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Methodological Advances of AI and Business Intelligence in Nutrition: Techniques, Applications, and Future Directions

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Abstract

Artificial Intelligence (AI) and Business Intelligence (BI) are increasingly transforming nutritional science by enabling precise dietary assessment, personalized nutrition planning, and data-driven health monitoring. This review provides an integrated analysis of methodological advancements in AI and BI techniques applied within nutrition research. A structured search was conducted across PubMed, Scopus, Web of Science, Google Scholar, and ScienceDirect. After removing duplicates and applying predefined inclusion and exclusion criteria—focusing on studies that utilized AI, machine learning, deep learning, or BI frameworks for dietary assessment, nutrient estimation, predictive modeling, or personalized dietary recommendations—a total of 73 studies met the eligibility criteria and were included in the final synthesis. The review categorizes methodological approaches, highlights their strengths and limitations, and evaluates their practical implications for clinical and public-health nutrition. While AI holds significant promise for improving accuracy, scalability, and personalization in nutrition, several challenges remain, including dataset limitations, model interpretability, and ethical considerations. The findings emphasize the need for culturally diverse datasets, explainable models, and integrated AI–BI architectures to advance future research and real-world implementation. Integrating AI and nutrition, it still faces several data-related, methodological, and ethical limitations.

Keywords: DMachine Learning, Nutrition, Deep Learning, Artificial Intelligence.

1 | Introduction

1.1 | Background and Motivation

In general, the term "food nutrition" refers to the heat energy and nutrients that are obtained by the human body from the consumption of food. These nutrients include things like protein, fat, carbs, and so on [1]. Nutrition provides numerous health benefits, including disease prevention, management, and overall well-being. Controlling one's nutritional intake is critical for disease prevention and management. Proper nutrition is crucial for disease prevention, management, and treatment, with a well-established link between the two[2]. Nutritional management is essential for managing chronic diseases like diabetes, hypertension, and cardiovascular disease. Controlling sodium, sugar, and saturated fat intake can aid in managing and controlling these disorders. Diabetes patients must monitor and regulate their carbohydrate intake to maintain healthy blood sugar levels. Balanced meals and portion control improve blood glucose control, and limiting salt

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consumption is crucial for regulating blood pressure. Consuming fruits, vegetables, whole grains, and avoiding processed foods can improve blood pressure regulation [3]. Dietary recording technologies include web-based tools, mobile apps, camera-based image analysis, wearable sensors, and classic approaches such as Food Frequency Questionnaires (FFQs) or 24-hour dietary recording. Previous methods for documenting food consumption have been inaccurate due to difficulties with determining portion sizes and restricted ingredient lists [4].

A clearer methodological distinction can be drawn between classical machine learning approaches and the more recent deep learning and large language model–based methods. Classical ML techniques—including Decision Trees, Random Forests, Support Vector Machines, Naïve Bayes, and logistic regression—have traditionally been applied to structured nutritional datasets, focusing on tasks such as nutrient prediction, malnutrition risk classification, and obesity forecasting. These models depend heavily on handcrafted features and domain-driven preprocessing. In contrast, deep learning methods, particularly Convolutional Neural Networks, generative models, and multimodal transformers, learn hierarchical representations directly from raw data and have become dominant in food-image recognition, calorie estimation, and ingredient detection. More recently, large language models have introduced a new category of AI tools capable of conversational nutrition counseling, automated diet planning, and multimodal reasoning that integrates textual, visual, and clinical data. This progression from classical ML to deep learning and LLM-based systems reflects the growing availability of large datasets, increased computational power, and broader ambitions for automation and personalization in nutrition research.

AI has experienced exponential growth over the past decades, as shown in Figure 1, leading to the emergence of large deep networks and AI agents with remarkable capabilities, sometimes achieving performance on par with humans across various sectors [5]. These technological advancements have paved the way for substantial opportunities in numerous areas that contribute to human well-being [6]. Among these areas, nutrition is one where AI presents previously unheard-of possibilities and revolutionary breakthroughs. AI can precisely evaluate food intake, forecast each person's nutritional requirements, and create customized meal plans based on medical problems, cultural preferences, and health objectives by utilizing machine learning, computer vision, and data-driven analytics. AI-powered solutions are transforming the way that people, doctors, and researchers approach eating and health, from automated food detection to precision nutrition informed by genetic and metabolic data. These developments have the potential to streamline clinical and research workflows, increase public health outcomes, prevent chronic diseases, and improve dietary adherence [7]. Nutrition is a multifaceted discipline that examines the relationship between diet, health, and disease [8]. Nutrition is considered the basis for maintaining life activities, promoting growth and development, preventing chronic diseases, improving mental health, and maintaining a good physiological state [9].

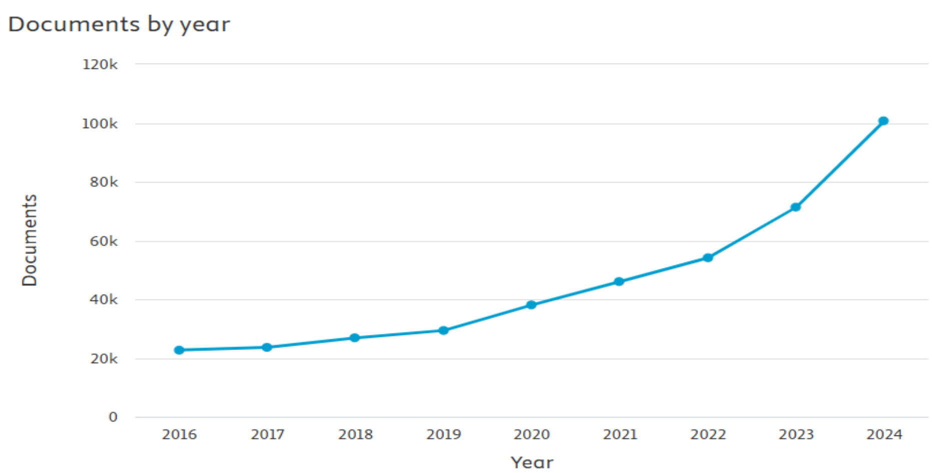

Figure 1. Number of Scopus search results for "artificial intelligence" with an exponential growth in the number of published articles between 2016 and 2024.

