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Literature Review of AI-Driven Body Shape Analysis for Sarcopenia

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Abstract

Sarcopenia, a debilitating skeletal muscle disorder fueling frailty, disability, and mortality in aging societies, is increasingly targeted by cutting-edge artificial intelligence (AI) for enhanced detection and evaluation. This comprehensive review spotlights AI-driven body shape analysis for sarcopenia, spanning medical imaging techniques (CT, MRI, DXA, ultrasound) and innovative 3D body surface scanning. Drawing from 962 publications across key databases (January 2015 to August 2025), our methodology incorporated search terms for medical imaging alongside 3D body shape, morphometry, and computer graphics. Strikingly, while encompassing these expansive terms, results underscore AI's heavy reliance on medical imaging, leaving 3D scanning as a promising yet untapped avenue for accessible, non-invasive screening. Studies chiefly leverage convolutional neural networks for precise muscle segmentation at L3, machine learning models (Random Forest, SVM, XGBoost) for risk forecasting, and deep learning for skeletal muscle index computation, aligned with standards like EWGSOP2 and AWGS 2019. Highlights include AI's prowess in boosting diagnostic accuracy via automated, consistent metrics and unlocking opportunistic screening from everyday scans. Yet, hurdles persist in data uniformity, inclusivity, model transparency, and real-world testing. Looking ahead, priorities encompass explainable AI for clarity, harnessing 3D body analysis for broader reach, and rigorous prospective studies for seamless clinical adoption. Setting this apart from static reviews, we introduce a dynamic companion website (https://aizierjiang.github.io/AI4SarcopeniaLiteratureDaily) that auto-updates with fresh references daily; its open-source code here serves as an adaptable template for other domains via simple keyword and scope configurations, while a fixed compilation of references from this review is available at https://aizierjiang.github.io/lr4sarcopenia , ensuring perpetual currency.

Keywords

3d body scanning, ai for healthcare, body composition, body shape analysis, computing and processing, deep learning, general topics for engineers, machine learning, medical imaging, muscle segmentation, sarcopenia

Literature Review of AI-Driven Body Shape Analysis for Sarcopenia

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Abstract*—Sarcopenia, a debilitating skeletal muscle disorder fueling frailty, disability, and mortality in aging societies, is increasingly targeted by cutting-edge artificial intelligence (AI) for enhanced detection and evaluation. This comprehensive review spotlights AI-driven body shape analysis for sarcopenia, spanning medical imaging techniques (CT, MRI, DXA, ultrasound) and innovative 3D body surface scanning. Drawing from 962 publications across key databases (January 2015 to August 2025), our methodology incorporated search terms for medical imaging alongside 3D body shape, morphometry, and computer graphics. Strikingly, while encompassing these expansive terms, results underscore AI's heavy reliance on medical imaging, leaving 3D scanning as a promising yet untapped avenue for accessible, non-invasive screening. Studies chiefly leverage convolutional neural networks for precise muscle segmentation at L3, machine learning models (Random Forest, SVM, XGBoost) for risk forecasting, and deep learning for skeletal muscle index computation, aligned with standards like EWGSOP2 and AWGS 2019. Highlights include AI's prowess in boosting diagnostic accuracy via automated, consistent metrics and unlocking opportunistic screening from everyday scans. Yet, hurdles persist in data uniformity, inclusivity, model transparency, and real-world testing. Looking ahead, priorities encompass explainable AI for clarity, harnessing 3D body analysis for broader reach, and rigorous prospective studies for seamless clinical adoption. Setting this apart from static reviews, we introduce a dynamic companion website (https://aizierjiang.github.io/AI4SarcopeniaLiteratureDaily) that auto-updates with fresh references daily; its open-source code here serves as an adaptable template for other domains via simple keyword and scope configurations, while a fixed compilation of references from this review is available at https://aizierjiang.github.io/lr4sarcopenia, ensuring perpetual currency.

***Index Terms*—sarcopenia, body shape analysis, medical imaging, deep learning, muscle segmentation, 3D body scanning, body composition, machine learning, AI for healthcare**

I. Introduction

The rapid advancement of machine learning (ML) has progressively woven AI into nearly every facet of daily life. However, certain domains (Figure1), especially those requiring subtle human intervention and careful care, still demand extensive efforts in the exploration, implementation, and rigorous verification of AI models. This is important to not only achieve optimal outcomes but also to confirm their sustained safety and efficacy over time. This imperative is especially pronounced in the field of healthcare and medical applications, where foundation models, which have surged in popularity in recent years, appear at first glance to greatly alleviate the burden of human effort in the diagnosis, analysis, and treatment of a wide array of diseases and symptoms, yet continue to necessitate thorough validation and, in many cases, re-diagnosis by professional doctors based on the outputs generated by AI-driven methodologies, thereby raising critical questions about whether these AI-driven solutions have truly realized their potential to enhance operational speed while steadfastly upholding the highest standards of safety and accuracy in their implementation.

One critical area where AI-driven approaches are being rigorously explored is in the diagnosis and management of sarcopenia, a condition that exemplifies the need for precise assessment and targeted intervention in healthcare.

Sarcopenia, as defined by the European Working Group on Sarcopenia in Older People (EWGSOP), is a progressive and generalized skeletal muscle disorder characterized by the accelerated loss of muscle mass and function, associated with increased risks

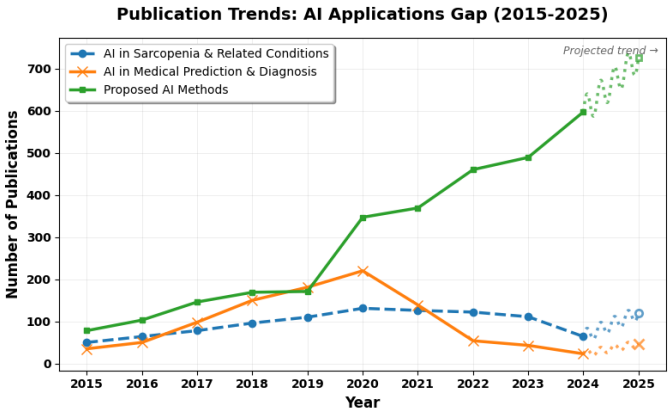

Fig. 1. Publication trends from January 2015 to August 2025 reveal a significant gap between proposed AI methods and their application in healthcare, and sarcopenia research.

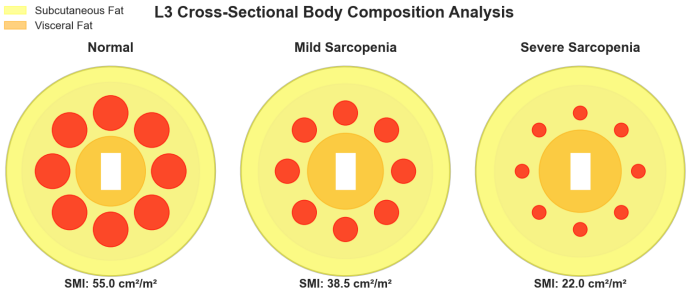

Fig. 2. Clinically simplified schematic of L3 cross-sectional body composition analysis illustrating progressive reduction in skeletal muscle index (SMI) with increasing sarcopenia severity. From left to right: normal skeletal muscle mass (illustrative SMI ≈ 55.0 cm^2/m^2, within commonly reported reference ranges for adult males), low skeletal muscle mass consistent with sarcopenia (illustrative SMI $\approx$ 38.5 cm^2/m^2, near or below widely used diagnostic cutoffs), and markedly reduced skeletal muscle mass (illustrative SMI $\approx$ 22.0 cm^2/m^2), representing extreme muscle wasting observed in advanced disease states. Skeletal muscle is depicted schematically as red regions surrounding the vertebral body (white), with subcutaneous adipose tissue shown in yellow and visceral adipose tissue in orange. SMI values are illustrative and not intended as universal diagnostic or severity thresholds.

of adverse outcomes such as falls, frailty, functional decline, and mortality [1]. Figure 2 illustrates a clinically simplified conceptual L3 cross-sectional body composition analysis, depicting sarcopenia severity through representative L3 cross-sections. This condition, which is intricately linked to changes in body composition, especially the reduction in skeletal muscle mass, highlights the importance of accurate body shape analysis as a key part for its diagnosis and management. Body shape analysis encompasses both internal body composition assessment through medical imaging and external body surface analysis through 3D scanning technologies. The close relationship between sarcopenia and body shape makes AI-driven body shape analysis a promising avenue for improving diagnostic precision and enabling early interventions, thereby reducing the burden on healthcare systems and improving patient outcomes [2]–[6].

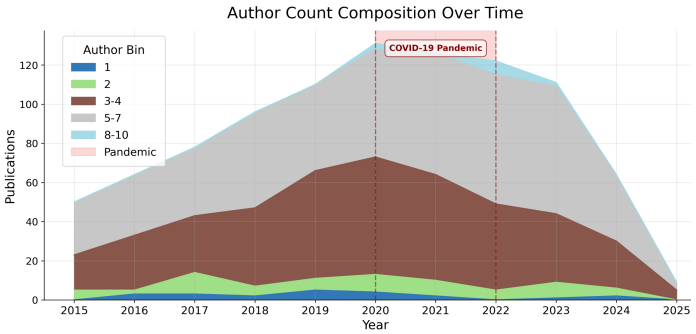

Fig. 3. Author composition trends from January 2015 to August 2025 reveal an increase in researchers conducting AI and sarcopenia research during the pandemic period, with a subsequent decrease after 2022.

To understand the role of AI in this domain, this paper conducts a review of 962 studies (selected from an initial pool of 1000 papers) published between January 1, 2015, and August 15, 2025. As illustrated in Figure 3, the research community engaged in AI and sarcopenia studies has evolved considerably over this period, with notable fluctuations in author participation. Given the intrinsic connection between sarcopenia and body shape, this review examines AI-driven approaches targeting body shape analysis, including both medical imaging-based body composition assessment and 3D body surface scanning technologies. Notably, our systematic search reveals that while AI applications for medical imaging-based sarcopenia assessment have matured substantially, the application of 3D body shape analysis (e.g., point clouds, surface meshes, optical body scanning) to sarcopenia detection remains nascent, representing a significant gap in the current literature. By synthesizing insights from this extensive body of literature, this study aims to evaluate the efficacy, limitations, and future potential of AI-driven methodologies in sarcopenia assessment, offering a strong foundation for advancing both clinical practice and research in this critical area of healthcare.

This paper is structured as follows: Section 2 details the methodological framework employed in this literature review, encompassing the search strategy, inclusion and exclusion criteria, study selection procedures, and quality assessment using the optimized Critical Appraisal Skills Programme (CASP) [7]. Section 3 synthesizes the findings of the reviewed literature, highlighting significant advancements and computational innovations in sarcopenia research between 2015 and 2025. Section 4 explores the practical applications of AI-driven body composition analysis in the diagnosis, monitoring, and treatment of sarcopenia, emphasizing translational relevance to healthcare practice. Section 5 critically examines existing research gaps, methodological challenges, and technical limitations in applying AI-based approaches to sarcopenia. Section 6 outlines prospective directions for future research, offering targeted recommendations informed by prevailing trends in AI and biomedical imaging. Finally, Section 7 presents concluding remarks, synthesizing key insights, evaluating this literature review against the AMSTAR2 [8], reaffirming the review's contributions, and highlighting its broader implications for academia and clinical practice.

