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Role of Generative Artificial Intelligence (GenAI) in Food and Nutrition Education: State of The Art Review.

Papel de la Inteligencia Artificial Generativa (IAGen) en la Educación Alimentaria y Nutricional: Revisión del Estado del Arte

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Abstract. Generative artificial intelligence (GenAI) is emerging in food and nutrition education, offering adaptive learning tools and counseling support while raising concerns about accuracy, integrity, and equity. This review critically examines the role of GenAI through four dimensions—applications, benefits, challenges, and contributions to personalized learning—to answer the question of what is the role of GenAI in food and nutrition education. Peer-reviewed English- and Spanish-language studies (January 2021–August 2025) addressing generative or conversational AI (e.g., large language models, chatbots) in educational or applied nutrition contexts were included. Exclusions comprised non-nutrition topics, purely technical reports, opinion papers, preprints, duplicates, and non-generative AI. Searches in PubMed, Scopus, and Web of Science yielded nine studies after dual screening. Narrative synthesis identified applications of GenAI in university teaching, family nutrition programs, and clinical dietetics to generate readable materials, tailor quizzes and feedback, and support dietary learning. Reported benefits included improved parental nutrition knowledge, enhanced student engagement under supervision, and associations between digital nutrition literacy and sustainable eating behaviors. Challenges encompassed inconsistent adherence to dietary guidelines in complex cases, sensitivity to language and prompt framing, risks to academic integrity and privacy, and digital inequities requiring AI literacy and oversight. Overall, GenAI functions most effectively as a supervised adjunct that enhances access and personalization while safeguarding quality. Ensuring alignment with professional standards, expert review, transparency, and contextual adaptation is essential to responsibly advance its educational value.

Keywords: Generative Artificial Intelligence, Chat GPT, Food and Nutrition Education, Nutrition Education.

Resumen. La inteligencia artificial generativa (IAG) está emergiendo en la educación alimentaria y nutricional, ofreciendo herramientas de aprendizaje adaptativo y apoyo al asesoramiento, aunque también generando inquietudes sobre su precisión, integridad y equidad. Esta revisión examina críticamente el papel de la IAG a través de cuatro dimensiones: aplicaciones, beneficios, desafíos y contribuciones al aprendizaje personalizado, para responder a la pregunta de cuál es su función en la educación alimentaria y nutricional. Se incluyeron estudios revisados por pares, publicados en inglés y español (enero de 2021 a agosto de 2025), que abordaban la IA generativa o conversacional (p. ej., modelos de lenguaje complejos, chatbots) en contextos educativos o de nutrición aplicada. Se excluyeron los temas ajenos a la nutrición, los informes puramente técnicos, los artículos de opinión, las preimpresiones, los duplicados y la IA no generativa. Las búsquedas en PubMed, Scopus y Web of Science arrojaron nueve estudios tras una doble revisión. La síntesis narrativa identificó aplicaciones de GenAI en la docencia universitaria, programas de nutrición familiar y dietética clínica para generar materiales accesibles, personalizar cuestionarios y retroalimentación, y apoyar el aprendizaje dietético. Entre los beneficios reportados se incluyeron una mejora en el conocimiento nutricional de los padres, una mayor participación estudiantil bajo supervisión y la relación entre la alfabetización nutricional digital y los comportamientos alimentarios sostenibles. Los desafíos abarcaron la adherencia inconsistente a las guías dietéticas en casos complejos, la sensibilidad al lenguaje y al enfoque de las preguntas, los riesgos para la integridad académica y la privacidad, y las desigualdades digitales que requieren alfabetización en IA y supervisión. En general, GenAI funciona de manera más efectiva como un complemento supervisado que mejora el acceso y la personalización, a la vez que salvaguarda la calidad. Garantizar la alineación con los estándares profesionales, la revisión por expertos, la transparencia y la adaptación contextual es esencial para promover responsablemente su valor educativo.

Palabras clave: Inteligencia Artificial Generativa, Chat GPT, Educación Alimentaria y Nutricional, Educación Nutricional.

1. Introduction

Generative artificial intelligence (GenAI) has emerged as a transformative tool in various fields, including food and nutrition education. By utilizing GenAI's advanced capabilities, significant improvements can be made in personalized nutrition interventions, learning experiences, and dietary education. GenAI, including tools such as ChatGPT, refers to systems capable of creating new content (text, images, or data responses) based on patterns learned from vast datasets. In educational settings, these tools can simulate dialogue, personalize learning materials, or generate diet-related explanations. In clinical settings, GenAI supports healthcare professionals in developing individualized nutrition plans, predicting nutritional outcomes, and efficiently processing large datasets, providing real-time, evidence-based insights (1). In educational environments, GenAI models are being employed to teach students about the benefits of healthy dietary habits, enhancing their understanding of nutrition and promoting long-term health benefits (2).

In this context, GenAI is also playing a pivotal role in personalizing education by adapting to the unique needs of each learner. This personalization enhances student engagement, boosts academic performance, and accelerates skill development (3). Moreover, GenAI can generate personalized meal plans and dietary content tailored to clinical nutrition needs, ensuring that meal plans are not only clinically appropriate but also dynamically aligned with evolving dietary recommendations (4). Furthermore, GenAI can generate food images for dietary assessments, a feature that supports the automatic evaluation of nutrition through visual data, which is essential for personalized dietary recommendations (5).

However, implementing GenAI in food and nutrition education is not without its challenges. Ethical concerns, such as data privacy, GenAI biases, and resistance to change among educators and students accustomed to traditional teaching methods, must be carefully addressed (6-7). Despite these challenges, the benefits of integrating GenAI in food and nutrition education are clear. The technology offers personalized learning experiences, enhances student engagement, and provides healthcare professionals with tools for effective nutrition interventions. This leads us to the question: What is the role of generative artificial intelligence in food and nutrition education?

