Clinical Interventions in Aging

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ORIGINAL RESEARCH

# Multimodal AI Model for Sarcopenia Detection: Integrating Chest CT and Clinical Parameters in Older Adults

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**Background:** Sarcopenia, an age-related syndrome marked by progressive loss of skeletal muscle mass and function, is associated with frailty, disability, falls, and increased mortality among older adults. However, existing diagnostic methods, such as dual-energy X-ray absorptiometry (DXA) and physical performance tests, are often inaccessible in routine clinical practice due to equipment and time constraints.

**Objective:** This study aimed to develop and validated a multimodal, explainable AI model for identifying sarcopenia using routinely available chest CT scans and outpatient clinical data in older adults.

**Methods:** A total of 290 participants (mean age 67.6 ± 5.8 years; 38.9% female) were included. A weakly supervised segmentation framework combining the Segment Anything Model (SAM) and Contrastive Language-Image Pretraining (CLIP) was employed to extract muscle features at the T12 level. Clinical variables, including anthropometric indices, lifestyle behaviors, and biochemical markers, were encoded and fused with imaging-derived features. A multi-layer perceptron (MLP) was trained to classify sarcopenia based on 2019 AWGS criteria. Model interpretability was assessed using SHAP (Shapley Additive Explanations) values.

**Results:** The model achieved an AUC of 0.88 (95% CI: 0.83–0.92), accuracy of 0.85 (95% CI 0.82–0.89), sensitivity of 0.79 (95% CI: 0.70–0.987), and specificity of 0.88 (95% CI: 0.83–0.92). SHAP analysis revealed that gender, total triiodothyronine, creatine kinase, body mass index and creatinine were the most influential predictors. The fusion of weakly supervised learning and multimodal data enabled effective muscle region segmentation and improved diagnostic performance.

**Conclusion:** In summary, we developed and internally validated an explainable multimodal AI model that integrates chest CT–derived muscle features with routine outpatient clinical variables for sarcopenia detection in older adults. The model demonstrated strong diagnostic performance and interpretability, highlighting its potential for opportunistic risk stratification in routine clinical workflows. Future multi-center validation and prospective studies are warranted to confirm its generalizability and long-term clinical utility.

**Keywords:** sarcopenia, deep learning, chest CT, multimodal fusion, segment anything model, CLIP, SHAP, older adults, weakly supervised learning

## Introduction

Sarcopenia is an age-related syndrome characterized by progressive loss of skeletal muscle mass and function and is strongly associated with frailty, falls, disability, hospitalization, and increased mortality among older adults.[1–3] With accelerating global population aging, early identification and risk stratification of sarcopenia have become critical for preventive geriatric care. Current diagnostic approaches rely primarily on dual-energy X-ray absorptiometry (DXA), bioelectrical impedance analysis (BIA), and physical performance testing.[4] However, these methods require dedicated equipment and clinical time, limiting their integration into routine outpatient workflows and large-scale screening programs.

https://doi.org/10.2147/CIA.S590955
Received: 7 January 2026
Accepted: 18 March 2026
Published: 18 April 2026

Computed tomography (CT) has emerged as a promising modality for opportunistic body composition analysis.[5] Single-slice CT–derived muscle measurements correlate strongly with whole-body skeletal muscle mass and have been widely applied in oncologic and geriatric populations.[6–8] Although abdominal CT at the L3 level has been most frequently studied,[9] thoracic levels-including T12-also demonstrate reliable associations with systemic muscle mass and adverse outcomes.[10–13] Given the widespread use of chest CT for cardiopulmonary evaluation, leveraging these routinely acquired scans for sarcopenia assessment offers a scalable and cost-effective strategy. Nevertheless, existing CT-based studies remain heterogeneous in anatomical level selection and segmentation methodology, and many rely on manual or semi-automated workflows, limiting scalability and clinical implementation.

Recent advances in artificial intelligence (AI) and deep learning have enabled automated muscle segmentation and quantitative feature extraction from CT data, with several studies demonstrating robust performance of convolutional neural networks (CNNs) in this domain, substantially reducing manual workload and improving reproducibility.[14–16] Furthermore, multimodal learning frameworks integrating imaging biomarkers with structured clinical variables have demonstrated superior predictive performance compared with single-modality models in various medical applications.[17,18] However, most CT-based sarcopenia models remain imaging-centric and rarely incorporate routinely available outpatient clinical parameters within a unified framework, potentially restricting generalizability and real-world translation.

