International Journal of Research in Science and Technology
ISSN 2394 - 9554
Volume 12, Issue 03: July – September 2025

Integrating Emerging Digital and AI-Based Dietary Assessment Tools with Traditional Methods: Advancements and Challenges

Jagathiswari.G. G [1*], Dr.B. Premagowri [2]

Assistant Professor [1], Assistant Professor and Head [2],
Department of Clinical Nutrition and Dietetics,
PSG College of Arts & Science, Tamil Nadu, India

*** E-mail: jagathiswari@psgcas.ac.inAbstract**

Abstract
Dietary assessment is essential in supporting nutritional monitoring, clinical care and planning health programs for the community. Despite being traditional ways to gather data, such as food frequency questionnaires (FFQs), 24-hour dietary recalls, and food diaries have a high risk of memory bias and can be inaccurate. Digital technologies that use AI help design new methods for measuring what people eat with increased precision, scalability, and user engagement. This review brings together information from 18 open-access research articles (2020–2025) to compare digital and AI-based assessment tools to the traditional methods used in nutrition care setting. Thus, exploring their respective strength, weakness, barriers to adopt it on wide scale, the issues they encounter, how they are used in clinical practice and if they can be used in combination. The article emphasizes that AI-based instruments have become much more accurate, they are being used more in clinics and communities, but adoption is hindered by concerns over privacy, getting patients to use them and potential biases in the technology. A unified strategy is put forward to promote responsible, expandable and successful use of both AI and traditional methods in dietary assessments.

Keywords: *AI-based dietary tools, nutrition assessment, mobile health, food recognition, traditional methods, integration.*

1. INTRODUCTION

Proper nutritional assessment underpins the planning of public health systems, individual health progression and clinical dietary management. For many years, nutritionists have relied on FFQs, 24HRs and weighed food logs or records. Such methods, approved by the World Health Organization (WHO) and the Indian Council of Medical Research - National Institute of Nutrition (ICMR-NIN), help with population diet monitoring. Despite this, both organizations agree that there are shortcomings in using diet information provided by individuals, because it can be distorted by memories, including recall bias, underreporting, and subjectivity (Barouti et al. 2024).

Advances in digital and AI tools have made it possible to close these gaps in the last few years. WHO's 2022 plan on digital health explains that AI-based technology is being used to enhance nutrition monitoring, making sure the data is accurate and easier to reach. To improve the precision of reporting what people consume, the ICMR-NIN has encouraged the piloting digital nutrition surveillance. They are based on image recognition using AI, mobile apps, deep learning algorithms and wearable sensors that can quickly estimate portion size and nutrient intake for users (Nogueira-Rio et al. 2024). This review aims to critically analyses the evolution and integration of digital and AI driven dietary assessment tools

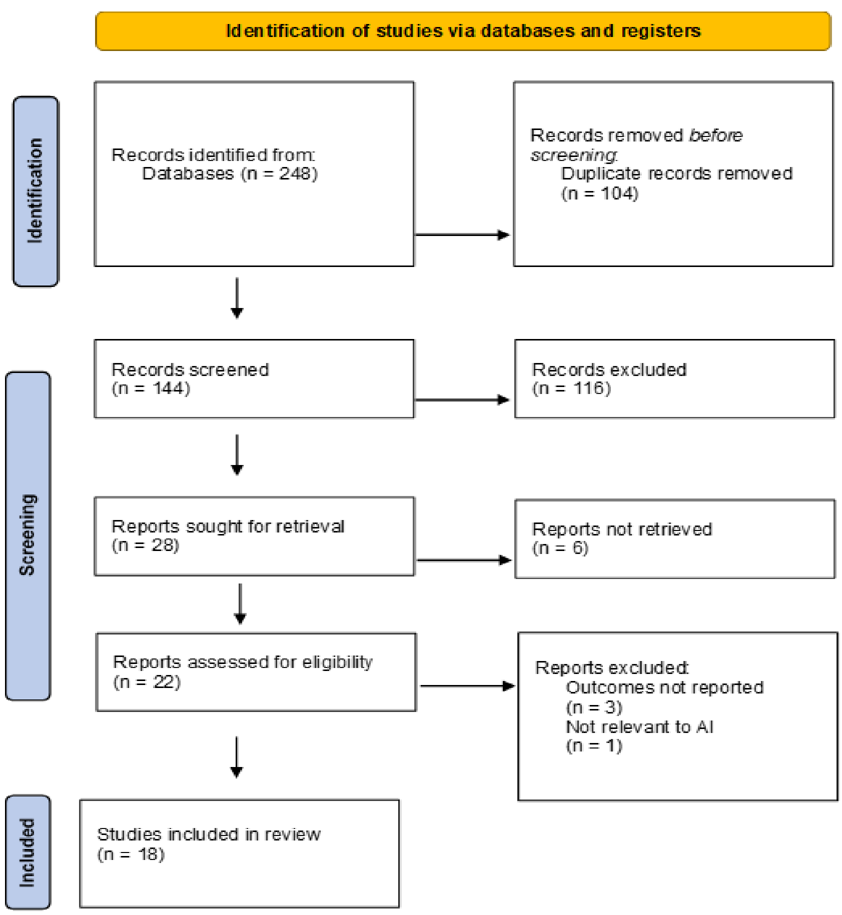
https://doi.org/10.64151/PSGCARE-10

with traditional conventional methods. By systematically examining 18 recent studies from 2020 to 2025, this study inspects their comparative effectiveness, readiness for clinical and public health intervention and its practical challenges. It discloses a crucial knowledge gap by plotting current technological advancements in dietary assessment and directing future efforts toward balanced, inclusive, and evidence-based implementation. For instance, using FFQs in combination with real-time digital logging can enhance data granularity while preserving population-level comparability (Skinner et al. 2020).