Despite the growing interest in artificial intelligence applications within health and nutrition sciences, no previous review has systematically synthesized the educational implications of generative AI specifically in food and nutrition education. Existing studies have primarily focused on technical performance or clinical outcomes rather than pedagogical dimensions. Therefore, this state-of-the-art review uniquely integrates evidence from both educational and clinical perspectives, providing a comprehensive framework that clarifies GenAI's current contributions, challenges, and future directions in nutrition education. This focus positions the present study as the first to map how generative AI reshapes learning processes, professional training, and public engagement in the nutrition domain.

2. Methods

The reporting of information sources and search methods follows PRISMA-S (Preferred Reporting Items for Systematic reviews and Meta-Analyses literature search extension) (8). The completed PRISMA-S checklist is provided in Table S1.

Eligibility Criteria

We considered peer-reviewed studies (January 2021–August 2025; English/Spanish) that (i) explicitly examined generative or conversational AI (e.g., LLMs, ChatGPT, or chatbot-based NLP tools) in food and nutrition education, aligned with our four analytic lenses: Key Applications, Benefits, Challenges, and Contribution to Personalized Learning; (ii) were situated in academic or applied nutrition/healthcare contexts, such as undergraduate dietetics/nursing programs, parental education campaigns (e.g., Nutripedia), gamified chatbots for families, or clinician-/educator-led patient interventions addressing non-communicable diseases (NCDs) and perinatal nutrition; and (iii) employed empirical methods (randomized, quasi-experimental, observational, mixed-methods) or structured ethical/narrative analyses grounded in explicit frameworks. We excluded documents outside food or nutrition education, those without educational/ethical relevance, purely technical AI-performance reports, opinion pieces/editorials lacking methodological grounding, preprints/unpeer-reviewed literature, duplicates, and studies on "classical" AI without linguistic interaction or direct educational application. This methodological framework was designed to ensure both rigor and accessibility, allowing readers from educational and nutritional backgrounds to understand how GenAI has been studied across empirical and conceptual domains.

Information Sources and Search Strategy

We searched in PubMed, Scopus, and Web of Science. The window spanned January 2021 to August 2025, with searches performed between August 14 and 15, 2025 (last update: August 15, 2025). No geographic limits were applied; records in English/Spanish were eligible. Full, exact strategies as run are provided in Table S2. Reporting of information sources and search methods followed the PRISMA-S extension. The completed PRISMA-S checklist is available as Table S1. To ensure comprehensive coverage and minimize the risk of omitting relevant evidence, we performed forward and backward citation tracking of key studies and cross-checked recent conference proceedings and open-access repositories for additional records. This complementary verification step aimed to identify any significant or emerging research on generative AI in nutrition education that may not have been indexed in the main databases. All records retrieved from the databases were exported (RIS/CSV), consolidated in a shared spreadsheet by A.H.L.L., and deduplicated using Rayyan (9). QCRI's duplicate detection plus manual verification. Deduplicated records were screened independently in Rayyan by eleven investigators (G.P.Z.Z., A.H.L.L., E.F.O.B., W.J.E.E., N.M.P.R., J.A.C.O., A.M.S., P.C.A.M., T.P.V.S., R.Y.V.M., and S.C.P.A.). Disagreements at title/abstract were adjudicated by G.P.Z.Z. by discussion. The same group reviewed full texts, with any remaining discrepancies resolved by A.H.L.L. Screening occurred between August 14 and 15, 2025. We identified 10 records (databases = 3; registers = 10). One duplicate was removed, leaving 9 records for title/abstract screening. Nine reports were assessed at full text, and 9 studies were included in the review.

3. Results

Study Selection

All articles that meet the eligibility criteria, adhere to the temporal restriction (2021-2025), and are available in open access will be included in the review. Studies will be screened for relevance based on their abstract and full-text content, with a focus on those directly addressing the research question: "What is the role of generative artificial intelligence in food and nutrition education?" Articles that do not meet these criteria will be excluded (Figure 1) (10).

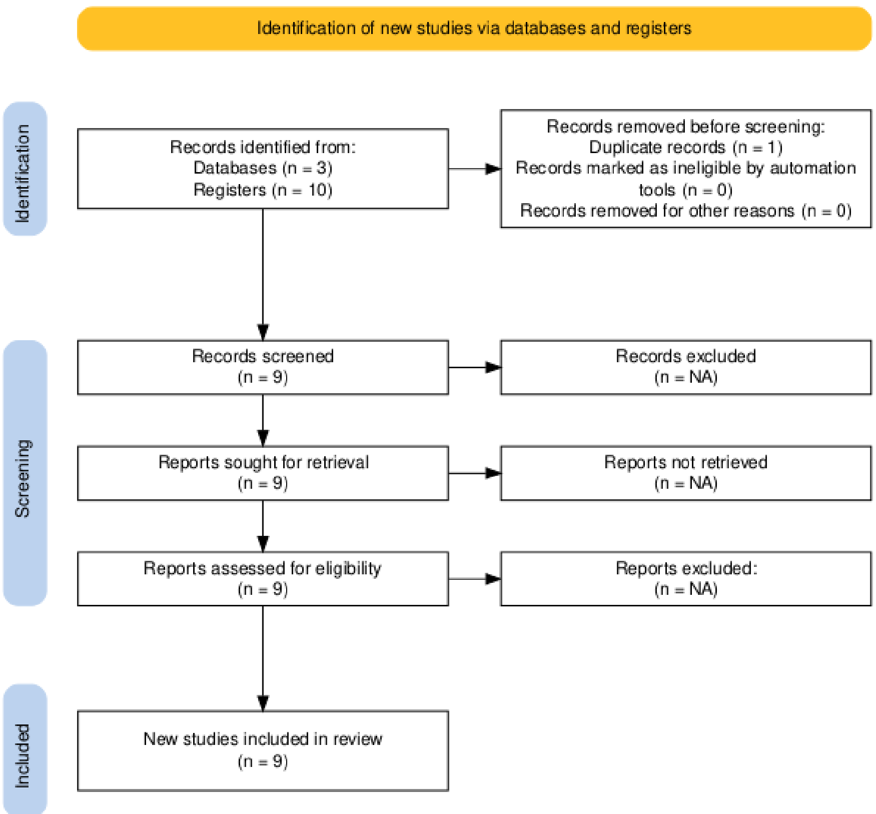

Figure 1. PRISMA 2020 flow diagram.

