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Review article

Artificial intelligence in nutrition and ageing research – A primer on the benefits☆

Pol Grootswagers [a,*], Tijl Grootswagers [b,c]

[a] Wageningen University, Division of Human Nutrition and Health, 6708 PB Wageningen, the Netherlands
[b] The MARCS Institute for Brain, Behaviour and Development, Western Sydney University, Sydney, NSW, Australia
[c] School of Computer, Data and Mathematical Sciences, Western Sydney University, Sydney, NSW, Australia

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ABSTRACT

Artificial intelligence (AI) is increasingly impacting multiple domains. The application of AI in nutrition and ageing research has significant potential to transform healthcare outcomes for the ageing population. This review provides critical insights into how AI techniques—such as machine learning, natural language processing, and deep learning—are used in the context of care for older people to predict health outcomes, identify risk factors, and enhance dietary assessments. Trained on large datasets, AI models have demonstrated high accuracy in diagnosing malnutrition, predicting bone mineral density abnormalities, and forecasting risks of chronic diseases, thereby addressing significant gaps in early detection and intervention strategies.

In addition, we review novel applications of AI in automating dietary intake assessments through image recognition and analysing eating behaviours; these offer innovative tools for personalised nutrition interventions. The review also discusses and showcases the integration of AI in research logistics, such as AI-assisted literature screening and data synthesis, which can accelerate scientific discovery in this domain.

Despite these promising advancements, there are critical challenges hindering the widespread adoption of AI, including issues around data quality, ethical considerations, and the interpretability of AI models. By addressing these barriers, the review underscores the necessity for interdisciplinary collaboration to best harness AI's potential.

Our goal is for this review to serve as a guide for researchers and practitioners aiming to understand and leverage AI technologies in nutrition and healthy ageing. By bridging the gap between AI's promise and its practical applications, this review directs future innovations that could positively affect the health and well-being of the ageing population.

1. Introduction

The advancements in artificial intelligence (AI) in the last decade have delivered new potential solutions for problems across many domains, including healthcare and biomedical research. As life expectancy keeps on rising, while birthrates slowly decline [1], the proportion of older individuals is increasing. According to the World Health Organization, by 2050, the world's population aged 60 years and older is expected to account for 22 % (2 billion) of the total population, up from 12 % (900 million) in 2015 [2]. This demographic shift underscores the importance of keeping older adults fit and productive for as long as possible, with diet playing a central role in promoting healthy ageing [3].

Research efforts are intensifying to uncover how lifestyle interventions, especially dietary modifications, can delay the ageing process and the onset of age-related diseases [4] such as cardiovascular disease, diabetes, and neurodegenerative disorders. However, improving targeted nutritional strategies depends highly on our understanding of the mechanistical pathways underlying the hallmarks of ageing [5]. Additionally, high-throughput techniques are needed to

Abbreviations: ADL, Activities of Daily Living; AI, Artificial Intelligence; ALB, Albumin; ASReview, Automated Systematic Review; BMD, Bone Mineral Density; BMI, Body Mass Index; CT, Computed Tomography; FRAX, Fracture Risk Assessment Tool; GLIM, Global Leadership Initiative on Malnutrition; GPT, Generative Pre-trained Transformer; LLM, Large Language Model; NHANES, National Health and Nutrition Examination Survey.

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* Corresponding author at: Stippeneng 4, 6708 WE Wageningen, the Netherlands.
E-mail addresses: pol.grootswagers@wur.nl (P. Grootswagers), t.grootswagers@westernsydney.edu.au (T. Grootswagers).

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efficiently screen nutritional compounds for their role into ageing. Such identification studies are being carried out, but need to be upscaled to completely understand the vast array of potential compounds and their interactions [6].

Machine-learning approaches—including deep learning, natural-language processing, and large language models—are now being applied to large-scale data in nutrition and ageing research [7]. Machine learning algorithms, including supervised and unsupervised methods, are being trained on enormous amounts of nutritional and biomedical data to predict health outcomes, identify risk factors, and classify dietary patterns. Deep learning on unstructured data such as images is used for dietary intake assessment through image recognition of food items [8]. Large language models enhance natural language processing capabilities in screening and summarising scientific literature [9], enabling researchers to stay on top of the rapidly expanding body of knowledge.

Despite the potential, the application of AI in nutrition and ageing research is not without challenges. On one hand, promising AI applications like AI-assisted abstract screening have yet to find their way into widespread use among researchers and practitioners. These tools can significantly reduce the time and effort required in systematic reviews and meta-analyses by automating the screening process of large numbers of abstracts and articles. On the other hand, there is a tendency for AI companies to overpromise and underdeliver, leading to over-reliance and misunderstandings. Issues such as data quality, lack of standardised methodologies, ethical concerns, and interpretability of AI models pose significant barriers to the adoption of AI in this field [10].

