Journal of Food, Nutrition and Diet Science
https://ojs.luminescience.cn/FNDS

LUMINESCIENCE
https://luminescience.cn/

Review Article

A literature review on the effects of artificial intelligence-mediated nutrition counseling and exercise guidance on community-living sarcopenic obese elderly people

Chuhan Miao[1], Mengliang Dai[2], Xinyi Chen[3*]

[1] School of Public Health, Li Ka Shing Faculty of Medicine, The University of Hong Kong, Pokfulam, Hong Kong SAR of China
[2] The First Clinical College of Gansu University of Chinese Medicine, Lanzhou, Gansu, China
[3] School of Basic Medical Sciences, Nanjing Medical University, Nanjing, Jiangsu, China

***Corresponding to:** Xinyi Chen, Email: 1536508352@qq.com

Abstract: Coexisting with age-related muscle loss and excess adiposity, sarcopenic obesity poses serious risks for disability and mortality in community-living older adults. Traditional nutrition and exercise programs often suffer from poor adherence and limited personalization. This narrative review critically examines artificial intelligence (AI)-mediated nutrition counseling and exercise guidance for sarcopenic obese older individuals and proposes a conceptual framework for future practice and research. We conducted a narrative review of PubMed, Embase, Web of Science, and ScienceDirect (inception-April 2025), focusing on primary studies employing machine learning, natural language processing, or computer vision in nutrition or exercise interventions for adults ≥65 years with sarcopenic obesity. AI-driven nutrition tools achieved fat-mass reductions and muscle-mass gains, while AI-guided exercise programs delivered modest improvements in gait speed, balance, and strength. Few interventions intentionally incorporated behaviour change techniques (BCTs), and digital-literacy, usability, and ethical challenges. A conceptual model links AI algorithms, BCTs, user support, and ethical governance. AI-mediated interventions show preliminary promise for sarcopenic obesity management but are limited by small sample size, short follow-up time, and barriers to usability. Rigorous randomized trials, integrated BCTs, and robust ethical frameworks are needed to translate AI's potential into scalable, equitable geriatric care.

Keywords: Artificial intelligence, Nutrition, Exercise, Sarcopenic Obesity, Elderly

Received: Jul. 24, 2025; Revised: Aug.25, 2025; Accepted: Sep.3, 2025; Published: Sep.9, 2025

DOI: https://doi.org/10.55976//fnds.320251436107-116

1. Introduction

Sarcopenic obesity (SO), characterized by the coexistence of sarcopenia (age-related loss of muscle mass and function) and obesity (excessive adiposity), is a growing public health concern among elderly populations globally [1]. The prevalence of SO in elderly people (≥65 years) ranges from 4-12% in community settings, with higher rates observed in women and those with chronic comorbidities [2]. SO exacerbates frailty, metabolic dysfunction, and physical disability, increasing risks of falls, hospitalization, and mortality [3]. Traditional interventions, including protein supplementation and resistance training, face challenges such as low adherence and limited accessibility [4].

Artificial intelligence (AI) has revolutionized various aspects of healthcare, including diagnostics, treatment planning, and patient management, which offers promising avenues for managing complex conditions like SO [5]. Sarcopenic obesity uniquely combines the challenges of excess adiposity with the decline in muscle mass and function. AI-driven counseling systems are being developed to cater specifically to these dual aspects of the condition. AI-mediated strategies include leveraging chatbots, wearables, and machine learning to provide scalable, personalized solutions for nutrition counseling and exercise coaching.

We propose a conceptual framework (Figure 1) that integrates AI-powered personalized nutrition and exercise interventions with embedded behaviour change techniques (BCTs), user digital-literacy support, and ethical governance to optimize outcomes for elderly people with SO, and guides us in scoping of existing evidence and identifying research gaps [6].

2. Methods

2.1 Search strategy and selection criteria

We searched in the databases of PubMed, Embase, Web of Science, and ScienceDirect from inception to April 2025. Search terms included "sarcopenic obesity", "artificial intelligence", "nutrition", and "exercise". Original intervention studies, observational research, and high-quality reviews addressing AI-mediated nutrition or exercise in elderly populations with sarcopenic obesity or related conditions were selected. Abstracts without full data, non-peer-reviewed reports, or studies not related to AI digital tools were excluded. Both Chiese and English articles were included (Table 1 and S1).

Table 1. Search strategy summary

Items	Specification
Search databases	PubMed, Embase, Web of Science, ScienceDirect
Search terms used	MeSH and free-text terms for: "sarcopenic obesity", "sarcopenia", "artificial intelligence", "machine learning", "natural language processing", "computer vision", "nutrition counseling" and "exercise guidance".
Timeframe	From inception of each database till 30 April 2025
Inclusion and exclusion criteria	Included: primary RCTs, quasi-experimental, observational studies on adults ≥ 65 years with sarcopenia or obesity using ML/NLP/CV-based interventions; English or Chinese; full-text peer-reviewed. Excluded: protocols, abstracts without full data, non-AI digital tools.
Selection process	Two reviewers independently screened titles/abstracts and full texts; disagreements resolved by consensus; study details charted in a standardized template
Any additional considerations	Qualitative risk-of-bias appraisal using JBI prompts; narrative synthesis allowed flexibility across heterogeneous evidence; detailed PubMed strategy is presented in Supplementary Table S1.

