

An Interdisciplinary Approach to Long-Term Care: Artificial Intelligence Applications for Monitoring Nutritional Status and Social Well-Being

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Abstract

The global rise in the older adult population brings complex, interrelated biopsychosocial challenges, including nutritional inadequacies, sarcopenia, social isolation, and sleep disturbances. Dealing with these interconnected issues in institutional care settings is increasingly difficult given the restrictions of traditional approaches. This descriptive review analyzes, from a multidisciplinary perspective, the role of Artificial Intelligence (AI)-based technologies in monitoring nutritional status, predicting clinical risks such as malnutrition and sarcopenia, and enhancing psychosocial well-being in elder care. Relevant literature was identified through searches in PubMed/MEDLINE, Scopus, and Web of Science (2016–2026), focusing on peer-reviewed studies published in English. Current literature indicates that AI-based image-processing systems can accurately monitor dietary intake, while machine learning algorithms can enable earlier risk stratification for sarcopenia and inflammatory trajectories using biomarker data. Furthermore, social robots and non-contact sensors have been shown to reduce loneliness among older adults, improve sleep quality, and indirectly enhance motivation for eating. From a social work perspective, AI is considered an effective tool that increases organizational efficiency in case management and facilitates a shift from crisis-oriented intervention to predictive and preventive care models. The success of this technical transformation depends on establishing an ethical framework that supports privacy, dignity, and the principles of person-centered care. Overall, AI provides evidence-informed decision support for dietitians and social work professionals, helping to develop a holistic care ecosystem that optimizes the well-being of older adults.

Keywords: Artificial intelligence, elder care, nutrition, social isolation, sarcopenia, social work.

Uzun Süreli Bakımda Disiplinlerarası Bir Yaklaşım: Beslenme Durumu ve Sosyal Refahın İzlenmesinde Yapay Zekâ Uygulamaları

Öz

Yaşlı nüfusun küresel olarak artması, beslenme yetersizlikleri, sarkopeni, sosyal izolasyon ve uyku bozuklukları gibi karmaşık ve birbirleriyle ilişkili biyopsikososyal zorlukları beraberinde getirmektedir. Geleneksel yaklaşımların sınırlılıkları nedeniyle, kurumsal bakım ortamlarında bu birbiriyle bağlantılı sorunların yönetimi giderek daha güç hale gelmiştir. Bu anlatı derlemesi, yaşlı bakımında yapay zekâ (YZ) tabanlı teknolojilerin beslenme durumunun izlenmesindeki, malnütrisyon ve sarkopeni dâhil klinik risklerin öngörülmesindeki ve psikososyal refahın artırılmasındaki rolünü multidisipliner bir bakış açısıyla değerlendirmektedir. Güncel literatür, YZ destekli görüntü işleme sistemlerinin besin alımını yüksek doğrulukla izleyebildiğini; makine öğrenmesi algoritmalarının ise biyobelirteç verilerini kullanarak sarkopeni ve inflamatuvar seyre yönelik erken risk sınıflandırmasına olanak tanıdığını göstermektedir. Ayrıca sosyal robotların ve temassız sensörlerin yaşlılarda yalnızlığı azaltabildiği, uyku kalitesini

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iyileştirebildiği ve dolaylı olarak yeme motivasyonunu artırabildiği bildirilmektedir. Sosyal hizmet perspektifinden, YZ vaka yönetiminde kurumsal verimliliği artıran ve kriz odaklı müdahaleden öngörülü ve önleyici bakım modellerine geçişi destekleyen stratejik bir araç olarak görülmektedir. Bununla birlikte, bu teknolojik dönüşümün başarısı mahremiyeti, onuru ve kişi merkezli bakım ilkelerini koruyan bir etik çerçevenin oluşturulmasına bağlıdır. Genel olarak YZ, diyetisyenler ve sosyal hizmet uzmanları için kanıta dayalı karar desteği sunmakta ve yaşlı bireylerin iyilik hâlini optimize eden bütüncül bir bakım ekosisteminin geliştirilmesine katkı sağlamaktadır.