The world is currently experiencing a global obesity epidemic, with prevalence rates rising at alarming levels, particularly in low- and middle-income countries. In many cases, the increasing incidence of obesity is accompanied by persistent undernutrition, with both conditions coexisting within the same household. This phenomenon, known as the double burden of malnutrition, encompasses both undernutrition and overnutrition. Overnutrition refers to excessive consumption of calories and/or macronutrients, while undernutrition involves deficiencies in essential nutrients. Both forms of malnutrition are associated with numerous adverse health outcomes, making the development of practical solutions a pressing public health priority [10].

In this context, AI emerges as a powerful tool capable of driving transformative change in the field of nutrition. Through machine learning, deep learning, and natural language processing, AI can enhance personalized dietary recommendations and improve overall health and quality of life . It can accurately estimate the nutritional content and calorie counts of dishes [11]. assist in monitoring and managing dietary intake [12]. and even generate customized meal plans for individuals [13]. These capabilities open the door to more precise and effective nutritional strategies that can help reduce the double burden of malnutrition and improve health outcomes on a global scale.

The purpose of this research is to provide a comprehensive analysis of the current applications of AI in the field of nutrition, with a particular focus on its diverse roles in research and practice. By systematically examining these areas, the review aims to explore and evaluate how AI is being applied within nutrition and to understand its potential future impact. The investigation was guided by the central research question: In what ways have AI, machine learning (ML), and deep learning (DL) been utilized to improve the understanding, monitoring, and optimization of nutritional outcomes?

To address this question, the study pursued the following objectives:

- Comprehensive literature review – Examine the existing body of research on AI applications in nutrition, identifying studies that employ technologies such as ML and DL for various purposes within the discipline.
- Classification of AI methods – Organize and categorize the AI techniques used in nutritional research, with particular emphasis on ML and DL approaches.
- Methodological assessment – Evaluate the rigor and quality of the selected studies based on established criteria to ensure that conclusions are both reliable and valid.
- Challenges, limitations, and prospects – Identify the barriers to integrating AI into nutritional science, discuss the limitations of current research, and propose future research directions informed by the review's findings.

Despite the rapid growth of AI applications in nutrition, current research remains limited by several critical gaps. Most studies rely on small or culturally homogeneous datasets, which restrict generalizability and bias model performance. Existing approaches often focus on isolated tasks—such as food recognition, chatbot interaction, or predictive modeling—rather than providing integrated, multimodal frameworks capable of supporting real-world nutritional decision-making. Furthermore, few AI-driven systems have undergone long-term clinical validation, and their methodological assumptions are rarely compared systematically. These gaps highlight the need for a comprehensive review that synthesizes methodological advancements, evaluates their limitations, and identifies opportunities for developing more robust, transparent, and clinically relevant AI and BI systems in nutrition.

The main contributions of this research are as follows:

The novelty of this review lies in its integrated examination of AI, machine learning, deep learning, business intelligence, and large language model applications within nutrition—an intersection that has not been comprehensively addressed in prior surveys. Unlike earlier reviews that focus primarily on food recognition, dietary assessment tools, or predictive modeling, this study offers a structured methodological synthesis that spans multiple analytical domains while also incorporating ethical, dataset-related, and system-level considerations. This multidimensional perspective provides a more holistic understanding of current advances and gaps in AI-driven nutrition research.

- Systematic mapping and classification – This review systematically maps and categorizes existing studies at the intersection of Business Intelligence (BI) and nutrition, highlighting thematic trends and emerging technological directions.
- Identification of research gaps – It identifies critical gaps in the literature, particularly the limited exploration of integrating real-time dietary monitoring with predictive analytics
- Methodological insights – The study provides a comparative evaluation of BI techniques—including dashboards, data visualization, data mining, and machine learning—applied in nutrition contexts.
- Practical implications – It emphasizes the practical relevance of BI adoption for enhancing evidence-based decision-making among nutrition professionals, policymakers, and the food industry.
- Future research directions – It proposes opportunities for future work that combine BI with Internet of Things (IoT) technologies, wearable health devices, and personalized nutrition systems

2 | Related Work

The integration of Artificial Intelligence (AI) into the field of nutrition has evolved significantly, with applications ranging from image-based dietary assessment to personalized decision-support tools. Prior studies can be broadly categorized into four major thematic areas: food recognition and portion estimation, conversational agents and chatbots, personalized dietary recommendation systems, and predictive modeling for health and nutrition outcomes. Each of these areas has contributed distinct methodological advancements while addressing specific challenges in dietary monitoring and nutritional science.

For clarity, this review distinguishes between the main analytical domains. AI is the broader field, within which ML represents data-driven predictive modeling, and DL refers to neural-network–based approaches widely used in food recognition. BI serves as the data-management and visualization layer that operationalizes AI outputs. LLMs such as ChatGPT function as advanced language-processing models enabling conversational nutrition support. These distinctions provide a clear framework for interpreting the methods reviewed. Figure 2 shows A conceptual overview illustrating the hierarchical relationship between AI, ML, and DL, and the distinct yet complementary roles of Large Language Models (LLMs) and Business Intelligence (BI).

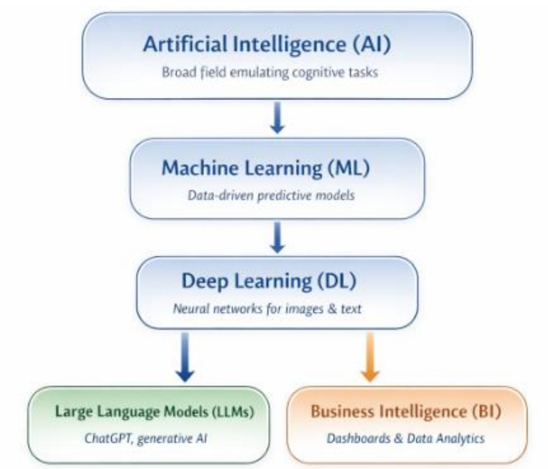

Figure 2. Conceptual Relationships Among AI, ML, DL, LLMs, and BI.

2.1 | Food Recognition and Portion Estimation

Over the past decade, computer vision and deep learning have become increasingly important in automating dietary assessments, particularly in food recognition and portion size estimation. Abdusalomov et al. (2022) applied Convolutional Neural Networks (CNNs) to classify food items and estimate their caloric values, achieving notable accuracy in image-based nutrition monitoring. In a similar direction [14]. Papastratis et al. (2021) designed a mobile application capable of identifying meal photos and evaluating diet quality using the Diet Quality Index–International (DQI-I). Their work demonstrated the potential of artificial intelligence to be integrated into everyday dietary tracking, although the systems still struggled with dataset limitations, cultural variations in eating habits, and the inherent difficulty of estimating portion sizes from two-dimensional images [5].