Therefore, it is necessary to critically assess where exactly the possibilities lie for AI within nutrition and ageing research. This review provides an overview of the potential applications of AI in this field, examining both the opportunities and limitations. We emphasise that this work is a narrative review, designed to highlight specific applications and challenges rather than provide exhaustive coverage of all research in the field. We aim to guide researchers in understanding and harnessing the potential of AI to advance nutrition and ageing research. By showcasing the practical implications of AI on research and practice in nutrition and healthy ageing, we help differentiate media hype from real impact.

2. Methods

For this review, we employed several AI tools in the process. The sequence in which these tools were used is depicted in Fig. 1. We wrote an outline for the subjects of the review. For every subject, a search string was constructed with help from ChatGPT o1-preview. This string was entered into SCOPUS, and the amount of hits were fed back into ChatGPT o1-preview until a reasonable amount of hits was found (between 50 and 500 papers). The prompts leading to the final strings, and the number of total and relevant, are presented in **Supplementary materials 1.** These hits were exported in .ris format and imported into ASReview for title and abstract screening. The suggested ASReview protocol was followed [11]. Screening stopped when 10 papers in a row were irrelevant. The relevant papers were again exported as .ris, imported in EndNote, and supplemented with their full text PDFs. These PDFs were imported into NotebookLM, a language model that only uses information in presented PDFs, where summaries of the research papers were created, which were restructured to academic text using ChatGPT o1-preview and Claude Sonnet 3.5. The AI-generated summaries were manually reviewed and edited by the authors to ensure fidelity to the original sources and to prevent omission or misrepresentation of information.

3. Results

3.1. Body composition

AI can play a big role in predicting body composition from limited information. A chest radiographic prediction model showed to be able to predict actual height and weight and can be combined with information regarding clinical nutrition factors for rapid assessment of risk for malnutrition [12]. Recent advancements in machine learning have led to the development of effective predictive models for diagnosing malnutrition in elderly patients. In a highly accurate model, key predictors like Activities of Daily Living (ADL), Albumin (ALB), Body Mass Index (BMI), and age were identified [13]. Another study developed the MUST-Plus tool, a machine-learning based screening tool, in a large urban health system, significantly improving the early diagnosis and documentation of malnutrition, with high acceptance among registered dietitians [14]. MUST-Plus is based on demographics, anthropometrics and laboratory data and demonstrated superior performance with significantly higher sensitivity and specificity compared to the classic MUST score [15]. A third study reanalysed data from a multicentre cohort, utilizing models such as light gradient boosting machine and random forest, and identified BMI, weight loss, and calf circumference as the strongest predictors of malnutrition according to the GLIM criteria, with the top models achieving diagnostic values that indicate clinical applicability.

Moreover, recent studies have demonstrated the efficacy of machine learning and deep learning models in predicting bone mineral density (BMD) abnormalities and diagnosing osteoporosis. By using neural networks and nomograms to analyse data from the National Health and

