0 (perfect discrimination), with values between 0.7 and 0.8 considered acceptable and those above 0.8 considered excellent [39, 40]. The model with the highest recall and F1-score was selected as the final predictive model.

Feature importance

To evaluate the contribution of each feature to the prediction of possible sarcopenia, we calculated Shapley additive explanations (SHAP) values using the best-performing predictive model. SHAP provides a theoretically grounded and model-agnostic framework for quantifying the contribution of each feature to the model's predictions [41]. This approach systematically evaluates and ranks important predictors, which enhances model transparency and facilitates the interpretation of results.

Results

General characteristics of participants and possible sarcopenia group

Table 1 shows the general characteristics of the study participants stratified by the possible sarcopenia group based on the AWGS 2019 criteria. Of the 1,761 study participants, 500 were categorised as having possible sarcopenia (28.4%) and 1,261 as having non-possible sarcopenia (71.6%). The mean age of participants was 81.6 ± 3.62 (median age = 81) years. Of the total sample, 53.3% were women and 46.7% were men.

Compared with the no possible sarcopenia group, the possible sarcopenia group was significantly older, had lower educational levels, and had higher rates of living alone and being a living security recipient (all p-values ≤ 0.05). Compared with the group of no possible sarcopenia, the possible sarcopenia group showed lower mean BMI; higher rates of using a walking aid, fall experiences, hospital or LTCF admission during the past year, being at risk of malnutrition or malnutrition, unintentional weight loss, and exhaustion status; and lower rates

Table 1 General characteristics of participants according to possible sarcopenia status (*N* = 1761)

Variables (available data, *n*)	Total participants (*N* = 1761)	Possible sarcopenia (*n* = 500)	No possible sarcopenia (*n* = 1261)		
	Median [IQR] or *n* (%)	Median [IQR] or *n* (%)	Median [IQR] or *n* (%)	t or x^2	*p*
Sociodemographic characteristics					
Age (years)	81 [79–84]	83 [80–86]	81 [78–83]	−10.358	< 0.001
Sex				42.677	<0.001
Men	823 (46.7)	172 (34.4)	651 (51.6)		
Women	938 (53.3)	328 (65.6)	610 (48.4)		
Educational level (n=1759)*				77.890	<0.001
≤ Elementary school	792 (45.0)	307 (61.5)	485 (38.5)		
Middle school	276 (15.7)	62 (12.4)	214 (17.0)		
≥ High school	691 (39.3)	130 (26.1)	561 (44.5)		
Living arrangement (n=1760)*				22.438	<0.001
Living alone	506 (28.7)	184 (36.9)	322 (25.5)		
Living with someone	1254 (71.3)	315 (63.1)	939 (74.5)		
Living security recipient (*n* = 1752)*	119 (6.8)	44 (8.9)	75 (6.0)	4.859	0.027
Health status characteristics					
Diagnosed diseases					
Diabetes (*n* = 1760)*	450 (25.6)	148 (29.6)	302 (24.0)	8.643	0.013
Hypertension (*n* = 1758)*	1111 (63.1)	308 (61.6)	803 (63.7)	0.686	0.710
Dyslipidaemia (*n* = 1751)*	857 (48.7)	207 (41.4)	650 (51.5)	15.520	< 0.001
Any type of cancer	108 (6.1)	38 (7.6)	70 (5.6)	2.611	0.106
Other chronic diseases	1312 (74.5)	388 (77.6)	924 (73.3)	3.525	0.060
Mental diseases	210 (11.9)	72 (14.4)	138 (10.9)	4.072	0.044
Vision problems (*n* = 1725)*	466 (26.5)	120 (24.8)	346 (27.9)	1.602	0.206
Hearing aid use (*n* = 1754)*	163 (9.3)	44 (8.9)	119 (9.4)	0.122	0.727
Walking aid use (*n* = 1701)*	185 (10.5)	131 (28.5)	54 (4.4)	201.543	< 0.001
Fall experience (*n* = 1760)*	426 (24.2)	163 (32.6)	263 (20.9)	26.832	< 0.001
Fear of falling (*n* = 1758)*	1315 (74.8)	424 (85.1)	891 (70.7)	39.409	< 0.001
Hospitalisation in the past year (*n* = 1759)*	264 (15.0)	98 (19.7)	166 (13.2)	11.878	< 0.001
LTCF admission in the past year (*n* = 1760)*	10 (0.6)	6 (1.2)	4 (0.3)	4.959	0.026
Health behavioural and physical characteristics					
Current smoker	56 (3.2)	13 (2.6)	43 (3.4)	0.763	0.382
Alcohol drinker	450 (25.6)	92 (18.4)	358 (28.4)	18.783	< 0.001
Unintentional weight loss (*n* = 1734)*	145 (8.2)	55 (11.3)	90 (7.2)	7.693	0.006
MNA-SF (*n* = 1754)*					
Normal	1416 (80.4)	324 (65.3)	1092 (86.8)	114.263	< 0.001
At risk of malnutrition	321 (18.2)	158 (31.9)	163 (13.0)		
Malnutrition	17 (1.0)	14 (2.8)	3 (0.2)		
Total K-ADL (7–16)	7 [7–7]	7 [7–8]	7 [7–7]	−6.715	< 0.001
Total K-IADL (10–32)	10 [10–10]	10 [10–12]	10 [10–10]	−8.002	< 0.001
Vigorous activity (METs-min/week)	0 [0–0]	0 [0–0]	0 [0–0]	2.607	0.009
Moderate activity (METs-min/week)	240 [0–1440]	0 [0–840]	400 [0–1680]	2.285	0.023
Walking activity (METs-min/week)	924 [462–1386]	693 [297–1386]	990 [594–1617]	6.844	< 0.001
Psychological and cognitive characteristics					
Exhaustion (*n* = 1758)*	483 (27.4)	222 (44.4)	261 (20.7)	101.051	< 0.001
MMSE-KC_score (0–30) (*n* = 1748)*	27 [24–28]	25 [22–27]	27 [25–28]	11.888	< 0.001
EQ-VAS (0–100) (*n* = 1754)*	75 [60–85]	70 [50–80]	80 [70–90]	10.512	< 0.001
SGDSK-score (0–15) (*n* = 1756)*	2 [0–5]	4 [1–8]	2 [0–4]	−9.571	< 0.001
Anthropometric measurements and physical performance					