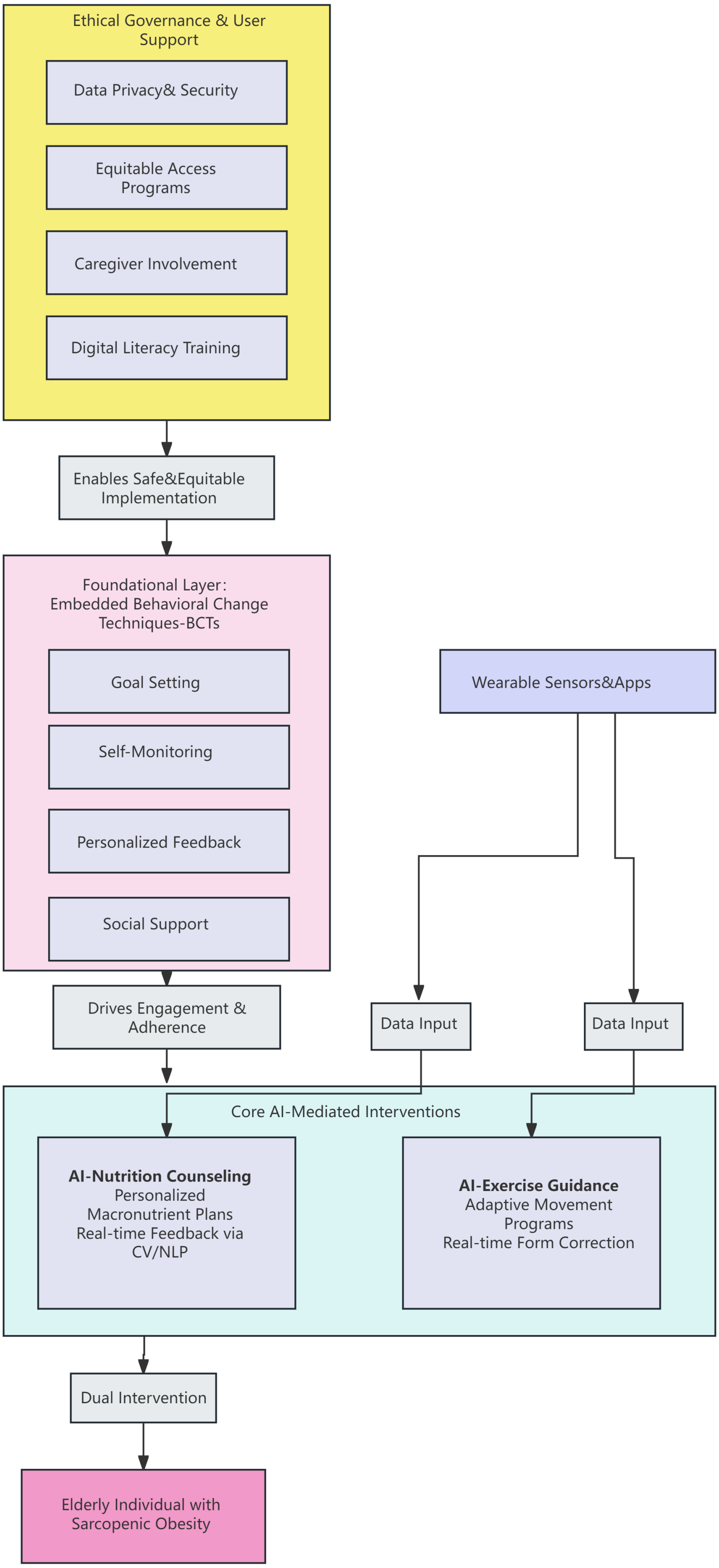

Figure 1. A conceptual framework that integrates the core components

Population: Community-dwelling adults≥65 years with sarcopenic obesity or related sarcopenia/obesity phenotypes. Focus: Interventions explicitly leveraging AI-machine learning models for dietary analysis, chatbots, or computer vision for exercise monitoring.

2.2 Synthesis and conceptualization

The results were organized by intervention type (nutrition vs. exercise) and outcome domain (body composition, function, adherence). Highlighted methodological strengths/limitations, contextual barriers (digital literacy, comorbidities), and design opportunities (BCT integration, caregiver involvement).

As a narrative review, this synthesis has inherent methodological limitations. While it provides a broad, critical examination of the emerging field, it does not employ the systematic methodology of a systematic review or meta-analysis. Consequently, the selection and interpretation of studies may be influenced by the authors, and the results are qualitative and hypothesis-generating rather than quantitatively conclusive. This approach was chosen to reflect the diverse and rapidly evolving landscape of AI applications for SO and to propose a conceptual framework for future research.