Anahtar Sözcükler: Yapay zeka, yaşlı bakımı, beslenme, sosyal izolasyon, sarkopeni, sosyal hizmet.

Introduction

The rapid growth of the older adult population worldwide is placing unprecedented pressure on medical care systems and institutional care models. The aging process is characterized not only by an increased prevalence of chronic diseases but also by complex, interrelated biopsychosocial problems, including nutritional inadequacies, sarcopenia, sleep disturbances, and social isolation¹. In particular, among individuals residing in long-term care facilities, malnutrition and frailty contribute to the acceleration of inflammatory processes and a marked decline in quality of life². The literature indicates that these processes are not independent; for instance, inadequate nutrition can precipitate loss of muscle mass (sarcopenia), which in turn restricts physical activity and thereby intensifies social isolation and depressive symptoms³.

The labor-intensive nature of conventional monitoring methods, their reliance on periodic assessments, and their susceptibility to human error have made digital transformation and the embedding of Artificial Intelligence (AI) in geriatric care increasingly essential. Contemporary AI systems, through deep learning and machine learning algorithms, can detect latent patterns in clinical presentations far more rapidly and with greater accuracy than the human eye⁴. Computer vision technologies can analyze meal consumption and plate waste in real time to identify macro and micronutrient deficiencies. At the same time, wearable sensors can record sleep-wake cycles and provide early warning signals of cognitive decline⁵.

Moreover, social robots and AI-based interactive systems are positioned not as substitutes for staffing shortages in nursing homes, but rather as “digital assistants” that support residents’ social well-being. In older adults with dementia, the use of therapeutic robots such as Paro has been observed to reduce agitation, improve social interaction, and even minimize the need for pharmacological interventions⁶. Situated at the intersection of nutrition/dietetics and social work, these applications serve not only as tools for clinical monitoring but also as preventive interventions that preserve dignity and optimize quality of life.

From a social work standpoint, the integration of AI into elder care can be conceptually anchored in the ecological systems approach, which frames an older adult's well-being as the product of continuous interactions across micro- (individual biological and psychological status), meso- (family, care staff, and the immediate institutional

environment), and macro-level (health and social policy) systems. Within this framework, AI-derived data serve to render these interacting systems visible: individual-level indicators (e.g., nutritional intake, biomarkers, sleep patterns) can be linked to interpersonal and environmental factors (e.g., commensality, social interaction, staffing levels) to inform assessment and intervention across system levels. At the same time, deploying these technologies in line with social work values requires grounding in an empowerment- and rights-based approach, in which older adults are positioned not as passive objects of monitoring but as active agents who retain autonomy, dignity, and control over their own data and care decisions. Situating AI applications within these theoretical and ethical frameworks ensures that technological efficiency remains subordinate to the profession's core commitment to person-centered care and social justice^{7,8}.

Accordingly, this review assesses, from a multidisciplinary perspective and based on current evidence, the role of AI-based systems in long-term care settings for monitoring nutritional status, predicting clinical risks such as sarcopenia and malnutrition, and safeguarding social well-being.

Material and Methods

This study was designed as a narrative (descriptive) review aiming to synthesize current evidence on the role of AI-based technologies in monitoring nutritional status and supporting psychosocial well-being in long-term care. Literature searches were conducted in the PubMed/MEDLINE, Scopus, and Web of Science databases, covering publications from January 2016 to February 2026. The search combined keywords related to three domains: (i) population and setting ("older adults", "long-term care", "nursing home", "elder care"), (ii) technology ("artificial intelligence", "machine learning", "deep learning", "social robot", "smart sensor"), and (iii) outcomes ("nutritional status", "malnutrition", "sarcopenia", "social isolation", "sleep", "psychosocial well-being"). Priority was given to peer-reviewed original studies, systematic reviews, and meta-analyses published in English. Studies were included based on their relevance to the interdisciplinary intersection of nutrition/dietetics and social work; theoretical, technical, and conceptual sources that contextualized the clinical findings were also incorporated. Given the descriptive nature of the review, no formal quality-appraisal or risk-of-bias assessment was performed.