More advanced techniques have continued to emerge. Sun et al. (2023) proposed an image recognition framework based on Dino V2, which surpassed previous models in accuracy. The framework was tested in the context of type 2 diabetes management, offering nutritional advice and meal tracking support. Despite promising results, the system faced scalability concerns, largely due to the constraints of large language models (LLMs) in handling wide-ranging queries [15]. Meanwhile, Lei et al. (2020) extended recognition tasks by developing a recipe generation model that incorporates nutritional data. Their approach, which combined autoencoders, non-negative matrix factorization (NMF), and a fused autoencoder (FAE), helped address the issue of sparse data in large recipe collections and revealed meaningful correlations between ingredients and nutrient composition [16].

Even higher recognition rates have been reported in more recent studies. Vasudha et al. (2024) used deep CNNs to achieve 99.89% accuracy in food recognition and calorie measurement, while also providing a user-friendly web interface for accessibility. Shi et al. (2024) introduced a hybrid method that combines deep learning with 3D reconstruction techniques to estimate calorie intake from dishes and vegetables, achieving a classification accuracy of 83.74%. Although this approach mitigated some of the shortcomings of 2D estimation, the variability of food shapes and sizes continued to pose challenges for 3D modeling [17].

To better address cultural dietary diversity, Shen et al. (2020) built a client–server system trained on large datasets that included culturally specific meals. This strategy improved classification performance through the more effective use of pre-trained models, but recognition of complex or mixed foods remained problematic [18]. More recently, Feng et al. (2025) tailored their model to Chinese cuisine by combining online recipe data with the Chinese Food Composition Tables to produce detailed nutritional labels. Despite strong results, dataset imbalance remained a limiting factor [19].

Taken together, these studies highlight the steady advancement of AI-driven food recognition systems. The field has progressed from basic CNN classifiers to multimodal frameworks that integrate visual, textual, and structured nutritional information. Nevertheless, challenges such as cultural bias in datasets, the difficulty of accurately estimating portion sizes, and the complexity of identifying mixed dishes remain unresolved. These gaps highlight the need for more robust, generalized, and clinically validated solutions

2.2 | Conversational Agents and Chatbots

The use of conversational AI in nutrition counseling has grown rapidly, as these systems offer real-time, interactive, and scalable dietary support. Kaçar et al. (2021) developed a chatbot that combined natural language processing (NLP) with machine learning to act as a virtual dietitian, providing instant feedback on users' food choices. Although engagement levels were high, the system faced difficulties in tailoring recommendations to individual preferences and adapting across different cultural contexts.

The rise of large language models (LLMs) has further enhanced the naturalness and fluidity of dialogue. For example, Haman (2023) noted that ChatGPT-like models enable more engaging and human-like interactions. However, despite these improvements, issues such as limited explainability, potential inaccuracies, and ethical concerns continue to restrict their adoption in clinical nutrition practice [20]. Kaya et al. (2025) expanded chatbot capabilities by incorporating the Diet Quality Index–International (DQI-I) to assess various aspects of dietary quality, including balance, adequacy, and moderation. Their findings suggested that while chatbots can effectively evaluate general diet quality, they are less reliable in ensuring accurate macronutrient and fatty acid distributions [21].

Other studies have benchmarked AI-generated diet plans against official dietary guidelines. For instance, Bayram et al. (2025) compared meal plans produced by conversational AI with the Turkish Dietary Guidelines (TDG-2022). Results revealed frequent underestimation of calorie requirements and insufficient coverage of macro- and micronutrients. Although these AI-driven systems demonstrated short-term consistency and accuracy, their responses often varied over time, and they lacked the ability to provide sustainable, long-term nutritional planning [22].

2.3 | Personalized Dietary Recommendation Systems

Personalization is a key factor in dietary adherence, and recent advances in artificial intelligence have enabled the design of systems that tailor meal plans to an individual's health profile, lifestyle, and cultural background. Wang et al. (2020) proposed hybrid machine learning approaches that integrated patient health data with nutritional databases to deliver customized diet plans. Similarly, reinforcement learning has been applied to adjust dietary suggestions dynamically, based on user behavior and compliance, thereby improving relevance and long-term engagement. Despite these advantages, such systems require extensive data collection, raising concerns about scalability and privacy [23].

Building on this direction, Liu et al. (2024) introduced an AI framework grounded in the Taiwanese dietary guidelines. Their model incorporated multiple food sources—including home-cooked dishes, restaurant meals, and recipes—to achieve more precise calculations of nutrients. While this significantly improved the accuracy of recommendations, it also created challenges in harmonizing and standardizing diverse datasets. Earlier [12]. Mazzei et al. (2015) had presented the idea of a "virtual dietitian," combining mobile technology and AI to evaluate recipes, provide adaptive nutritional advice, and even allow controlled deviations from strict dietary rules to encourage user compliance. However, their system encountered difficulties in estimating liquid quantities, which affected the accuracy of nutrient assessments [13].

The impact of personalized nutrition systems has also been tested through mobile health (mHealth) interventions. Zahid et al. (2023) conducted a randomized controlled trial that compared an AI-driven diet-tracking application with traditional pamphlet-based counseling. Participants using the AI tool showed modest improvements in weight control and nutritional intake, although the study's duration was limited, preventing long-term conclusions [24]. Similarly, Dias et al. (2022) developed the PROTEIN mobile application, powered by AI, which was evaluated through the modified Technology Acceptance Model (mTAM). Their results highlighted the importance of usability, personalization, and perceived utility in shaping adoption and behavior change. Nonetheless, the study faced constraints, including a small sample size and limited generalizability [25].

Overall, these works demonstrate how AI can support individualized dietary recommendations, while also highlighting the ongoing need for larger datasets, stricter standardization, and clinically validated evidence before such systems can be widely adopted in real-world nutrition management.

2.4 | Predictive Modeling for Health and Nutrition Outcomes

Artificial intelligence has also been widely applied to forecasting health risks associated with dietary behaviors. A range of machine learning algorithms—such as Random Forests, Gradient Boosting, and Deep Neural Networks—have been employed to estimate the likelihood of conditions including obesity, diabetes progression, and metabolic disorders. Haman (2022), for example, combined dietary intake records with demographic information to predict obesity trends, showing that explainable AI (XAI) can provide clinically meaningful insights. However, many of these predictive studies are limited by skewed datasets, insufficient longitudinal validation, and weak integration with clinical health records.