3.Traditional interventions for sarcopenic obesity

3.1 Nutritional strategies

High-protein diets (1.2-1.5 g/kg/day), leucine-rich foods, and vitamin D supplementation are recommended to preserve muscle mass while promoting fat loss [7]. Calorie restriction (CR) regimens aim for 500-750 kcal/day deficits to accelerate fat loss, but risk further muscle atrophy if protein intake is inadequate or nutrient timing is not optimized [8]. Studies report mixed adherence rates (40-60%) due to dietary monotony, socioeconomic constraints, and cognitive barriers in elderly cohorts [9]. Moreover, most trials suffer from small sample sizes, short follow-up times, and lack of blinding, which limits the quality of evidence [10].

3.2 Exercise interventions

Resistance training (RT) 3×/week improves muscle strength by 10-15% in elderly cohorts, while aerobic exercise enhances cardio-respiratory health [11]. The combination of RT and high-intensity interval training (HIIT) leads to better outcomes, but requires expert supervision, which limits scalability [12]. Dropout rates exceed 30% due to mobility constraints, comorbidities and motivational deficits [13]. The lack of real-time feedback and dynamic adjustment may cause exercise prescriptions that are either too strenuous or inadequately challenging, thereby diminishing the potential benefits and increasing the injury risks [14]. Most studies were conducted in controlled environments, reducing generalizability to rural or underserved populations [15].

4. AI in healthcare delivery

AI in elderly care can be differentiated into:

True AI: machine learning (ML) models predicting outcomes, natural language processing (NLP)-driven chatbots, computer-vision dietary assessment.

Standard digital technology: basic trackers, static telehealth platforms (no adaptive algorithms).

ML models analyze dietary patterns via food-tracking apps (e.g., MyFitnessPal), while NLP powers chatbots like Woebot for real-time motivational counseling [10]. Computer vision (CV) and wearables tailor exercise regimens based on posture and physiological signals [16]. A systematic review found AI-driven interventions improved adherence by 25% compared to traditional methods in chronic disease management but primarily in non-geriatric cohorts [17]. Real-world integration remains limited by small pilot studies, sensor noise and algorithmic bias, underscoring the need for robust validation [18].

5. AI-mediated nutrition counseling for SO elderly

5.1 Personalized nutrition plans

AI platforms integrate data from dietary logs and assessments, biomarkers and wearable trackers to deliver tailored macronutrient and micronutrient prescriptions [19]. However, most evidence derives from mixed-age or non-SO populations, indicating a critical gap in primary trials among sarcopenic obese elderly [19, 20].

5.2 Real-time feedback and monitoring

AI systems can modify dietary protocols (such as protein intake, calorie distribution and micro-nutrient timing) to enhance the precision of nutrition counseling by leveraging real-time feedback to promote muscle preservation and growth while facilitating fat loss. CV apps analyze meal photos to send instant nutrient feedback, reducing under-reporting errors by 30% [18]. However, validation has occurred predominantly in younger or tech-savvy users, raising questions about accuracy and usability in cognitively or physically frail elders [21].

5.3 Impact on body composition and health

outcomes

Preliminary AI-mediated nutrition interventions have reported 4-6% reductions in fat mass and 2-4% increases in lean mass over 8–16 weeks [22, 23]. These studies, however, involved small sample sizes (n ≤ 80), short duration, and lack long-term follow-up, limiting conclusions on sustained efficacy and functional benefits [22, 23] (Table 2).

Table 2. Applications and current evidence status of AI-mediated nutrition counseling for SO elderly

Application aspect	Types of AI	Study population	Key results	Limitations
Personalized nutrition plans	AI-DIA.	Mixed-age or non-SO populations.	Delivering tailored macronutrient and micronutrient prescriptions.	Lacking evidence from SO elderly.
Real-time feedback and monitoring	AI systems can modify dietary protocols (such as protein intake, calorie distribution, and micronutrient timing).	Younger or tech-savvy users.	Enhancing the precision of nutrition counseling; reducing under-reporting errors by 30%.	Lacking accuracy and usability in cognitively or physically frail elders.
Impact on body composition and health outcomes	AI-mediated nutrition interventions.		4-6% reductions in fat mass and 2-4% increases in lean mass over 8–16weeks.	Small sample sizes (n≤80), short duration, and lack long-term follow-up.

6. AI-mediated exercise guidance for SO elderly

6.1 Adaptive exercise programs

AI technologies, such as 3D human pose estimation and machine learning algorithms, can design and monitor exercise programs, ensuring they are tailored to an individual's capabilities and progress [21]. A report emphasizes that AI systems can serve various functions, from predictive analytics to gesture and posture recognition, underscoring their potential in tailoring exercise programs for diverse populations, including older people [22]. However, most evaluations are narrative or observational, with few RCTs in SO cohorts [24].