II. Methodology

A. Integrated Search and Selection Framework

To ensure methodological rigor, transparency, and reproducibility, a systematic search was conducted to identify relevant literature for this review. Publications were drawn from leading scholarly databases, publisher platforms, and specialized repositories spanning medicine, nutrition, oncology, cardiology, endocrinology, rheumatology, computer science, and related technical fields including engineering, vision, and graphics. Key sources included established medical and clinical databases such as PubMed, PMC, medRxiv, and medArxiv, alongside high-impact journals and publisher collections from Elsevier, Springer, Karger, Wiley, Taylor & Francis, Nature Publishing Group, Frontiers, and Clinical Nutrition journals. Technical and computer science literature was accessed through IEEE Xplore, ACM Digital Library, dblp, arXiv, and other open-access repositories including MDPI, ResearchGate, Academia.edu, CORE, and DSpace. Regional and specialty journals were also consulted to maintain broad coverage across disciplines. This strategy enabled inclusion of both well-established and emerging research, maintaining a broad, balanced, and high-quality representation of the literature.

A systematic framework was applied to capture, filter, and prioritize these publications for inclusion in the review. Let $\mathcal{P}$ denote the universal set of all academic papers. The publication date interval I is defined as:

$$I = [2015.\text{Jan.}1, 2025.\text{Aug.}15]$$

The search keywords are categorized into three disjoint sets, representing the thematic scope of this review, as summarized in Table I.

Here, the wildcard $(*)$ denotes any suffix in the keyword patterns. The Boolean query Q used for initial retrieval is defined as:

$$Q = \left(\bigvee_{k \in K_A} k\right) \wedge \left(\bigvee_{t \in K_T} t\right) \wedge \left(\bigvee_{p \in K_P} p\right)$$

Let $P_Q \subseteq \mathcal{P}$ represent the set of papers satisfying Q with publication dates within I:

$$P_Q = \{p \in \mathcal{P} \mid p \text{ satisfies } Q \wedge \text{pub\_date}(p) \in I\}$$

From P_Q, a subset $P_{1000} \subseteq P_Q$ containing at most 1000 papers is retained, prioritized according to a ranking criterion (e.g., relevance score or citation count):

$$|P_{1000}| \leq 1000$$

For each paper $p \in P_{1000}$, the publication age $a(p)$ is defined relative to the reference year (2025):

$$a(p) = 2025 - \text{year}(\text{pub\_date}(p))$$

To enforce stricter inclusion criteria for older publications, a piecewise citation threshold function $\theta(a)$ is applied:

$$\theta(a) = \begin{cases} 10 & \text{if } 7 \leq a \leq 10, \\ 7 & \text{if } 5 \leq a < 7, \\ 5 & \text{if } 3 \leq a < 5, \\ 0 & \text{if } 0 \leq a < 3, \\ \infty & \text{otherwise} \end{cases}$$

This formulation confirms that older works are subject to more stringent citation requirements, reflecting the expectation that influential papers accrue citations over time.

TABLE I
SET DEFINITIONS FOR KEYWORDS (PUBLICATION INTERVAL: JANUARY 2015 TO AUGUST 2025)

Category	Set Definition
Application Keywords (K_A)	{"sarcopenia", "sarcopenic", "sarcopenia obesity"}
Technology Keywords (K_T)	{"machine learning", "deep learning", "AI", "computer vision", "computer graphics", "3D body", "morphometry", "body shape"}
Purpose Keywords (K_P)	$\{ w \mid w$ matches "diagnos*" $\vee$ "detect*" $\vee$ "assess*" $\vee$ "predict*" $\vee$ "treat*"$\}$

The final set of included studies S is thus defined as:

$$S = \{p \in P_{1000} \mid C(p) > \theta(a(p))\}$$

where $C(p)$ denotes the citation count of paper p. This approach aims to confirm a systematic, reproducible, and quantitatively justified selection process that aligns with best practices in evidence synthesis.

B. Quality Assessment

Our review employed the optimized Critical Appraisal Skills Programme (CASP) [7] to evaluate the methodological quality of included studies, confirming strong and reliable synthesis for the literature review on AI-driven body composition analysis for sarcopenia. The optimized CASP was selected for its adaptability to both qualitative and quantitative studies, especially suited for assessing AI-driven research, which often combines diagnostic accuracy metrics with methodological transparency. This process enabled a systematic evaluation of study design, data collection, validation rigor, and clinical relevance, emphasizing transparency and theoretical alignment.

Our process for applying the optimized CASP involved a structured, criterion-based approach adapted to AI studies. We adapted the standard CASP qualitative checklist by incorporating a novel question on the theoretical and epistemological framework, confirming alignment with AI model development and validation paradigms. The appraisal process was conducted as follows:

1) **Study Selection**: We screened studies for relevance to AI-driven body composition analysis (e.g., imaging, wearables) and sarcopenia detection, confirming alignment with the research question.
2) **Initial Appraisal**: Each study was evaluated using the 11 standard CASP questions, focusing on methodological rigor, ethical considerations, and clarity of findings.
3) **Novel Question Application**: An additional question assessed whether the study's AI model assumptions (e.g., training data, validation protocols) were clearly articulated and appropriate.
4) **Rating and Classification**: Responses were rated as Yes (Fully Satisfactory), Partial (Somewhat Satisfactory), No (Not Satisfactory), or Not Applicable. Studies were classified based on cumulative ratings to identify methodological strengths and areas requiring additional scrutiny.
5) **Synthesis Weighting**: Studies demonstrating transparent validation and clinical relevance were prioritized in the synthesis to enhance reliability.
6) **Documentation**: All appraisals were recorded systematically for transparency, with findings summarized in a quality assessment table.

The optimized CASP questions are presented in Table II, with explanations and rating options to confirm consistent evaluation.

III. TECHNOLOGICAL LANDSCAPE AND RESEARCH PROGRESS

From a resource utilization perspective, several AI-powered software programs and mobile applications have emerged for sarcopenia detection [9]. Early developments include an IoT-based wearable prototype within an Ambient Assisted Living system [10], which analyzes gait speed, muscle activity, and force for active assessment, though it has only been tested in laboratory settings without patient validation. The HTS Mayor software [11] subsequently

TABLE II
OPTIMIZED CASP QUESTIONS FOR METHODOLOGICAL APPRAISAL

Question	Explanation	Response
Clear statement of research aims?	Assesses whether the study's purpose is explicit and relevant to sarcopenia detection.	Yes / Partial / No
Appropriate methodology?	Evaluates if the chosen methods suit the research question.	Yes / Partial / No
Appropriate research design?	Determines if the study design aligns with stated objectives.	Yes / Partial / No
Appropriate recruitment strategy?	Checks if participant or data selection supports study goals.	Yes / Partial / No
Appropriate data collection?	Assesses data collection methods (e.g., imaging protocols, dataset size).	Yes / Partial / No
Researcher-participant relationship considered?	Evaluates reflexivity and potential bias in AI model development.	Yes / Partial / No
Ethical issues considered?	Confirms ethical approval, data privacy, and bias considerations.	Yes / Partial / No
Thorough data analysis?	Checks depth and validity of analysis (e.g., validation rigor).	Yes / Partial / No
Clear statement of findings?	Confirms transparency of results (e.g., accuracy metrics, outcomes).	Yes / Partial / No
Theoretical framework articulated?	Evaluates alignment of AI model assumptions with research aims.	Yes / Partial / No
Scope and applicability?	Assesses contribution to sarcopenia detection and clinical translation.	Broad / Moderate / Limited

applied adapted EWGSOP criteria with anthropometric equations to estimate muscle mass from grip strength, demonstrating high sensitivity (82.1%) and specificity (94.9%) compared with dual-energy X-ray absorptiometry (DXA), and offering a low-cost, user-friendly diagnostic option. The Rapid Geriatric Assessment (RGA) Clinic app [12] was later introduced to screen for geriatric syndromes including sarcopenia through questionnaires such as the FRAIL scale, SARC-F, Simplified Nutritional Appetite Questionnaire, and Rapid Cognitive Screen; it is fast (under 5 minutes) and reliable but does not replace standard diagnostics and requires further validation for eHealth integration. Digital performance-based assessments such as the electronic Short Physical Performance Battery (eSPPB) and electronic Quick Physical Performance Battery (eQPPB) [13] have shown high accuracy in classifying sarcopenia (C-statistics 0.83 and 0.85, respectively), with eQPPB offering shorter measurement times though both remain focused solely on physical performance. The Sit-to-Stand app [14] uses video analysis of timed sit-to-stand tests to evaluate lower limb strength, performing well in community-dwelling older adults, though requiring precise camera placement that may introduce errors.

More recently, a nursing guidance application [15] has applied ML to identify risk factors and provide educational resources on self-assessment, exercise, and nutrition, improving user knowledge and satisfaction but relying on self-reported data without proven long-term efficacy. In parallel, a portable digital system [16] has integrated external Bluetooth devices (e.g., Gripwise, Lipowise) to assess grip strength, muscle mass, gait speed, and sit-to-stand performance in alignment with EWGSOP/AWGS consensus criteria, supporting longitudinal tracking but requiring additional hardware and further validation against gold-standard measures.

González-Martin et al. [17] developed ML models using anthropometric measurements to predict low ALMI, offering a practical screening alternative in settings where advanced imaging is unavailable.

Shafiee et al. [18] and Petermann-Rocha et al. [19] conducted systematic reviews and meta-analyses examining the global prevalence of sarcopenia. These analyses estimated prevalence rates of approximately 10% in older adults, with large variation (up to 27%) depending on diagnostic criteria employed. The condition affects a large proportion of the elderly population worldwide, with higher prevalence observed in non-Asian regions, especially among

individuals aged 60 years and older. Measurement inconsistencies across studies, including variations in DXA and bioelectrical impedance analysis (BIA) protocols, emphasize diagnostic challenges and highlight the possibility for AI-driven body composition analysis to enable more standardized early detection [20]–[23].

Albano et al. [24] demonstrated that ultrasound provides accurate evaluation of muscle trophism, especially in the thigh musculature. Although current clinical application for sarcopenia assessment remains limited, the modality's potential for non-invasive, cost-effective monitoring presents opportunities for integration with AI-driven analysis to improve early detection and longitudinal tracking. Holmes et al. [25] emphasized that accurate body composition assessments using DXA, CT, or emerging 3D body scanners are important for tailoring nutritional interventions to optimize muscle mass. This process can be improved through AI-driven body composition analysis, enabling automated and precise sarcopenia detection and measurement.

Chianca et al. [26] evaluated traditional imaging techniques for sarcopenia assessment, identifying that DXA benefits from widespread availability and established diagnostic cutoffs, while CT and MRI offer better accuracy but lack standardized threshold values. Ultrasound remains underutilized despite potential. The authors emphasized that AI-driven methods, including automated CT segmentation and radiomic feature extraction, can reduce interobserver variability, streamline muscle quantification, and improve prognostic accuracy.