Data synthesis

Given the considerable heterogeneity across included studies, ranging from cross-sectional surveys and pilot interventions (e.g., gamified chatbots for parents, digital healthy eating literacy surveys) to comparative content analyses of ChatGPT outputs, narrative reviews, and professional commentaries, we did not prespecify nor undertake a quantitative meta-analysis. Instead, we applied a narrative thematic synthesis: (i) we summarized study characteristics and mapped their contributions to the four analytic lenses (Key Applications, Benefits, Challenges, and Contribution to Personalized Learning); (ii) we extracted and reported key quantitative findings from empirical studies, such as improvements in parental nutrition knowledge scores, measures of guideline concordance in NCD-related dietary advice, and associations between digital literacy and Mediterranean diet adherence, without statistical pooling; and (iii) we integrated qualitative insights from reviews and ethical analyses, highlighting issues of accuracy, privacy, and professional oversight, to derive implications for pedagogical design and safe implementation of GenAI in food and nutrition education. Sensitivity analyses and publication-bias assessments were not applicable given the diversity of study types and the absence of a pooled quantitative synthesis.

Outcomes

The outcomes of this review focus on how GenAI is shaping food and nutrition education across the four analytic lenses. Regarding Key Applications, studies demonstrated that AI chatbots and large language models (LLMs) are being integrated into diverse contexts, from perinatal health campaigns (e.g., Nutripedia) and university classrooms to clinical dietetics and patient counseling, yielding engagement metrics such as chatbot downloads, interaction frequency, and expert-evaluated guideline concordance (i.e., the extent to which AI-generated dietary recommendations align with recognized clinical nutrition guidelines). In terms of Benefits, empirical evidence showed improvements in parental nutrition knowledge through gamified chatbots, enhanced nutrition literacy among college students, and associations between digital healthy eating literacy (defined as the ability to find, understand, and use online information to make healthier food choices) and adherence to sustainable diets such as the Mediterranean model. Concerning Challenges, outcomes highlighted frequent accuracy gaps in multimorbidity scenarios (i.e., complex cases involving multiple coexisting chronic conditions such as diabetes, obesity, and kidney disease), risks of misinformation, automation bias (a tendency to over-trust AI outputs and overlook human judgment errors), and variable performance across languages and question framings in perinatal counseling. Finally, in Contribution to Personalized Learning, outcomes revealed the potential of GenAI to deliver tailored quizzes, adaptive content, and interactive explanations that support individualized learning trajectories, though requiring validation and human oversight. Collectively, these outcomes emphasize both the promise and the risks of GenAI in nutrition education, underscoring the need for pedagogical safeguards, transparency, and integration of GenAI literacy into curricula.

Data Extraction

Data were extracted with a standardized form structured around the pre-specified items and contextualized to the four analytic lenses (Key Applications, Benefits, Challenges, and Contribution to Personalized Learning in Food and Nutrition Education). For each included study, the form captured: Author(s), Year of publication, Country of origin, Aim/purpose, Population and sample size, Methodology/methods, Type of intervention (with comparator and duration, if applicable), Outcomes (and how measured), and Key findings on the role of GenAI in food and nutrition education. Discrepancies in data extraction were resolved by consensus, and, when necessary, with adjudication by a third reviewer. Items not reported (NR) were explicitly noted, and country of study was inferred from author affiliations when absent (Table S3).

In accordance with the objectives of a state-of-the-art review, a formal risk-of-bias evaluation was not performed, as the included evidence comprised a heterogeneous mix of empirical, narrative, and commentary-based sources. Instead, we appraised methodological transparency and reporting completeness across studies through structured data-extraction fields (study design, comparators, outcomes, and limitations). This approach is consistent with PRISMA-ScR and Joanna Briggs Institute (JBI) methodological guidance for scoping reviews, which emphasize mapping the evidence base rather than weighting it by quantitative quality scores.

4. Discussion

This discussion critically examines the role of GenAI in food and nutrition education across four interconnected dimensions: (i) Key Applications, analyzing how generative models are being used to support formal and non-formal instruction, enhance nutrition literacy, generate didactic resources, and deliver tailored dietary guidance in both educational and clinical contexts; (ii) Benefits, emphasizing the immediacy and versatility of access to evidence-based nutritional information, the improvement of learner engagement through interactive and adaptive tools, and the facilitation of more efficient development of learning activities and assessments; (iii) Challenges, addressing limitations such as accuracy and completeness of generated content, risks of misinformation, issues of academic rigor, and inequalities in access that condition effective implementation in diverse settings; and (iv) Contribution to Personalized Learning, highlighting how adaptive quizzes, formative feedback, and individualized learning pathways can strengthen understanding of complex nutritional concepts and connect dietary education with learners' personal contexts. Together, these dimensions provide an integrated perspective on the transformative potential of GenAI in reshaping food and nutrition education while identifying areas where further research and validation are required (11-19).

Key Applications of Generative Artificial Intelligence in Food and Nutrition Education

Across the evidence base, to begin with, key applications of GenAI in food and nutrition education cluster into three interlinked domains: population-level communication and literacy, clinical and patient education for NCDs, and personalized, learner-centered instruction. In particular, LLMs and chatbots can scale guideline-based messages, produce instructional materials, and support decision-making when coupled with expert oversight and alignment to standards (12, 17-19).