2. Materials and Methods

A systematic literature search was carried out across multiple scientific databases including PubMed, DOAJ, Scopus, and Web of Science, covering the publication period from 2020 to 2025. The keywords such as "AI in nutrition", "nutritional apps", "digital dietary assessment" and "food recognition" were used in combination to search for appropriate articles. The inclusion criteria were carefully defined to have only (1) original research or review articles published in English, (2) studies that estimated digital or artificial intelligence tools in comparison to traditional dietary assessment methods, and (3) articles in the open access publications.

From an initial set of approximately 250 records, duplicates were eliminated and titles and abstracts were filtered for relevance. Following full-text screening, 22 studies met the defined eligibility criteria, of which 18 articles were deemed methodologically sound and sufficiently detailed for in-depth qualitative synthesis. The selected articles serve as the base for conducting this systematic review. A flow diagram based on the PRISMA method is included in (Figure 1) to show the method used for selecting studies.



https://doi.org/10.64151/PSGCARE-10

Figure. 1: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Flow Diagram

3. Critical Evaluation

3.1 Traditional Methods of Dietary Assessment

Researchers and clinical nutritionists have used tools such as Food Frequency Questionnaires (FFQs), 24-hour dietary recalls (24HR) and weighed food records for long time. These tools are inevitable in nutritional epidemiology as they are simple, cost efficient and help trace how about peoples' usual eating behavior over time (Lo et al. 2020). FFQs, in particular, have been extensively used in large-scale cohort studies to estimate average nutrient intake over prolonged periods. Similarly, 24HR recalls and food diaries provide more detailed accounts of short-term dietary intake and are often used in dietary validation and calibration studies. The methodological rigor and validation of these tools have made them widely accepted by global health authorities, including WHO and ICMR-NIN.

However, these traditional methods are inherently limited by their reliance on participant self-reporting, which introduces various biases such as underreporting, overestimation, and recall inaccuracies. These issues are further compounded in populations with low literacy levels, among the elderly, or in children, where caregiver reporting becomes necessary. The manual nature of data collection and analysis makes them time-consuming and labor-intensive, posing logistical challenges in large-scale dietary surveillance and individualized clinical care. Several studies have documented the underestimation of energy intake, particularly among overweight and obese populations, due to social desirability bias or memory lapses (Lo et al. 2020; Dalakleidi et al. 2022). Furthermore, the lack of real-time data capture hinders the application of these methods in dynamic nutritional monitoring and intervention.

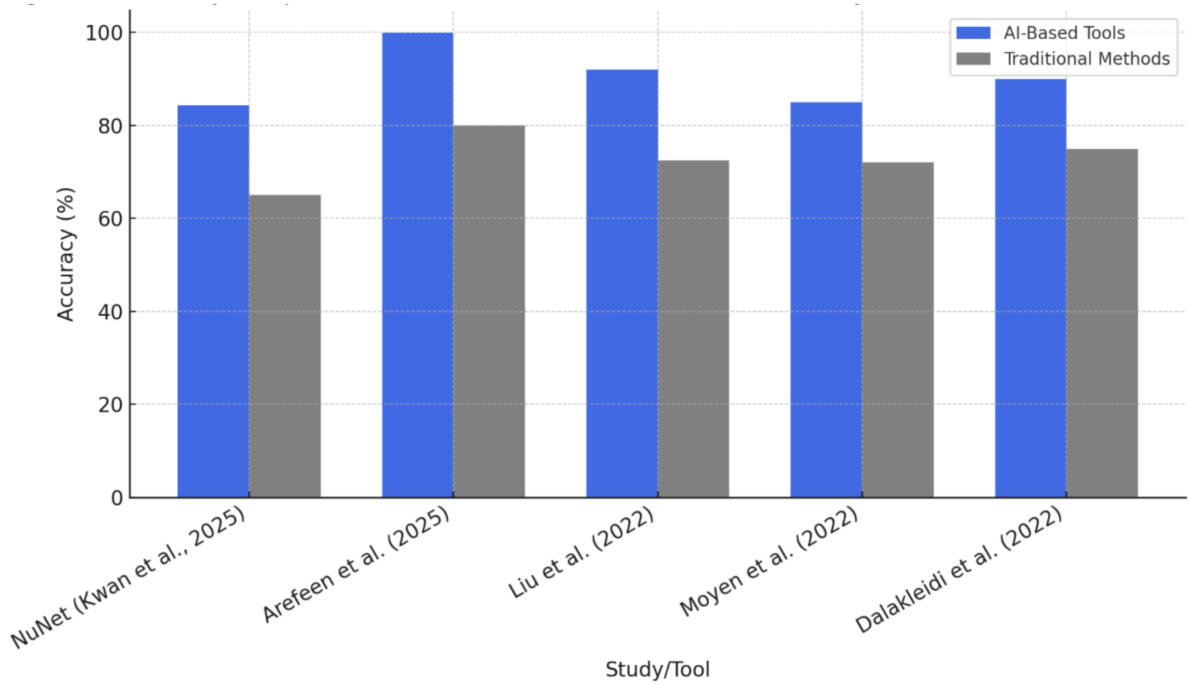
Despite these limitations, traditional tools remain valuable benchmarks and are often employed as reference standards in the validation of emerging technologies. The integration of these established methods with AI-enhanced tools presents an opportunity to overcome their respective limitations. For instance, using FFQs in combination with real-time digital logging can enhance data granularity while preserving population-level comparability.