Beyond conventional assessment approaches, recent research has proposed new composite metrics for sarcopenia identification. Huo et al. [27] introduced the Grip-Strength-Lean-Mass Index (GSLMI), a composite measure integrating handgrip strength with ALM. This index demonstrated improved diagnostic accuracy compared to individual measures and represents a feasible option for managing sarcopenia in cancer patients, where both strength and mass decline frequently coexist.

Analysis of the collected publications reveals venue diversity, as illustrated in Figure 4. The distribution of publication sources reflects the multidisciplinary nature of AI-driven sarcopenia research, spanning clinical medicine, radiology, computer science, and

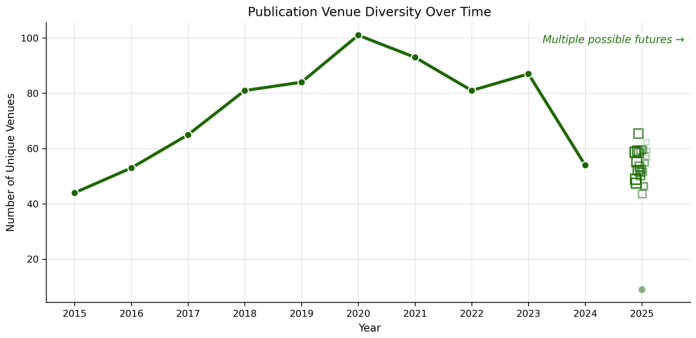

Fig. 4. Publication venue diversity from January 2015 to August 2025, demonstrating the multidisciplinary nature of AI-driven sarcopenia research across clinical, technical, and translational journals.

nutrition science. Figure 6 presents the citation impact distribution, while Figure 7 identifies the leading venues contributing to this literature. And the Figure 5 illustrates the distribution of these papers across various academic disciplines.

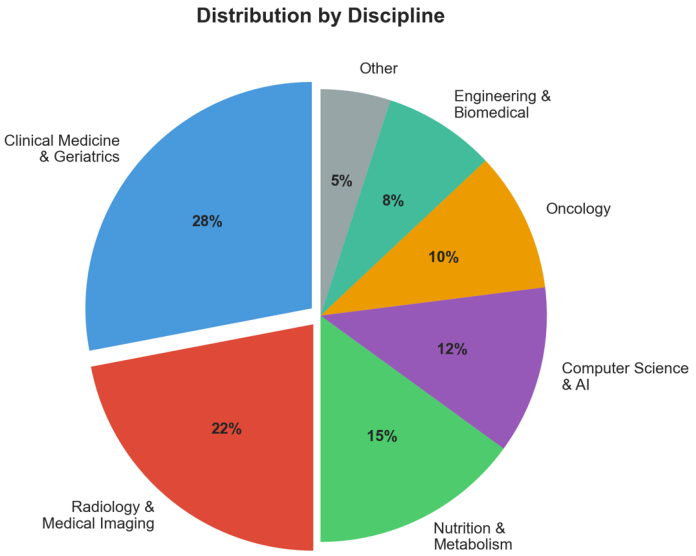

Fig. 5. Distribution of the collected publications categorized by academic discipline.

In practice, each included study was reviewed, and 11 questions were addressed to identify methodological strengths and limitations. Studies were classified based on cumulative ratings (8 or more Yes responses indicating good methodology; 5 to 7 indicating moderate methodology; fewer than 5 requiring careful interpretation). Studies demonstrating good external validation and transparent reporting were given greater weight in the synthesis. This approach confirmed that our findings on AI-driven body composition analysis for sarcopenia

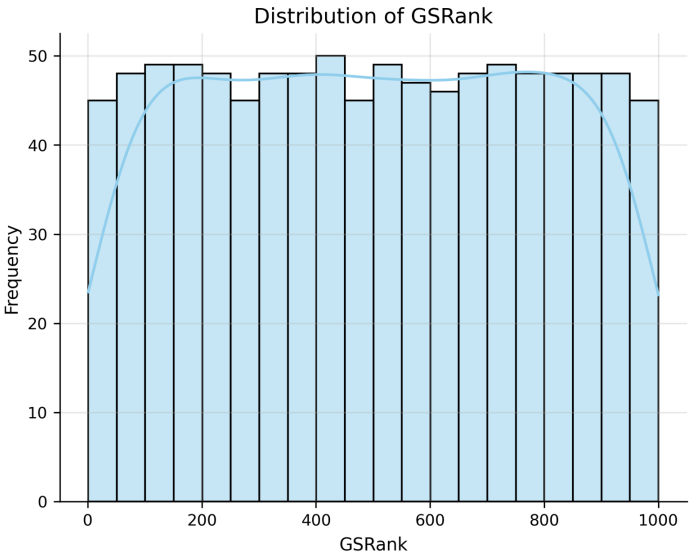

Fig. 6. Distribution of Google Scholar ranks among reviewed publications from January 2015 to August 2025, illustrating citation impact across the sarcopenia and AI literature.

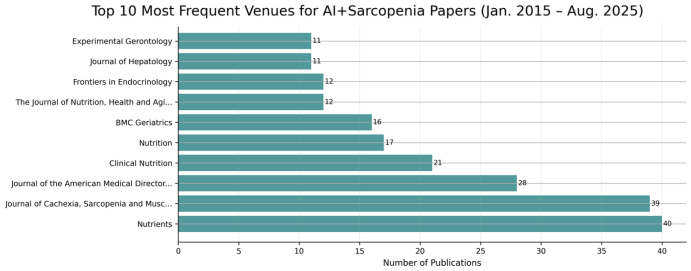

Fig. 7. Top 10 publication venues for AI and sarcopenia research from January 2015 to August 2025, highlighting the concentration of contributions in clinical nutrition, radiology, and oncology journals.

were grounded in good evidence, addressing challenges such as model overfitting, data bias, and clinical relevance. Results of the comprehensive CASP quality assessment are presented in Table III and Table IV, which integrates study characteristics with detailed methodological appraisal scores for each of the 11 CASP criteria.

This systematic appraisal process strengthened the credibility of our synthesis by confirming that conclusions regarding AI applications in sarcopenia detection derive from methodologically sound, transparent, and clinically relevant evidence. The CASP assessment revealed that all included studies demonstrated clear research aims (Q1), appropriate methodology (Q2), and thorough data analysis (Q8). The most common limitation across studies was incomplete consideration of researcher-participant relationships (Q6), particularly regarding potential biases in AI model development and training data selection. Studies with multi-center validation (e.g., Gu et al., Magudia et al.) and those employing explainable AI approaches (e.g., Kim et al.) achieved the highest quality ratings due to their transparent validation protocols and broad clinical applicability. Review articles and meta-analyses, while valuable for evidence synthesis, are discussed separately in the narrative text rather than included in technical methodology summaries.

A. Advances in Imaging and Data Acquisition

The assessment of sarcopenia relies on accurate body composition measurement, with imaging modalities serving as the foundation for quantifying muscle mass and quality. CT has been treated as the gold standard for muscle mass assessment, offering high spatial resolution and the ability to distinguish between different tissue types based on Hounsfield unit (HU) attenuation values [24], [26]. The L3 vertebral level has become the standard anatomical landmark for cross-sectional body composition analysis, with skeletal muscle index calculated as total muscle area divided by height squared ($\mathrm{cm}^2/\mathrm{m}^2$) [36], [37]. Fully convolutional networks (FCNs) and vision models like YOLOv3 have been integrated to create end-to-end systems for automatic L3 slice selection considering anatomic variations and segmentation of abdominal muscle and fat areas on CT scans [38]. CT-based measurements enable simultaneous assessment of skeletal muscle area, visceral adipose tissue, subcutaneous adipose tissue, and intramuscular adipose tissue, providing thorough body composition profiles [39], [40].

Magnetic Resonance Imaging (MRI) offers better soft tissue contrast without ionizing radiation, making it especially valuable for longitudinal studies and pediatric populations [41], [42]. Advanced MRI techniques, including chemical shift-based water-fat separation and Dixon imaging, enable precise quantification of muscle volume and fat infiltration [43]. However, the higher cost and limited accessibility of MRI compared to CT restricts its widespread clinical application for routine sarcopenia screening. DXA remains the most widely adopted clinical method for appendicular lean mass (ALM) measurement, forming the basis for ALM index (ALMI)

TABLE III
CASP QUALITY ASSESSMENT OF INCLUDED AI-BASED SARCOPENIA STUDIES: STUDY CHARACTERISTICS AND KEY CONTRIBUTIONS

Study	**AI Technique**	**Application**	**Key Contributions**
Bhardwaj et al. (2025) [28]	DL (Transfer/SSL)	SMA Segment.	L3-level CT, DSC 0.93, SMA error $\pm 3\%$
Gu et al. (2023) [4]	CNN Segment.	Auto. Diagnosis	Multi-center, DSC 0.91–0.98, AUC 0.874
Kim et al. (2022) [29]	XAI with SHAP	Gait Detection	Interpretable, accuracy 93.75%
Nowak et al. (2022) [30]	Cascaded CNN	Auto. Pipeline	End-to-end, quality control
Magudia et al. (2021) [31]	U-Net Variant	Population Analysis	Reference curves (n=12,128), stratification
Koitka et al. (2021) [32]	Cascaded CNN	Auto. Pipeline	3D segmentation (n=50), DSC 0.96
Burns et al. (2020) [33]	DL (e.g. U-Net)	Sarcopenia Estimation	Cross-scanner (n=102), DSC 0.94–0.95
Lera et al. (2020) [11]	Regression	Community Screening	Anthropometric, 82% sensitivity v.s. DXA
Graffy et al. (2019) [34]	U-Net	Longitudinal Screening	Large cohort (n=9,310), DSC 0.938
Kang et al. (2019) [35]	RF, SVM, GB, LR	Risk Prediction	Feature selection (n=4,020), AUC 0.82

TABLE IV
CASP QUALITY ASSESSMENT OF INCLUDED AI-BASED SARCOPENIA STUDIES: QUALITY ASSESSMENT SCORES

Study	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**Q11**
Bhardwaj et al. (2025) [28]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	M
Gu et al. (2023) [4]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	B
Kim et al. (2022) [29]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	B
Nowak et al. (2022) [30]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	M
Magudia et al. (2021) [31]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	B
Koitka et al. (2021) [32]	✓	✓	✓	○	✓	○	✓	✓	✓	✓	M
Burns et al. (2020) [33]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	M
Lera et al. (2020) [11]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	B
Graffy et al. (2019) [34]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	B
Kang et al. (2019) [35]	✓	✓	✓	✓	✓	○	✓	✓	✓	✓	M

CASP Questions: Q1 = Clear aims; Q2 = Methodology; Q3 = Design; Q4 = Recruitment; Q5 = Data collection; Q6 = Bias; Q7 = Ethics; Q8 = Analysis; Q9 = Findings; Q10 = Framework; Q11 = Scope (B = Broad, M = Moderate). **Legend:** ✓ = Yes ○ = Partial × = No

calculations used in EWGSOP2 and AWGS diagnostic criteria [41], [44], [45]. DXA offers lower radiation exposure than CT and enables whole-body composition assessment within minutes. Recent advances include ML models for predicting total and regional appendicular skeletal muscle mass from DXA body composition measurements [46]. However, DXA cannot distinguish between different muscle groups or assess muscle quality, and measurements are affected by hydration status and cannot detect myosteatosis [25], [47].