Research in specific population groups has also demonstrated the potential of predictive modeling. Siy Van et al. (2021) compared classical statistical approaches with machine learning techniques to identify undernutrition among school-aged children in the Philippines. Their findings indicated that Random Forests offered the highest predictive accuracy, although the dataset lacked national representativeness [26]. Likewise, Aryuni et al. (2023) applied supervised learning models, including Decision Trees (C4.5), K-Nearest Neighbors (KNN), and Naïve Bayes, to assess malnutrition risks in Indonesian children under five. The Decision Tree approach achieved the strongest results, with an F1-score of 91.67% and an accuracy rate of 89.87%, underscoring the potential role of AI in early detection of stunting and wasting [27].

Taken together, these studies demonstrate that predictive modeling can serve as an effective tool for anticipating nutritional and health outcomes. Nevertheless, they also highlight key limitations, such as small and imbalanced datasets, a lack of large-scale longitudinal studies, and challenges in clinical integration. Addressing these shortcomings is crucial to advancing predictive models from experimental applications to reliable, real-world healthcare solutions.

2.5 | Critical Observations

Despite significant progress in various thematic areas, several recurring limitations remain evident in current research. A major issue is the heavy reliance on small or culturally homogeneous datasets, which restricts the generalizability of findings and limits the applicability of models across diverse populations. Without broader, more representative data, the effectiveness of AI-driven nutritional tools cannot be fully established.

Another persistent challenge is the lack of long-term clinical validation. Most AI-based systems have been tested in short-term studies or controlled environments, making it difficult to assess their sustained impact and reliability in real-world healthcare settings. This gap reduces confidence in their clinical adoption and long-term effectiveness.

In addition, much of the existing work tends to adopt siloed approaches, focusing narrowly on a single modality, such as image recognition, natural language processing, or predictive modeling. While these studies provide valuable insights, the absence of multimodal frameworks that integrate diverse data types (e.g., images, text, clinical records, and behavioral data) limits the potential for more holistic and accurate nutritional assessment.

Together, these observations underline the need for broader, clinically validated, and multimodal approaches that can bridge the gap between experimental models and practical, patient-centered applications.

2.6 | Research Gap and Positioning of this Study

Although prior studies clearly demonstrate the potential of artificial intelligence in dietary monitoring and nutritional guidance, several critical gaps remain unaddressed. Existing systems often concentrate on a single aspect—such as food recognition, chatbot interaction, or predictive analytics—rather than offering a fully integrated framework. This fragmented approach limits their effectiveness, as real-world nutrition management requires solutions that combine multiple data sources and analytical techniques.

Another important shortcoming is the absence of comprehensive clinical validation. While many models perform well in controlled experiments, few have been tested in long-term, real-world healthcare settings. As a result, their clinical reliability and practical usefulness remain uncertain. Furthermore, ethical considerations—including transparency, user privacy, and cultural adaptability—are frequently overlooked, despite being essential for adoption in diverse populations.

This study positions itself to address these shortcomings by conducting a systematic review of AI applications in nutrition across various domains. It emphasizes not only the technological advancements but also the practical challenges and limitations that hinder implementation as shown in the Table 1. By highlighting the need for multimodal integration, advanced machine learning models, and rigorous clinical validation, this work aims to provide a foundation for future research that bridges the gap between experimental innovation and real-world dietary practice.

A comparative synthesis of the reviewed studies reveals several cross-cutting patterns that extend beyond their individual contributions. Classical ML models generally perform well on structured dietary or clinical datasets but exhibit limited scalability and struggle with complex food representations, whereas deep learning models consistently outperform them in image-based recognition tasks due to their ability to extract hierarchical features from raw visual input. Across multiple studies, performance differences can be traced back to dataset quality, cultural diversity, and annotation consistency, with models trained on culturally diverse datasets demonstrating superior generalizability. Chatbot-based systems show promise for user engagement but remain constrained by variability in nutrient estimation and inconsistent adherence to dietary guidelines. Personalized nutrition frameworks benefit from integrating multiple data sources, yet their accuracy is heavily dependent on the completeness and standardization of input data. Taken together, these findings indicate that methodological choices—not only model architecture but also dataset composition and evaluation design—play a decisive role in determining model effectiveness. This synthesis highlights the necessity for cross-modal datasets, standardized evaluation metrics, and integrated AI–BI frameworks to support reliable and transferable nutrition-related applications.

To improve clarity and highlight methodological patterns more effectively, the studies included in this review have been reorganized into thematic groups rather than listed individually. These themes reflect the major research domains identified in the literature: (1) food recognition and portion-size estimation using computer vision and deep learning, (2) conversational agents and chatbot-based nutrition assistants, (3) personalized nutrition and AI-driven dietary recommendation systems, and (4) predictive modeling for disease and nutritional risk outcomes. Grouping the studies in this way allows for clearer comparison within and across categories, emphasizing shared methodologies, dataset characteristics, and limitations. This thematic presentation provides a more coherent synthesis of prior work and enables readers to better understand the progression and diversity of AI and BI approaches in nutrition research.

Table 1. Comparison of distinct methodological advancements in dietary monitoring and nutritional science.

Group 1: Food Recognition and Portion-Size Estimation (Computer Vision & Deep Learning)				
Study	Methodology	Application/Contribution	Strengths	Limitations
Abdusalomov et al. (2022)	CNN (Computer Vision)	Food recognition and calorie estimation	Demonstrated high accuracy in image-based nutrition monitoring	Struggled with dataset bias and difficulty in estimating portion sizes
Papastratis et al. (2021)	Mobile App + DQI-I	Meal recognition and diet quality assessment	Successfully integrated dietary indices into an app-based tool	Limited transferability across different cultural food contexts
Vasudha et al. (2024)	Deep CNNs	Food recognition and calorie estimation	Reached extremely high recognition accuracy	Provided limited nutritional detail
Shi et al. (2024)	DL + 3D Reconstruction	Calorie estimation in dishes/vegetables	Improved estimation beyond 2D methods	Accuracy reduced by varied food shapes and sizes
Shen et al. (2020)	ML + DL	Food recognition and nutrition estimation	Achieved high classification accuracy with cultural datasets	Weak performance on complex or mixed meals
Feng et al. (2025)	ML + DL	Chinese cuisine dietary assessment	Generated detailed nutritional labels with high accuracy	Dataset imbalance affected reliability
Group 2: Conversational Agents and Chatbots (NLP, LLMs, Dialogue Systems)				
Kaçar et al. (2021)	Chatbot (NLP + ML)	Virtual dietitian providing real-time feedback	Reported strong user engagement	Faced challenges in personalization and cultural adaptation