3.2 AI-Based Tools: Accuracy and Innovation

Dietary assessment has improved a lot due to the role of artificial intelligence in nutritional science. The NuNet model introduced by Kwan et al. (2025) adds depth sensing to a transformer model. In a similar fashion, Liu et al. (2022) based their CNN on EfficientDet to handle the multi-dish recognition task and achieved over 90% accuracy. Zheng et al. (2024) revealed exceptional accuracy – identifying almost all foods with 99.85% precision which is shown in Figure 2. In their study, Alam et al. (2025) built a system that used decision trees and neural networks together to assess a person's nutritional status. Lu et al. (2020) pointed out that a nutrient assessment system using AI could work well as part of clinical monitoring during a hospital stay.

Figure. 2: Comparative Accuracy of AI-Based vs Traditional Dietary Assessment Methods

https://doi.org/10.64151/PSGCARE-10



Source: Kwan et al. (2025), Arefeen et al. (2025), Liu et al. (2022), Moyen et al. (2022), Dalakleidi et al. (2022)

3.3 Mobile Apps and Digital Interfaces

Nowadays, dietary assessments depend on mobile applications and digital tools as they are user-friendly, automated and scalable. Arefeen et al. (2025), Keenoa and FRANI (Kim et al. 2024) assist with tracking eating habits by letting users capture, scan barcodes or speak the names of their foods. The authors (Barouti et al. 2024) tested a web-based dietary assessment tool against 24HR recalls in adults who have type 1 diabetes (2024). These apps rely on algorithms to examine meals, estimate the nutrients included and advise users following clinical advice. The accessibility of nutrition apps on phones and tablets helps them become popular, since users can keep track of what they eat with little daily hassle.According to Nogueira-Rio et al. (2024), many mobile nutrition education apps are utilizing AI by offering portion guessing, sorting foods and reviewing the user's diet. For example, MealMeter combines images, sensor data and extra info about the setting to help with dietary monitoring. Keenoa was also compared to 24HR recalls and shown to be comparable in tracking daily calorie and macronutrient intake which is shown in Table 1.

They help users be more involved and also provide automatic ways for users to gain valuable tips on improving their eating habits. Researchers, doctors and nutritionists now use them more often for studies and personal advice. Even so, problems exist with how users use the app, errors when entering food data and the variety in the food database. Besides, most apps have difficulty recognizing unfamiliar or multicultural foods which means they require more diverse data and improvements to their algorithms. Still, using digital interfaces supports higher access to dieting and behavior support, because of the help of AI and evidence-based methods.

https://doi.org/10.64151/PSGCARE-10

ISSN 2394 - 9554

Table 1. Mobile App Features and Validation

App/Platform	Features	Validation Method	Target Users	Key Findings
Keenoa	Barcode scan, image logging	Compared with 24HR	General population	Accurate for macronutrient tracking
MealMeter	Multimodal sensing + feedback	Sensor + visual test	Adults	High accuracy and usability
FRANI	Food photo-based intake monitor	Qualitative analysis	Youth, adolescents	Enhanced engagement, ease of use
NuNet	Depth sensing, auto estimation	Mixed meal test	Clinical test group	Realistic for complex meal analysis

3.4 Integration with Traditional Methods

Using digital tools and AI together with traditional methods allows the strengths of each to work together and reduce the disadvantages of each. Most hybrid methods depend on AI-powered diet tracking daily and occasionally require FFQs or 24HR to maintain connection to earlier data and be able to monitor large populations. It allows researchers to get accurate diet details in real time while preserving their ability to compare repeated measurements and follow established guidelines which is shown in Figure 3.

A paper by Moyen et al. (2022) found it possible to improve 24HR recall by using a mobile image-assisted app with AI. The results indicated that the app gave accurate energy and nutrient values, so its use is possible in research and clinical settings. Folson et al. (2023) used mobile AI to assess intake in adolescents from Ghana, then cross-checked their answers with records from food scales and their 24HR record. The study established that the tool was reliable and can be used when trained dietitians are not available in low resource settings. Sosa-Holwerda et al. (2024) discussed on combining traditional food logs with recording food intakes on phones in public health nutrition.