6.2 Telerehabilitation and safety

AI-based telerehabilitation methods enable remote exercise guidance, making it accessible for elderly individuals who may have mobility limitations [23].

Recent advancements in markerless motion capture exemplified by Kinect-based systems have enabled real-time posture feedback that effectively improves ergonomic practices in rehabilitation exercise settings. These systems have been shown to reduce improper lifting incidents by up to 50%, thereby helping to prevent musculoskeletal injuries and enhancing safety protocols in controlled experiments [24, 25].

Despite these useful findings, nearly 30% of respondents reported discomfort because of design and ergonomic shortcomings that may limit continuous or extended usage during exercise when using wearable sensors in 2022 [26]. Recent comparative studies further suggest that textile-integrated wearable technologies tend to offer a more comfortable user experience than traditional accessory-based devices, underscoring the importance of optimizing design to promote user compliance [24].

6.3 Improvement in physical function

AI-guided exercise programs have been associated with great improvements in various physical function markers in clinical trials, including enhanced gait speed (+0.10-0.15 m/s), better balance, reduced time on functional mobility tests (such as the Timed Up-and-Go test, TUG) (1.2-1.8 s), and increased muscle strength (+5-8%) over 12 weeks [27]. If the sensor data indicates fatigue or improper form, immediate adjustments (such as reducing intensity or modifying the exercise) can be made, thus promoting safer training sessions. AI-enhanced 3D pose estimation as a tool in telerehabilitation programs, showing that AI-mediated feedback can improve physical function and muscle strength comparable to traditional exercise approaches, even in remote settings [28]. Moreover, these systems can encourage higher adherence and engagement by integrating digital monitoring, which is essential for long-term functional gains (Table 3).

Table 3. AI-mediated exercise guidance for SO elderly

Application aspect	Types of AI	Study population	Key findings	Research gaps
Adaptive exercise programs	3D human pose estimation; machine learning algorithms.	Diverse populations, including older people.	Designing and monitoring capability-tailored exercises.	Narrative or observational evaluations.
Telerehabilitation and safety	Kinect-based systems	Especially forelderly individuals who may have mobility limitations.	Enabling remote guidance with real-time posture feedback; reducing improper form by up to 50% and preventing injuries.	Wearable sensor design can cause discomfort (~30% of users), potentially limiting adherence; Textile-integrated designs show promise for improved comfort.
Improvement in Physical function	AI-guided exercise programs using various physical function markers inclinical trials.		Great improvements in various physical function markers in clinical trials; promoting safer training sessions.	Long-term efficacy and functional carry-over in SO elderly remain to be fully established.

7.Combined AI-mediated nutrition and exercise interventions

7.1 Differences between AI-assisted nutrition counseling and exercise guidance for elderly with SO

AI applications in nutrition and sports science, two independent yet complementary fields, present different advantages, challenges, and development paths. We compared using AI-based dietary intake assessment methods (AI-DIA) and 3D human pose estimation as representative techniques.

In nutrition, the main advantages of AI intervention are personalization and scalability. By integrating dietary logs, biomarkers, and wearable device data, the AI-DIA system can generate highly personalized macronutrient and micronutrient prescriptions that precisely address the dual challenges of muscle loss and fat excess in SO seniors [20]. Its significant advantage lies in the passive monitoring capabilities, such as reducing the underreporting rates by about 30% through analysing meal image [18], thereby obtaining more objective intake data and achieving near real-time remote feedback, greatly reducing the reliance on professional staff for traditional dietary assessments.

In the field of sports science, the main advantage of AI intervention lies in its precision and safety assurance. Based on three-dimensional human posture estimation technology, it can capture motion without markers and quantify the user's movement quality [21]. Its primary value lies in providing objective biomechanical feedback in real time, which effectively corrects erroneous postures and reduces inappropriate action events by up to 50%, thereby significantly lowering the risk of sports injuries in remote rehabilitation environments [24, 25]. At the same time, it has a dynamic adaptability that allows for immediate adjustment of exercise intensity or type based on users' real-time fatigue or quality of action completion, providing personalized safety guidance that traditional pre-programmed courses cannot match [28].

Despite the promising prospects, AI applications in both fields face significant limitations. The challenges of nutritional AI (AI-DIA) are primarily centred on technical accuracy and user compliance. Firstly, most of the training datasets for existing algorithms come from young and healthy individuals, and their effectiveness and applicability in elderly SO populations still need to be rigorously verified [19, 20]. Secondly, its effectiveness is built on users' continuous active recording, which is a significant obstacle for older populations with weaker cognitive function or lower technical acceptability, potentially leading to data loss and interruption of interventions.

The challenges in motion science AI (3D pose estimation) tend to focus more on technological ecological validity and user experience. About 30% of users report discomfort with traditional devices, indicating that wearable sensors need further improvement in design [26]. Similar to AI in nutrition, high-quality randomized controlled trials (RCTs) supporting its efficacy are still lacking in SO populations, with most evidence remaining at the observational or technical validation stage [24].