In addition, limited model interpretability represents a barrier to clinical adoption. Complex machine learning systems are often perceived as "black boxes," which may undermine clinician trust.[19,20] Explainable AI (XAI) techniques, such as Shapley Additive Explanations (SHAP), provide quantitative insights into feature contributions at both global and individual levels, thereby enhancing transparency and facilitating clinical understanding.[21,22] Despite these methodological advances, explainable multimodal AI models leveraging routinely acquired chest CT and outpatient data for opportunistic sarcopenia detection remain insufficiently explored.

Therefore, we developed and internally validated an explainable multimodal AI model integrating chest CT–derived T12 muscle features with routinely collected outpatient clinical variables for opportunistic sarcopenia detection in older adults. By combining scalable automated segmentation with interpretable multimodal prediction, this study aims to address current limitations in CT-based sarcopenia assessment and provide a clinically feasible framework for early identification in routine practice.

# Materials and Methods

## Study Population and Data Collection

A total of 290 adults aged ≥ 60 years from Huzhou Central Hospital (2022–2024) who underwent chest CT and comprehensive geriatric assessment were included. Sarcopenia was defined according to the 2019 AWGS criteria, combining low muscle mass and decreased strength or function. All participants provided informed consent, and the study was approved by the institutional ethics committee (Approval No. HZCH2021-031). Exclusion criteria included active cancer, acute infection, or advanced organ failure.

## CT Imaging Protocol and Muscle Feature Extraction

A weakly supervised segmentation framework based on the Segment Anything Model (SAM) and Contrastive Language–Image Pretraining (CLIP) was employed to extract skeletal muscle regions at the T12 vertebral level. The model was pretrained on annotated datasets and fine-tuned for thoracic anatomy using weak labels. Two experienced radiologists independently reviewed all segmentation outputs, confirming that > 95% were clinically acceptable without manual correction.

## Clinical Variables

Clinical parameters included age, sex, BMI, anthropometric indices (eg., calf circumference), lifestyle factors (smoking, drinking, exercise), and biochemical markers (albumin, CK, creatinine, T3, etc). Missing values (< 10%) were imputed using KNN (k = 5), while variables with higher missing rates were excluded. Zero-padding was applied to missing components in high-dimensional image embeddings to represent missingness during multimodal fusion. All continuous variables were standardized before modeling.

## Model Development and Evaluation

A multimodal AI architecture was developed to integrate imaging and clinical features. Feature vectors extracted from chest CT images and clinical variables were concatenated and fed into a multi-layer perceptron (MLP) classifier. To mitigate class imbalance (42 sarcopenia vs 248 non-sarcopenia cases), SMOTE-based oversampling and weighted sampling were applied to the training data, while the original ratio was preserved in the validation set.

Model training was conducted using Python 3.10, PyTorch 2.1.2, Torchvision 0.16.2, and PyTorch Lightning 2.1.3, with additional libraries (scikit-learn 1.3.2, time 0.9.12, SHAP $\geq$ 0.42).

Performance was evaluated using five-fold stratified cross-validation, reporting accuracy, sensitivity, specificity, AUC, and 95% confidence intervals. Model interpretability was assessed using Shapley Additive exPlanations (SHAP), which quantifies the contribution of each predictor to the model output. This interpretive framework enhanced transparency and facilitated clinical understanding of the AI decision-making process. All statistical analyses were performed in Python; $p < 0.05$ was considered statistically significant.

# Results

## Participants Selection

A total of 320 patients aged ≥60 years were initially assessed for eligibility. Thirty patients were excluded due to missing chest CT scans (n=15), incomplete clinical or laboratory data (n=10), or other reasons (n=5). Finally, 290 participants were included in the analysis. According to the 2019 AWGS reference standard, 42 participants (11.5%) were diagnosed with sarcopenia and 248 (88.5%) were classified as non-sarcopenia. All participants were included in the AI model evaluation. The flow of participants through the study is shown in Figure 1.