At the population level, multichannel initiatives (exemplified by Nutripedia) demonstrate that a curated ecosystem (website, social media, and a chatbot) can counter misinformation during pregnancy and early childhood, deliver tailored advice, and sustain high user engagement with expert-moderated content. Consequently, this positions conversational agents as scalable vehicles for early nutrition literacy and myth-busting in family contexts (19).

Regarding clinical education and patient self-management in NCDs, LLMs can structure diet counseling, generate menu suggestions, and cue self-care behaviors; however, performance varies by condition complexity. For example, in standardized prompts spanning several NCDs, responses ranged from appropriate to inadequate relative to international guidelines, and a multimorbidity case (type 2 diabetes + obesity + chronic kidney disease) revealed notable omissions, thus underscoring the need for human-in-the-loop designs, verification by licensed professionals, and continuous updating (12, 14, 18).

Similarly, within formal education, GenAI can enhance nutrition literacy and produce readable learning resources, yet expert quality control remains essential. Evaluations with university students and dietetics professionals highlight useful readability and structure but also gaps in completeness, practicality, and rigor that warrant academic supervision in order to ensure sufficiency and applicability (13, 17).

Moreover, personalized learning gains traction when chatbots are embedded in hybrid programs and use motivational mechanics. Indeed, a gamified chatbot coupled with weekly seminars improved parental nutrition knowledge and sustained participation, illustrating how GenAI can deliver tailored feedback, track progress, and maintain engagement through interactive tasks (16, 20).

In addition, population-level competencies also matter: digital healthy eating literacy correlates with more sustainable food choices and better adherence to healthy patterns such as the Mediterranean diet. Therefore, integrating this literacy component into GenAI-mediated programs can amplify the benefits of personalization and catalyze healthier, more sustainable dietary shifts in communities (11).

Furthermore, contextual sensitivity is pivotal in perinatal and multilingual settings. Performance varies by language and by how questions are framed, with implications for safety, interpretation, and cultural appropriateness, hence, the importance of language validation, clear quality-control protocols, and explicit escalation pathways to professionals when uncertainty or risk is present (13, 15).

Finally, GenAI applications in diet assessment and monitoring (e.g., food recognition, nutrient estimation, and menu generation) open opportunities for more timely feedback and richer learning/clinical loops, provided that they are anchored in nutrition-science methods and robust data governance. In this sense, this translational space connects educational use with analytics pipelines in nutrition research and practice, supporting educators and clinicians with higher-value time for supervision and individualized feedback (12, 14, 21).

While previous reviews on artificial intelligence in education have broadly examined pedagogical transformations and digital adaptation processes, this state-of-the-art review contributes a distinctive perspective by situating generative AI within the specific context of food and nutrition education. Beyond generic educational frameworks, our synthesis integrates clinical, community, and pedagogical dimensions, illustrating how GenAI not only facilitates adaptive learning but also supports evidence-based dietary guidance, sustainable nutrition literacy, and ethical oversight in health-related education. This dual educational–clinical focus distinguishes the present review from prior analyses limited to general classroom or higher-education settings.

Benefits of Using Generative Artificial Intelligence in Food and Nutrition Education

To begin with, GenAI strengthens personalized learning by adapting explanations, examples, and formative feedback to learner needs while maintaining readable, structured outputs; in fact, evaluations with university students and dietetics professionals indicate gains in understandability and organization, thereby supporting nutrition-literacy aims when expert supervision is present (16, 17, 25). At the population level, multichannel programs that embed chatbots (such as Nutripedia) have demonstrated large-scale reach and sustained engagement during pregnancy and early childhood, a life stage in which timely, trustworthy guidance counters misinformation and facilitates evidence-based behaviors among families (19). Moreover, in clinical and patient-education contexts, GenAI can accelerate access to tailored diet education and self-management support: narrative reviews highlight capabilities such as recipe personalization, nutrient estimation, multilingual translation, and food-image recognition that complement existing workflows in chronic kidney disease and related NCDs; in addition, this translational arc also links educational use with analytics pipelines in clinical nutrition (1, 12, 14).

A further benefit emerges around quality culture and professional roles: when dietitians use GenAI outputs as draft material to refine, compare, and teach against guideline standards, they can scaffold critical appraisal skills for learners while protecting patient safety. Indeed, evidence from guideline-concordance testing shows where LLM advice is appropriate and where expert correction adds value; likewise, professional commentary frames GenAI as an adjunct that can streamline education and documentation without displacing credentialed judgment (13, 18). Additionally, benefits accrue in perinatal and multilingual education: standardized evaluations in maternity nutrition show that performance varies by language and question framing, which if properly leveraged, encourages localized content, clearer prompts, and bilingual resources that improve comprehension and safety for diverse users, especially when combined with expert moderation (15, 19).

For parents and caregivers, in particular, hybrid Online-Merge-Offline (OMO) programs that pair weekly nutrition sessions with a gamified chatbot have improved knowledge and engagement, thus illustrating how GenAI can sustain motivation through quizzes, nudges, and personalized tips, and therefore extend teacher reach beyond the classroom (16, 24). At the community level, integrating digital healthy-eating literacy with GenAI experiences supports more sustainable, health-promoting choices and adherence to quality dietary patterns (e.g., Mediterranean diet). Consequently, programs which embed e-literacy alongside generative tools can magnify behavior change and long-term adherence (11, 20). Furthermore, GenAI can improve efficiency and scalability for educators by summarizing diverse sources, generating first-draft learning materials, and supporting rapid feedback cycles, thereby freeing instructor time for higher-value mentoring and assessment while maintaining transparency about model limits and needed oversight (13, 22, 23).