Clinical Monitoring and Artificial Intelligence in Older Adults

One of the most important components of clinical management in long-term care facilities is the prompt recognition of nutritional inadequacies (malnutrition) and the subsequent development of sarcopenia. Conventional screening instruments (e.g., MNA, NRS-2002) typically provide static data and often yield actionable findings only once the condition has become established or chronic. However, recent studies indicate that AI-based predictive systems can detect risk at much earlier stages, thereby permitting more timely and preemptive intervention⁴.

Digital Monitoring of Dietary Intake and Image Processing

In older adults, monitoring meal consumption is typically based on staff-recorded “plate waste” observations, a process that is largely manual and highly subjective. Recent AI-based computer vision technologies, however, have substantially digitized this workflow, thereby minimizing errors. Deep learning structures, particularly convolutional neural networks (CNNs), can analyze pre- and post-meal plate photographs within seconds to identify food type and portion volume and, consequently, estimate energy intake and macronutrient consumption, with reported accuracy rates reaching up to 94% in older adults in long-term care and hospital settings^{9–11}. Notably, systems such as MealVision have been shown to reduce dietitians’ manual data-entry burden by approximately 80% while allowing real-time reporting of inadequate protein intake, a key trigger for sarcopenia^{12,13}.

AI applications are not limited to visual analytics; they also track dietary intake through smart utensils and wearable sensors. Smart forks and spoons can monitor eating speed and bite count, thereby enabling the assessment of physical risks, such as rapid eating or chewing/swallowing difficulties (dysphagia)¹⁴. In addition, micro-electromagnetic sensors placed on the neck or acoustic (sound-based) recognition systems are able to analyze swallowing sounds to inform social work professionals about an individual’s daily fluid intake or the frequency of skipped meals^{15,16}.

To protect privacy in residential care settings, “ambient intelligence” systems are increasingly preferred over camera-based monitoring¹⁷. IoT (Internet of Things) sensors embedded in kitchen cabinets or refrigerators, when combined with AI algorithms, can track changes in kitchen-related activities (e.g., the refrigerator being opened less frequently than usual) and flag possible risks such as concealed anorexia or cognitive decline¹⁸. These data can help social work professionals better understand the correlation between loneliness and reduced appetite, hence supporting timely psychosocial interventions.

Assessment of Sarcopenia and Inflammatory Processes

Sarcopenia is strongly associated with adverse outcomes in older adults, including a higher risk of falls and fractures, as well as downstream functional decline that can compromise independent living. Conventional diagnostic approaches such as dual-energy X-ray absorptiometry (DXA) and bioelectrical impedance analysis (BIA) typically require clinic-based assessment and provide only snapshot measurements that do not reflect short-term changes in inflammatory activity. In contrast, machine-learning approaches can integrate routinely collected blood biomarkers, among them C-reactive protein (CRP) and pro-inflammatory cytokines such as interleukin-6 (IL-6) and tumor necrosis factor-alpha (TNF- α), with clinical and functional variables to support earlier risk stratification and prediction of sarcopenia-related trajectories, assisting timely nutritional intervention targeted at mitigating inflammation-driven muscle catabolism^{19,20}.

AI-based ultrasound analysis is also transformative for the diagnosis of sarcopenia. Whereas manual ultrasound measurements are highly susceptible to operator-related variability, AI algorithms can automatically evaluate muscle echogenicity (an indicator of muscle quality) and architectural characteristics (e.g., pennation angle), thereby producing quantitative reports of muscle loss²¹. One study also emphasizes that AI can integrate these radiologic features with dietary data, particularly leucine and vitamin D intake, to estimate an individual's "muscle regeneration capacity"²².