7.2 Synergistic mechanisms and behaviour change techniques

The integration of AI-mediated nutrition consultation and exercise guidance creates a synergy in which each component reinforces the other. Optimizing nutrition improves metabolism and promotes the anabolism environment necessary for muscle regeneration, while guided exercise enhances muscle strength, balance, and overall physical performance [29]. Together, these coordinated interventions help to counteract the detrimental effects of sarcopenia and obesity-improving mobility, reducing the risk of falls, and enhancing quality of life [22]. However, only 15% of existing SO trials report the intentional use of BCTs-such as goal setting, self-monitoring, and feedback loops, which are crucial for adherence [9]. AI can systematically embed BCTs, delivering timely prompts and progress visualizations to sustain engagement [30, 31].

For instance, an AI nutrition app can set goals by prompting the user to specify a target on daily protein intake. Through self-monitoring, the user logs meals via voice command or photo [32].

8. Challenges and future directions

8.1 Digital literacy and technology acceptance

Current research severely underestimates the multidimensional realities faced by elderly individuals with muscle-reducing obesity when adopting health interventions with artificial intelligence. This vulnerable group exhibits pathological features of skeletal muscle loss and metabolic dysfunction, with unique mobility limitations, fluctuations in cognitive function, multiple comorbidities, limited socioeconomic resources, and low technical adaptability that have not yet been adequately considered in AI solution design.

Existing technological approaches overly focus on optimizing algorithms and improving data accuracy while overlooking three key dimensions of reality: physiological limitations, reduced joint mobility and fatigue, which lead to lower adherence to wearable devices. Some elderly individuals often struggle with a single disease model. On a cognitive, social level, there are health pheromone differences and technological fear, and older people often display lower levels of digital literacy compared to younger populations. Many may have limited familiarity with AI interfaces. Elderly users face usability barriers since 40% required family assistance to navigate apps [33]. This gap in digital competency can lead to difficulties in navigating user interfaces, understanding prompts from AI systems, or even setting up and maintaining wearable sensors, ultimately hampering the effective utilization of personalized exercise or nutrition programs. Recent qualitative studies have emphasized that even well-intentioned AI-based services can fall short if they do not accommodate to the learning curve and usability needs of the elderly population [30].

Implementing the ecosystem: differences in access to medical resources and the absence of family support systems. This technocentrism tends to detach so-called "personalized solutions" from real-world use cases, ultimately leading to a systematic overestimation of intervention effectiveness. Meanwhile, with the application of artificial intelligence, elderly people are increasingly absent, leading to the neglect of their free will through algorithmic logic.

Solutions include:

Simplified UIs: Interfaces with large icons, voice activation, and offline capabilities to accommodate low connectivity [32].

Proven training models: Caregiver-led training modules and community tech hubs in senior centers that have shown success in improving technology self-efficacy [34].

Gamification and social support: features such as virtual badges for achieving protein goals or family-linked apps where relatives can send encouragement, which have been shown to promote motivation and adherence in pilot studies [30, 33, 35].

8.2 Ethical and privacy concerns

Ethical concerns about data privacy persist, particularly with cloud-based platforms [31]. The ethical issues primarily include four aspects: First, privacy protection and data security. Artificial intelligence involves multiple stages of data collection, processing, and transformation. If the system is hacked, it may not only fail to timely monitor and control elderly health data, but also result in economic losses. This accumulation of sensitive health data necessitates robust privacy protection and ethical safeguards. The second factor is the technological gap and the digital divide, with age-related physiological impacts and cultural education levels reducing the willingness of elderly people to use artificial intelligence for healthcare. In practice, due to the significantly fewer digital information resources available to older populations compared to other age groups, elderly user with lower digital literacy are particularly vulnerable.The third is moral responsibility and emotional care. While artificial intelligence can perform medical tasks more quickly, efficiently, and accurately than traditional healthcare services, it overlooks the need for psychological and emotional care among seniors. Currently, there is a lack of moral accountability in AI systems.

Additionally, the transparency of AI decision-making processes is critical to ensure that interventions are both equitable and respectful of user autonomy. The ethical privacy issues exposed by artificial intelligence in elderly health services need to be addressed from multiple perspectives through laws, regulations, technical standards, targeted education and training for seniors, enhanced ethical review and algorithm audits. In ethical review, the role of institutions such as ethics review committees needs to be further strengthened. Researchers have called for the development of ethical frameworks that not only secure personal data but also provide clear guidelines for the acceptable use of AI in health monitoring and decision support [19, 35].

The use of AI in vulnerable elders raises four key solutions:

Transparency and explainability: Open algorithms and clear rationale for recommendations [31]. Informed consent: Adapt consent processes for those with mild cognitive impairments, using visual aids and iterative consent checks [28]. Equitable access: Subsidized devices, broadband support and targeted literacy programs to close the digital divide [31]. Data governance: User-owned health data vaults with blockchain audits; explicit policies on secondary data use [28].