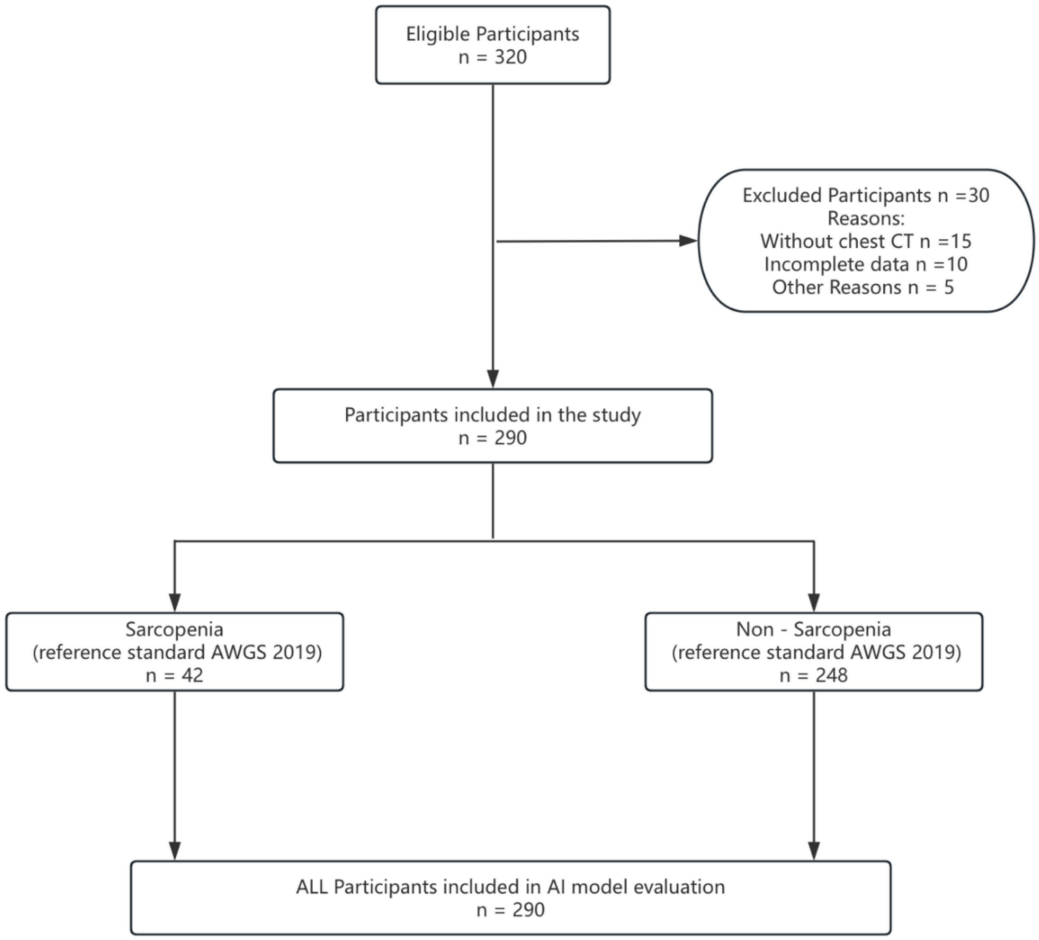


**Figure 1** STARD flow diagram of participant selection and analysis in the study.


https://doi.org/10.2147/CIA.S590955

**Table 1** Overall and Cross-Validation Performance of the Multimodal MLP Model (Stratified 5-Fold)

| Fold | Accuracy (95% CI) | AUC (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|
| Overall | 0.85(0.82–0.89) | 0.88(0.83–0.92) | 0.79(0.70–0.87) | 0.88(0.83–0.92) |
| Fold 1 | 0.87(0.79–0.94) | 0.93(0.86–0.98) | 0.83(0.64–1.00) | 0.88(0.79–0.96) |
| Fold 2 | 0.93(0.87–0.99) | 0.92(0.82–0.99) | 0.83(0.64–1.00) | 0.96(0.90–1.00) |
| Fold 3 | 0.81(0.71–0.90) | 0.83(0.70–0.93) | 0.61(0.38–0.82) | 0.88(0.79–0.96) |
| Fold 4 | 0.74(0.63–0.84) | 0.81(0.69–0.92) | 0.78(0.56–0.95) | 0.73(0.60–0.85) |
| Fold 5 | 0.91(0.84–0.97) | 0.91(0.82–0.98) | 0.89(0.72–1.00) | 0.92(0.85–0.98) |

**Abbreviations**: AUC, area under the curve; CI, confidence interval.

## Baseline Characteristics

The mean age of participants was 67.6 ± 5.8 years, and 38.9% were female. Compared with those without sarcopenia, patients with sarcopenia had significantly lower BMI (20.0 vs. 23.6 kg/m$^2$, p<0.001), smaller calf circumference (30.0 vs. 33.4 cm, p<0.001), and lower serum albumin (37.5 vs. 39.6 g/L, p=0.007).