Table 1 (continued)

Variables (available data, *n*)	Total participants (*N* = 1761)	Possible sarcopenia (*n* = 500)	No possible sarcopenia (*n* = 1261)		
	Median [IQR] or *n* (%)	Median [IQR] or *n* (%)	Median [IQR] or *n* (%)	t or x^2	*p*
BMI (kg/m^2) (*n* = 1759)*	24.02 [21.96–26.17]	22.47 [20.61–24.61]	24.63 [22.61–26.52]	10.602	< 0.001
Four-meter walking speed (m/sec) (*n* = 1694)*	1.02 [0.88–1.18]	1.21 [1.05–1.45]	0.96 [0.86–1.09]	−14.131	< 0.001

Continuous variables were non-normally distributed and are reported as median [IQR]; categorical variables are shown as n (%). Group comparisons used independent t-tests or χ^2 tests, as appropriate. *Analyses were conducted with available data; missing values ranged from 0.0 to 3.8% across variables

Abbreviations: BMI body mass index, *EQ-VAS* EuroQol Visual Analogue Scale, *IQR* interquartile range, *K-ADL* Korean Activities of Daily Living, *K-IADL* Korean Instrumental Activities of Daily Living, *LTCF* long-term care facilities, *METs* metabolic equivalents, *MMSE-KC* Mini-Mental State Examination in the Korean version of the Consortium to Establish a Registry for Alzheimer's Disease (CERAD) assessment packet, *MNA-SF* Mini Nutritional Assessment-Short Form, *SGDSK* Korean version of the Geriatric Depression Scale-Short Form