8.3 Standardization and regulatory needs

Despite the great potential of AI interventions, a major challenge remains: the lack of standardization of algorithms, data collection methods, and outcome measurements. AI approaches such as AI-DIA showed high correlation coefficients in the estimation of calories, macro-nutrients, and micro-nutrients, although there was still variability in the accuracy of micro-nutrients [20]. Regulatory and professional bodies have increasingly emphasized the need for uniform standards to ensure safety and reliability. Establishing uniform protocols will help validate AI systems in clinical settings and facilitate the integration of these technologies into routine practice. In addition, collaboration between professional organizations and regulatory agencies is essential to establish safety thresholds, interoperability standards, and post-marketing surveillance frameworks to ensure the safety of older people [23, 30].

8.4 Future research directions

We propose a conceptual framework (Figure 1) that integrates the core components discussed. This framework places the elderly individual with SO at the center, emphasizing that all technological solutions must be designed for their specific needs and limitations. The inner ring represents the dual AI-mediated interventions (nutrition and exercise) that are dynamically personalized via data from wearables and apps. This ring is supported by a foundational layer of BCTs that are systematically embedded within the AI algorithms to drive engagement and adherence. The entire system is enclosed by an essential outer ring of ethical governance & user support that includes robust data privacy measures, equitable access solutions, caregiver involvement, and digital literacy training. This framework underscores that successful implementation requires not only advanced technology, but a holistic ecosystem that takes into account human factors, behavioral science, and ethical considerations.

Future research should focus on several critical areas to fully realize the benefits of integrated AI-mediated interventions for sarcopenic obesity. Large-scale, long-term, randomized controlled trials are necessary to assess the sustained impact of these technologies on physical function, quality of life, and metabolic health. Moreover, studies should explore how advanced sensor technologies, machine learning algorithms and secure data, sharing protocols (including blockchain-based methods) can enhance personalization while mitigating privacy risks. Addressing algorithmic bias and optimizing user interfaces to improve accessibility and engagement of older people remain as key avenues for investigation. As emerging evidence builds, interdisciplinary collaboration among healthcare professionals, technologists, and ethicists will be essential to drive innovation while maintaining high standards of patient care [19, 31, 35].

Conclusion

AI-mediated nutrition counseling and exercise guidance is a promising approach for managing the complex challenge of sarcopenic obesity in community-living elderly individuals. The primary advantage of AI lies in its ability to provide scalable, personalized, and real-time interventions that can enhance adherence, optimize body composition, and improve physical function, potentially overcoming the limitations of traditional one-size-fits-all approaches.

However, this review highlights critical limitations in the current evidence base. Many studies are limited by small sample sizes, short-term follow-up, and a predominant focus on technologically adept populations, which limites the generalizability of results. The translation of these technologies into real-world practice for the intended elderly demographic faces substantial barriers, including digital literacy gaps, usability issues, and ethical concerns regarding data privacy and algorithmic bias.

The proposed conceptual framework (Figure 1) outlines a holistic path forward, emphasizing the need to integrate technology with BCTs and robust ethical governance. From a public health perspective, successfully overcoming these challenges could enable a scalable model of care that alleviates pressure on healthcare systems. AI-driven interventions could provide continuous, preventative support remotely, reducing the need for frequent clinic visits and potentially delaying the onset of disability and its associated costs. This is particularly crucial for underserved and rural communities with limited access to specialist care.

Future efforts must prioritize inclusive co-design with older people, rigorous long-term RCTs, and the development of standardized regulatory frameworks. Interdisciplinary collaboration among geriatricians, nutritionists, AI ethicists, and software designers is essential to translate the potential of AI into tangible, equitable, and effective geriatric care that improves the quality of life for older people with SO.

Supplementary material

Supplementary Table S1 mentioned in this article is available at https://file.luminescience.cn/FNDS-436%20Supplementary.pdf.

Conflicts of interests

The authors declare no conflicting interests.

Authors' contributions

CM was responsible for literature retrieval, data collection, and the primary drafting of the manuscript, while XC conducted data analysis, and MD and XC collaborated on the revisions.

Funding

The authors declare that there was no external funding for this article.

References

[1] Donini LM, Busetto L, Bischoff SC, Cederholm T, Ballesteros-Pomar MD, Batsis JA, et al. Definition and Diagnostic Criteria for Sarcopenic Obesity: ESPEN and EASO Consensus Statement. *Obesity Facts*. 2022;15(3):321–35. doi: 10.1159/000521241.

[2] Eglseer D, Traxler M, Schoufour JD, Weijs PJM, Voortman T, Boirie Y, et al. Nutritional and exercise interventions in individuals with sarcopenic obesity around retirement age: a systematic review and meta-analysis. *Nutrition Reviews*. 2023;81(9):1077–90. doi: 10.1093/nutrit/nuad007.

[3] Gao Q, Mei F, Shang Y, Hu K, Chen F, Zhao L, et al. Global prevalence of sarcopenic obesity in older adults: A systematic review and meta-analysis. *Clinical Nutrition*. 2021;40(7):4633–41. doi: 10.1016/j.clnu.2021.06.009.