In parallel, the age-related process of chronic, low-grade inflammation (inflammaging) can be examined using AI-based data-mining approaches that jointly evaluate clinical findings, biomarkers (e.g., CRP, IL-6), dietary records, and genetic variants. This integrated analytic framework can help identify which genomic profiles are most likely to show improvements in inflammatory markers and derive greater clinical benefit from Mediterranean-style eating patterns or other anti-inflammatory dietary strategies²³. Those insights support the development of care plans for older adults in social care settings that are not simply "adequate," but optimized and explicitly anti-inflammatory.

Psychosocial Well-Being and Technological Support

In later life, the preservation of psychosocial well-being is as critical as physical health parameters for sustaining general well-being and stabilizing nutritional status. Among older adults receiving institutional care, social isolation and the chronic sense of loneliness that often accompanies it not only threaten mental health but also cause physiological consequences, including diminished appetite, skipped meals, and sleep disturbances²⁴. In this context, AI-based applications deliver comprehensive support by functioning both as passive monitoring mechanisms and as active intervention tools.

The Negative Cycle Between Social Isolation and Nutrition

In later life, social isolation is not simply a psychological condition; it also constitutes a biological risk factor that can precipitate nutritional inadequacy and physical decline. The literature links "eating alone" (i.e., reduced commensality) directly to lower overall food intake and poorer meal quality among older adults²⁵. Within institutional care places where social interaction is limited, individuals' motivation to eat may diminish, thereby initiating a cycle of appetite loss commonly described as the "anorexia of aging," a term referring to the physiological and psychosocial decline in appetite and food intake that frequently accompanies advancing age²⁶.

AI-based analytic systems can detect this negative cycle before it crystallizes into a clear clinical presentation. AI-based emotion recognition and voice-analysis technologies can monitor speech rate, lexical diversity, and melancholic shifts in vocal tone to quantify levels of social withdrawal²⁷. For example, an older adult's preference for staying in their room rather than attending the dining hall, or abrupt decreases in the duration of social interactions, may be labeled by AI algorithms as "risk of social isolation". At the same time, concurrent effects on dietary intake (e.g., skipped meals, reduced portion size) are reported²⁸.

In addition, interaction data collected via therapeutic robots and digital companions can provide social work professionals with quantitative indicators of an individual's level of "social hunger". Through studying the quality of an older person's bond with a robot or digital assistant, AI can identify the times of day when loneliness peaks and determine how these periods correlate with eating behaviors²⁹. This evidence-based approach enables social work professionals to design targeted "social support interventions" tailored not only to general activities but also to meal times when individuals may be most vulnerable, thereby providing preventive protection against loneliness-related nutritional disturbances³⁰.

Monitoring Sleep Quality with Smart Sensors and Its Relationship with Nutrition

Sleep disturbances in older adults can disrupt circadian rhythms and adversely affect hormonal balance that regulates appetite, particularly ghrelin & leptin levels. Poor-quality or insufficient sleep may reduce metabolic rate and, the following day, contribute to blunted appetite that can culminate in the "anorexia of aging" or lead to irregular and inferior food choices³¹. Conventional sleep-monitoring methods such as polysomnography are invasive, could aggravate agitation in older individuals, and are difficult to implement in institutional care settings³².

In this context, AI-based non-contact sensors and smart-bed technologies offer a disruptive and minimally burdensome approach to monitoring sleep hygiene in older adults³³. AI algorithms can continuously analyze sleep phases, respiratory rate, heart rate variability (HRV), and involuntary nocturnal movements to generate an integrated "sleep score"³⁴. For instance, when AI detects REM-sleep fragmentation or repeated awakenings, these data can be linked to nutritional monitoring interfaces. If a sustained decline in sleep quality is observed, the system can send early alerts to care staff, indicating that the pattern may increase malnutrition risk via appetite loss³².