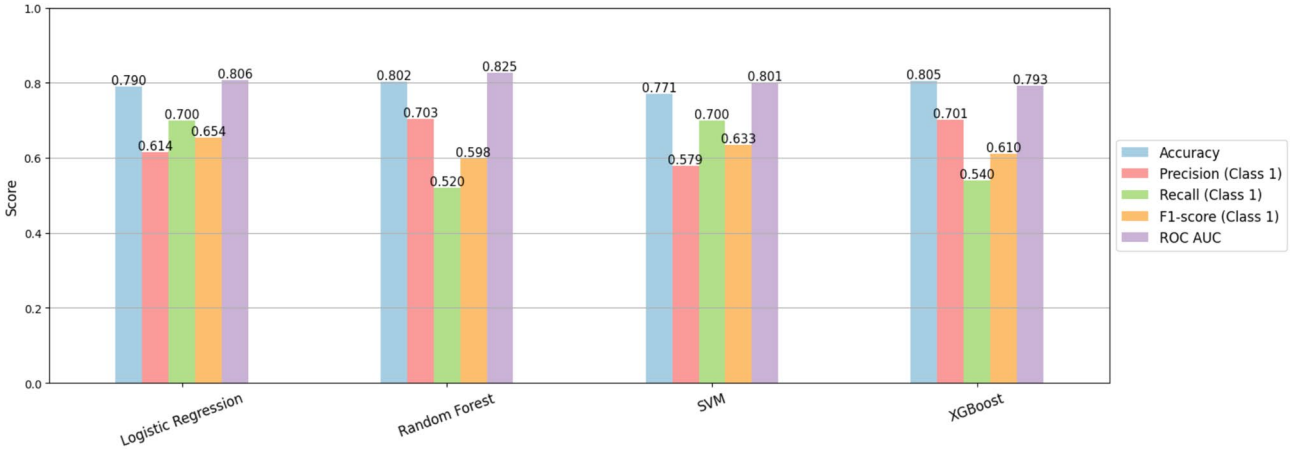

Fig. 2 Model performance comparison across multiple metrics. Abbreviations: ROC AUC, receiver operating characteristic curve area under the curve; SVM, support vector machine; XGBoost, extreme gradient boosting

of alcohol drinking (all *p*-values ≤ 0.05). The possible sarcopenia group also reported poorer general health status, cognitive function, and physical activities, more functional impairments based on ADLs and IADLs, higher depressive symptoms, and a longer four-meter walking speed compared with the no possible sarcopenia group (all *p*-values ≤ 0.05).

Performance of predictive models

Figure 2 illustrates the comparative analysis of model performance across evaluation metrics (accuracy, precision, recall, F1-score, and ROC AUC) for the models developed using logistic regression, random forest, SVM, and XGBoost algorithms to classify possible sarcopenia. All models achieved a consistent ROC AUC of 0.793 or higher on the test set, indicating moderate or excellent overall discriminative performance. Among the four models, logistic regression was selected as the optimal predictive model for possible sarcopenia, demonstrating the highest recall (0.700) and F1-score (0.654), along with the ROC AUC of 0.806 (95% confidence interval [CI] = 0.744–0.863). These results indicate high sensitivity in detecting true-positive cases and a well-balanced discriminative performance. Although the random forest model achieved the highest ROC AUC (0.825, 95% CI = 0.769–0.874), its lower recall (0.520) may have resulted in missed cases, making it less appropriate for screening purposes. SVM also produced comparable recall (0.700) but a slightly lower F1-score (0.633), while XGBoost showed balanced performance but with suboptimal recall (0.540).

Feature importance

Figure 3 shows the SHAP values derived from the logistic regression model. The model had the highest recall and F1-score among the evaluated models. In this model, BMI, walking aid use, cognitive function, age, and exhaustion were identified as the five most influential predictors. SHAP analysis indicated that lower BMI, walking aid use, cognitive impairment, older age, and exhaustion were significant contributors to predicting possible sarcopenia.

Discussion

This study was conducted to develop a machine learning based model to predict possible sarcopenia using readily obtainable measures and to determine the most informative predictors to guide early identification and referral. This can enable risk screening without physical performance tests or specialised equipment (e.g. DXA/