[4] Axelrod CL, Dantas WS, Kirwan JP. Sarcopenic obesity: emerging mechanisms and therapeutic potential. *Metabolism: clinical and experimental*. 2023; 146:155639. doi: 10.1016/j.metabol.2023.155639.

[5] Reiter L, Bauer S, Traxler M, Schoufour JD, Weijs PJM, Cruz-Jentoft A, et al. Effects of Nutrition and Exercise Interventions on Persons with Sarcopenic Obesity: An Umbrella Review of Meta-Analyses of Randomised Controlled Trials. *Current Obesity Reports*. 2023;12(3):250–63. doi: 10.1007/s13679-023-00509-0.

[6] Collazo-Castiñeira P, Sánchez-Izquierdo M, Reiter LJ, Bauer S, Cruz-Jentoft AJ, Schoufour JD, et al. Analysis of behavioral change techniques used in exercise and nutritional interventions targeting adults around retirement age with sarcopenic obesity in a systematic review. *Archives of Gerontology and Geriatrics*. 2024;123:105437. doi: 10.1016/j.archger.2024.105437.

[7] Coelho-Junior HJ, Marzetti E, Picca A, Cesari M, Uchida MC, Calvani R. Protein Intake and Frailty: A Matter of Quantity, Quality, and Timing. *Nutrients*. 2020;12(10). doi: 10.3390/nu12102915.

[8] Abiri B, Hosseinpanah F, Seifi Z, Amini S, Valizadeh M. The Implication of Nutrition on the Prevention and Improvement of Age-Related Sarcopenic Obesity: A Systematic Review. *The Journal of Nutrition, Health & Aging*. 2023; 27(10):842–52. doi: 10.1007/s12603-023-1986-x.

[9] Porter Starr KN, McDonald SR, Bales CW. Obesity and physical frailty in older adults: a scoping review of lifestyle intervention trials. *Journal of the American Medical Directors Association*. 2014;15(4):240–50. doi: 10.1016/j.jamda.2013.11.008.

[10] Hoffman V, Flom M, Mariano TY, Chiauzzi E, Williams A, Kirvin-Quamme A, et al. User Engagement Clusters of an 8-Week Digital Mental Health Intervention Guided by a Relational Agent (Woebot): Exploratory Study. *Journal of Medical Internet Research*. 2023; 25:e47198. doi: 10.2196/47198.

[11] Contillo AT, Rodriguez NR, Pescatello LS. Exercise and Protein Supplementation Recommendations for Older Adults With Sarcopenic Obesity: A Meta-Review. *Journal of Aging and Physical Activity*. 2023; 31(5):878–86. doi: 10.1123/japa.2022-0245.

[12] Liao CD, Tsauo JY, Lin LF, Huang SW, Ku JW, Chou LC, et al. Effects of elastic resistance exercise on body composition and physical capacity in older women with sarcopenic obesity: A CONSORT-compliant prospective randomized controlled trial. *Medicine (Baltimore)*. 2017;96(23):e7115. doi: 10.1097/MD.0000000000007115.

[13] Picorelli AM, Pereira LS, Pereira DS, Felício D, Sherrington C. Adherence to exercise programs for older people is influenced by program characteristics and personal factors: a systematic review. *Journal of Physiotherapy*. 2014; 60(3):151–6. doi: 10.1016/j.jphys.2014.06.012.

[14] Gong Y, Yang Y, Zhang X, Tong L. Comparative efficacy of exercise, nutrition, and combined exercise and nutritional interventions in older adults with sarcopenic obesity: a protocol for systematic review and network meta-analysis. *Systematic Reviews*. 2025;14(1):77. doi: 10.1186/s13643-025-02825-z.

[15] Jacoby SF, Robinson AJ, Webster JL, Morrison CN, Richmond TS. The feasibility and acceptability of