BIA has gained popularity as a portable, non-invasive, and cost-effective alternative for muscle mass estimation [48], [49]. Multi-frequency BIA devices estimate appendicular skeletal muscle mass through validated prediction equations, with phase angle emerging as a promising indicator of muscle quality and cell membrane integrity [50], [51]. Notably, next-generation consumer smartwatches incorporating BIA sensors have demonstrated promising accuracy for whole-body composition estimation in diverse, multiethnic populations [52], and hybrid approaches combining 3D optical imaging with BIA have achieved rapid multicompartment body composition modeling [53]. Despite accessibility advantages, BIA measurements are influenced by hydration status, body position, and electrode placement, requiring standardized protocols for reliable assessment [54], [55].

Ultrasound has emerged as a promising modality for point-of-care sarcopenia assessment, offering portability, real-time imaging, and absence of radiation [56], [57]. Measurements of rectus femoris thickness, cross-sectional area, and echogenicity have demonstrated correlations with DXA-derived muscle mass [58], [59]. Recent developments in quantitative ultrasound, including elastography for muscle stiffness assessment, extend its diagnostic utility beyond simple morphometric measurements [59], [60]. The development of standardized measurement protocols and population-specific reference values remains critical for widespread clinical adoption of ultrasound-based sarcopenia assessment [61], [62].

Beyond conventional medical imaging, 3D body surface scanning technologies represent a new area in non-invasive body shape assessment. Optical 3D body scanners capture detailed body surface geometry, enabling derivation of anthropometric measurements and estimation of body composition parameters through validated prediction models [25], [63]–[65]. Recent advances have demonstrated that 3D body shape strongly correlates with internal body composition: Qiao et al. [66] developed ML models predicting total and regional body composition from 3D body shape captured via smartphone applications, while Tian et al. [67] introduced 3D convolutional deep learning approaches for nonlinear estimation of body composition from whole-body morphology. Earlier work by Lu et al. [68] established Bayesian network frameworks for 3D shape-based body composition inference. The D3BT (Dynamic 3D Body Transformer) architecture [69] represents a recent innovation applying transformer-based deep learning to temporal 3D body shape sequences for body fat percentage assessment. **Notably, despite including search terms such as "3D body," "body shape," "morphometry," and "computer graphics" in our systematic literature search, we found that AI-driven 3D body surface analysis for sarcopenia detection remains remarkably underexplored.** The vast majority of identified studies focus on medical imaging modalities (CT, MRI, DXA, ultrasound), with 3D optical body scanning appearing primarily in general body composition research rather than sarcopenia-specific applications [70], [71]. While not yet established as diagnostic tools for sarcopenia, these technologies offer potential for community-based screening and longitudinal monitoring applications, representing a significant opportunity for future research to develop non-invasive, radiation-free sarcopenia screening methods using external body shape features.

B. Computational Techniques for Body Composition Analysis

The application of AI to sarcopenia assessment has evolved from traditional ML approaches to complex deep learning architectures, changing the landscape of automated body composition analysis. Here we examine the computational techniques employed across the reviewed literature, categorizing methods by their algorithmic foundations and clinical applications.

1) Traditional Machine Learning Approaches: Classical ML algorithms have demonstrated great utility in sarcopenia prediction and risk stratification

tasks. Random Forest classifiers, Support Vector Machines (SVM), and Gradient Boosting methods (XGBoost, LightGBM) have been applied to structured clinical and demographic data for sarcopenia screening [3], [35], [72]. Feature selection techniques, including recursive feature elimination and mutual information-based methods, have identified key predictors such as grip strength, gait speed, calf circumference, and serum biomarkers as highly discriminative for sarcopenia classification [17], [73].

Logistic regression models remain prevalent for risk prediction, offering interpretability advantages important for clinical adoption [33], [74]. Ensemble methods combining multiple base learners have showed better performance over individual algorithms, with meta-learning approaches achieving area under the receiver operating characteristic curve (AUC-ROC) values exceeding 0.751 and 0.785 for men and women for sarcopenia detection [35], [75].

Anthropometric-based ML models have special relevance for resource-limited settings where imaging facilities are unavailable. González-Martin et al. [17] developed ML models using anthropometric measurements (circumferences, skinfolds) to predict low ALMI, achieving acceptable sensitivity and specificity for sarcopenia screening. These approaches enable population-level screening without requiring expensive imaging equipment.

2) Deep Learning for Image Analysis: Convolutional Neural Networks (CNNs) have changed automated body composition analysis from medical images. Deep learning-based segmentation architectures, especially U-Net and its variants (V-Net, Attention U-Net), have achieved near-human-level accuracy in automated muscle and adipose tissue delineation from CT and MRI images [28], [34], [76], [77].

The AI Body Part Measure System (AIBMS) developed by Gu et al. [4] shows the integration of deep learning into clinical workflows, providing automated detection and quantification of sarcopenia from routine abdominal CT scans. The system employs cascaded neural networks for body region localization followed by tissue-specific segmentation, achieving Dice Similarity Coefficients (DSC) exceeding 0.9 in segmenting body parts, while the constructed sarcopenia classification model based on cutoff values (Auto SMI model) demonstrates high accuracy in predicting sarcopenia with an AUC of 0.874.

Fully automated pipelines have been developed for opportunistic sarcopenia screening from clinically acquired CT scans, eliminating the need for additional imaging protocols [30], [31], [78]. These systems automatically identify L3 vertebral level, perform tissue segmentation, and calculate body composition indices, enabling large-scale retrospective studies and prospective screening programs.

Transfer learning approaches, using pre-trained networks from ImageNet or medical imaging datasets, have accelerated model development for sarcopenia-related tasks, especially when training data is limited [79], [80]. Domain adaptation techniques address the challenge of scanner variability across institutions, improving model generalizability to diverse clinical settings.

Recent advances incorporate 3D volumetric analysis rather than single-slice measurements, providing more thorough body composition assessment [77], [80]. Whole-body CT segmentation enables total muscle volume quantification, potentially improving diagnostic accuracy compared to L3-only measurements. Parallel developments in 3D body surface analysis have applied deep 3D convolutional graph networks and nonlinear Gaussian process regression for body composition estimation from optical scans [67], while transformer architectures have been adapted for temporal body shape analysis [69].

3) Radiomics and Texture Analysis: Radiomics approaches extract high-dimensional quantitative features from medical images, capturing texture, shape, and intensity characteristics beyond visual interpretation [81]. First-order statistical features (mean, variance, skewness) and higher-order texture features (gray-level co-occurrence matrix, gray-level run-length matrix) characterize muscle quality and heterogeneity associated with myosteatosis and sarcopenia [82].

ML models trained on radiomic features have demonstrated prognostic value for predicting clinical outcomes in cancer patients with sarcopenia, including treatment response, toxicity risk, and survival [81]. Feature selection and dimensionality reduction techniques (principal component analysis, LASSO regularization) address the high-

dimensional nature of radiomic data while maintaining predictive performance.

4) Hybrid and Multi-Modal Approaches: Advanced systems increasingly integrate multiple data modalities and analytical approaches. Hybrid models combining imaging-derived features with clinical variables, laboratory biomarkers, and functional assessments achieve superior predictive performance compared to single-modality approaches [6], [83]. Multi-task learning frameworks jointly optimize for multiple related objectives (e.g., muscle mass estimation, sarcopenia classification, survival prediction), using shared representations across tasks.

The integration of wearable sensor data with imaging and clinical information represents a new research direction. Kim et al. [29] developed an XAI system combining gait analysis from wearable sensors with body composition measurements for sarcopenia and osteopenia identification, demonstrating the potential of multi-modal assessment in daily life settings.

C. Key Studies and Research Highlights

The analysis of literature between 2015 and 2025 reveals several landmark studies that have advanced the field of AI-driven body composition analysis for sarcopenia. Here we highlight key research contributions, emerging trends, and methodological innovations that define the current state of the field.

1) Foundational Prevalence and Diagnostic Criteria Studies: The establishment of standardized diagnostic criteria has been fundamental to sarcopenia research. The revised EWGSOP2 guidelines [1] and the Asian Working Group for Sarcopenia (AWGS) 2019 consensus [84] provided operational definitions incorporating muscle mass, strength, and physical performance assessments. These consensus documents established ALMI cutoffs (males: below 7.0 kg/m^2; females: 5.5 to 6.0 kg/m^2 depending on methodology) and emphasized the importance of functional assessments alongside morphometric measurements.

Global prevalence meta-analyses have quantified the sarcopenia burden across populations. Petermann-Rocha et al. [19] analyzed 263 studies encompassing 692,056 participants (with 151 included in the meta-analysis), estimating pooled prevalence of 10% to 27% in older adults, with large variation based on diagnostic criteria and population characteristics. Shafiee et al. [18] reported an overall pooled prevalence of 10% (95% CI: $8 \sim 13\%$) for both men and women, noting that estimates varied significantly by assessment method (higher with Bio-electrical Impedance Analysis) and region (higher in non-Asian populations), though they were unable to stratify prevalence by age group due to limited data.

2) AI-Based Body Composition Assessment: The systematic review and meta-analysis by Bedrikovetski et al. [76] evaluated AI methods for CT-based body composition and sarcopenia assessment, synthesizing evidence from 24 studies (15 in the meta-analysis) involving 2,8801 patients. Deep learning-based segmentation achieved excellent agreement with manual measurements, with a pooled Dice coefficient of 0.941 for skeletal muscle (values for adipose tissue and bone were higher, ranging from 0.963 to 0.978). The review highlights the potential of AI to automate the otherwise time-consuming manual process, though it primarily analyzed segmentation accuracy.

Burns et al. [33] developed an ML algorithm for sarcopenia estimation from abdominal CT, achieving correlation coefficients exceeding 0.95 with manual measurements. The model demonstrated strong performance across diverse patient populations and scanner types, supporting clinical implementation for large-scale screening. Graffy et al. [34] applied deep learning muscle segmentation to a longitudinal adult screening cohort, enabling the establishment of population-based normative values and the assessment of sarcopenia trajectory over time, demonstrating the feasibility of automated opportunistic CT screening, identifying that age-related muscle density (attenuation) loss is steeper than muscle area loss, a finding that may improve the detection of patients at risk for adverse outcomes.

3) Machine Learning for Risk Prediction: Turimov and Kim [3] provided a thorough survey of ML applications in sarcopenia, categorizing methods for detection, progression prediction, and treatment response assessment. Their analysis identified Random Forest and ensemble methods as consistently top-performing algorithms for classification tasks, while neural networks demonstrated advantages for imaging-based applications. The study by Kang et

al. [35] applied feature selection and ML to identify optimal predictors for sarcopenia from clinical databases. Key predictive features included age, body mass index, grip strength, gait speed, and serum albumin, with XGBoost achieving AUC-ROC of 0.87 for sarcopenia detection.