## Model Performance

The model yielded an overall accuracy of 0.85 (95% CI 0.82–0.89), AUC of 0.88 (95% CI 0.83–0.92), sensitivity of 0.79 (95% CI 0.70–0.87), and specificity of 0.88 (95% CI 0.83–0.92). Across five cross-validation folds, the model demonstrated stable and robust discrimination (AUC range = 0.81–0.93; accuracy = 0.74–0.93), as summarized in Table 1, confirming the internal validity and generalizability of the proposed model. Figure 2 illustrates the receiver operating

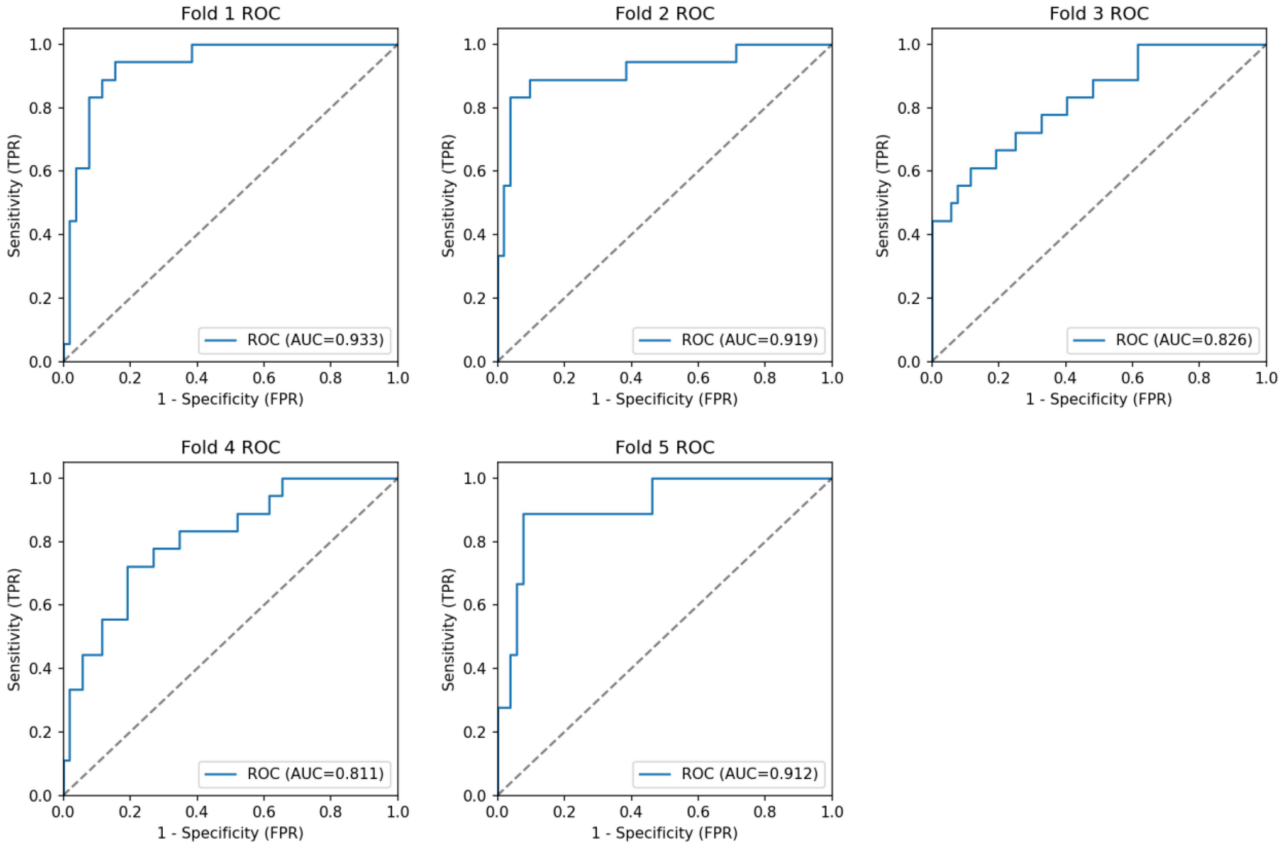


**Figure 2** Receiver operating characteristic (ROC) curves across the five cross-validation folds.

characteristic (ROC) curves across the five folds, showing consistent model performance and supporting the robustness of the multimodal AI model.