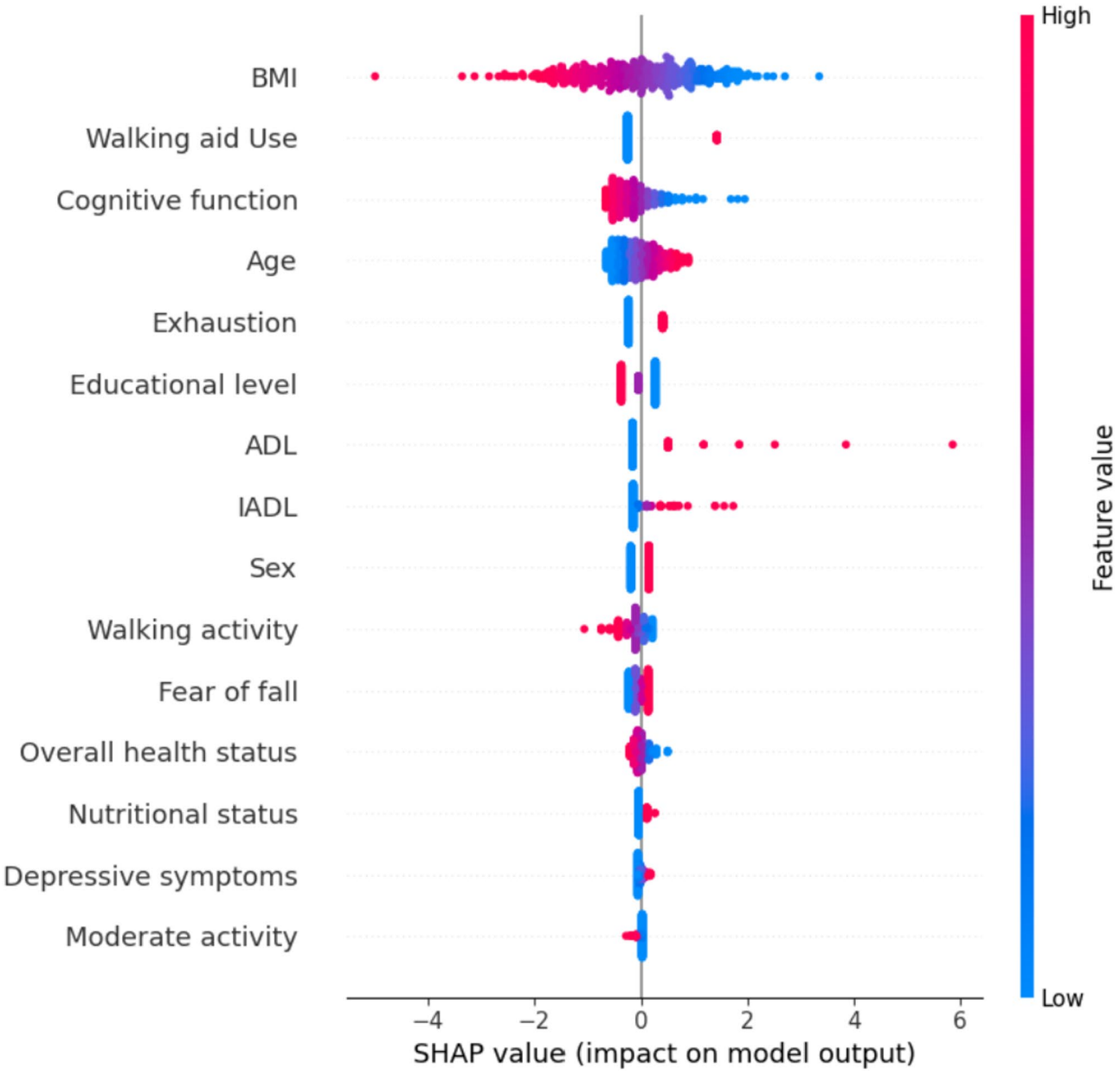

Fig. 3 Top important features in the logistic regression model for predicting possible sarcopenia. Abbreviations: BMI, body mass index; ADL, activities of daily living; IADL, instrumental activities of daily living; SHAP, Shapley additive explanations

BIA), thus fitting with community screening and digital health deployment. Across the algorithms, the logistic regression model was ultimately selected, and five features—BMI, walking aid use, cognitive function, age, and exhaustion— emerged as the most informative predictors, consistent with prior evidence indicating that individuals with possible sarcopenia tend to have lower BMI, poorer mobility, greater cognitive impairment, and older age [10–12, 42]. Since the required inputs can be collected via brief measurements and questionnaires, the model is readily adaptable to community health services and could be integrated into existing screening infrastructures. For instance, Korea's National General Health Screening Program includes not only routine basic disease screening every other year but also nutrition questionnaires, fall history, physical performance tests (Timed Up and Go and balance), the Patient Health Questionnaire-9, and osteoporosis screening for adults aged ≥ 54 years, with examination scheduled at designated ages [43]. The program also screens for frailty and links results to appropriate services [43]. Therefore, we recommend routine screenings for possible sarcopenia using the brief items identified in this study at public healthcare centres to enable early identification and

timely, multifaceted prevention, thereby improving quality of life for older adults. In addition, digital health applications implementing this predictive algorithm can be developed for community screening.