Using integrated models allows for more detailed information, reduces respondent burden and improves personal nutrition advice. Clinicians depend on logs to offer immediate diet advice and FFQs to detect and measure typical eating behaviors. Using digital logs in public health surveillance, possible dietary trends and nutrient gaps can be deeply explored and studied which is shown in Figure 4. But challenges with mixing different systems, arranging the data and willingness of groups to adapt continue to make it difficult to unite systems smoothly. It is necessary to both use joint data frameworks and educate practitioners in order to promote hybrid dietary assessment.

Figure. 3: Conceptual Framework: Integration of AI and Traditional Nutritional Assessment Tools

https://doi.org/10.64151/PSGCARE-10

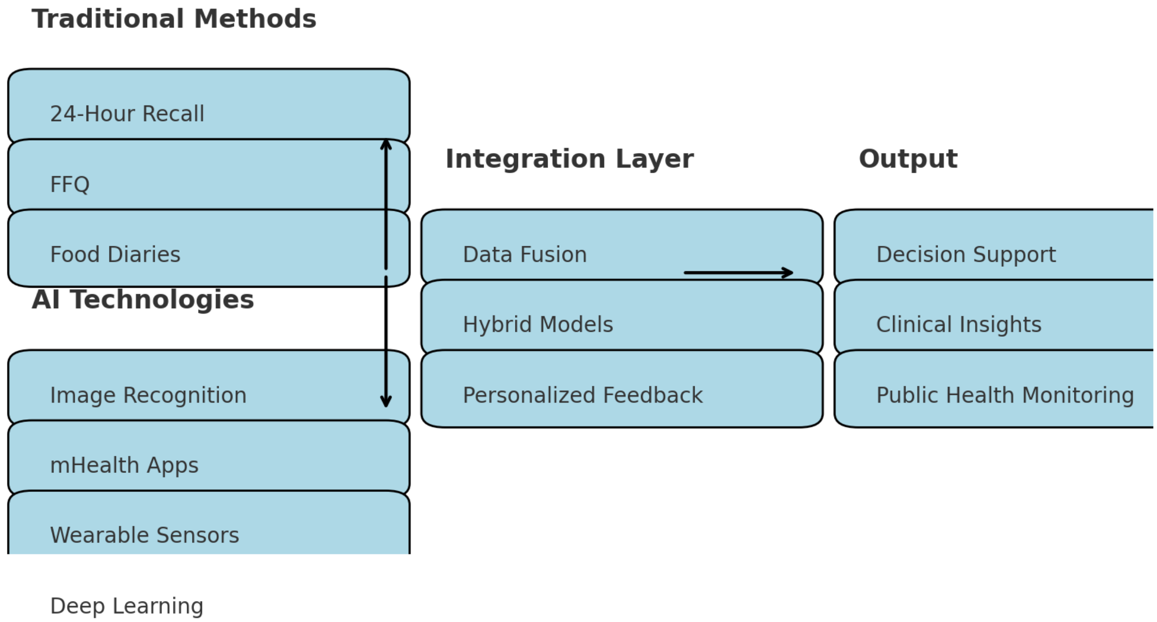
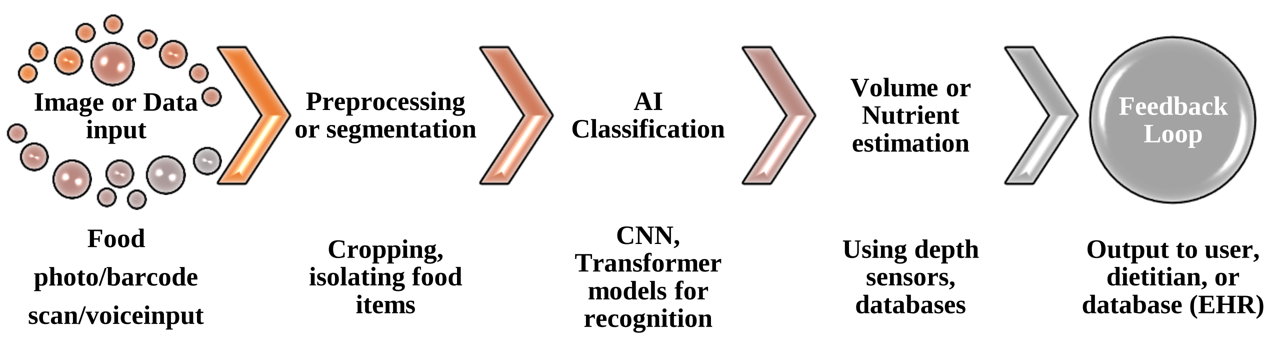


Figure. 4: Workflow of AI-Based Nutritional Assessment Tools



3.5 Clinical Applications and Public Health Relevance

AI in dietary assessment has become very useful in areas that need regular monitoring and individual nutrition plans. Early dietary intervention is inevitable for cancer patients with cachexia and malnutrition. Sguanci et al. (2025) studied the role of AI which aid oncology nutritionists in early detection of nutritional risks, reducing length of stay (LOS) in hospitals and makes treatment more tolerable for patients.AI has also showed potential in critical care settings, where diet is crucial to immune function and recovery. Early applications of AI in acute care nutrition, specifically in detecting malnutrition and modifying enteral nutrition techniques, were reviewed by ASPEN in 2024. ICUs are perfect for implementing predictive models that adjust to real-time physiological data because of their data-rich nature, even with the lack of clinical trials.