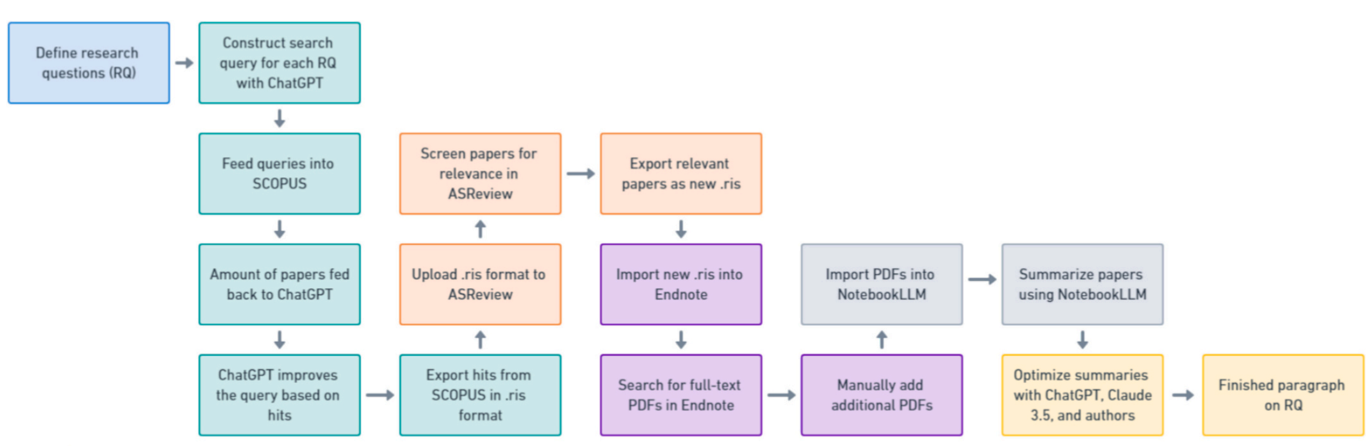

Fig. 1. Visual representation of the workflow used in this mini-review. Graph constructed with Whimsical GPT plugin. The colours represent the main tool used in that step (ChatGPT+Scopus green, ASReview orange, EndNote purple, NotebookLM grey, Claude 3.5 + ChatGPT yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Nutrition Examination Survey (NHANES), surprising key risk factors such as caffeine intake, carbohydrate consumption, BMI, height, and various blood electrolytes were identified [16]. Their model demonstrated clinical utility in predicting BMD abnormalities, especially with dietary and electrolyte variations. Another study used deep learning models on opportunistic CT scans to classify osteoporosis and predict bone density, achieving high accuracy and strong correlations with quantitative CT results, indicating potential for reducing radiation exposure and expanding osteoporosis screening [17]. Machine learning algorithms, applied to NHANES data to identify individuals with low bone density using demographic and blood biochemical data, showed that a logistic regression model outperformed other models and effectively classified low BMD, supporting clinical decision-making for osteoporosis prevention and management [18].

For sarcopenia risk prediction, studies have demonstrated the effectiveness of machine learning models using non-invasive methods. In the Korea National Health and Nutrition Examination Survey, a sarcopenia prediction model using physical characteristics and activity-related variables was developed [19]. The study found that their algorithm achieved the highest accuracy, with BMI, weight, and waist circumference being the most important predictors, suggesting this model's utility in early detection of sarcopenia in resource-limited settings [19]. A different study explored an innovative approach using oculomics to predict sarcopenia. By analysing ophthalmological and demographic data with their model, the study achieved good diagnostic values, indicating that eye examinations can effectively predict sarcopenia risk, facilitating early intervention and personalised treatment plans [20].

3.2. Disease risk

Machine learning is more and more implemented in predicting disease risks, for example for several cancers [21,22], age-related macular degeneration [23], atrial fibrillation [24], gout [25,26], delirium [27], hyponatremia [28], cognitive impairment [29], atherosclerosis [30] and diabetes [31]. Interestingly, these mainly machine-learning based prediction models found several nutritional targets, including dietary fibre for gout [25], dietary inflammatory index for cognitive impairment [29], and triglycerides for type 2 diabetes [31]. The field of AI disease prediction will advance further, leading to the identification and confirmation of several nutritional factors that could be targeted to improve healthy ageing.

Apart from disease outcomes, AI models are increasingly being used to predict functional declines such as kidney function, bone mass loss, muscle strength, and fall risks. Researchers have developed a machine learning model to predict "kidney age" using computed tomography (CT) scans and clinical data, identifying individuals at risk for kidney function decline, even when creatinine levels are normal [32]. Machine learning models also show promise for predicting osteoporotic fractures [26,33]. Studies have used algorithms like gradient boosting, random forest, decision tree, and logistic regression to predict fracture risk in women, achieving higher accuracy than traditional methods like the FRAX score [33]. In predicting muscle loss, AI models have demonstrated 80–90 % accuracy in identifying sarcopenia by using data on physical activity, obesity, socioeconomic status, and quality of life [34,35]. Additionally, a study used machine learning to predict fall risks in older adults by combining electronic health records with comprehensive geriatric assessments, illustrating AI's potential in anticipating fall risks using diverse data sources [36]. Collectively, these advancements indicate that the growing role of AI in predicting disease risks and functional declines could significantly improve preventive healthcare and promote healthier ageing.