Further SHAP beeswarm analysis revealed distinct directional effects of the key predictors (see details in Figure 3A). Male sex predominantly contributed positive SHAP values, indicating higher risk, while female sex showed a protective effect. For total triiodothyronine (T3), lower values clustered in the positive SHAP range, suggesting increased risk, whereas higher values were associated with protection. High creatine kinase (CK) values clustered in the negative SHAP range, indicating a protective effect, while lower CK values were associated with increased risk. Body mass index (BMI) showed that low values increased risk, while higher values exerted a protective effect. In contrast, creatinine demonstrated an opposite pattern, where higher values were associated with increased risk and lower values appeared protective.

To complement these qualitative trends, quantitative SHAP analysis was performed across the entire test set. The top five features ranked by mean absolute SHAP value were gender (0.05), TT3 (0.03), CK (0.03), BMI (0.03) and Creatine (0.03). These values indicate the relative magnitude of each predictor's contribution to model output, improving transparency in feature importance interpretation. To further illustrate case-level interpretability, Figure 3B presents an individual prediction example.

## Discussion

This study demonstrates the feasibility of AI-enabled multimodal integration of chest CT and routine clinical data for opportunistic sarcopenia assessment in older adults. Beyond high diagnostic accuracy, the incorporation of SHAP-based interpretability allows clinicians to understand how each variable contributes to risk estimation, thereby enhancing transparency and trust in clinical decision-making.

The SHAP beeswarm analysis highlights the clinical relevance of several key predictors. Male sex was associated with higher predicted risk, consistent with known sex-related differences in muscle mass distribution.[23,24] Low T3 values were linked to increased risk, aligning with the "low T3 syndrome" commonly observed in chronic illness or malnutrition.[25–27] Similarly, low CK levels contributed to higher risk, possibly reflecting muscle reserve, while higher CK levels appeared protective in this context. Low BMI increased predicted risk, whereas moderately higher BMI exerted a protective effect, consistent with the so-called "obesity paradox", where greater energy and muscle reserves may confer survival advantage.[28,29] In contrast, elevated creatinine was associated with increased risk, potentially reflecting metabolic or renal burden. Collectively, these findings emphasize the multidimensional nature of sarcopenia, involving nutritional status, endocrine regulation, and metabolic balance.[30,31]

Our results are consistent with the expanding literature on CT-derived muscle biomarkers. Prior studies using abdominal CT at the L3 level have demonstrated associations between low skeletal muscle mass and adverse outcomes, including postoperative complications and mortality. By leveraging thoracic CT at the T12 level, our approach extends opportunistic muscle assessment to routinely acquired chest scans in outpatient settings. Importantly, integrating CT-derived muscle features with accessible clinical parameters such as albumin and calf circumference reflect the complex, multifactorial pathophysiology of sarcopenia.

From a translational perspective, the proposed framework could be integrated into existing hospital information systems or EHR platforms. Automated quantification of T12 muscle features and structured risk reporting could enable real-time sarcopenia alerts without additional patient burden. Because the model utilizes already acquired CT images, it represents a cost-effective and scalable strategy for opportunistic screening.

Despite the promising performance of the proposed model, several limitations should be acknowledged. First, this was a single-center study conducted in a relatively homogeneous population, which may limit the generalizability to other healthcare settings or ethnic groups. External validation in multi-center cohorts is needed to confirm the robustness and applicability. Second, the cross-sectional design without prospective follow-up precludes evaluation of long-term clinical outcomes and temporal risk prediction. Future longitudinal studies are needed to evaluate the model's prognostic value. Third, only the T12 vertebral level was analyzed. Although T12 muscle metrics have been shown to correlate with whole-body muscle mass, they may not fully capture muscle distribution heterogeneity. Future studies incorporating multi-level or whole-body analysis and longitudinal validation are warranted.