This study ultimately selected the logistic regression as a predictive model for possible sarcopenia after evaluating four machine learning algorithms. In screening-oriented applications, the balance between recall (sensitivity) and overall discrimination (AUC) is critical. While the random forest model in our study achieved a higher ROC AUC (0.825), its substantially lower recall (0.520) and F1-score (0.598) at clinically relevant thresholds imply more missed cases, undermining its value for case finding. By contrast, logistic regression yielded a higher recall (0.700) with a solid F1-score (0.654) and a competitive AUC (0.806), making it more suitable in this context. This trade-off reflects a broader principle: Screening tools must prioritise sensitivity to minimise false negatives, given the potential clinical and public health costs of undetected cases [39]. Moreover, ROC AUC, being threshold-independent, may obscure inadequate sensitivity at a chosen decision threshold, particularly in imbalanced datasets [44]. In addition, the F1-score—the harmonic mean of precision and recall—is important because it summarises performance by balancing false positives and false negatives [39]. Our findings supported that, for screening purposes, prioritising recall with acceptable F1-score and AUC is more clinically meaningful than maximising AUC alone.

Lower BMI was the most informative anthropometric predictor of possible sarcopenia in this study. BMI is a widely used screening tool for classifying weight status–underweight, overweight, and obesity– based on body weight and height [45]. Older adults frequently show a J-shaped association between BMI and mortality. Underweight and unintentional weight loss are consistently linked to higher mortality, whereas overweight often shows neutral or lower risk relative to the normal range [46, 47]. Consistent with geriatric nutrition guidance, routine intentional weight loss is generally not recommended for overweight older adults in the absence of obesity-related complications [48]. These patterns indicated that low BMI should trigger targeted evaluation for possible sarcopenia. Chalemsri et al. proposed assessing mortality risk using a combination of BMI and possible sarcopenia severity rather than relying on either factor alone [47]. Given the predictive value of low BMI for possible sarcopenia, older adults with low BMI should be evaluated for possible sarcopenia. Early, multifaceted intervention including nutrition support, and progressive resistance exercise with physical performance training should be prioritised to prevent progression of sarcopenia and related adverse outcomes.

Walking aid use is commonly linked to reduced mobility and muscle weakness and, in our study, was a key predictor of possible sarcopenia. Walking aids—canes, walkers, rollators—are designed to improve mobility [49]. However, the association likely reflects reverse causation. Skeletal muscle loss compromises independent ambulation and precipitates walking aid adoptions [50]. Many community-dwelling older adults adopt walking aids based on perceived functional decline, often without objective assessment [51]. Since walking aid use is directly observable and implies muscle weakness [49, 50], these individuals should be prioritised for screening and intervention for possible sarcopenia.

Cognitive impairment emerged as a predictor of possible sarcopenia in this study, aligning with prior evidence that sarcopenia is associated with a higher prevalence of cognitive impairment than in non-sarcopenic peers [10, 42]. Older adults with sarcopenia are more likely to experience impairments in both cognitive and physical functions than those without sarcopenia, and this link appears to be driven more by muscle strength than by muscle mass [52]. In the aforementioned study, participants in the lowest quartile of handgrip strength (low muscle strength) had a significantly higher likelihood of the combined cognitive–physical impairment index (odds ratio [OR] 2.673, 95% CI = 1.213–5.627), whereas low muscle mass was not significant (OR 1.946, 95% CI = 0.816–4.639) [52]. These findings support the close association between cognitive function and handgrip strength–a core screening criterion for possible sarcopenia– and support the potential value of interventions combining muscle strengthening with cognitive function training for individuals at risk of possible sarcopenia.