Kim et al. [85] applied feature selection and ML to identify optimal predictors for sarcopenia using data from the Korea National Health and Nutrition Examination Survey (KNHANES). Key predictive features BMI, age, red blood cell count, white blood cell count, blood urea nitrogen, and nutritional factors such as water and fiber intake, with Random Forest and Logistic Regression models achieving an AUC-ROC of up to 0.82 for sarcopenia detection in men and 0.78 in women.

developed ML models combining CT-derived body composition parameters with clinical variables for sarcopenic obesity detection in gastric cancer patients, demonstrating the prognostic value of AI-based assessment for treatment planning.

4) Mobile Health and Software Applications: The emergence of mobile health (mHealth) applications represents a significant trend in sarcopenia screening accessibility. Prabhu et al. [9] conducted a scoping review of mobile applications for sarcopenia detection, identifying several clinically validated tools including screening questionnaire apps (SARC-F implementations), physical performance assessment apps (using smartphone sensors for gait analysis), and remote monitoring platforms.

Lera et al. [11] developed and validated software for community-based sarcopenia diagnosis, integrating anthropometric equations with grip strength measurements to estimate muscle mass. The system achieved 82.1% sensitivity and 94.9% specificity compared to DXA reference standards, demonstrating feasibility for primary care implementation.

The RGA Clinic app [12] enables screening for multiple geriatric syndromes including sarcopenia within 5 minutes, combining SARC-F questionnaire with validated assessment tools. Integration with electronic health records (EHRs) helps longitudinal tracking and clinical decision support.

5) Emerging Trends and Methodological Innovations: Analysis of publication trends reveals several emerging research directions:

Opportunistic Screening: The utilization of routine clinical CT scans for incidental body composition assessment has gained great momentum, with automated pipelines enabling population-scale sarcopenia screening without additional imaging burden [86], [87].

Multi-vertebral Analysis: While L3 remains the standard measurement location, research has explored alternative vertebral levels (T10-L5) and multi-slice aggregation to improve measurement reliability and enable analysis from chest CT or non-abdominal protocols [88], [89].

Prognostic Applications: AI-based sarcopenia assessment has showed consistent prognostic value across cancer types and treatment modalities, with sarcopenia independently associated with increased mortality, treatment toxicity, and postoperative complications [90]–[92].

Sarcopenic Obesity: The intersection of sarcopenia and obesity (sarcopenic obesity) has emerged as a distinct phenotype with adverse health outcomes, requiring specialized assessment approaches that simultaneously evaluate muscle mass and adiposity [93]–[95].

The key methodological characteristics and performance metrics from some methodological studies in sarcopenia assessment are summarized in Table III and Table IV.

IV. Applications of AI-Driven Body Composition Analysis in Sarcopenia

A. Diagnostic Applications

AI-driven approaches have advanced the diagnostic landscape for sarcopenia, addressing limitations of traditional assessment methods while enabling scalable screening programs. Here we examine the clinical applications of AI in sarcopenia detection, screening, and early diagnosis across diverse healthcare settings.

1) Automated Muscle Segmentation and Quantification: The automation of body composition analysis from medical images represents the most developed application of AI in sarcopenia diagnostics. Deep learning-based segmentation algorithms have achieved performance levels approaching or exceeding manual expert measurements, with typical processing times reduced from 20 to 30 minutes to under one minute per scan [76], [77]. These

systems automatically delineate skeletal muscle, subcutaneous adipose tissue, visceral adipose tissue, and intramuscular fat from CT images at the L3 vertebral level.

The clinical validation of automated systems has progressed. Magudia et al. [31] applied deep learning segmentation to 12,128 outpatient CT scans, establishing age-, sex-, and race-specific reference curves for skeletal muscle cross-sectional area. These population-scale normative data enable standardized sarcopenia diagnosis across diverse patient populations and address the need for validated cutoff values.

Commercial software platforms incorporating AI-based body composition analysis have entered clinical practice. Toolkits such as CoreSlicer, Slice-O-Matic with automated modules, and dedicated AI platforms integrate with picture archiving and communication systems (PACS) for smooth clinical workflow integration [96]. Quality control mechanisms, including automated detection of measurement errors and flagging of anatomical anomalies, enhance reliability for clinical decision-making.

2) Opportunistic Screening from Routine Imaging: A shift toward opportunistic screening uses the large volume of CT scans performed for other clinical indications. Cancer staging, trauma assessment, cardiovascular evaluation, and surgical planning routinely generate abdominal CT images suitable for body composition analysis [86], [87]. AI-enabled automated analysis transforms these existing images into valuable diagnostic data without requiring additional imaging protocols or radiation exposure.

The value of opportunistic screening is compelling in oncology, where body composition assessment provides prognostic information influencing treatment planning. Studies show associations between CT-derived sarcopenia and adverse outcomes including increased mortality, chemotherapy toxicity, and postoperative complications across cancer types [90]–[92], [97].

Implementation of opportunistic screening programs requires consideration of workflow integration, incidental finding management, and result communication. Nowak et al. [30] developed an end-to-end automated pipeline with integrated quality control for opportunistic sarcopenia assessment, addressing practical implementation challenges in radiology.

3) Community-Based and Primary Care Screening: Extension of sarcopenia screening beyond specialized imaging centers represents an important area for early detection. AI-enhanced screening tools using non-imaging assessments enable implementation in primary care and community settings where advanced imaging facilities are unavailable.

ML models incorporating anthropometric measurements, grip strength, and questionnaire responses achieve useful accuracy for sarcopenia risk stratification [17], [35]. The SARC-F questionnaire and its modified versions (SARC-CalF incorporating calf circumference) serve as validated initial screening tools, with AI-enhanced interpretation improving sensitivity for identifying at-risk individuals [98]–[100].

Smartphone-based applications represent a new platform for community sarcopenia screening. Video analysis of physical performance tests (Sit-to-Stand, Timed Up and Go) using vision-based algorithms extracts objective functional measurements comparable to laboratory assessments [14], [101]. Integration of smartphone accelerometer and gyroscope data enables continuous gait monitoring and physical activity assessment relevant to sarcopenia risk evaluation [29].

Wearable devices and Internet of Things (IoT) platforms extend monitoring capabilities beyond clinical encounters. Addante et al. [10] developed an IoT-based wearable prototype within an Ambient Assisted Living system for dynamic sarcopenia assessment through gait speed, muscle activity, and force measurements. While requiring further clinical validation, such systems enable longitudinal monitoring in home environments.

4) Sarcopenia Screening in Specific Clinical Contexts: AI-driven sarcopenia assessment demonstrates clinical utility in specific patient populations and care settings:

Preoperative Assessment: Sarcopenia identification before major surgery enables risk stratification and potential prehabilitation interventions. Automated CT analysis has been integrated into preoperative evaluation workflows for gastrointestinal, hepatobiliary, and oncologic surgery [102]–[104].

Chronic Disease Management: Patients with chronic conditions including cirrhosis [105], [106], chronic kidney disease [107], [108], chronic ob-

structive pulmonary disease [109], [110], and inflammatory bowel disease [111] exhibit elevated sarcopenia prevalence, warranting routine assessment integrated into disease management protocols.

Cancer Care: Body composition assessment has emerged as standard of care in many oncology settings, with sarcopenia independently predicting survival and treatment tolerance across cancer types [39], [91], [112]. AI automation enables routine assessment without additional clinical burden.

Geriatric Care: Thorough geriatric assessment increasingly incorporates sarcopenia screening, with AI tools facilitating implementation across diverse care settings from outpatient clinics to nursing homes [113]–[115].

B. Monitoring Disease Progression

Longitudinal monitoring of sarcopenia progression is important for evaluating intervention efficacy, predicting clinical trajectories, and enabling timely treatment modifications. AI-driven approaches help automated, reproducible tracking of body composition changes over time, overcoming limitations of manual assessment including inter-observer variability and resource constraints.

1) Longitudinal Body Composition Tracking: Serial CT imaging performed for clinical indications provides opportunities for monitoring muscle mass trajectories without additional radiation exposure. Automated analysis of sequential scans enables quantification of muscle loss rates, identification of accelerated decline patterns, and assessment of intervention effects [34], [116].

Studies examining body composition changes during disease progression and treatment have yielded clinically actionable insights. In cancer patients, skeletal muscle loss during chemotherapy predicts adverse outcomes and potential treatment intolerance, supporting dose modification or supportive care intensification [117]–[119]. Progressive sarcopenia following surgical resection similarly portends poor prognosis across malignancies [120], [121].

The Copenhagen Sarcopenia Study [122] established age-related trajectories of lean mass, strength, and function in healthy adults aged 20 to 93 years, providing reference data for identifying pathological decline patterns. AI-enabled monitoring against these normative trajectories could enable early detection of accelerated muscle loss warranting intervention.

2) Risk Assessment and Prognostic Modeling: AI algorithms integrate body composition parameters with clinical, laboratory, and imaging features to predict clinical outcomes and guide care decisions. Prognostic models incorporating sarcopenia show incremental predictive value beyond traditional risk factors across diverse clinical contexts.

In oncology, sarcopenia-incorporated prognostic models outperform conventional staging systems for predicting survival, treatment toxicity, and disease recurrence [90], [123], [124]. ML approaches combining sarcopenia indices with inflammatory markers, nutritional status, and performance scores achieve better discrimination compared to individual parameters [125].

Preoperative risk prediction incorporating body composition enables personalized surgical planning and informed consent discussions. Sarcopenia-adjusted risk models for postoperative complications have been developed for hepatobiliary surgery [103], [126], colorectal surgery [127], [128], and esophageal surgery [129], [130].

In chronic diseases, body composition trajectories predict disease progression and mortality. For liver cirrhosis, sarcopenia predicts hepatic decompensation, hepatocellular carcinoma development, and post-transplant outcomes [105], [131]. Monitoring muscle mass enables optimized transplant timing and identification of candidates requiring pre-transplant optimization.

3) Automated Change Detection and Alerting: Clinical implementation of longitudinal monitoring requires systems that automatically detect meaningful changes and alert care providers. Change detection algorithms must distinguish pathological muscle loss from measurement variability and normal age-related decline.

Statistical process control approaches establish individual baseline measurements and identify deviations exceeding expected variability thresholds. AI models trained on longitudinal datasets learn patterns distinguishing significant decline from measurement noise, improving alert specificity while maintaining sensitivity for detecting true deterioration.

Integration with EHRs enables automated generation of alerts, care recommendations, and referrals when significant sarcopenia progression is detected. Clinical decision support systems contextualize body composition changes within the patient's clinical status and care plan, helping appropriate response.

4) Treatment Response Assessment: Monitoring body composition changes during therapeutic interventions enables objective assessment of treatment efficacy. Exercise interventions, nutritional supplementation, and pharmacological treatments for sarcopenia require validated outcome measures demonstrating muscle mass and function improvements.

AI-enabled automated assessment helps large-scale clinical trials evaluating sarcopenia interventions by providing fast, reproducible endpoint measurements [132], [133]. Standardized automated analysis reduces measurement variability compared to manual assessment, improving statistical power for detecting treatment effects.

In cancer treatment, monitoring body composition during systemic therapy identifies patients experiencing significant muscle loss who may benefit from dose reduction, treatment holiday, or supportive interventions [134], [135]. Serial assessment enables adaptive treatment strategies optimizing therapeutic benefit while minimizing toxicity.