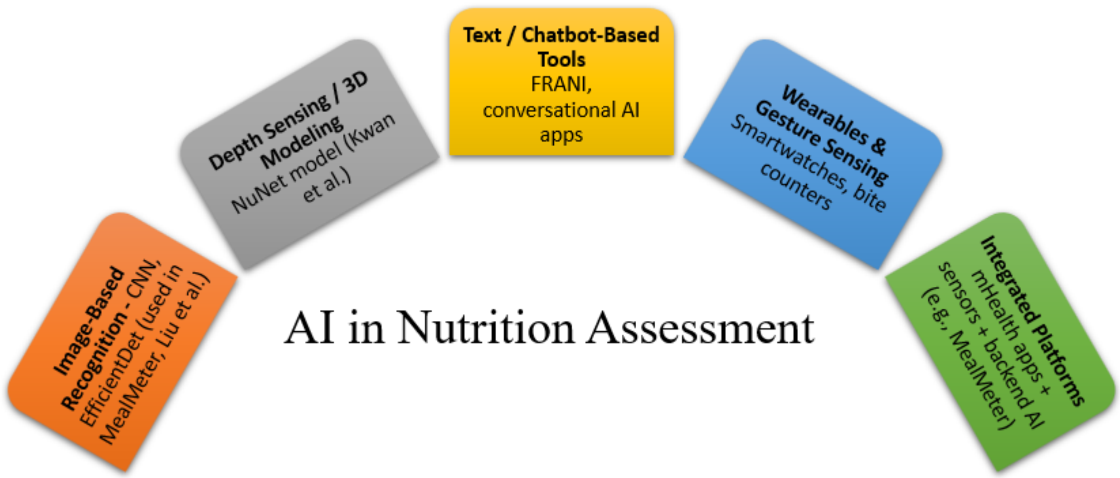
In addition to emergency care, Barouti et al. (2024) and Lu et al. (2020) also point out that AI tools now

https://doi.org/10.64151/PSGCARE-10

play a role in managing diseases such as diabetes, obesity and cardiovascular disease on a regular basis. Glycemic control support, including chatbots giving diet advice and apps for logging results, help patients follow their care plans which is shown in Figure 5. For public health, these tools make it easier to nutritional surveillance in large groups, mainly in places where the nutrition experts are scarce. Mobile health platforms can watch and control dietary developments in communities which can provide potential data to policymakers for framing food programs.

In any case, for implementation in clinics or at the population level, strong evidence, proper government regulation are needed and should align with clinical guidelines. AI tools can also be used with electronic health records (EHRs) and decision support systems which may help bring dietary monitoring into routine healthcare practices.

Figure. 5: Categories of AI-Based Tools for Nutrition Assessment



3.6 Challenges and Ethical Considerations

Although AI-assisted tools have the potential to develop nutritional assessment, their use and effectiveness are slowed down by certain technical, ethical and computational difficulties. An important problem is algorithmic bias, since machine learning systems created with limited datasets could have poor performance in people that eat varieties of food or live in varied ways (Lo et al. 2020). Because of this, the results from dietary assessments may not be entirely correct and could maintain health disparities if data practices aren't inclusive.

People are also worried about their privacy and the ability to control what happens with their data. These AI tools often save information about users such as images, where they are and their biometrics. According to Zheng et al. (2024), if there's not enough transparency about data storage, ownership and how it is shared, the lack of trust might stop many people from joining in. In digital health, following the General Data Protection Regulation (GDPR) and similar data laws requires strict attention to compliance during design and implementation.

Ethical challenges also come up when AI and personal care meet. Without doctors supervising how algorithms are followed by patients, it is unclear who should be held accountable in situations involving

https://doi.org/10.64151/PSGCARE-10

the elderly, teens and those with constant health problems. Janssen et al. (2024) point out that including dietitians, software engineers, ethicists and users in the design of AI systems can make them clearer, fairer and fit better with local needs.

Because it is challenging for users to log in every day, take photos, handle technology and have consistent online access, usability poses a challenge to sustained user engagement (Nogueira-Rio et al. 2024). In places with limited resources, people are also faced with challenges because of a lack of digital tools and language problems. Resolving these problems will be possible through both better technology and strategies that give equal rights to all, encourage digital learning and include cultural awareness in design.

All these challenges which is shown in Figure 6 agree on the requirement for strong ethical guidelines, teamwork between experts from different fields and ongoing checks to confirm the safety, fairness and ability of AI tools in dietary assessment are sustained (Table 2).