Moreover, AI models integrated with smart-home systems and wearable technologies can go beyond monitoring sleep quality by optimizing the sleep surroundings (e.g., light levels and room temperature) in accordance with an individual's biological clock, therewith supporting circadian regulation³⁵. From a social work perspective, this electronic intervention represents a non-pharmacological strategy to improve sleep quality, enabling individuals to start their morning meals feeling more rested and with greater appetite. In turn, it can act as a critical defensive shield against the development of frailty syndrome associated with undernutrition³⁶.

Digital Companions and Enhancing Social Interaction

Therapeutic robots and voice-based AI assistants are increasingly integrated into institutional care as "digital companions" to reduce the harmful effects of social isolation among older adults^{37,38}. Particularly in individuals living with dementia or cognitive decline, the use of biomimetic robots such as *Paro* has been associated with significant reductions in agitation and anxiety, therewith enhancing residents' capacity to engage

with their surroundings^{6,39}. This technology-based intervention not only provides psychological relief but may also reduce disruptive behaviors noted during meals (e.g., wandering, refusal to eat), thus rendering food intake more calm and efficient^{6,39}.

AI-based interactive systems can further provide cognitive and social stimulation through verbal and/or embodied interaction, and many are designed to support daily self-care via personalized prompts (e.g., hydration, medicine schedules, and meal-time reminders)^{38,39}. In addition, AI algorithms can monitor reaction time and lexical richness during these communications and deliver real-time reports to social work professionals regarding possible declines in cognitive functioning⁴⁰.

From a social work perspective, digital companions are not intended to replace staff workload; rather, they provide older adults with a sense of “companionship” and “safety” during periods when personnel are not physically present⁴¹. This form of “continuous social presence” can help disrupt the appetite-loss cycle triggered by loneliness, strengthen older adults’ adaptation to institutional living, and make an indirect yet substantial contribution to the sustainability of nutritional status². Ultimately, these technologies are positioned as strategic adjunct tools in elder care, supporting rather than supplanting human touch while improving biopsychosocial well-being⁵.

AI Applications from a Social Work Perspective

The discipline of social work seeks to protect individuals’ biopsychosocial integrity and improve social welfare. In long-term care settings, the deployment of artificial intelligence provides social work professionals with analytics-based capacity in case management, risk assessment, and resource allocation⁴². Whereas intervention processes in traditional care models are largely reactive (i.e., initiated after an event occurs), AI enables a more proactive orientation through facilitating earlier detection and preventive action⁴³.

Organizational Effectiveness and Clinical Decision Support Systems

Institutional elder care is an operational context with low tolerance for error, requiring the management of complex health needs under limited staffing resources. In conventional care models, a substantial proportion of staff time is devoted to routine data entry and documentation, which in turn limits opportunities for direct social interaction with residents⁴⁴. AI-based Clinical Decision Support Systems (CDSS) can improve these administrative demands, thereby improving organizational efficiency and also boosting the overall quality of care⁴⁵.

AI algorithms can concurrently analyze electronic health records (EHRs), nutrition-tracking interfaces, and sensor-derived data to generate “smart task lists” for social work professionals and dietitians⁴⁶. For instance, the system may integrate indicators such as sudden weight loss, deteriorating sleep quality, and decreased interaction with a social robot, and subsequently issue a “high-priority case” alert to relevant professionals⁴⁷. Rather than citing a single fixed percentage improvement, the literature more

consistently supports that well-designed dashboards and digital decision-support can improve task execution time, decision-making, and conformance to evidence-based processes, depending on usability and implementation quality⁴⁸.

Moreover, the objective datasets generated by AI-based systems can shift multidisciplinary in-house meetings (case conferences) from personal interpretations toward evidence-informed analyses. Social workers, dietitians, and physicians can jointly review an older adult's status via a shared, digital, and up-to-date dashboard, permitting timely revisions to intervention plans⁴⁸. In this sense, the digital ecosystem functions not only as organizational automation but also as a safety net that helps guarantee continuity and accuracy in the services provided to older adults⁴⁵.