Haman (2023)	ChatGPT-like LLMs	Conversational nutrition counseling	Improved naturalness and interactivity of dialogue	Concerns over reliability and lack of explainability
Kaya et al. (2025)	Chatbots (Gemini, Copilot, ChatGPT-4)	Quantitative assessment of diet quality	Provided structured diet quality evaluation	Inconsistent outputs across AI tools
Bayram et al. (2025)	AI Chatbot (ChatGPT)	Menu planning vs. national guidelines	High short-term accuracy and consistency	Often underestimated caloric and nutrient needs
Group 3: Personalized Nutrition & Recommendation Systems (Hybrid ML, RL, Framework Models)				
Wang et al. (2020)	Hybrid ML Models	Personalized diet planning	Delivered tailored meal recommendations	High data demands and privacy concerns
Liu et al. (2024)	AI Framework	Personalized nutrition based on Taiwanese guidelines	Enhanced precision in nutrient calculation and dietary planning	Limited by dataset size and diversity
Mazzei et al. (2015)	AI-powered Mobile App	Recipe evaluation and adaptive dietary advice	Allowed flexible dietary management and adaptive recommendations	Difficulty in normalizing quantities, especially liquids
Zahid et al. (2023)	AI Mobile Application	Nutrition management post-surgery	Reported improved outcomes in children	Short study duration limited conclusions
Dias et al. (2022)	AI Mobile Application	Personalized nutrition and diet planning	Automated portion size estimation from images	Small sample size and low generalizability
Group 4: Predictive Modeling for Disease & Malnutrition Outcomes (Classical ML)				
Haman (2022)	RF + Deep Learning	Obesity risk prediction	Combined dietary and demographic data for improved predictions	Imbalanced datasets and limited validation
Siy Van et al. (2021)	ML (RF, SVM, LDA, LR)	Undernutrition prediction	Random Forest achieved strong predictive performance	Dataset not nationally representative
Aryuni et al. (2023)	ML (DT, KNN, NB)	Malnutrition prediction in children	Decision Tree achieved strong accuracy and F1-score	Limited by small dataset size
Knights et al. (2023)	RF + Neural Networks	Obesity management	High predictive accuracy of health outcomes	Constrained by small dataset size

This thematic grouping highlights clear methodological patterns across studies. Deep learning models dominate food recognition tasks due to their hierarchical feature-learning capabilities, whereas classical machine learning approaches remain prevalent in structured prediction problems such as malnutrition and obesity risk assessment. Chatbot and LLM-based systems contribute primarily to user engagement and counseling, but their accuracy and consistency remain variable. Personalized nutrition frameworks show promise by integrating multiple data sources, yet depend heavily on dataset completeness and standardization. Together, these patterns demonstrate that model effectiveness is shaped more by methodological fit and dataset quality than by algorithmic complexity alone.

3 | Method

The Figure 1 were generated from the final set of 73 included studies. Publication trends reflect the year-by-year distribution of these studies from 2010 to 2025, while application categories were assigned through manual coding based on each study's primary methodological focus. All visualizations therefore correspond directly to the screened and eligible dataset.

3.1 |Datasets in Nutrition Research

Datasets form the foundation of AI and BI research in nutrition by supplying the data necessary to train, validate, and benchmark predictive and analytical models. The most widely used datasets differ in scope, structure, and purpose—ranging from large-scale food image collections to structured nutritional databases.

The Food-101 dataset is one of the most extensively used open-access image datasets, containing approximately 101,000 labeled images divided into 101 food categories [28]. It has served as a benchmark for developing Convolutional Neural Network (CNN) architectures used in food recognition and caloric estimation. However, its limited number of classes restricts its ability to capture global dietary diversity, thereby limiting its use for comprehensive nutrient estimation.

The Protein NAP (Nutrition and Physical Activity Plans) dataset provides a structured resource developed by nutrition professionals under WHO and EFSA standards. It includes 84,000 daily meal plans across 3,000 virtual user profiles, covering a wide range of health and demographic conditions [29]. This dataset is especially valuable for research in personalized nutrition and adaptive meal recommendation systems, as it combines diet and physical activity data in a unified framework.

The Chinese Food Composition Database contributes nutritional composition data for over 1,100 food items, supporting studies focused on Asian dietary behavior [30]. Its associated recipe dataset contains standardized measures of raw ingredients, condiments, and cooked weights, collected under controlled conditions by certified nutritionists, ensuring high data reliability and cultural diversity.

The Yelp dataset, by contrast, is an unstructured, real-world dataset containing restaurant profiles, user reviews, menus, and over 280,000 food-related images [31]. Although it introduces labeling inconsistencies, it provides a unique opportunity to train and test food recognition models in non-laboratory, real-world conditions, improving generalization performance.

Collectively, these datasets underpin the majority of contemporary AI research in nutrition. While image-based datasets such as Food-101 and Yelp drive advancements in visual food recognition, structured datasets like Protein NAP and Chinese Food Composition support nutrient modeling and personalized dietary analytics. Integrating these complementary datasets into multimodal AI and BI frameworks improves model robustness, accuracy, and adaptability, enabling more holistic and culturally inclusive nutrition systems [32, 33].

A structured literature search was conducted across PubMed, Scopus, Web of Science, Google Scholar, and ScienceDirect, covering the period 2010–2025. The search used combinations of the following keywords: "AI and nutrition", "machine learning dietary assessment", "deep learning food recognition", "business intelligence nutrition", and "LLM nutrition counseling". After removing duplicates, studies were screened through titles, abstracts, and full texts using predefined inclusion criteria requiring the application of AI, ML, DL, BI, or LLM techniques in nutrition-related tasks. Studies lacking methodological relevance or full-text availability were excluded. A total of 73 studies met the criteria and were included in the final review.

Although datasets form the foundation of AI-driven nutrition systems, many reviewed studies rely on data that exhibit demographic or cultural bias, inconsistent annotation practices, and class imbalance. Such limitations can inflate reported performance, reduce generalizability, and obscure real-world applicability. Addressing these issues requires standardized annotation protocols, balanced and representative data collection, and transparent reporting of dataset characteristics to support reliable model evaluation and comparison.

3.2 |AI and BI Techniques in Nutrition

The comprehensive analysis of recent literature demonstrates that the integration of Business Intelligence (BI) and Artificial Intelligence (AI) within nutritional science has fundamentally transformed the way dietary data are collected, analyzed, and applied. The findings highlight eight interrelated areas: AI and BI techniques in nutrition, deep learning in nutrition, ChatGPT and generative AI applications, dietary assessment, personalized nutrition and diet planning, obesity management, disease prediction and management, and food recognition and analysis.