In summary, when embedded with expert review, aligned to guidelines, localized linguistically, and paired with digital-literacy education, GenAI offers concrete benefits across learner engagement, clinical education, and program scalability, all while avoiding displacement of the central role of trained nutrition professionals (12, 14, 17). Nevertheless, while the reviewed studies collectively indicate promising educational benefits, the empirical evidence supporting these outcomes remains preliminary. Most reports describe perceived improvements or short-term knowledge gains rather than longitudinal or experimentally verified impacts on learning performance or behavioral change. Therefore, claims about educational effectiveness should be interpreted cautiously, emphasizing potential rather than confirmed outcomes. Strengthening the empirical base through controlled and longitudinal designs will be essential to substantiate these early observations.

Challenges of Implementing Generative Artificial Intelligence in Food and Nutrition Education

Primarily, a central challenge is clinical accuracy and patient safety. Benchmarking studies show that LLM outputs for multiple NCDs can range from guideline-concordant to inappropriate, and performance deteriorates in multimorbidity where key recommendations are omitted, therefore, conditions that make "human-in-the-loop" oversight (meaning that AI-generated advice is always reviewed and validated by qualified professionals before implementation) non-negotiable in educational and clinical contexts (12, 14, 18).

Beyond correctness, however, educational quality is uneven. While responses are typically readable, expert raters highlight shortfalls in completeness, practicality, and rigor, which implies that unsupervised use may encourage superficial understanding and overconfidence in learners. Moreover, this risk is amplified by professional commentary warning about misinformation and the proper scope of GenAI in dietetics training (13, 17). In addition, language, framing, and cultural-context sensitivity introduce additional failure modes. Accuracy varies across languages and depends on how questions are posed, with the result that perinatal education may face safety issues when ambiguous prompts or non-localized content are present. Consequently, early-life campaigns further underscore the need for expert moderation to avoid amplifying myths in high-stakes family settings (15, 19). Furthermore, equity and digital-literacy gaps complicate deployment. Associations between digital healthy-eating literacy and healthier, more sustainable dietary patterns suggest that GenAI tools may preferentially benefit more digitally fluent users, thus risking widened disparities unless literacy scaffolds and inclusive design are built in from the outset (11).

From a methods and validation standpoint, emerging GenAI workflows (e.g., food recognition, macro/micronutrient estimation, automated menu generation) still require robust, condition-specific validation and careful integration into clinical/educational pipelines. Otherwise, educators may inadvertently teach with tools whose underlying assumptions and error rates are opaque (12, 14). Similarly, generalizability and implementation realism also limit confidence. Evidence from school–family pilots show promise but is hampered by small samples, attrition, and short durations, all of which constrain external validity and make it difficult to separate chatbot effects from co-interventions such as seminars or tutoring (16).

Beyond sample size and duration constraints, a more critical appraisal of study designs reveals important methodological asymmetries across the included evidence. Most empirical contributions were cross-sectional or pilot interventions with limited control groups, while few adopted quasi-experimental or longitudinal approaches that could demonstrate sustained learning or behavioral change. Narrative and commentary-based papers, though conceptually rich, often lacked methodological transparency or replicable frameworks. This imbalance underscores the need for stronger research designs—particularly randomized, mixed-methods, and longitudinal studies—to establish causal links between generative AI use and measurable educational or clinical outcomes. Finally, governance and professional role clarity remain works in progress. Commentaries and reviews emphasize that GenAI should augment (not replace) credentialed judgment. Therefore, programs need clear boundaries (scope of use, escalation pathways, audit trails) and explicit supervision models in order to prevent automation bias, ensure transparency about limitations, and align with prevailing standards in dietetics and clinical nutrition (13, 14, 18).

Moreover, contextual considerations from broader literature reinforce these concerns: constraints in data quality and availability, algorithmic bias, privacy/security, teacher AI-literacy gaps, and systems-integration and scalability hurdles all complicate routine classroom and clinic adoption. Hence, institutional policies, professional development, and technical safeguards are pivotal complements to content-level fixes (1, 26-30).

Contribution of Generative Artificial Intelligence to Personalized Learning in Food and Nutrition Education

At the outset, GenAI enables learner-centered personalization by tailoring explanations, scaffolds, and formative feedback to users' goals, prior knowledge, and constraints across academic and clinical settings. In particular, in higher-education contexts, evaluations show that ChatGPT produces readable and structured guidance for students but still requires expert supervision to ensure completeness and rigor, an arrangement that fits personalized learning models where faculty curate, correct, and contextualize outputs (13, 17). Moreover, contextual literature likewise highlights adaptive pathways and custom learning-path design as core mechanisms through which GenAI individualizes instruction (3, 31).

Similarly, for families and caregivers, hybrid OMO programs demonstrate how GenAI can personalize engagement at home: a gamified chatbot paired with weekly seminars delivered interactive quizzes, bite-sized explanations, and individualized tips that improved parental nutrition knowledge and sustained participation, features that map directly onto adaptive, just-in-time learning (16). Consequently, these designs generalize the idea of personalization beyond classrooms, using conversational agents to pace difficulty, resurface misconceptions, and nudge practice between sessions (17). In addition, complementary work in education technology underscores GenAI's capacity to generate tailored materials and feedback loops that reduce friction for learners while keeping instructors in the loop (32).

In the clinical sphere, and more specifically in patient-facing nutrition education, GenAI's contribution to personalization appears in multimodal support: recipe and meal-plan generation aligned to clinical constraints, nutrient estimation, multilingual translation, and food-image recognition can be orchestrated to meet individual needs and preferences, especially in chronic kidney disease and related NCDs (12, 14). Nevertheless, personalization must be coupled with safeguards: benchmarking against guideline scenarios shows that performance can slip (particularly under multimorbidity) therefore, human-in-the-loop review, explicit guardrails, and transparent provenance are essential to keep individualized advice both accurate and safe (13, 18).