Predictive Social Work and Preventive Intervention

Traditional social work practice is frequently reactive in nature, typically being activated only after a problem has emerged (e.g., falls, acute malnutrition, severe depression). In contrast, machine learning-based predictive analytics models can identify low-intensity alterations within big datasets, thereby creating a “pre-crisis” window for social work⁴⁸. This approach constitutes a new paradigm in the discipline, often referred to as predictive social work, which aims to manage risks before they materialize⁴.

AI algorithms can integrate subtle reductions in appetite, micro-changes in sleep duration, and patterns of social withdrawal into a single composite risk score. For example, a slight slowing of gait speed coupled with decreased protein intake may be flagged by the system as an “impending frailty episode” or “elevated fall risk”^{46,47}. From a social work perspective, this shifts the focus from post-event rehabilitation following injury or illness to the prompt initiation of preventive interventions such as modifying the individual's living environment or increasing nutritional support without delay⁴².

Predictive systems can likewise play a key role in preventing adverse mental health outcomes such as severe depression or suicide by monitoring the impact of loneliness on older adults through digital interaction data²⁸. These AI-based “early warnings” enable social work professionals to move beyond intuitive decision-making toward evidence-informed, appropriately timed interventions, which have been associated with meaningful reductions in hospitalization rates and morbidity in nursing home settings⁴². Within this integrated framework, the social worker's role shifts from that of a “crisis responder” to a proactive “architect of well-being,” responsible for actively shaping and sustaining older adults' quality of life².

Technology, Social Justice, and Access to Services

Artificial intelligence is increasingly positioned as a strategic tool for overcoming the physical, geographic, and socioeconomic barriers that older adults face in accessing health and social services⁴³. In line with the core social work principle of social justice, AI can “democratize” access to high-quality monitoring and intervention services for disadvantaged groups, older adults with disabilities, and long-term care facilities in rural

or under-resourced settings where staffing is limited⁴². Remote monitoring technologies and AI-based telehealth systems allow specialists to extend care beyond institutional boundaries and reach broader populations in accordance with the principle of “aging in place”^{2,43}.

The objective and continuous datasets generated by AI algorithms may also help minimize implicit bias and discriminatory practices in service delivery, thereby supporting the provision of fair and equitable care plans tailored to each older adult’s level of need^{5,41}. In traditional systems, more “active” or outspoken residents may receive disproportionate attention; by contrast, AI-based systems can identify even the most “invisible” individuals who silently experience social isolation or appetite loss, bringing them to the attention of social work professionals⁶. This enables the rational allocation of limited social work resources based on need, thereby strengthening institutional equity.

In addition, AI-based natural language processing and translation technologies can help older adults from diverse ethnic backgrounds or those experiencing language barriers accurately communicate their dietary preferences and social needs to care staff⁴³. From a social work perspective, such technological integration can function as an advocacy tool to reduce the digital divide, supporting older adults in becoming not merely passive recipients of care but active agents with voice and authority over their health data and rights². Overall, AI serves as a lever that promotes health equity, universalizes access to services, and aligns the humanistic values of social work with the opportunities of the digital era³.

Ethical Debates and Challenges

The deployment of artificial intelligence and digital monitoring systems into long-term care facilities introduces profound socio-ethical dilemmas that extend beyond the operational benefits these technologies may offer. The pace of technological innovation often outstrips the development of legal and ethical structures designed to regulate its impact on human values⁴³. Accordingly, the use of AI in institutional care necessitates scrutiny across core ethical domains, including privacy protection, individual autonomy, and algorithmic impartiality.