Throughout this review, BI systems are defined as the data integration and visualization layer that enables monitoring, reporting, and decision-support workflows, whereas AI models represent the analytical layer responsible for prediction, classification, and automated reasoning. Maintaining this distinction ensures a consistent interpretation of how BI operationalizes insights generated by AI and how both components function within integrated nutrition informatics systems.

The integration of Internet of Things (IoT) technologies plays an increasingly important role in advancing AI- and BI-driven nutrition systems. IoT-enabled devices such as wearable activity trackers, smart scales, continuous glucose monitors, and intelligent kitchen tools generate real-time physiological, behavioral, and dietary data that enhance the granularity and accuracy of nutritional assessments. When combined with BI platforms, these sensor streams support continuous monitoring, automated pattern detection, and personalized dietary interventions thro ugh interactive dashboards and decision-support tools. Furthermore, AI models benefit from the high-frequency, multimodal data produced by IoT devices, enabling more robust predictions of dietary behaviors and health outcomes. Despite these advantages, IoT applications remain underrepresented in current literature, highlighting the need for more integrated frameworks that leverage IoT as a primary data source for AI- and BI-based nutrition analytics.

3.2.1 | Evaluating Machine Learning Technologies for Food Computing

The adoption of AI and BI techniques in nutrition has enabled the conversion of large-scale, heterogeneous dietary data into actionable insights. AI algorithms—particularly machine learning (ML) and predictive modeling—allow for the detection of complex patterns across nutritional intake, lifestyle habits, and health outcomes [28].

BI platforms complement these techniques by providing data visualization dashboards, multidimensional analytics, and decision-support systems that help clinicians and policymakers interpret results efficiently. Through data warehousing and mining, BI aggregates nutritional data from clinical records, food databases, and wearable devices, offering a unified analytical environment.

Recent studies show that integrating AI into BI workflows enhances dietary monitoring accuracy, supports predictive risk modeling for diseases such as diabetes and obesity, and facilitates real-time, data-driven decision-making in nutritional therapy [34]. Consequently, BI and AI together form a foundational layer for intelligent nutrition ecosystems that are both adaptive and evidence based.

3.2.2 | Deep Learning in Nutrition

The post-2016 period has seen an acceleration in the use of deep learning (DL) for food computing and nutritional analysis. Convolutional Neural Networks (CNNs) have become the backbone of automated food recognition and calorie estimation, outperforming earlier machine learning methods in accuracy and scalability [29, 35].

DL models can extract hierarchical visual features directly from food images, eliminating the need for manual feature engineering. Architectures such as ResNet, Inception-V3, and EfficientNet have achieved accuracy rates exceeding 90% in major datasets like Food-101 and UEC-Food256. These models are further enhanced by transfer learning, allowing pretrained networks (e.g., on ImageNet) to be fine-tuned for food classification tasks with smaller nutritional datasets [30].

In addition to image recognition, deep learning techniques have expanded to multi-modal applications, combining visual, textual, and numerical data. For instance, ingredient detection, recipe generation, and nutrient prediction have benefited from attention-based neural networks and transformer architectures, which enable context-aware interpretation of food items and their relationships [36]. Overall, DL has revolutionized nutrition research by enabling automatic food identification, calorie estimation, and nutrient analysis at unprecedented scale and speed.

3.2.3 |ChatGPT and Generative AI in Nutrition

The emergence of large language models (LLMs) such as ChatGPT has introduced a new dimension to nutrition informatics. ChatGPT's natural language understanding capabilities allow it to process dietary records, answer user queries, and provide personalized nutrition counseling in conversational form [31].These generative models can synthesize information from extensive nutrition databases and clinical guidelines, delivering tailored recommendations aligned with users' age, medical conditions, and lifestyle. Furthermore, ChatGPT can support automated nutrition education, meal plan generation, and interactive health coaching, reducing the burden on healthcare professionals.

Recent research has also shown that LLMs can serve as explainable AI (XAI) tools—translating complex predictive outcomes from ML or DL systems into user-friendly explanations. By integrating ChatGPT into BI dashboards, users can interact with their dietary data using natural language queries, turning static analytics into an interactive, human-centric decision support system [32]. While ethical considerations such as bias, accuracy, and data privacy remain, ChatGPT and similar LLMs represent a transformative step toward intelligent, accessible, and conversational nutrition technologies.

4 |Results and Discussion

The analysis of recent studies confirms that Artificial Intelligence (AI) and Business Intelligence (BI) have reshaped the nutritional sciences into a data-driven, evidence-based domain. Findings reveal 10 major focus areas: applications of AI in nutrition; datasets; AI and BI techniques; deep learning; ChatGPT and generative AI; dietary assessment; personalized nutrition and diet planning; obesity management; disease prediction and management; and food recognition and analysis.

To provide a clearer conceptual structure, this review introduces a taxonomy that aligns major AI techniques with their corresponding nutrition tasks Figure 3. Classical machine learning methods are primarily applied to structured prediction tasks such as nutrient estimation, malnutrition risk assessment, and obesity forecasting. Deep learning models dominate image-based applications including food recognition, portion estimation, and calorie analysis. Large language models support conversational nutrition guidance and automated dietary counseling. Business intelligence tools enable data integration, visualization, and decision-support workflows that operationalize AI outputs . This taxonomy offers a unified framework that clarifies the methodological landscape and the functional roles of AI technologies within nutrition research.

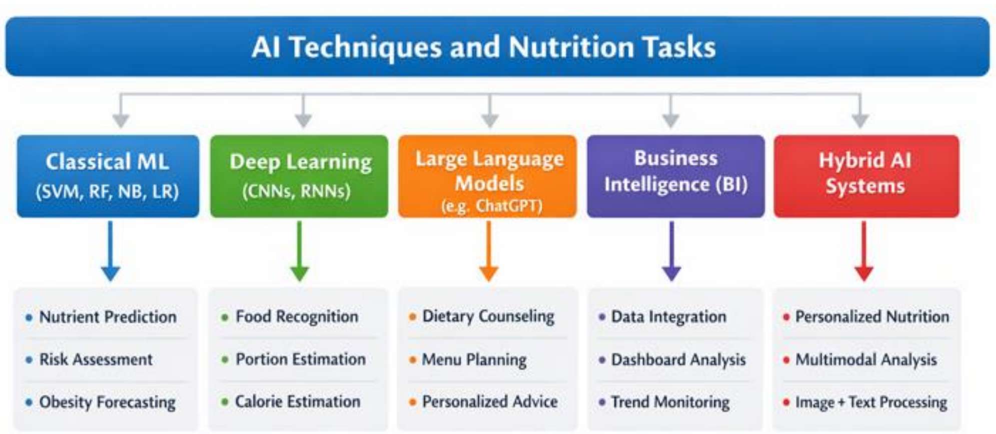

Figure 3. Taxonomy of AI Techniques and Nutrition Tasks.