C. Treatment Personalization and Predictive Analytics

The integration of AI-driven body composition analysis with clinical decision-making represents a shift toward personalized medicine in sarcopenia management. Predictive analytics enable individualized risk stratification, intervention planning, and outcome prediction, tailoring care approaches to patient-specific characteristics.

1) Personalized Risk Stratification: ML algorithms integrate diverse patient characteristics to generate individualized risk profiles extending beyond population-level estimates. Multi-parametric models combining body composition indices with functional assessments, comorbidities, medications, and biomarkers provide subtle risk characterization enabling targeted intervention allocation.

Sarcopenia phenotyping distinguishes patient subgroups with differing pathophysiology and prognosis. Patients with isolated low muscle mass differ from those with combined mass and strength deficits (sarcopenia) or severe sarcopenia with physical performance impairment [1]. AI clustering approaches identify additional phenotypic subgroups beyond consensus classification, potentially informing intervention selection.

The intersection of sarcopenia with other conditions creates distinct clinical phenotypes requiring specialized assessment. Sarcopenic obesity, characterized by concurrent low muscle mass and excess adiposity, carries adverse cardiometabolic and mortality risks [93], [94]. Osteosarcopenia, combining osteoporosis and sarcopenia, increases fracture risk [136]. AI models accounting for these composite phenotypes provide more accurate prognostication than single-condition assessment.

2) Intervention Planning and Response Prediction: Predictive models identifying patients likely to benefit from specific interventions enable good resource allocation and personalized treatment selection. ML approaches have been applied to predict response to exercise interventions [132], nutritional supplementation [137], and combined multimodal programs [138].

In surgical planning, body composition-based risk prediction informs decisions regarding operative approach, extent of resection, and perioperative optimization strategies. Patients with severe sarcopenia may benefit from neoadjuvant prehabilitation programs incorporating exercise and nutritional optimization before proceeding to major surgery [139], [140].

Pharmacokinetic implications of altered body composition affect drug dosing and toxicity in sarcopenic patients. Reduced muscle mass and increased adiposity alter drug distribution volumes and metabolism, potentially causing increased toxicity with weight-based or body surface area-based dosing [141], [142]. AI models incorporating body composition parameters could optimize chemotherapy dosing for cancer patients with sarcopenia.

3) Clinical Decision Support Systems: Integration of AI-driven body composition analysis into clinical decision support systems (CDSS) uses research findings for practical care delivery. CDSS components include automated screening triggers, risk score

calculation, intervention recommendations, and outcome tracking.

Effective CDSS implementation requires attention to workflow integration, alert fatigue mitigation, and clinician acceptance. Point-of-care display of sarcopenia status within EHRs raises awareness without requiring active provider search. Risk-stratified recommendations prioritize alerts for patients most likely to benefit from intervention.

Natural language processing approaches extract sarcopenia-relevant information from clinical notes, radiology reports, and discharge summaries, enriching structured data capture. Automated identification of sarcopenia mentions in text enables retrospective cohort identification and quality metric tracking.

4) Outcome Prediction and Shared Decision Making: AI-generated outcome predictions help informed discussions between clinicians and patients regarding treatment options, expected outcomes, and care goals. Visualization of survival probabilities, complication risks, and functional trajectories supports shared decision-making aligned with patient values and preferences.

For patients with advanced illness, sarcopenia presence influences prognosis discussions and care planning. Severe sarcopenia may indicate limited benefit from aggressive interventions, supporting conversations about palliative care or hospice referral when aligned with patient goals [143].

Quality of life considerations extend beyond survival prediction. Sarcopenia impacts functional independence, mobility, and falls risk, affecting living situation decisions and care needs planning [144]–[146]. AI models predicting functional trajectories inform discharge planning and community support service requirements.

V. Challenges and Limitations

Despite rapid progress in AI-driven body composition analysis for sarcopenia, major challenges impede widespread clinical implementation and research advancement. This section critically examines data-related limitations, algorithmic constraints, and implementation barriers that must be addressed to realize the full potential of AI in sarcopenia assessment.

A. Data Availability, Quality, and Heterogeneity

1) Dataset Limitations and Accessibility: The development and validation of reliable AI models requires large, diverse, and well-annotated datasets, yet available resources for sarcopenia research remain limited compared to other medical AI domains. Most publicly available body composition datasets are small (hundreds to low thousands of subjects), derived from single institutions, and lack standardized annotations [147].

Manual segmentation of body composition from CT images is labor-intensive and expensive, requiring approximately 20 to 30 minutes per scan by trained analysts. This annotation burden limits dataset creation and introduces potential for annotator fatigue affecting label consistency. Semi-automated and weakly supervised approaches reduce annotation requirements but may introduce systematic biases [80].

Data sharing barriers including privacy regulations, institutional policies, and commercial interests restrict access to clinical imaging datasets. While research repositories (e.g., The Cancer Imaging Archive, UK Biobank, etc.) provide valuable resources, these datasets may not represent typical clinical populations or scanning protocols.

2) Population Diversity and Generalizability: Existing datasets and validated AI models predominantly derive from Western populations (North America, Europe), with limited representation of Asian, African, and Latin American populations who may exhibit different body composition characteristics and sarcopenia prevalence patterns [18], [84]. Age-specific, sex-specific, and ethnicity-specific cutoff values are important for accurate sarcopenia diagnosis, yet most AI tools lack validation across diverse populations.

The underrepresentation of specific patient populations creates concern for clinical implementation. Elderly patients with multiple comorbidities, who bear the highest sarcopenia burden, may be underrepresented in training datasets skewed toward healthier populations undergoing screening CT. Cancer patients, where sarcopenia assessment has most clinical relevance, exhibit altered body composition profiles that may differ from general population training data.

3) Measurement Standardization Challenges: Large heterogeneity exists in measurement protocols, anatomical landmarks, tissue classification criteria, and reference standards across studies [148], [149]. The L3 vertebral level is most commonly used, but variation in slice selection, HU thresholds for tissue classification, and software platforms introduces measurement variability limiting cross-study comparison.

Diagnostic criteria heterogeneity compounds measurement standardization challenges. Different definitions (EWGSOP, EWGSOP2, AWGS, IWGS, SDOC) employ varying muscle mass indices, cut-off values, and functional assessments, producing different prevalence estimates and patient classifications [150]–[152]. AI models trained on one definition may not transfer to clinical settings employing alternative criteria.

Scanner variability across manufacturers, models, and acquisition protocols affects body composition measurements and may degrade AI model performance when applied to images from different sources than training data [42]. Harmonization techniques and domain adaptation approaches partially address this challenge but require validation for sarcopenia applications.

B. Algorithmic Reliability, Interpretability, and Generalizability

1) Model Performance and Reliability: While AI models achieve high performance on development datasets, degraded accuracy on external validation data represents a challenge. Distribution shift between training and deployment environments occurs when patient populations, imaging protocols, or clinical contexts differ from training conditions. Domain generalization techniques improve reliability but cannot eliminate performance variability across settings.

Edge cases and atypical anatomy pose challenges for automated analysis. Patients with extensive abdominal surgery, large tumors, ascites, or anatomical variants may produce segmentation errors requiring manual correction [30]. Quality control mechanisms must identify unreliable measurements to prevent clinical decision-making based on erroneous data.

Adversarial vulnerability represents a concern as AI systems assume clinical responsibilities. While malicious attacks on medical AI are unlikely, understanding failure modes and reliability limitations remains important for responsible deployment.

2) Interpretability and Explainability: The "black box" nature of deep learning models limits clinical acceptance and regulatory approval. Clinicians require understanding of why AI systems generate specific predictions to integrate recommendations into clinical judgment and communicate findings to patients [153].

XAI techniques including attention visualization, feature attribution methods (e.g., SHAP, LIME, etc.), and concept-based explanations provide insight into model decision-making [29]. For body composition analysis, visualization of segmentation boundaries and highlighting of anatomical regions contributing to classifications improve interpretability.

In practice, clinical validation must extend beyond statistical performance metrics to assess real-world utility. Whether AI-derived sarcopenia assessments improve patient outcomes, change clinical management, or provide actionable information remains incompletely demonstrated through prospective implementation studies.

3) Generalizability Across Clinical Contexts: AI models developed in specific clinical contexts (e.g., oncology, liver disease) may not generalize to different patient populations or applications. Disease-specific alterations in body composition, such as cancer cachexia or cirrhotic ascites, create domain-specific patterns that may confound general sarcopenia assessment tools [154], [155].

Temporal generalization represents an additional concern. As imaging technology evolves, models trained on historical data may become outdated, requiring continuous validation and potential retraining on contemporary datasets.

Pediatric sarcopenia assessment presents challenges given ongoing growth and development. Adult-derived models and reference values are inappropriate for children, yet limited pediatric datasets constrain development of age-appropriate tools [156]–[158].

C. Ethical, Regulatory, and Implementation Considerations

1) Data Privacy and Security: AI systems for sarcopenia assessment require access to sensitive medical imaging and clinical data, raising privacy concerns. Compliance with healthcare data regulations including the Health Insurance Portability and Accountability Act in the United States, General Data Protection Regulation in Europe, and equivalent frameworks internationally governs data collection, storage, and sharing practices [159].

Federated learning approaches enable model training across multiple institutions without centralizing sensitive patient data, addressing privacy concerns while using diverse datasets for improved model development [160]. Differential privacy techniques add mathematical guarantees against reidentification from aggregated training data.

The use of retrospective clinical data for AI development raises questions regarding informed consent. Patients undergoing routine imaging may not anticipate secondary use of their data for algorithm development, necessitating ethical frameworks for opportunistic screening applications.

2) Algorithmic Bias and Health Equity: AI systems trained predominantly on specific demographic populations may exhibit degraded performance for underrepresented groups, potentially exacerbating healthcare disparities [161]. Body composition varies greatly across racial and ethnic groups, with Asian populations demonstrating higher disease risk at lower adiposity levels and potentially different muscle mass distributions compared to European-derived populations [84].

Historical underrepresentation of minority populations in medical imaging datasets propagates bias through AI training processes. Explicit efforts to collect diverse training data, evaluate performance across demographic subgroups, and address identified disparities are important for equitable AI deployment [162].

Age-related bias represents a concern for sarcopenia applications. Models trained primarily on middle-aged adults may perform suboptimally for the oldest-old (> 85 years) who have the highest sarcopenia prevalence and potentially different body composition characteristics.

3) Regulatory Pathways and Clinical Validation: Medical AI systems require regulatory approval before clinical deployment. The United States Food and Drug Administration (FDA) has cleared or authorized numerous AI/ML-based medical devices, including body composition analysis software, through the 510(k) clearance and De Novo pathways [163]. In the European Union, the Medical Device Regulation establishes a distinct risk-based regulatory framework for market access through CE marking.

Pre-market clinical validation must demonstrate safety and effectiveness for intended use populations. Post-market surveillance monitors real-world performance and enables detection of previously unidentified failure modes. In the rapidly evolving and competitive landscape of foundation models, the adaptive nature of ML systems is increasingly evident, particularly for applications that rely on such models. This pace of evolution may further accelerate with the adoption of agentic AI methodologies. Such inherent dynamism poses significant regulatory challenges for medical applications, which the U.S. FDA seeks to address, in part, through the use of predetermined change control plans for AI/ML-enabled medical devices.