Figure. 6: Challenges & Barriers in AI-Driven Nutrition Assessment

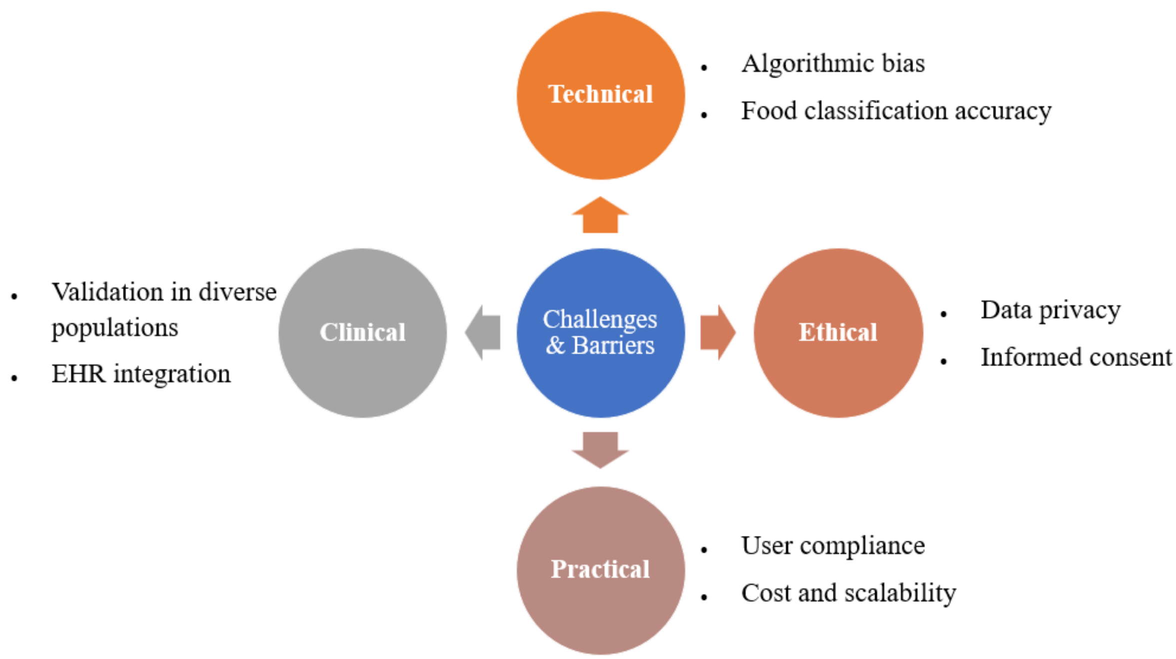


Table 2. Challenges in Implementation

Challenge Area	Description	Implications	Suggested Solutions
Algorithmic Bias	AI underperforms on underrepresented foods	Inequity in results	Diverse, multilingual training datasets

https://doi.org/10.64151/PSGCARE-10

Privacy & Ethics	Sensitive image/audio data collection	Risk of non-compliance	GDPR alignment, consent mechanisms
User Compliance	Burden of image capture and app use	Drop in long-term engagement	Simplified UIs, reminder notifications
Technical Access	Lack of digital literacy/infrastructure	Limits rural/public health scalability	Government incentives, mHealth outreach

3.7 Future Directions

AI is set to help future assessments of what people eat by giving more accurate information and advising on nutrition and wellness. Systems that improve and adapt to new data can be useful for giving individual dietary advice that keeps up with people's changing lifestyle, illnesses and cultural settings. Reinforcement learning and predictive analytics make personalization possible which could lead to major improvements in precision nutrition (Janssen et al. 2024).Being able to link with electronic health records (EHRs) is an important development, because this ensures data can move easily from diet trackers to tools used by healthcare providers. With such integration, healthcare professionals could offer nutrition advice at the appropriate time, whether a patient is in the hospital or getting out patient care. Standardizing the validation of performance and ensuring the process are clear help AI-based assessment tools become trustworthy, reliable and able to meet regulations (Lu et al. 2020).

Using open datasets and teaming up in research groups is needed as it reduces bias in algorithms and ensure that models function well for different people. Developing inclusive, multilingual and diverse dietary databases will allow AI tools to be effectively used in different places around the world (Sosa-Holwerda et al. 2024) and (Cofre et al. 2025). Also, strong government policies for digital health tools, payment systems and ethics are needed for digital health to become widespread in healthcare. Since these trends are coming together, it is clear that nutrition scientists, engineers, clinicians, policymakers and end-users must continue to work together to achieve the full benefits of AI in nutritional assessment (Table 3).

Table 3. Future Research Directions

Focus Area	Rationale	Current Gaps	Proposed Research
Adaptive AI Models	Personalization for behavior change	Static algorithms lack context adaptation	Reinforcement learning in nutrition
EHR Integration	Seamless clinical feedback	Few tools link directly to EHRs	Pilot models in outpatient clinics
Cultural Validation	Improve equity across dietary patterns	Datasets skewed toward Western diets	Cross-cultural, multilingual food sets
Real-World Testing	Move from lab to field settings	Many tools validated only in labs	Community-based implementation trials

https://doi.org/10.64151/PSGCARE-10

ISSN 2394 - 9554
Volume 12, Issue 03: July – September 2025

4. Conclusion

Many of the review tools have shown that AI and digital technologies are transforming nutritional assessment. NuNet, MealMeter and Keenoa serve as examples of platforms that are powered by images and are capable of real-time analyzing food and record what you eat. FRANI and apps aided by chatbots help with keeping track of diets and transformer-based and CNN models improve the accuracy of finding what is in food and the portion sizes. Some of their roles are calorie checking, breaking down nutrients, noticing regular meal patterns and connecting to health records.