A comparative examination of the reviewed studies indicates clear methodological patterns that move beyond descriptive reporting. Classical machine learning models perform reliably on structured nutritional datasets but show limited adaptability in heterogeneous or culturally diverse settings. Deep learning approaches achieve higher accuracy in image-based tasks, yet their effectiveness remains closely tied to the quality and diversity of training data. Chatbot- and LLM-based systems provide new forms of personalized dietary interaction, though their outputs remain inconsistent across user groups. These observations highlight that dataset representativeness, evaluation design, and methodological alignment exert more influence on performance than the choice of algorithm alone, underscoring the need for more rigorous, comparative, and integrative research frameworks.

Despite the high accuracy values reported in several studies—particularly those involving food recognition, portion estimation, and calorie analysis—these results require careful contextual interpretation. In many instances, such performance levels are achieved using datasets that are limited in size, geographically or culturally homogeneous, or collected under controlled experimental conditions that do not reflect real-world variability. Consequently, models may demonstrate excellent internal validation performance while exhibiting substantially lower generalizability when applied to heterogeneous food environments or mixed dishes with complex visual characteristics. Studies employing broader, more diverse datasets typically report more moderate accuracy levels, suggesting that dataset composition plays a critical role in shaping algorithmic performance. Therefore, accuracy metrics should not be interpreted in isolation; rather, they should be evaluated alongside the characteristics, representativeness, and ecological validity of the datasets used. Contextualizing these results is essential to avoid overstating model capabilities and to support the development of more robust and transferable AI systems in nutrition research.

4.1 | Global Distribution and Metadata Analysis of AI-Driven Nutrition Studies

The distribution of the papers included in this review by nation income categorization is shown in Figure 4, which illustrates the global heterogeneity in research output concerning applications of business intelligence (BI) and artificial intelligence (AI) in nutrition. According to the data, 49% of the studies came from high-income nations, 34% from upper-middle-income nations, and 15% from lower-middle-income nations; 2% of the research did not specify which country they came from.

This distribution indicates that AI-related nutritional research is still heavily concentrated in technologically advanced regions, where access to computational resources, research funding, and large-scale datasets is more readily available. Conversely, the relatively low contribution from lower-middle-income regions highlights ongoing disparities in data access and research capacity, underscoring the need for broader international collaboration and equitable data-sharing initiatives. Regarding country-level representation, the largest share of studies was conducted in the United States, with five studies identified [19, 25, 37-39]. Australia contributed two studies [40, 41]. while China accounted for seven studies [15-16, 18, 42-44, 50]. reflecting China's growing engagement in AI-powered food computing research. Greece contributed three studies [10, 46, 47]. and Switzerland [48]. Portugal [49]. Iraq and Switzerland [51]. Italy [13]. Canada [52]. Czech Republic [20]. Ethiopia [53]. Pakistan [24]. and the Philippines [26]. each contributed one study.

Additionally, Korea presented four studies [11, 45, 54, 56]. Taiwan contributed four [12, 55, 57, 2]. India provided four [17, 30, 58, 59]. Indonesia two [27, 60]. North Macedonia one [61]. and Turkey four [21-22, 62-63].

Overall, the dominance of high- and upper-middle-income nations in AI-driven nutrition studies underscores a geographical imbalance that parallels global digital inequality. These findings point to an urgent need for capacity building in low-resource settings, open-access dataset development, and international collaboration frameworks to support inclusive, cross-regional AI nutrition research

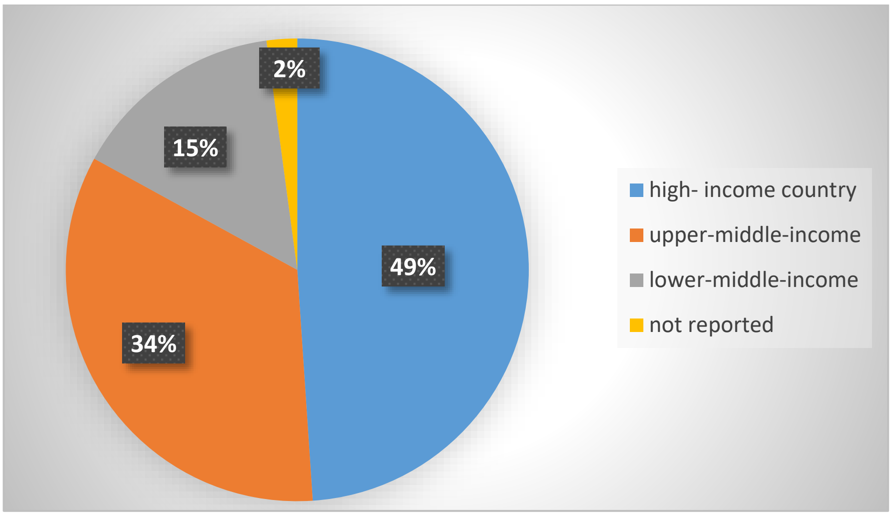

Figure 4. Studies' distribution included in the review by country income classification**.**

4.2 | Applications of AI in nutrition

AI technologies are being applied across multiple nutritional domains, as illustrated in Figure 5, which summarizes their primary use cases. The largest portion (36%) corresponds to dietary assessment and food-image recognition, reflecting the dominance of computer vision techniques, such as Convolutional Neural Networks (CNNs), for food identification and caloric estimation [28, 35]. Personalized nutrition and diet planning represent about 17%, emphasizing the growing importance of data-driven, individualized meal recommendations based on genetic, lifestyle, and biometric information [34]. Food composition analysis (19%) focuses on evaluating macro- and micronutrients through predictive modeling and structured nutritional databases [30].

Smaller but rapidly growing segments include AI chatbots for lifestyle intervention (13%) [31], disease prediction and management (13%) [37], and obesity management (2%) [29].

These statistics highlight how AI tools are evolving from simple image-classification tasks toward holistic nutritional intelligence systems capable of integrating behavioral, clinical, and environmental data for comprehensive dietary decision-making.