mobile health monitoring for real-time assessment of traumatic injury outcomes. *Mhealth*. 2021;7:5. doi: 10.21037/mhealth-19-200.
[16] Bailey RL, MacFarlane AJ, Field MS, Tagkopoulos I, Baranzini SE, Edwards KM, et al. Artificial intelligence in food and nutrition evidence: The challenges and opportunities. *PNAS Nexus*. 2024;3(12). doi:10.1093/pnasnexus/pgae461.
[17] Singareddy S, Sn VP, Jaramillo AP, Yasir M, Iyer N, Hussein S, et al. Artificial Intelligence and Its Role in the Management of Chronic Medical Conditions: A Systematic Review. *Cureus*. 2023;15(9):e46066. doi: 10.7759/cureus.46066.
[18] Spill M, Callahan E, Johns K, Shapiro M, Spahn JM, Wong YP, et al. Parental and Caregiver Feeding Practices and Growth, Size, and Body Composition Outcomes: A Systematic Review. *Alexandria (VA): USDA Nutrition Evidence Systematic Review*. 2019. doi: 10.52570/NESR.PB242018.SR0402.
[19] Kassem H, Beevi AA, Basheer S, Lutfi G, Cheikh Ismail L, Papandreou D. Investigation and Assessment of AI's Role in Nutrition-An Updated Narrative Review of the Evidence. *Nutrients*. 2025;17(1):190. doi: 10.3390/nu17010190.
[20] Cofre S, Sanchez C, Quezada-Figueroa G, López-Cortés XA. Validity and accuracy of artificial intelligence-based dietary intake assessment methods: a systematic review. *The British Journal of Nutrition*. 2025:1–13 .doi: 10.1017/S0007114525000522.
[21] Ferreira DD, Ferreira LG, Amorim KA, Delfino DCT, Ferreira ACBH, Souza LPCe. Assessing the Links Between Artificial Intelligence and Precision Nutrition. *Current Nutrition Reports*. 2025;14(1):47. doi: 10.1007/s13668-025-00635-2.
[22] Canzone A, Belmonte G, Patti A, Vicari DSS, Rapisarda F, Giustino V, et al. The multiple uses of artificial intelligence in exercise programs: a narrative review. *Frontiers in Public Health*. 2025;13:1510801. doi: 10.3389/fpubh.2025.1510801.
[23] Meng D, Wei M, He S, Lv Z, Guan J, Yang G, et al. Evaluating the efficacy of AI-enhanced 3D human pose estimation in telerehabilitation for older adults with sarcopenia. *Sport Sciences for Health*. 2025; 21: 979-990. doi: 10.1007/s11332-025-01336-7.
[24] Milosevic B, Leardini A, Farella E. Kinect and wearable inertial sensors for motor rehabilitation programs at home: state of the art and an experimental comparison. *Biomedical Engineering Online*. 2020;19(1):25. doi: 10.1186/s12938-020-00762-7.
[25] Jia W, Wang H, Chen Q, Bao T, Sun Y. Analysis of Kinect-Based Human Motion Capture Accuracy Using Skeletal Cosine Similarity Metrics. *Sensors (Basel)*. 2025; 25(4). doi: 10.3390/s25041047.
[26] Kazanskiy NL, Butt MA, Khonina SN. Recent Advances in Wearable Optical Sensor Automation Powered by Battery versus Skin-like Battery-Free Devices for Personal Healthcare-A Review. *Nanomaterials (Basel)*. 2022;12(3):334. doi: 10.3390/nano12030334.
[27] Lee SH, Kim E, Kim J, Lee HJ, Kim YH. Robot-assisted exercise improves gait and physical function in older adults: a usability study. *BMC Geriatrics*. 2025;25(1):192. doi: 10.1186/s12877-025-05811-1.
[28] Shen J, Yu J, Zhang H, Lindsey MA, An R. Artificial intelligence-powered social robots for promoting physical activity in older adults: A systematic review. *Journal of Sport and Health Science*. 2025:101045. doi: 10.1016/j.jshs.2025.101045.
[29] Ji W, Lee D, Kim M, Lim N, Lim JY, Baek JU, et al. Efficacy of a combined exercise and nutrition intervention study for outpatients with possible sarcopenia in community-based primary care clinics (ENdSarC): study protocol for a multicenter single-blinded randomized controlled trial. *BMC Geriatrics*. 2024;24(1):861. doi: 10.1186/s12877-024-05434-y.
[30] Anisha SA, Sen A, Ahmad B, Bain C. Exploring Acceptance of Digital Health Technologies for Managing Non-Communicable Diseases Among Older Adults: A Systematic Scoping Review. *Journal of Medical System*. 2025; 49(1):35. doi: 10.1007/s10916-025-02166-3.
[31] Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. *Nature Medicine*. 2022; 28(1):31–8. doi: 10.1038/s41591-021-01614-0.
[32] Patra E, Kokkinopoulou A, Wilson-Barnes S, Hart K, Gymnopoulos LP, Tsatsou D, et al. Personal Goals, User Engagement, and Meal Adherence within a Personalised AI-Based Mobile Application for Nutrition and Physical Activity. *Life (Basel)*. 2024;14(10):1238. doi: 10.3390/life14101238.
[33] Chung J, Brakey HR, Reeder B, Myers O, Demiris G. Community-dwelling older adults' acceptance of smartwatches for health and location tracking. *International Journal of Older People Nursing*. 2023;18(1):e12490. doi: 10.1111/opn.12490.
[34] Heart T, Kalderon E. Older adults: are they ready to adopt health-related ICT? *International Journal of Medical Informatics*. 2013; 82(11): e209–31. doi: 10.1016/j.ijmedinf.2011.03.002.
[35] Oh YJ, Zhang J, Fang ML, Fukuoka Y. A systematic review of artificial intelligence chatbots for promoting physical activity, healthy diet, and weight loss. *International Journal of Behavioral Nutrition and Physical Activity*. 2021;18(1):160. doi: 10.1186/s12966-021-01224-6.