Image-processing technologies and biometric sensors used for real-time monitoring of nutritional status and sleep quality require a delicate balance between an older adult’s right to privacy and the pursuit of improved care quality⁴². Continuous digital surveillance may risk exacerbating “institutionalization trauma” and undermining individuals’ sense of control over their own living space⁶. To address these concerns, the literature recommends prioritizing non-camera-based solutions and privacy-preserving modalities such as anonymized data streams (e.g., silhouette-based analysis or thermal sensors) and restricting data access to authorized professionals only⁵.

The clinical success of such systems largely depends on the attitudes of older adults and care staff toward technology. “Technophobia” and disparities in digital literacy may lead

some older individuals to resist AI-based robots or wearable biosensors. From a social work perspective, it is essential that technology does not become a coercive instrument and that individuals' right to informed consent is safeguarded³. In addition, if care staff perceive AI not as a supportive tool but as a threat to their professional roles, this can negatively affect system effectiveness and data entry quality⁴².

AI algorithms also carry the risk of reproducing sociocultural biases embedded in the datasets on which they are trained. This may result in inaccurate risk assessments for older adults from diverse dietary cultures⁴. A central ethical concern is the possibility that digitalization could weaken the "human touch" and empathic bonds that lie at the heart of social work practice. Consequently, it is ethically imperative to position AI as an auxiliary mechanism for data generation, while ensuring that final clinical decisions and emotional-support processes remain under the oversight of human professionals (e.g., social workers and dietitians) through a human-in-the-loop approach⁴³.

Conclusion and Recommendations

The integration of artificial intelligence into long-term care facilities demonstrates transformative potential, encompassing applications from nutritional status monitoring to the protection of psychosocial well-being. The literature reviewed indicates that AI-based systems can identify clinical risks, such as malnutrition and sarcopenia, at early stages and support interventions for complex issues, including loneliness and sleep disturbances, through social robots and smart sensors. However, the sustainability of these efficiency gains depends on maintaining a balance with privacy, ethical standards, and the principle of person-centered care.

In summary, AI serves as an essential decision-support mechanism for social work professionals and dietitians in addressing interconnected challenges such as the anorexia of aging, social isolation, and cognitive decline. In the future, AI-based smart nursing homes may evolve into holistic living environments that actively protect dignity, autonomy, and social connectedness through technology. In the Turkish context, these considerations carry particular relevance. Institutional elder care in Türkiye is delivered largely through nursing homes and elderly care and rehabilitation centers operating under the Ministry of Family and Social Services, alongside a growing number of private facilities. As the country undergoes rapid demographic aging, these institutions face increasing pressure from workforce shortages and rising care needs precisely the conditions under which AI-based decision-support and monitoring tools could offer the greatest value. Integrating such systems into the operational workflows of these centers, in a manner consistent with national data-protection legislation and the person-centered principles of the Ministry's elder-welfare policies, could support earlier detection of malnutrition and frailty, more equitable allocation of limited staff resources, and improved continuity of care. Realizing this potential will require locally validated tools, adequate digital infrastructure, and staff training tailored to the Turkish care setting. The success of this transformation will depend on integrating data-driven approaches with the empathetic values central to social work practice.

Limitations

Although the reviewed literature highlights considerable potential, several limitations temper an uncritical adoption of AI in long-term care. First, the empirical evidence is not uniformly positive: trials of socially assistive and therapeutic robots have yielded mixed or null results, with some studies reporting no significant improvement in loneliness, agitation, or quality of life, and effects that diminish once the novelty period passes or that depend heavily on the presence of a human facilitator. Second, algorithmic limitations remain substantial; models trained on non-representative datasets can produce biased or inaccurate risk estimates for underrepresented groups, and their real-world performance often falls short of the accuracy reported under controlled conditions. Concerns regarding the transparency of "black-box" models, data-privacy risks, and the potential erosion of human contact further constrain implementation. Finally, as a narrative review, this study did not employ a systematic search protocol or formal quality appraisal, which may introduce selection bias and limit the generalizability of its conclusions. These considerations underscore that AI should be regarded as a complement to, rather than a substitute for, human-centered professional judgment.

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