Achieving a thorough and fair nutritional assessment requires finding a balance between the advantages of both traditional and AI-based approaches. While AI technologies offer high-resolution, customised insights and automation, traditional instruments provide proven, population-level monitoring capabilities. When combined, these resources can overcome one another's shortcomings and provide complementary advantages in both community and clinical contexts. Strong surveillance, dynamic feedback, and contextual sensitivity are made possible by such a hybrid model, which is not possible with a single technique alone (Alam et al. 2025; Lu et al. 2020; Nogueira-Rio et al. 2024).This review has met its aim by combining how AI-related tools carry out and how they cover these tasks and what challenges they encounter in comparison with other existing methods. It underlines that using more than one field, adapting to different settings and ethics play a key role in moving dietary assessment forward. The research results suggest that move to systems that use latest evidence and are accessible on mobile devices.

Table 4. Summary of Included Studies.

Study	Country	Tool Name/Type	Methodology	Population	Key Findings
Alam et al. (2025)	Bangladesh	Hybrid AI model	Experimental with supervised learning	Clinical patients	High accuracy in nutritional status classification
Arefeen et al. (2025)	USA	MealMeter	Multimodal sensor + ML	General adult users	99.85% intake estimation accuracy
Barouti et al. (2024)	Sweden	Web-based app	Validation study against 24HR	Adults with type 1 diabetes	Significant agreement with traditional recall
Cofre et al. (2025)	Chile	Multiple AI methods	Systematic review	Multiple (review)	AI methods valid in multiple contexts
Dalakleidi et al. (2022)	Greece	Image-recognition tools	Systematic review	Multiple (review)	85–90% accuracy on average

https://doi.org/10.64151/PSGCARE-10

Folson et al. (2023)	Ghana	Mobile AI app	Field validation against weighed records	Adolescent females	Reliable alternative for field dietary assessment
Janssen et al. (2024)	Netherlands	N/A (review article)	Systematic literature review	Multiple (review)	Analyzed trends and identified ethical issues in AI for malnutrition
Kim et al. (2024)	South Korea	FRANI	Qualitative evaluation	Youth	High usability, enhanced adherence to healthy diets
Kwan et al. (2025)	Singapore	NuNet	Transformer + depth sensing	Experimental mixed-dish recognition	84.35% accuracy for complex foods
Liu et al. (2022)	China	EfficientDet-based model	Deep learning image classification	Public food photo datasets	>90% accuracy in food recognition
Lo et al. (2020)	UK	Multiple image tools	Narrative review	Multiple (review)	Identified limitations and improvements in AI tools
Lu et al. (2020)	Switzerland	AI-based nutrient system	Clinical AI model demonstration	Hospitalized patients	Demonstrated real-time nutrient tracking in hospital use
Moyen et al. (2022)	Canada	AI image-assisted app	Randomized crossover validation	Healthy adults	High correlation with 24HR recall
Nogueira-Rio et al. (2024)	Spain	Keenoa, others	Narrative review of mHealth apps	General users	AI-enhanced apps increase engagement and accuracy
Skinner et al. (2020)	UK	Wearable sensors	Perspective review	Multiple (review)	Advocated for integration of wearables in dietary logging
Sguanci et al. (2025)	Italy	Oncology-specific AI	Systematic review	Cancer patients	AI improves nutrition status tracking in oncology care

https://doi.org/10.64151/PSGCARE-10

Sosa-Holwerda et al. (2024)	USA	Digital logs + FFQ	Field-based mixed methods	Low-income communities	Supported hybrid model feasibility
Zheng et al. (2024)	USA	Multimodal AI platform	Scoping review	Multiple (review)	AI tools reach >95% accuracy in nutrient estimation