Furthermore, language, framing, and life-stage sensitivity are pivotal to effective personalization. For instance, in perinatal education, ChatGPT-4's accuracy varies by language and question framing, implying that tailored prompts, localized content, and culturally attuned messaging are prerequisites for safe and comprehensible guidance (15). Likewise, multichannel campaigns such as Nutripedia illustrate how expert-moderated chatbots, articles, and social content can be orchestrated to deliver trustworthy, individualized advice during pregnancy and early childhood, periods in which timely personalization is particularly impactful (19). Moreover, emerging examples in nutrition edtech (e.g., AR-enhanced serious games) further show how adaptive, feedback-rich environments can translate complex dietary concepts into situated, learner-specific experiences (20).

At the same time, personalization is also contingent on learners' digital capacities. Indeed, population data link digital healthy-eating literacy to more sustainable choices and stronger adherence to healthy patterns (e.g., Mediterranean diet), suggesting that GenAI-enabled personalization will work best when programs intentionally scaffold e-health literacy and include transparent rationales within the AI's explanations (11). Accordingly, instructors can leverage GenAI to generate tiered resources (basic to advanced), exemplars, and reflective prompts that align with learners' literacy levels while preserving professional oversight (13).

On the whole, GenAI contributes to personalized learning in food and nutrition by (a) adapting content, pacing, and modality to the learner; (b) extending individualized support beyond classrooms into homes and clinics; and (c) integrating multilingual, culturally aware messaging for sensitive life stages. Ultimately, realizing these gains depends on expert-curated workflows that check guideline concordance, language adequacy, and equity of access, thus ensuring that GenAI functions as an adjunct that strengthens, rather than substitutes for, professional judgment (11-19).

Limitations and Strength

Among the limitations of this review is the modest body of eligible studies (nine in total) and their substantial heterogeneity in aims, designs, populations, and outcomes, which precluded any quantitative synthesis or meta-analysis. Several included sources were narrative reviews or professional commentaries without empirical samples, limiting the strength of inference and generalizability of findings. Even the empirical studies often relied on small, short-term, or pilot designs (such as gamified chatbot interventions with limited participant retention or cross-sectional surveys dependent on self-reported literacy scores) thereby constraining causal interpretation and long-term outcome assessment. In addition, the field is still nascent, with most evidence published only between 2021 and 2025, meaning that ongoing trials and gray literature may not have been captured. Publication bias cannot be ruled out since only peer-reviewed sources in English/Spanish were considered, and gray literature was not systematically searched. Finally, across the evidence base, outcome measures were not directly comparable, and important endpoints such as sustained behavior change, clinical outcomes, or ethical impacts were rarely assessed in depth.

Although efforts were made to include studies published in both English and Spanish, most of the available empirical evidence on generative AI in food and nutrition education is concentrated in English-language journals. This predominance reflects the current global distribution of research in this emerging field rather than an intentional exclusion of regional or Spanish-language studies. Future research from Latin American and Spanish-speaking contexts will be essential to expand regional representation and strengthen cross-cultural perspectives on AI in nutrition education.

In terms of strengths, this review applied a rigorous and transparent methodology consistent with PRISMA-S guidance, included a peer-reviewed multi-database strategy (PubMed, Scopus, Web of Science), and implemented independent, two-phase screening with consensus resolution in Rayyan. It explicitly mapped findings across four analytic lenses (Key Applications, Benefits, Challenges, and Contribution to Personalized Learning) and extracted standardized information on authors, populations, interventions, comparators, outcomes, and key contributions. This structured and reproducible process not only enhances the transparency and credibility of the synthesis but also provides a clear baseline for future research on the role of GenAI in food and nutrition education.

Future Directions

Next-step research should extend beyond small pilot trials, cross-sectional surveys, and narrative commentaries by adopting rigorous randomized and longitudinal designs that directly compare structured, faculty- or clinician-guided uses of GenAI against unstructured or unsupervised access. Future studies must incorporate objective endpoints (including measurable nutrition literacy gains, guideline concordance in multimorbidity dietary scenarios, sustained parental knowledge retention, and behavioral outcomes such as adherence to healthy or sustainable dietary patterns) while also integrating ethical dimensions such as privacy, equity, and professional role clarity. To ensure comparability, intervention fidelity, prompting protocols, and outcome measures should be reported in standardized detail, with core outcome sets developed across education, clinical dietetics, and perinatal care. Implementation-science frameworks are needed to evaluate feasibility, acceptability, and scalability in diverse contexts, including resource-constrained, multilingual, and digitally heterogeneous populations. Moreover, participatory co-design with educators, dietitians, students, and families, coupled with faculty development in AI literacy and transparent governance structures (audit trails, human-in-the-loop oversight, and data-protection safeguards), will be essential to embed GenAI safely and sustainably in food and nutrition education.

5. Conclusions

- GenAI plays a multifaceted role in food and nutrition education, spanning public-facing communication, formal instruction, and patient counseling. It expands access to timely, evidence-informed content, supports the development of nutrition literacy, and helps educators and clinicians design more efficient, engaging learning experiences.
- At the intersection of education and clinical practice, GenAI enables personalization by adapting explanations, feedback, and learning pathways to user needs and contexts. Its utility, however, is conditioned by the accuracy and completeness of outputs, which can vary with problem complexity, language, and framing. As a result, expert oversight,

alignment with professional standards, and careful localization are essential to ensure safety and relevance.

- For personalized learning, GenAI facilitates adaptive assessment, formative feedback loops, and multimodal resources that can sustain motivation and deepen understanding of complex nutritional concepts. Realizing these benefits equitably requires integrating digital literacy supports so that learners with different skill levels can critically appraise and effectively use AI-mediated guidance.
- Taken together, the role of GenAI is best conceived as a transformative adjunct (amplifying, not replacing, the work of trained professionals). Its responsible adoption depends on clear governance, validation against recognized standards, transparent communication of limitations, and equity-sensitive instructional design. When these conditions are met, GenAI can strengthen learner engagement, enhance educational efficiency, and contribute to safer, more personalized nutrition education across settings.