3.3. AI for dietary intake assessment

AI-based dietary assessment systems are being developed to improve the accuracy of food intake tracking for better management of nutrition and health, including applications in ageing populations [37–39]. These systems use deep learning models to analyse images and videos of meals, enabling the identification of food types, segmentation of food items, and estimation of food volume [38–40]. For instance, systems like goFOODTM can work with dual-camera smartphones or images from different angles to reconstruct the 3D food volume and estimate calorie and macronutrient content by referencing nutritional databases. The technology has shown promising results, with goFOODTM demonstrating superior performance compared to experienced dietitians in analysing normal central-European meals [39]. While challenges remain in accurately estimating portion sizes, particularly in real-world settings with diverse food types and preparations, researchers are exploring innovative solutions, such as leveraging depth information from 3D-cameras to enhance portion size estimation accuracy [41]. Currently, AI models are validated using suboptimal reference methods rather than gold standards. To improve accuracy and reliability, it is recommended to compare AI-based assessments with more rigorous techniques, such as the doubly-labelled water method. In addition to image-based nutrient detection, research has explored the potential of AI to automatically analyse eating behaviour in videos, going beyond the basic recognition of food types and quantities. This includes efforts to automatically detect and count individual bites, chews, and other eating gestures. For example, using deep-learning algorithms to analyse a set of face markers extracted from videos to identify and count bites [42,43]. These algorithms can track the movement of the mouth, such as the distance between the upper and lower lips, to determine when a bite is taken. Other approaches involve models trained on inertial sensor data from wearable devices to detect wrist micro-movements characteristic of eating behaviour [44,45]. Deep learning methods, which can detect more sophisticated patterns in large datasets, may be better suited for tasks like chewing detection compared to conventional video-based tracking, as chewing often involves more subtle mouth movements compared to the distinct opening and closing of the mouth during biting [42].

In sum, recent developments in AI-based analysis of eating behaviour have the potential to significantly benefit dietary assessment and intervention strategies, but more robust comparisons against gold-standard methods are essential to ensure accuracy and reliability.

3.4. AI for research logistics

AI is already being regularly used in ageing research, mainly in AI driven drug discovery. AI-based drug discovery platforms can analyse large chemical libraries and prioritise molecules that are most likely to have anti-ageing properties [46]. This reduces the reliance on expensive and time-consuming high-throughput screening methods [46]. Where these techniques currently still mainly focus on pharmacological discoveries, they can be adapted to address nutrient and food compound discovery. Aside from discovering new compounds, AI is also used to better understand ageing processes and identifying intervention targets to mitigate the ageing process [47]. AI's ability to discover subtle patterns in enormous data will enable a step change in the discovery of food compounds that influence ageing.

Additionally, AI can be used to better summarize documented findings. For example, the program ASReview leverages machine learning to highlight relevant articles for researcher screening, potentially reducing the time and effort required for literature reviews [11,48]. Beyond identifying relevant publications, AI can also analyse large volumes of text to extract key knowledge and identify research gaps by analysing patterns and relationships [49], ultimately aiding in the synthesis of information for review papers [46,50]. However, it is important to remember that these tools still require researchers to provide accurate input during the initial "training" phase to ensure the AI model learns to identify relevant material effectively [48], and apply extreme caution with interpretations as correctness of AI output is never guaranteed.

4. Discussion

The integration of artificial intelligence (AI) into nutrition and ageing research has opened new avenues for understanding and promoting healthy ageing. This mini-review highlights the multifaceted applications of AI, ranging from predicting body composition to enhancing dietary assessment and research logistics. While the potential is immense, it is crucial to critically evaluate these developments to ensure they translate into practical benefits for both researchers and the ageing population.

One of the most promising areas is the use of AI in predicting body composition and related health risks. Machine learning models have demonstrated high accuracy in diagnosing malnutrition, osteoporosis and sarcopenia among older patients. Interestingly, these models often relied on easily accessible data, such as BMI and waist-circumference [20], which is essential for practical implementation in settings where advanced resources are unavailable, and even open up avenues for implementation at home. In settings where CT scans are available, models can be run that already show to outperform conventional approaches in sarcopenia diagnosis [51]. Earlier risk recognition of such ageing phenotypes is pivotal for proper intervention delivery to mitigate risks, for instance via nutrition and exercise regimens [52,53].

Beyond body composition, AI models are increasingly being used to predict risks of chronic diseases such as cancer, diabetes, and cardiovascular conditions [21–31]. These models often identify nutritional factors as significant predictors, highlighting the intertwined relationship between diet and disease. For example, dietary fibre was found to be a key factor in predicting gout [25], and the dietary inflammatory index was significant in predicting cognitive impairment [29]. Such findings underscore the importance of nutrition in prevention and management of age-related diseases, and open the doors for targeted, or even personalised, lifestyle interventions.

AI's role in dietary assessment is another area of significant advancement. Image-based dietary assessment systems using deep learning can accurately identify food items and estimate portion sizes, improving the accuracy of dietary intake data [37–41]. While challenges remain in accurately estimating portion sizes in real-world settings, the continuous improvement of these technologies holds promise for both clinical and research applications. Moreover, the development of AI algorithms to analyse eating behaviour, such as bite and chew detection from videos, offers novel methods to study eating patterns and their impact on health [42–45]. While the models are becoming increasingly valid in estimating dietary intake, they are still far away from implementation in nutrition research. However, further developments could lead to higher validity of these AI methods over conventional methods such as food records or food frequency questionnaires, which would have great implications for nutrition research. Apart from the increased validity, the lower burden on participants could facilitate dietary assessment in more studies, over more days and in more participants.