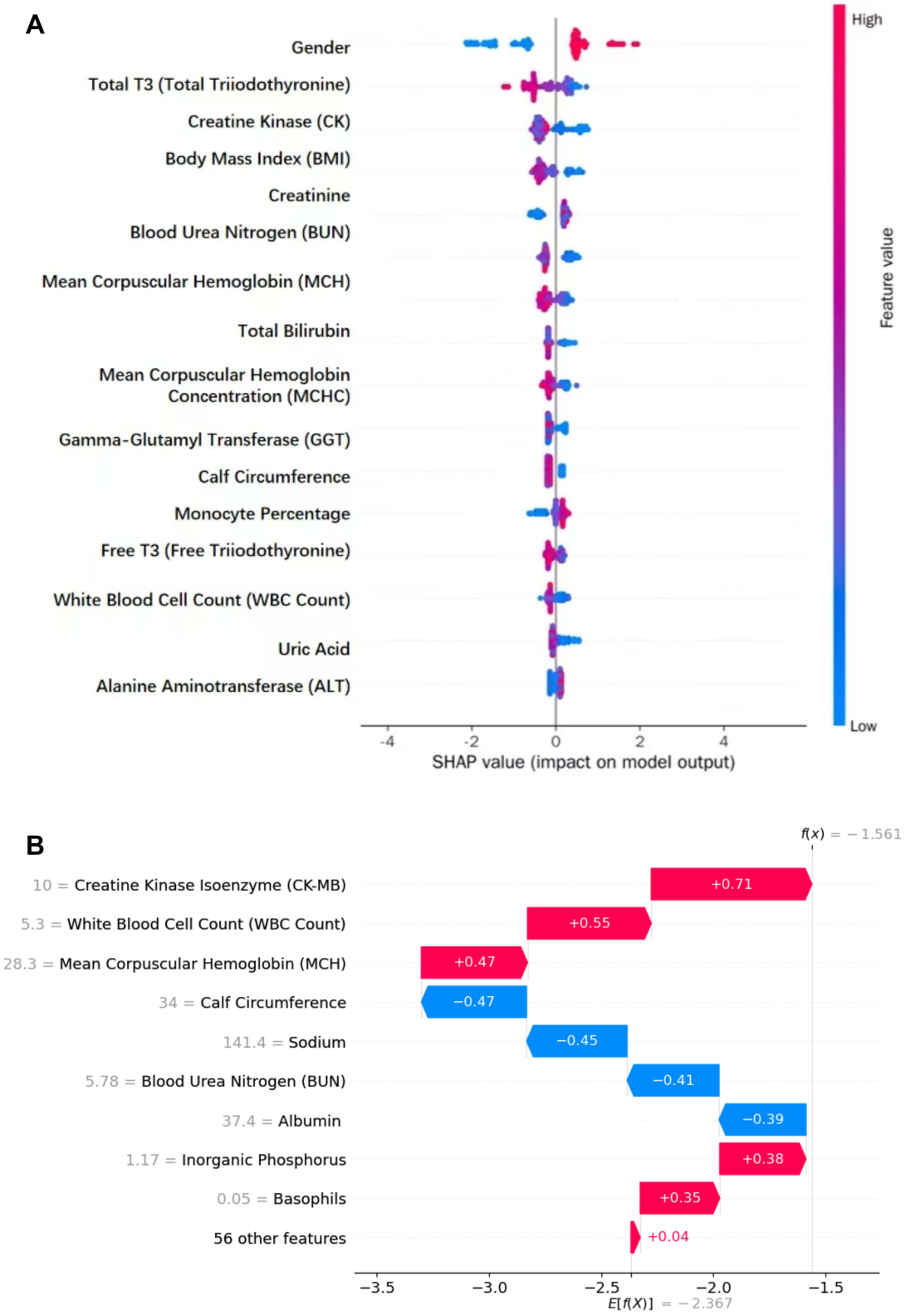


**Figure 3** SHAP-based interpretability of the multimodal AI model. (**A**) SHAP summary plot showing the distribution and magnitude of feature impacts on sarcopenia prediction. Each dot represents an individual observation. The horizontal axis indicates the SHAP value (impact on model output), where positive values increase the predicted probability of sarcopenia and negative values decrease it. Red indicates higher feature values, and blue indicates lower feature values. (**B**) Case-level SHAP force plot for an individual patient illustrating variable contributions to the final prediction. Red bars represent features that increase the predicted probability of sarcopenia (positive SHAP values), while blue bars represent features that decrease it (negative SHAP values). E[f(X)] denotes the model's baseline output, and f(x) represents the final predicted output for the individual case.


https://doi.org/10.2147/CIA.S590955

## Conclusion

In summary, we developed and internally validated an explainable multimodal AI model integrating chest CT–derived T12 muscle features with routinely available outpatient clinical variables for opportunistic sarcopenia detection in older adults. The model demonstrated robust discrimination (AUC range: 0.81–0.93) with stable cross-validation performance and maintained interpretability through SHAP-based analysis. By leveraging routinely acquired chest CT scans, this framework provides a clinically feasible and cost-effective strategy for opportunistic screening. The integration of imaging-derived muscle metrics with accessible clinical parameters enhances risk stratification and reflects the multi-dimensional nature of sarcopenia.