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Table 1. PRISMA-S checklist.

Section/topic	#	Checklist item	Location(s) Reported
		INFORMATION SOURCES AND METHODS	
Database name	1	Name each individual database searched, stating the platform for each.	1- 4, 7
Multi-database searching	2	If databases were searched simultaneously on a single platform, state the name of the platform, listing all of the databases searched.	NR
Study registries	3	List any study registries searched.	4
Online resources and browsing	4	Describe any online or print source purposefully searched or browsed (e.g., tables of contents, print conference proceedings, web sites), and how this was done.	NR
Citation searching	5	Indicate whether cited references or citing references were examined, and describe any methods used for locating cited/citing references (e.g., browsing reference lists, using a citation index, setting up email alerts for references citing included studies).	NR
Contacts	6	Indicate whether additional studies or data were sought by contacting authors, experts, manufacturers, or others.	NR
Other methods	7	Describe any additional information sources or search methods used.	NR
		SEARCH STRATEGIES	
Full search strategies	8	Include the search strategies for each database and information source, copied and pasted exactly as run.	7
Limits and restrictions	9	Specify that no limits were used, or describe any limits or restrictions applied to a search (e.g., date or time period, language, study design) and provide justification for their use.	3-4
Search filters	10	Indicate whether published search filters were used (as originally designed or modified), and if so, cite the filter(s) used.	NR

Prior work	11	Indicate when search strategies from other literature reviews were adapted or reused for a substantive part or all of the search, citing the previous review(s).	NR
Updates	12	Report the methods used to update the search(es) (e.g., rerunning searches, email alerts).	3-4
Dates of searches	13	For each search strategy, provide the date when the last search occurred.	3-4
PEER REVIEW			
Peer review	14	Describe any search peer review process.	NR
MANAGING RECORDS			
Total Records	15	Document the total number of records identified from each database and other information sources.	4,8
Deduplication	16	Describe the processes and any software used to deduplicate records from multiple database searches and other information sources.	4

NR= Not reported

Table S2. Bibliographic search strategy.

Engine	Strategy	Results
PUBMED	#1= ("Generative Artificial Intelligence" OR "Artificial Intelligence, Generative" OR "Chat GPT" OR "Chat-GPT" OR "ChatGPT" OR "ChatGPTs" OR "Chatbot" OR "Chatbots") #2= ("Food and Nutrition Education" OR "Nutrition Education") #3 = #1 AND #2	2
SCOPUS	#1= TITLE-ABS-KEY ("Generative Artificial Intelligence" OR "Artificial Intelligence, Generative" OR "Chat GPT" OR "Chat-GPT" OR "ChatGPT" OR "ChatGPTs" OR "Chatbot" OR "Chatbots") #2= TITLE-ABS-KEY ("Food and Nutrition Education" OR "Nutrition Education") #3 = #1 AND #2	2
WEB OF SCIENCE	#1= ("Generative Artificial Intelligence" OR "Artificial Intelligence, Generative" OR "Chat GPT" OR "Chat-GPT" OR "ChatGPT" OR "ChatGPTs" OR "Chatbot" OR "Chatbots") #2= ("Food and Nutrition Education" OR "Nutrition Education") #3 = #1 AND #2	6

Table S3. Characteristics of included studies.

Ref.	Year	Origin/ country	Aims/purpose	Population & sample size	Methodology	Intervention (type/comparator/duration)	Outcomes (how measured)	Key findings (Role of GenAI in Food & Nutrition Education)
19	2021	Italy	To present the development, implementation, and initial outcomes of Nutripedia, a multi-channel communication campaign designed to counteract fake news in nutrition during pregnancy and early life and to promote evidence-based practices.	Target population: parents and families during pregnancy and early childhood; No empirical sample size (descriptive study with digital engagement metrics).	Qualitative descriptive study and content analysis of usage patterns; formative research combined with monitoring of website, social media, and chatbot engagement metrics.	Intervention: Nutripedia campaign composed of (i) website with evidence-based articles, (ii) Facebook page with posts by bloggers, (iii) Nutripedia Chatbot mobile app delivering personalized nutrition advice. Comparator: NR (no control group).	Campaign duration: June 2018 – November 2020	Outcomes measured: website visits (220,000 total views), social media reach (>9 million users via bloggers' activation), chatbot downloads (14,698), user questions directed to experts (1,930), total chatbot responses (>24,000), blog posts (23 guest posts, >135,000 views).
13	2023	Switzerland and France	To analyze potential opportunities and risks of ChatGPT and future AI chatbots for credentialed nutrition and dietetics practitioners, including their influence on professional practice, patient care, and academic settings.	NR (commentary; no empirical sample)	Professional commentary and narrative analysis	No intervention; demonstration of ChatGPT outputs in nutrition-related scenarios (eg, type 2 diabetes, hemodialysis, food allergies, academic writing). Comparator: expert evaluation of ChatGPT responses.	NR	Outcomes: quality and accuracy of ChatGPT responses in nutrition practice scenarios, appropriateness of dietary advice, limitations of AI-generated texts, risks of misinformation, and implications for credentialed practitioners.