AI can be used to directly alter eating behaviour as well. Possibly, intervention studies in future will make use of AI platforms to change dietary intake and physical activity of the participants. Although AI chatbots and virtual coaches cannot fully replace human interaction, they can serve as cost-effective alternative to professional guidance [54]. AI-driven platforms can already provide general dietary advice and promote healthier lifestyles [55,56], albeit currently with limitations in personalisation for specific health conditions. Within the next few years, AI-driven coaching tools are expected to mature into personalised, sensor-integrated “digital-twin” systems that can dynamically nudge diet and activity, but real-world impact will hinge on richer shared datasets, transparent and bias-checked algorithms, unified data standards, clear regulatory pathways, and clinical validation [57].

AI also offers solutions for research logistics, particularly in handling large volumes of data and literature, facilitating the systematic review process [11,48]. Additionally, AI can assist in summarising findings and identifying research gaps, but the effectiveness of these tools depends on the quality of input data and still require manually checking the accuracy of its outputs. AI's ability to find patterns in big datasets offers great potential for nutrition and ageing research, where it is very likely that AI will be able to identify novel compounds that relate to slower ageing or prevention of age-related diseases and phenotypes.

4.1. Challenges and limitations

Despite promising advancements, several challenges hinder the widespread adoption of AI in nutrition and ageing research. Data quality and availability are significant concerns [58]. Many AI models require large datasets for training, which may not always be accessible or standardised across studies. Ethical considerations, such as data privacy and the potential for algorithmic bias, must also be addressed. For instance, AI models trained on data from specific populations may not be generalisable to others, potentially exacerbating health disparities [59]. In real-world healthcare settings, these issues can limit the effectiveness of AI-driven interventions, particularly in diverse populations. To maximize the benefits of AI, multidisciplinary collaboration is essential. Nutritionists, gerontologists, data scientists, and ethicists must work together to develop AI tools that are accurate, ethical, transparent and clinically relevant [60]. Such collaboration can help overcome adoption barriers ensuring AI applications are both practical and scalable in clinical practice. Standardising methodologies and creating robust frameworks for data sharing can enhance the quality and applicability of AI models.

Future research should focus on improving data quality and model transparency. Developing explainable AI models can help in understanding the underlying mechanisms of ageing and the impact of nutritional interventions. Additionally, integrating AI with other emerging technologies, such as wearable devices and electronic health records, can provide a more holistic approach to monitoring and promoting healthy ageing.

Potential limitations specific to this mini-review include the choice of data sources, limited to PubMed and SCOPUS, which may not capture all relevant literature and could introduce database-specific biases. The paper inclusion and exclusion criteria, while clearly defined, follow a pragmatic approach characteristic of narrative mini-reviews and thus may lack the saturation of systematic reviews. Additionally, the AI-assisted methodology used here might face challenges going forward, as emerging AI models increasingly rely on training data that includes AI-generated content, potentially leading to “model collapse”, a degradation in model performance due to feedback loops of synthetic data [61]. These factors should be considered when interpreting the findings and highlight the need for ongoing methodological refinement in AI-assisted literature synthesis.

In conclusion, AI holds substantial potential to revolutionise nutrition and ageing research. By facilitating early diagnosis, personalising interventions, and streamlining research processes, AI can contribute significantly to promoting healthy ageing. However, realising this potential requires progress on ethical issues, data quality, and interdisciplinary collaboration. Yet, even with human oversight and final accountability remaining a critical requirement, addressing these challenges will pave the way for AI to become an integral part of strategies aimed at enhancing the health and well-being of the ageing population.

CRediT authorship contribution statement

Pol Grootswagers contributed to conceptualization of the review, conducted the review of the literature, wrote the original draft, and participated in review and editing.

Tijl Grootswagers contributed to conceptualization of the review, and participated in review and editing.

Both authors saw and approved the final version and no other person made a substantial contribution to the paper.

Ethics

This review article does not involve any new studies with human participants or animals performed by any of the authors; therefore, ethical approval was not required.

Provenance and peer review

This article was commissioned and was externally peer reviewed.

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

During the preparation of this work the authors used GPT O-1 Preview, Claude Sonnet 3.5, ASReview, NotebookLM in order to search and summarise relevant research. After using these, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no competing interest.

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Appendix A. Supplementary data

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