Future multi-center validation and longitudinal studies are needed to confirm generalizability and prognostic value. This explainable multimodal approach may facilitate earlier identification and support strategies aimed at promoting healthy aging.

## Ethics Statement

This study was approved by the Ethics Committee of Huzhou Central Hospital (Approval No. 202209030-01). Written informed consent was obtained from all participants prior to enrollment. This study was conducted in accordance with the Declaration of Helsinki.

## Funding

This work was supported by Zhejiang medicine and health science and technology project under Grant No. 2023KY312.

## Disclosure

Yunfei Pan and Feimin Zhao contributed equally to this work and should be considered co-first authors. The authors declare no conflicts of interest in this work.

## References

1. Petermann-Rocha F, Balntzi V, Gray SR, et al. Global prevalence of sarcopenia and severe sarcopenia: a systematic review and meta-analysis. *J Cachexia Sarcopenia Muscle*. 2022;13(1):86–99. doi:10.1002/jcsm.12783
2. Cho MR, Lee S, Song SK. A review of sarcopenia pathophysiology, diagnosis, treatment and future direction. *J Korean Med Sci*. 2022;37(18):e146. doi:10.3346/jkms.2022.37.e146
3. Park WT, Shon OJ, Kim GB. Multidisciplinary approach to sarcopenia: a narrative review. *J Yeungnam Med Sci*. 2023;40(4):352–363. doi:10.12701/jyms.2023.00724
4. Kandayah T, Safian N, Azhar Shah S, Abdul Manaf MR. Challenges in the management of sarcopenia in the primary care setting: a scoping review. *Int J Environ Res Public Health*. 2023;20(6):5179. doi:10.3390/ijerph20065179
5. Pickhardt PJ. Value-added opportunistic CT screening: state of the art. *Radiology*. 2022;303(2):241–254. doi:10.1148/radiol.211561
6. Tolonen A, Pakarinen T, Sassi A, et al. Methodology, clinical applications, and future directions of body composition analysis using computed tomography (CT) images: a review. *Eur J Radiol*. 2021;145:109943. doi:10.1016/j.ejrad.2021.109943
7. Den Broeck JV, Sealy MJ, Brussaard C, Kooijman J, Jager-Wittenaar H, Scafoglieri A. The correlation of muscle quantity and quality between all vertebra levels and level L3, measured with CT: an exploratory study. *Front Nutr*. 2023;10:1148809. doi:10.3389/fnut.2023.1148809
8. Pickhardt PJ, Graffy PM, Zea R, et al. Utilizing fully automated abdominal CT-Based biomarkers for opportunistic screening for metabolic syndrome in adults without symptoms. *AJR Am J Roentgenol*. 2021;216(1):85–92. doi:10.2214/AJR.20.23049
9. Blankemeier L, Yao L, Long J, et al. Skeletal muscle area on CT: determination of an optimal height scaling power and testing for mortality risk prediction. *AJR Am J Roentgenol*. 2024;222(1):e2329889. doi:10.2214/AJR.23.29889
10. Yao L, Petrosyan A, Chaudhari AJ, Lenchik L, Boutin RD. Clinical, functional, and opportunistic CT metrics of sarcopenia at the point of imaging care: analysis of all-cause mortality. *Skeletal Radiol*. 2024;53(3):515–524. doi:10.1007/s00256-023-04438-w
11. He Q, Xia W. Analysis of the current status of computed tomography diagnosis of sarcopenia. *Arch Med Sci*. 2025;21(2):374–382. doi:10.5114/aoms/191297
12. Shen Y, Luo L, Fu H, et al. Chest computed tomography-derived muscle mass and quality indicators, in-hospital outcomes, and costs in older inpatients. *J Cachexia Sarcopenia Muscle*. 2022;13(2):966–975. doi:10.1002/jcsm.12948
13. Grigioni S, Lvovschi VE, Tamion F, et al. Low thoracic skeletal muscle index is associated with negative outcomes in 244 patients with respiratory COVID-19. *Clin Nutr*. 2023;42(2):102–107. doi:10.1016/j.clnu.2022.11.011
14. Van Dijk DPJ, Volmer LF, Brecheisen R, et al. External validation of a deep learning model for automatic segmentation of skeletal muscle and adipose tissue on abdominal CT images. *Br J Radiol*. 2024;97(1164):2015–2023. doi:10.1093/bjr/tqae191
15. Koitka S, Kroll L, Malamutmann E, Oezcelik A, Nensa F. Fully automated body composition analysis in routine CT imaging using 3D semantic segmentation convolutional neural networks. *Eur Radiol*. 2021;31(4):1795–1804. doi:10.1007/s00330-020-07147-3
16. Zhang R, He A, Xia W, et al. Deep learning-based fully automated segmentation of regional muscle volume and spatial intermuscular fat using CT. *Acad Radiol*. 2023;30(10):2280–2289. doi:10.1016/j.acra.2023.06.009