Professional society guidelines increasingly acknowledge AI-assisted body composition analysis. The Radiological Society of North America and European Society of Radiology have published position statements on AI in radiology practice, emphasizing the importance of validation, transparency, and physician oversight [164].

4) Implementation Barriers and Facilitators: Translation of AI research to clinical practice faces implementation barriers beyond technical performance. Workflow integration requires smooth incorporation into existing clinical information systems, PACS, and EHRs [165]. User interface design must accommodate diverse clinical users with varying technical expertise.

Financial sustainability models for AI deployment remain incompletely developed. Reimbursement mechanisms for AI-assisted sarcopenia assessment are not established in most healthcare systems, limiting adoption incentives for healthcare providers. Value demonstration through health economic analyses quantifying cost-effectiveness of

AI-enabled screening versus alternative approaches supports adoption decisions [166]–[171].

Clinical acceptance requires physician trust in AI recommendations. Transparent reporting of model limitations, confidence intervals, and uncertainty quantification enables appropriate clinical interpretation. Educational initiatives familiarizing clinicians with AI capabilities and limitations help integration into clinical reasoning processes [172]–[176].

Organizational factors including institutional culture, change management capacity, and IT infrastructure maturity influence implementation success. Champion physicians advocating for AI adoption, combined with organizational commitment to innovation, accelerate successful translation from research to practice.

VI. Future Directions

The field of AI-driven body composition analysis for sarcopenia continues to evolve rapidly, with new technologies and methodological innovations promising to address current limitations and expand clinical applications. This section examines anticipated developments across three key areas: multimodal data integration, XAI advancement, and clinical translation pathways.

A. Integration of Multimodal Data

1) Multi-Imaging Modality Fusion: Future sarcopenia assessment systems will increasingly use complementary information from multiple imaging modalities. CT provides precise cross-sectional muscle quantification, MRI offers better soft tissue characterization without radiation, ultrasound enables point-of-care functional assessment, and DXA provides whole-body composition context [24], [41]. Emerging 3D optical body scanning technologies offer radiation-free, accessible body shape assessment with demonstrated correlations to DXA-derived body composition [65]–[67]. AI systems capable of synthesizing information across modalities, either through sequential assessment or true multimodal fusion, will provide more complete sarcopenia characterization than any single modality alone.

Cross-modality prediction models represent a research direction. Deep learning systems trained to estimate CT-equivalent measurements from DXA or ultrasound could expand access to precise body composition assessment in settings where CT is unavailable or contraindicated. Transfer learning between modalities may address limited training data availability for less common imaging protocols.

2) Integration with Genomic and Biomarker Data: Sarcopenia pathophysiology involves complex interactions between genetic predisposition, environmental factors, and biological aging processes. Genome-wide association studies have identified genetic variants associated with muscle mass and strength, including genes involved in myostatin signaling, growth hormone pathways, and mitochondrial function [177]. Integration of genetic risk scores with imaging-derived body composition measurements may enable more precise risk stratification and identification of individuals who would benefit most from intervention.

Serum biomarkers including inflammatory cytokines (IL-6, TNF-α, CRP), hormones (testosterone, IGF-1, vitamin D), and new markers of muscle turnover (GDF-15, myostatin) provide complementary information regarding sarcopenia etiology and progression rate [178], [179]. AI systems integrating imaging phenotypes with biomarker profiles may distinguish sarcopenia subtypes with different underlying mechanisms and optimal treatment approaches.

3) Wearable Sensors and Continuous Monitoring: Consumer wearable devices, including smartwatches, fitness trackers, and smartphones, generate continuous data streams capturing physical activity patterns, gait characteristics, and sleep quality relevant to sarcopenia assessment [9], [29]. Integration of wearable-derived functional metrics with periodic imaging assessments enables longitudinal monitoring between clinical visits.

Accelerometer-based activity recognition algorithms estimate time spent in sedentary behavior, light activity, and moderate-to-vigorous physical activity, all factors strongly associated with sarcopenia risk and progression. ML fusion of imaging biomarkers with activity patterns may improve prediction of functional decline and identify optimal intervention timing.

4) Clinical Data Integration and Decision Support: Complete sarcopenia assessment requires integra-

tion across clinical domains including nutrition (dietary intake, malnutrition screening), function (grip strength, gait speed, chair stand), and comorbidities (diabetes, cardiovascular disease, cancer) [1], [180]. AI-enabled clinical decision support systems synthesizing EHR data, imaging findings, and patient-reported outcomes can provide personalized sarcopenia risk assessment and intervention recommendations.

Extraction of sarcopenia-relevant information via natural language processing techniques from unstructured clinical notes, including mobility limitations, falls, weight loss, and appetite changes, supplements structured data sources. Temporal modeling of disease trajectories through recurrent neural networks or transformer architectures enables prediction of future functional status based on historical patterns.

B. Explainable and Interpretable AI Models

1) Advances in Explainability Methods: The progression from black-box deep learning to interpretable AI represents a research priority for clinical translation. Post-hoc explanation methods including SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and gradient-based attribution techniques provide insight into model decision-making, but these approaches have limitations including computational cost, potential inconsistency, and approximation errors [29]. Inherently interpretable architectures designed with transparency as a primary objective offer advantages over post-hoc explanations. Attention mechanisms in deep learning highlight image regions contributing to predictions, enabling visualization of anatomical features driving sarcopenia classification. Concept bottleneck models constrain intermediate representations to meaningful concepts (e.g., muscle area, fat infiltration, fascial definition), confirming alignment between model reasoning and clinical understanding.

Prototype-based learning approaches identify exemplar cases similar to new patients, supporting explanation through comparison to reference cases familiar to clinicians. Case-based reasoning aligns with clinical education and practice patterns, potentially enhancing physician acceptance.

2) Uncertainty Quantification: Clinical application requires AI systems to communicate confidence in predictions, enabling appropriate weighting of AI recommendations in clinical judgment. Bayesian deep learning approaches provide principled uncertainty estimates through posterior distributions over model parameters. Monte Carlo dropout and deep ensembles offer computationally tractable approximations suitable for clinical deployment.

Calibration, confirming that predicted probabilities match observed frequencies, represents a distinct aspect of uncertainty communication. Well-calibrated models support clinical decision-making by enabling appropriate threshold selection for screening and diagnostic applications [181].

Distinguishing epistemic uncertainty (arising from limited training data) from aleatoric uncertainty (inherent randomness in outcomes) guides clinical interpretation. High epistemic uncertainty for novel patient presentations signals cases requiring careful human review, while high aleatoric uncertainty indicates intrinsic prediction limitations.

3) Regulatory Requirements for Transparency: Emerging regulatory frameworks increasingly mandate AI transparency. The European Union AI Act categorizes medical AI as high-risk, requiring documentation of training data, model architecture, performance characteristics, and known limitations. FDA guidance on AI/ML-based software emphasizes transparency regarding algorithm function, intended use, and validation evidence.

Standardized reporting frameworks including CONSORT-AI [182] (for clinical trials of AI interventions) and TRIPOD-AI [183] (for prediction model development) establish expectations for transparent documentation of AI performance [184]. Adherence to reporting standards helps peer review, replication, and clinical implementation.

4) Building Clinical Trust: Trust development requires demonstrated reliability through extensive validation, transparent communication of capabilities and limitations, and mechanisms for human oversight and override. Participatory design involving end-users (clinicians and patients) throughout development confirms AI systems address genuine clinical needs and accommodate workflow constraints [165].

Continuous performance monitoring in deployed settings detects degradation from distribution shift or emerging failure modes. Feedback mechanisms enabling clinicians to flag incorrect predictions support iterative model improvement and maintain trust through demonstrated responsiveness to identified errors.

C. Prospects for Clinical Translation and Real-World Implementation

1) Opportunistic Screening at Scale: The widespread availability of abdominal CT imaging for diverse clinical indications creates opportunity for population-scale sarcopenia screening. Fully automated analysis of routine clinical CT scans, including those obtained for cancer staging, trauma evaluation, or vascular assessment, enables incidental body composition assessment without additional imaging burden or cost [31], [86], [87].

Implementation of opportunistic screening requires integration with clinical workflows, including automated flagging of at-risk patients, structured reporting of body composition findings, and clinical decision support for appropriate follow-up. EHR integration enables tracking of longitudinal body composition changes and alerting to accelerated muscle loss.

Population health applications include identification of high-risk subgroups for targeted intervention programs, quality improvement initiatives monitoring sarcopenia prevalence across healthcare systems, and research cohort identification for clinical trials. Health systems implementing opportunistic CT screening report identification of previously unrecognized sarcopenia in 15 to 30% of adult patients [34].

2) Point-of-Care Applications: Translation of complex AI analysis to portable, low-cost platforms expands sarcopenia assessment beyond tertiary medical centers. Smartphone-based applications combining camera-based body measurements, questionnaire-based screening, and optional integration with portable devices (grip dynamometers, body composition scales) enable community and home-based assessment [9], [12].

Ultrasound-based sarcopenia assessment with AI-assisted measurement offers point-of-care capability with imaging precision approaching CT for specific applications. Edge computing deployment of deep learning models on portable ultrasound devices enables real-time muscle assessment at bedside, in primary care offices, or in community settings [57], [61].

Thinking more broadly, telehealth integration during the COVID-19 pandemic accelerated development of remote assessment capabilities. Video-based assessment of physical performance (chair stands, gait), combined with patient-reported outcomes and remote vital sign monitoring, enables sarcopenia evaluation without in-person visits.

3) Clinical Trial Integration: Sarcopenia serves as both a therapeutic target and a prognostic factor influencing treatment outcomes across disease areas. AI-standardized body composition assessment supports clinical trial design and analysis through consistent outcome measurement, patient stratification, and covariate adjustment [39], [90].

Pharmaceutical trials for sarcopenia treatment, including myostatin inhibitors, selective androgen receptor modulators, and other investigational agents, require precise, reproducible outcome measures demonstrating treatment effect on muscle mass and quality. AI-automated analysis reduces measurement variability compared to manual assessment, potentially improving statistical power to detect treatment effects.

Adaptive trial designs incorporating AI-predicted outcomes enable enrichment strategies identifying patients most likely to respond to specific interventions. Precision medicine approaches matching patients to optimal treatments based on body composition phenotypes and predicted trajectories represent a future application of AI in sarcopenia clinical trials.

4) Global Health Applications: Sarcopenia burden is especially high in low- and middle-income countries with aging populations and limited healthcare infrastructure [19], requiring AI technologies to be adapted for deployment in resource-constrained settings where CT and MRI are unavailable.

Mobile health applications requiring only smartphone access, anthropometric prediction models using low-cost measurements, and AI-enhanced ultrasound assessment offer pathways to sarcopenia evaluation in underserved populations. Transfer learning and domain adaptation techniques enable model

training on limited local data while using knowledge from well-resourced settings.

Capacity building through technology transfer, training programs, and open-source tool development supports global implementation. International collaboration confirming diverse representation in algorithm development and validation promotes equitable benefit from AI advances in sarcopenia assessment.