Exhaustion was also identified as one of the key predictors of possible sarcopenia. It represents perceived fatigue or low energy, reflecting diminished physiological reserve, and is a core frailty domain [1, 20]. In this study, it was assessed using two items: 'I felt that everything I did was an effort' and 'I could not get going', which reflect a multidimensional concept involving a sense of low energy and disrupted energy balance. Exhaustion is one of the five components of the frailty phenotype and has been revealed as an early indicator of the onset of frailty [53]. Self-reported exhaustion may serve as an important signal for highlighting individuals who are more likely to benefit from targeted screening for sarcopenia or possible sarcopenia. The findings suggest that early detection of exhaustion may aid in identifying individuals at risk for possible sarcopenia, thereby enabling timely interventions to prevent its progression.

Other limitations of this research include the following. First, we used data from a cohort consisting of Korean individuals aged 75 years and older, which may limit the generalisability of the results to broader populations or

diverse ethnic groups. Further studies using multinational approaches or data for individuals aged 65 years and older are therefore warranted. Second, although the predictive models based on machine learning demonstrated strong performance, they were developed and validated using cross-sectional data, which prevents making inferences about temporal ordering, thus limiting causal interpretation. Future research should incorporate longitudinal datasets to better assess causal relationships. Nonetheless, machine learning approaches offer valuable opportunities to identify complex and multifactorial factors that may be overlooked when using traditional statistical methods. In addition, this study supports evidence showing that both physical performance and cognitive function are significantly associated with the prediction of possible sarcopenia.

Conclusions

In a logistic regression model developed within a machine learning framework, BMI, walking aid use, cognitive function, age, and exhaustion were the most informative variables. Our findings indicate that a multidomain set of geriatric indicators can guide simple screening for possible sarcopenia in community-dwelling older adults. Using simple, accessible assessments of these predictors may facilitate earlier identification and referral for diagnostic evaluation. These results support incorporating multidomain indicators into community screening and prevention strategies for sarcopenia.

Abbreviations

ADLs	Activities of daily living
AWGS	Asian Working Group for Sarcopenia
BIA	Bioelectrical impedance analysis
BMI	Body mass index
CC	Calf circumference
CES-D	Centre for Epidemiologic Studies Depression Scale
CI	Confidence interval
DXA	Dual x-ray absorptiometry
EQ-VAS	EuroQol visual analogue scale
IADLs	Instrumental activities of daily living
IPAQ	International Physical Activity Questionnaire
IQR	Interquartile range
KFACS	Korean Frailty and Aging Cohort Study
LTCF	Long-term care facility
MMSE-KC	Mini-Mental State Examination in the Korean version of the Consortium to Establish a Registry for Alzheimer's Disease (CERAD) assessment packet
MNA-SF	Mini-Nutritional Assessment-Short Form
OR	Odds ratio
RFE	Recursive feature elimination
ROC AUC	Receiver operating characteristic curve area under the curve
SARC-F	Strength, Assistance in walking, Rising from a chair, Climbing stairs, and Falls
SARC-CalF	SARC-F combined with CC
SHAP	Shapley additive explanations
SMOTE	Synthetic minority oversampling technique
SVM	Support vector machine
XGBoost	Extreme gradient boosting

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

SK, conceptualisation, methodology, data curation, formal analysis, visualisation, validation, writing original draft and review and revising, funding acquisition; LK, conceptualisation, methodology, and writing review and revising; JW, investigation, methodology, supervision, writing review and revising, funding acquisition; NK, preparation of data, assisting with statistical analysis and writing review and revising; JC, investigation, methodology, data curation, writing review and revising; MK, conceptualisation, investigation, methodology, data curation, writing review and revising, funding acquisition; GK, conceptualisation, methodology, supervision, validation, writing review and editing, funding acquisition. All authors critically reviewed the manuscript, conducted significant editing, and approved the final manuscript.

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Data availability

The data that support the findings of this study are available from the KFACS but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the corresponding authors upon reasonable request and with permission of KFACS.

Declarations

Ethics approval and consent to participate

Written informed consent was obtained from all KFACS survey participants prior to the interviews. The data were anonymised and de-identified to remove any personal information and protect participants' confidentiality. This secondary data analysis was approved by the Institutional Review Board of Kyung Hee University (approval no. 2024-05-035).

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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