17. Lassau N, Ammari S, Chouzenoux E, et al. Integrating deep learning CT-scan model, biological and clinical variables to predict severity of COVID-19 patients. *Nat Commun*. 2021;12(1):634. doi:10.1038/s41467-020-20657-4
18. Captier N, Lerousseau M, Orlhac F, et al. Integration of clinical, pathological, radiological, and transcriptomic data improves prediction for first-line immunotherapy outcome in metastatic non-small cell lung cancer. *Nat Commun*. 2025;16(1):614. doi:10.1038/s41467-025-55847-5
19. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44–56. doi:10.1038/s41591-018-0300-7
20. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med*. 2019;17(1):195. doi:10.1186/s12916-019-1426-2
21. Lundberg SM, Erion G, Chen H, et al. From local explanations to global understanding with explainable AI for trees. *Nat Mach Intell*. 2020;2(1):56–67. doi:10.1038/s42256-019-0138-9
22. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. *Nat Med*. 2022;28(1):31–38. doi:10.1038/s41591-021-01614-0
23. Della Peruta C, Lozanoska-Ochser B, Renzini A, et al. Sex differences in inflammation and muscle wasting in aging and disease. *Int J Mol Sci*. 2023;24(5):4651. doi:10.3390/ijms24054651
24. Kim S, Won CW. Sex-different changes of body composition in aging: a systemic review. *Arch Gerontol Geriatr*. 2022;102:104711. doi:10.1016/j.archger.2022.104711
25. Chen J, Wei L, Zhu X, et al. TT3, a more practical indicator for evaluating the relationship between sarcopenia and thyroid hormone in the euthyroid elderly compared with FT3. *Clin Interv Aging*. 2023;18:1285–1293. doi:10.2147/CIA.S420558
26. Müller NA, Kaegi-Braun N, Durmisi M, et al. Low T3 syndrome on admission and response to nutritional support in malnourished medical inpatients. *J Clin Endocrinol Metab*. 2023;108(6):e240–e248. doi:10.1210/clinem/dgac743
27. Zhang L, Tu YY, Zhao Z, Jin J, Tao J, Zhang XY. Lower serum FT3 within the reference range is associated with mortality for older adults over 80 years of age with sarcopenia. *BMC Geriatr*. 2023;23(1):77. doi:10.1186/s12877-023-03783-8
28. Eitmann S, Matrai P, Hegyi P, et al. Obesity paradox in older sarcopenic adults - a delay in aging: a systematic review and meta-analysis. *Ageing Res Rev*. 2024;93:102164. doi:10.1016/j.arr.2023.102164
29. Luo Q, Zhang S, Liang Z, et al. The obesity paradox in osteoporosis risk among older adults is mostly driven by women: a population-based prospective study. *BMC Geriatr*. 2025;25(1):58. doi:10.1186/s12877-025-05704-3
30. Wang T, Zhu Y, Liu X, et al. Cystatin C and sarcopenia index are associated with cardiovascular and all-cause death among adults in the United States. *BMC Public Health*. 2024;24(1):1972. doi:10.1186/s12889-024-19137-x
31. Wu Y, Wang H, Tong Y, et al. Sarcopenia index based on serum creatinine and cystatin C is associated with mortality in middle-aged and older adults in Chinese: a retrospective cohort study from the China Health and Retirement Longitudinal Study. *Front Public Health*. 2023;11:1122922. doi:10.3389/fpubh.2023.1122922