VII. Conclusion

So far we have reviewed the state of AI-driven body composition analysis for sarcopenia assessment in this paper, synthesizing evidence from the rapidly evolving intersection of ML and musculoskeletal health research between 2015 and 2025. The analysis reveals advances alongside persistent challenges requiring continued research attention.

Summary of Main Findings

AI has changed body composition assessment for sarcopenia detection and monitoring. Deep learning-based segmentation of CT and MRI images now achieves human-level accuracy (Dice coefficients exceeding 0.95 for skeletal muscle) while reducing analysis time from 20 to 30 minutes for manual measurement to under one minute [4], [76]. This efficiency gain enables population-scale opportunistic screening from routine clinical imaging, identifying sarcopenia in patients who would otherwise go undiagnosed [31], [86].

ML algorithms integrating clinical variables, imaging features, and functional assessments achieve strong predictive performance for sarcopenia detection (AUC-ROC values of 0.78 to 0.89) and demonstrate prognostic value for clinical outcomes including mortality, treatment toxicity, and surgical complications [3], [90]. Radiomic analysis extends traditional morphometric assessment through high-dimensional texture features capturing muscle quality characteristics associated with myosteatosis and functional impairment [82].

The expansion of assessment modalities beyond traditional CT and DXA, including AI-enhanced ultrasound, smartphone-based applications, and wearable sensor integration, promises to expand sarcopenia screening across diverse clinical settings [9], [29], [61]. These technologies are especially relevant for point-of-care assessment, community screening, and longitudinal monitoring between imaging studies.

Contributions of AI-Driven Approaches

AI technologies contribute to sarcopenia assessment across multiple dimensions:

Standardization: Automated analysis eliminates inter-observer variability inherent in manual measurement, enabling consistent body composition assessment across institutions and studies. This standardization supports multi-center research and helps comparison of findings across diverse populations [33].

Scalability: Fast automated processing enables analysis of large imaging databases previously infeasible with manual methods. Population-scale studies using opportunistic CT screening have established body composition reference values and identified risk factors across tens of thousands of patients [34].

Discovery: ML identification of predictive features and radiomic signatures reveals associations between body composition and clinical outcomes that may escape visual detection. AI-driven analysis generates hypotheses regarding sarcopenia pathophysiology and treatment response prediction [81].

Accessibility: Mobile applications and point-of-care tools extend sarcopenia screening beyond tertiary imaging centers to primary care, community, and home settings. This democratization is important for addressing the unmet diagnostic need, especially in resource-constrained environments [11].

Persistent Challenges

Despite progress, challenges constrain clinical translation:

Data heterogeneity arising from variable imaging protocols, scanner manufacturers, and reconstruction parameters limits model generalizability across institutions [30]. The absence of standardized international diagnostic criteria, with EWGSOP2, AWGS, and other frameworks employing different cutoffs, complicates algorithm development and validation [1], [84].

Underrepresentation of diverse populations in training datasets perpetuates potential algorithmic bias, raising concerns regarding equitable performance

across demographic groups [161]. The interpretability limitations of deep learning models and incomplete demonstration of clinical utility through prospective implementation studies further constrain adoption [153].

Regulatory and reimbursement frameworks for AI-based sarcopenia assessment remain incompletely developed, creating uncertainty regarding pathways to clinical deployment and financial sustainability.

Academic and Clinical Implications

For researchers, this review identifies high-priority areas requiring continued investigation: external validation of AI models across diverse populations and imaging protocols; development of XAI methods appropriate for clinical deployment; prospective studies demonstrating that AI-guided sarcopenia assessment improves patient outcomes; and creation of open, diverse datasets supporting community algorithm development.

Self-Evaluation Against AMSTAR 2 Criteria

To ensure methodological transparency and rigor, we assessed our review methodology against the AMSTAR 2 framework [8], a validated checklist for evaluating systematic review quality. While AMSTAR 2 is traditionally applied by independent assessors, we use it here as a structured self-reflection tool to identify methodological strengths and acknowledge limitations:

- **PICO and inclusion criteria (Item 1):** The review employed clearly defined components including population (patients at risk for or with sarcopenia), intervention/exposure (AI-driven body composition analysis methods), and outcomes (sarcopenia detection, assessment, and monitoring), with explicit inclusion criteria and timeframe (January 2015 to August 2025) documented in Section II-A.
- **Protocol establishment (Item 2):** The search methodology and selection criteria were established prior to review conduct and documented in Section II-A, also providing the independent public repositories.
- **Study design justification (Item 3):** The inclusion of diverse study designs, diagnostic accuracy studies, cohort studies, systematic reviews, and methodological surveys, were appropriate for addressing questions about AI technologies in sarcopenia assessment, where evidence spans technical validation and clinical application studies.
- **Comprehensive search strategy (Item 4):** Systematic searches were conducted across multiple databases spanning medicine, computer science, and engineering, with documented keyword combinations (Table I) and coverage of both peer-reviewed publications and preprint repositories.
- **Study selection in duplicate (Item 5):** As a single-author review, study selection was not performed in duplicate, representing a methodological limitation that may introduce selection bias.
- **Data extraction in duplicate (Item 6):** Data extraction was performed by a single reviewer without independent verification, which may affect accuracy and consistency of extracted information.
- **Excluded studies documentation (Item 7):** The complete dataset of reviewed and excluded studies is available in the supplementary repository, with selection criteria explicitly defined in Section II-A.
- **Study description (Item 8):** Included studies are described with adequate detail regarding AI techniques, clinical applications, and key findings (Table III and Table IV, Section III).
- **Risk of bias assessment (Item 9):** The adapted CASP framework (Table II) was applied to evaluate methodological quality and potential biases in included studies, with results presented in Table III and Table IV.
- **Funding sources of primary studies (Item 10):** Funding sources of included studies were not systematically extracted or reported. This represents a limitation, as funding sources may influence study results and publication likelihood, particularly in AI technology development where industry sponsorship is common.
- **Statistical synthesis methods (Item 11):** Given the methodological heterogeneity across AI approaches, imaging modalities, and clinical applications, narrative synthesis was employed. Basic meta-analysis has been peformed and listed in Table III and Table IV.

- **Impact of risk of bias on synthesis (Item 12):** The narrative synthesis approach and heterogeneity of study designs, AI methodologies, and outcome measures precluded formal sensitivity analysis examining how risk of bias in individual studies affected overall conclusions. Methodological quality considerations are discussed qualitatively in Section V.
- **Risk of bias in interpretation (Item 13):** Methodological limitations and potential biases of included studies are discussed in Section V, with conclusions explicitly acknowledging evidence quality and generalizability constraints.
- **Heterogeneity explanation (Item 14):** Sources of heterogeneity across studies, including variations in AI methods, imaging modalities, patient populations, and diagnostic criteria, are discussed throughout the review.
- **Publication bias assessment (Item 15):** Formal investigation of publication bias through statistical tests or funnel plot analysis was not conducted. The inclusion of preprints and conference proceedings partially mitigates publication bias by capturing emerging research, though unpublished negative results and selective reporting of positive findings may remain underrepresented.
- **Conflicts of interest (Item 16):** The authors declare no conflicts of interest.

Limitations of this review: We acknowledges several methodological constraints. The absence of independent duplicate screening and data extraction (Items 5, 6) may introduce selection or interpretation bias. Funding sources of primary studies were not systematically documented (Item 10), limiting transparency regarding potential industry influences on study results. Formal sensitivity analysis examining the impact of risk of bias on synthesis conclusions was not conducted (Item 12), and publication bias was not formally assessed through statistical methods (Item 15). The rapidly evolving nature of AI technology means that methods published during the review period may have been superseded by subsequent advances. The inclusion of studies across multiple imaging modalities and AI architectures introduces heterogeneity in study designs and outcome measures. Additionally, the predominance of retrospective validation studies in the included literature highlights the need for prospective implementation research to fully establish real-world clinical effectiveness.

Clinical Implications

For clinicians, the evidence supports opportunistic CT-based sarcopenia screening for patients undergoing imaging for other indications, with the understanding that current AI tools require validation in specific clinical contexts before deployment. Integration of AI-derived body composition assessment into clinical decision-making should occur through structured reporting and clinical decision support rather than autonomous diagnostic systems.

For patients and healthcare systems, AI-driven sarcopenia assessment offers potential for earlier detection, personalized intervention, and improved outcomes. However, realizing this potential requires sustained investment in validation, implementation, and post-market surveillance to confirm that AI technologies deliver their promise of enhanced, equitable care for the growing population at risk for sarcopenia-related morbidity and mortality.

In conclusion, AI-driven body composition analysis represents a technology for sarcopenia assessment, with demonstrated technical capabilities now requiring translation to clinical practice. The convergence of aging populations, advancing AI capabilities, and increasing recognition of sarcopenia's clinical significance creates opportunity for continued development in this dynamic field. In recognition of the rapid evolution characterizing the AI landscape, this work extends beyond a conventional literature review by proposing a dynamic surveying methodology. To this end, we have developed an accompanying open-source website (https://aizierjiang.github.io/AI4SarcopeniaLiteratureDaily) that gathers the emerging references a living document automatically on a daily basis within the pertinent scope. This approach sets our contribution apart from traditional static reviews, facilitating the seamless integration of nascent research and thereby maintaining enduring relevance in a swiftly advancing field. Such a methodology could also serve as a adaptable template for literature reviews in other domains and the open-source codes for building the website at https://github.com/Aizierjiang/

AI4SarcopeniaLiteratureDaily can be treated as basic template and be utilized for other research by merely configuring the keywords and scopes into target domain. Concurrently, a static compilation of references featured in this review is accessible at https://aizierjiang.github.io/lr4sarcopenia.

CRediT authorship contribution statement

Aizierjiang Aiersilan: Writing. James Hahn: Supervising.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT, an AI language model developed by OpenAI, for polishing purposes, such as enhancing the clarity, readability, and wording of the written English. The tool was not employed for generating original content, ideas, or data. After using this tool, the authors carefully reviewed, edited, and refined the content as necessary and take full responsibility for the final publication.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

Appendix

In alignment with the rapid advancements in AI technologies, this review introduces a dynamic surveying methodology to maintain ongoing relevance. To support this, we have created a dedicated website that automatically collects and incorporates new references on a daily basis within the scope of AI applications for sarcopenia assessment. This platform functions as a living document, enabling the continuous integration of emerging research and distinguishing our work from traditional static literature reviews.

The methodology is designed for adaptability across various research domains. Researchers can utilize the open-source code available at https://github.com/Aizierjiang/AI4SarcopeniaLiteratureDaily as a foundational template, customizing it by adjusting keywords and scopes to suit specific fields. This facilitates broader application and promotes methodological reproducibility.

For immediate access to the dynamic content, visit https://aizierjiang.github.io/AI4SarcopeniaLiteratureDaily. Additionally, a static compilation of the references included in this review is provided at https://aizierjiang.github.io/lr4sarcopenia, offering a fixed snapshot for reference purposes.

This approach not only addresses the challenges posed by evolving AI capabilities and the growing clinical importance of sarcopenia in aging populations but also encourages collaborative development in related interdisciplinary areas.

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