References

1. Alam, M. M., Khan, A. I., Zafar, A., Sohail, M., Ahmad, M. T., & Azim, R. (2025). Advancing Nutritional Status Classification With Hybrid Artificial Intelligence: A Novel Methodological Approach. *Brain and Behavior*, *15*(5). https://doi.org/10.1002/brb3.70548
2. Arefeen, A., Fessler, S., Mostafavi, S. M., Johnston, C. S., & Ghasemzadeh, H. (2025). *MealMeter: Using Multimodal Sensing and Machine Learning for Automatically Estimating Nutrition Intake*. http://arxiv.org/abs/2503.11683
3. Barouti, A. A., Bonn, S. E., & Björklund, A. (2024). Validation of a web-based dietary assessment program against 24-h recalls in adults with type 1 diabetes. *Frontiers in Nutrition*, *11*. https://doi.org/10.3389/fnut.2024.1395252
4. Cofre, S., Sanchez, C., Quezada-Figueroa, G., & López-Cortés, X. A. (2025). Validity and accuracy of artificial intelligence-based dietary intake assessment methods: a systematic review. In *British Journal of Nutrition*. Cambridge University Press. https://doi.org/10.1017/S0007114525000522
5. Dalakleidi, K. V., Papadelli, M., Kapolos, I., & Papadimitriou, K. (2022). Applying Image-Based Food-Recognition Systems on Dietary Assessment: A Systematic Review. *Advances in Nutrition*, *13*(6), 2590–2619. https://doi.org/10.1093/advances/nmac078
6. Folson, G. K., Bannerman, B., Atadze, V., Ador, G., Kolt, B., McCloskey, P., Gangupantulu, R., Arrieta, A., Braga, B. C., Arsenault, J., Kehs, A., Doyle, F., Tran, L. M., Hoang, N. T., Hughes, D., Nguyen, P. H., & Gelli, A. (2023). Validation of Mobile Artificial Intelligence Technology–Assisted Dietary Assessment Tool Against Weighed Records and 24-Hour Recall in Adolescent Females in Ghana. *Journal of Nutrition*, *153*(8), 2328–2338. https://doi.org/10.1016/j.tjnut.2023.06.001
7. Janssen SM, Bouzembrak Y, Tekinerdogan B. Artificial Intelligence in Malnutrition: A Systematic Literature Review. *Advances in Nutrition*. 2024;15(9). doi:10.1016/j.advnut.2024.100264
8. Kim, D. W., Park, J. S., Sharma, K., Velazquez, A., Li, L., Ostrominski, J. W., Tran, T., Seitter Peréz, R. H., & Shin, J. H. (2024). Qualitative evaluation of artificial intelligence-generated weight management diet plans. *Frontiers in Nutrition, 11*. https://doi.org/10.3389/fnut.2024.1374834
9. Kwan, Z., Zhang, W., Wang, Z., Ng, A. B., & See, S. (2024). Nutrition Estimation for Dietary Management: A Transformer Approach with Depth Sensing. *IEEE Transactions on Multimedia*, *20*(20). http://arxiv.org/abs/2406.01938
10. Liu, Y. C., Onthoni, D. D., Mohapatra, S., Irianti, D., & Sahoo, P. K. (2022). Deep-Learning-Assisted Multi-Dish Food Recognition Application for Dietary Intake Reporting. *Electronics (Switzerland),*

https://doi.org/10.64151/PSGCARE-10

11(10). https://doi.org/10.3390/electronics11101626

11. Lo, F. P. W., Sun, Y., Qiu, J., & Lo, B. (2020). Image-Based Food Classification and Volume Estimation for Dietary Assessment: A Review. In *IEEE Journal of Biomedical and Health Informatics* (Vol. 24, Issue 7, pp. 1926–1939). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/JBHI.2020.2987943
12. Lu Y, Stathopoulou T, Vasiloglou MF, Christodoulidis S, Stanga Z, Mougiakakou S. An Artificial Intelligence-Based System to Assess Nutrient Intake for Hospitalised Patients. *IEEE Trans Multimedia*. 2021;23:1136-1147. doi:10.1109/TMM.2020.2993948
13. Moyen, A., Rappaport, A. I., Fleurent-Grégoire, C., Tessier, A. J., Brazeau, A. S., & Chevalier, S. (2022). Relative Validation of an Artificial Intelligence-Enhanced, Image-Assisted Mobile App for Dietary Assessment in Adults: Randomized Crossover Study. *Journal of Medical Internet Research*, *24*(11). https://doi.org/10.2196/40449
14. Nogueira-Rio, N., Varela Vazquez, L., Lopez-Santamarina, A., Mondragon-Portocarrero, A., Karav, S., & Miranda, J. M. (2024). Mobile Applications and Artificial Intelligence for Nutrition Education: A Narrative Review. *Dietetics*, *3*(4), 483–503. https://doi.org/10.3390/dietetics3040035
15. Sguanci, M., Morales Palomares, S., Cangelosi, G., Petrelli, F., Sandri, E., Ferrara, G., Mancin, S., & Polyclinic, A. O. (2025). Artificial intelligence in the management of malnutrition in cancer patients: A systematic review. *Advances in Nutrition*. https://doi.org/10.1016/j.advnut.2025.100438
16. Skinner, A., Toumpakari, Z., Stone, C., & Johnson, L. (2020). Future Directions for Integrative Objective Assessment of Eating Using Wearable Sensing Technology. In *Frontiers in Nutrition* (Vol. 7). Frontiers Media S.A. https://doi.org/10.3389/fnut.2020.00080
17. Sosa-Holwerda A, Park OH, Albracht-Schulte K, Niraula S, Thompson L, Oldewage-Theron W. The Role of Artificial Intelligence in Nutrition Research: A Scoping Review. *Nutrients*. 2024;16(13). doi:10.3390/nu16132066
18. Zheng, J., Wang, J., Shen, J., & An, R. (2024). Artificial Intelligence Applications to Measure Food and Nutrient Intakes: Scoping Review. In *Journal of Medical Internet Research* (Vol. 26, Issue 1). JMIR Publications Inc. https://doi.org/10.2196/54557