18	2024	Italy	To evaluate whether the dietary advice provided by ChatGPT aligns with international clinical guidelines for multiple non-communicable diseases (NCDs) and to assess ChatGPT's ability to manage a complex multi-morbidity scenario.	No human participants; NR for sample size. The unit of analysis was chatbot outputs generated in November 2023 using ChatGPT version 3.5.	Comparative content analysis: standardized patient-style prompts for seven NCDs (dyslipidemia, hypertension, type 2 diabetes, obesity, NAFLD, CKD, sarcopenia). Two blinded dietitians independently rated answers against international guidelines; disagreements resolved by a medical reviewer. A second experiment tested a complex case with T2DM + obesity + CKD.	No clinical intervention. Comparator: international dietary guidelines (e.g., ESC/EAS, ESH/ISH, ADA/EASD, AASLD/ESPEN, KDOQI/KDIGO, ESPEN/ICFSR).	NR	Outcomes: guideline concordance categorized as 'appropriate', 'not fully matched', 'general advice', 'unsupported', or 'inappropriate'; identification of missing recommendations. Measurement: expert rating of ChatGPT responses across conditions and qualitative appraisal of performance in a multi-condition scenario.
17	2024	Taiwan	To evaluate the quality of ChatGPT's dietary advice for college students from the perspectives of experienced dietitians, focusing on nutrition literacy achievement and response quality.	Participants: 30 registered dietitians (≥3 years of counseling experience) who assessed ChatGPT responses; additionally, 20 Taiwanese college students were recruited to generate prompts for ChatGPT inquiries.	Cross-sectional study using multidimensional evaluation: (i) scenario-based nutrition literacy test with 32 items, (ii) quality assessment of ChatGPT responses using seven evaluation indicators (accuracy, currency, completeness, understandability, readability, relevance, practicality), and (iii) feedback collection via online surveys.	Intervention: ChatGPT-3.5 was prompted with dietary inquiries derived from realistic student scenarios; Comparator: Taiwanese college students' nutrition literacy test scores.	NR (single-time evaluation, not a longitudinal intervention)	Outcomes: (1) Achievement of nutrition literacy indicators across five scenarios; (2) Response quality assessed by dietitians on seven criteria using a 1–10 Likert scale; (3) Objective performance on a 32-item nutrition literacy test; (4) Qualitative feedback from dietitians.
11	2025	Türkiye	To examine the associations between digital healthy eating literacy, environmentally responsible food choices,	Adults aged 18–65 years; N = 1,516 participants	Cross-sectional and descriptive study using an online survey distributed via social platforms.	No intervention; observational design. Comparator groups were defined by levels of	NR	Outcomes measured: digital healthy eating literacy (e-HDL questionnaire, max score 55), environmentally responsible food choices (7-item Likert scale, max

			and adherence to the Mediterranean diet (MedDiet), a sustainable dietary model, among adults in Türkiye.			adherence to the MedDiet (nonadherent <7 vs. adherent ≥7 on the MEDAS scale).		score 35), and Mediterranean Diet adherence (MEDAS, 14 items, score 0–14).
14	2025	Spain	To review the advances, challenges, and potential applications of generative artificial intelligence, particularly ChatGPT, in clinical nutrition.	NR (review article; no empirical sample)	Narrative review	No intervention; the study critically discusses applications of ChatGPT in clinical nutrition across assessment, diagnosis, intervention, and monitoring.	NR	Outcomes include analysis of ChatGPT's performance in tasks such as nutritional assessment, diagnostic support, dietary recommendations, personalized diet plans, and education. Comparisons were made with clinical guidelines and expert evaluations.
16	2025	Taiwan	To evaluate the effectiveness of an AI-powered gamified chatbot integrated with the Online-Merge-Offline (OMO) strategy in enhancing parental nutrition knowledge.	Parents of children in a public childcare center; 20 unique participants, majority female, aged 21–70; 77 total attendances across eight seminars; only 9 parents completed all pre- and post-tests.	Pilot study conducted in a Taiwanese childcare center; quantitative pre- and post-test design combined with engagement tracking and descriptive statistics.	Intervention: Eight weekly one-hour nutrition seminars by registered dietitians, integrated with a LINE-based gamified chatbot delivering interactive activities, quizzes, videos, and personalized feedback. Comparator: NR (no control group).	8 weeks (eight seminars, one per week)	Primary outcomes: parental nutrition knowledge measured by pre- and post-test scores administered via chatbot. Secondary outcomes: engagement metrics (interaction frequency, quiz completion, time on platform), demographic correlates (gender, age, education).
12	2025	USA, UK, Switzerland, The Netherlands	To review the current and potential applications of large language models (LLMs), particularly	NR (review article; no empirical population or sample size)	Narrative review and commentary based on literature synthesis and expert insights	No formal intervention; article examines ChatGPT and other LLMs in tasks including	NR	Outcomes: analysis of LLM-generated nutritional advice accuracy (macronutrient and micronutrient estimations), feasibility of recipe

			ChatGPT, to enhance nutritional recommendations in patients with chronic kidney disease (CKD), while also considering evidence from diabetes and obesity management.			recipe generation, nutritional estimation, general dietary advice, language translation, and image recognition. Comparator: expert evaluation and clinical guidelines.		personalization, translation quality across multiple languages, image-based food recognition accuracy, and integration with current CKD dietary workflows.
15	2025	Switzerland (multinational European authorship)	Primary: Evaluate ChatGPT's accuracy as an information source for women and maternity-care workers on 'nutrition' and 'red flags' in pregnancy. Secondary: Assess differences by language (French, English, German, Dutch) and by question framing ('Is it safe…' vs 'Is it dangerous…').	ChatGPT-generated responses assessed by 8 raters; two topics (nutrition; red flags); 10 subtopics per topic; up to 4 languages for nutrition and 3 for red flags.	Accuracy study comparing ChatGPT-4 recommendations with 'Key Response' elements derived from national professional guidelines; eight raters scored each item on a 5-point Likert scale; inter-rater reliability estimated with ICC (two-way mixed-effects model).	Exposure: ChatGPT-4 responses to standardized questions about perinatal nutrition and warning signs. Comparator: Key Response Elements extracted from national guidelines for each language.	NR	Outcomes: Median accuracy scores per subtopic and overall accuracy percentages by topic and language; inter-rater reliability (ICC with 95% CI). Measurements: 5-point Likert scale (1–5), ICC thresholds (poor–excellent).

NR = Not Reported