A clearer separation between AI-driven analytics and BI platforms is essential to understanding their respective roles in nutrition informatics. AI methods—including machine learning, deep learning, and large language models—focus primarily on predictive modeling, pattern extraction, automated nutrient estimation, and personalized recommendation generation [64]. These techniques learn from data and produce new insights that would be difficult to obtain through manual analysis. In contrast, BI platforms operate as the structural and organizational layer that aggregates data from multiple sources, performs multidimensional analysis, and presents results through dashboards, visualizations, and decision-support interfaces. While AI produces intelligent outputs such as predictions or classifications, BI provides the environment in which these outputs are interpreted, monitored, and integrated into clinical or public-health decision-making workflows. Together, they form a complementary ecosystem, but distinguishing their roles clarifies why AI is responsible for generating analytical intelligence, whereas BI is responsible for delivering that intelligence to end users in an actionable and interpretable form.

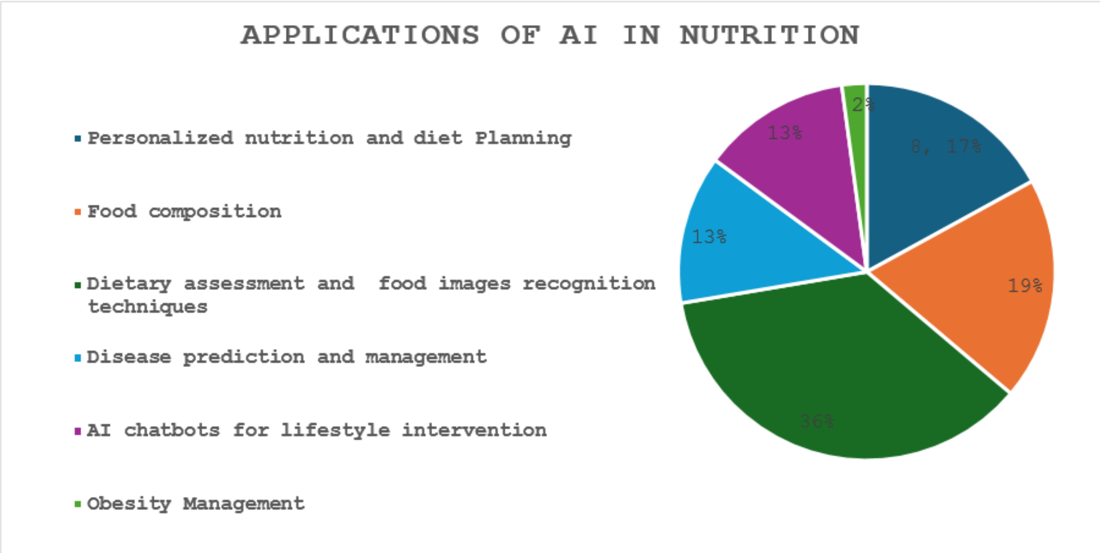

Figure 5. The nutrition areas in which the included articles used AI.

4.2.1 | Dietary Assessment

One of the principal applications of BI in nutrition involves the automation of dietary assessment processes, which traditionally relied on subjective and labor-intensive methods such as food diaries or recall questionnaires. BI tools, supported by AI algorithms, provide a more accurate and efficient approach by utilizing predictive analytics, data visualization dashboards, and machine learning–based classification systems [29].

Modern dietary assessment platforms employ computer vision algorithms capable of identifying food items from images, quantifying portion sizes, and estimating macronutrient and caloric values automatically. These systems minimize human error and improve the reliability of nutritional data collection. Furthermore, BI environments enable researchers and practitioners to interpret this data visually through dashboards that present aggregated patterns, allowing for real-time dietary monitoring and policy-level decision-making. Such analytical capabilities contribute directly to evidence-based nutrition strategies and more targeted interventions for individuals and communities [30].

4.2.2 | Personalized Nutrition and Diet Planning

The study's findings also emphasize BI's essential role in enabling personalized nutrition and individualized meal planning. Through the integration of demographic, clinical, behavioral, and genetic data, BI-driven frameworks can generate tailored dietary recommendations aligned with users' unique physiological and lifestyle needs.

Advanced BI platforms use predictive and prescriptive analytics to anticipate potential nutrient deficiencies and model how specific dietary changes may affect metabolic outcomes [30]. Meanwhile, AI-enhanced recommendation engines dynamically adapt meal plans based on continuous feedback, allowing for adjustments in real time. BI systems also support scenario simulation and what-if analysis, helping nutrition experts forecast the long-term effects of various dietary scenarios. This personalized, data-driven approach marks a significant evolution from generic nutritional guidelines toward precision nutrition, where dietary planning becomes both adaptive and evidence-based [34].

4.2.3 | Obesity Management

A third area of BI application is in obesity management, where BI platforms integrate data from diverse sources such as wearable sensors, fitness trackers, mobile health applications, and clinical databases. By combining these datasets, BI systems enable predictive modeling that identifies high-risk individuals and supports the design of targeted weight management programs [28].

Machine learning algorithms within BI frameworks analyze trends in caloric intake, physical activity, and physiological changes to forecast weight trajectories and evaluate intervention outcomes. Data visualization tools further allow healthcare providers to monitor patient adherence, behavioral progress, and motivational patterns. The integration of behavioral analytics and sentiment analysis adds another dimension, revealing the psychological and social determinants of obesity. These insights allow policymakers and clinicians to design more comprehensive, preventive obesity management strategies that address both physiological and behavioral dimensions [29].

4.2.4 | Disease Prediction and Management

BI, when coupled with AI, has proven highly effective in predicting and managing diet-related diseases, such as type 2 diabetes, cardiovascular disorders, and hypertension. By merging dietary records with medical and biochemical datasets, BI systems generate insights into early risk indicators and patterns associated with disease development [35].

Machine learning techniques are used to create predictive models that identify at-risk individuals based on their dietary and lifestyle profiles. These predictive analytics empower clinicians to take preventive action through timely dietary interventions. Moreover, BI dashboards equipped with interactive visualization allow continuous patient monitoring, supporting data-driven decisions in clinical nutrition. In this context, BI serves as an intelligent decision-support system, offering dynamic tracking of nutritional therapy outcomes and enabling personalized adjustments to optimize patient health [30].

4.2.5 | Food Recognition and Nutritional Analysis

Food recognition and nutritional analysis have emerged as some of the most dynamic areas in AI-assisted nutrition. Using deep learning and computer vision, BI-integrated systems can automatically detect, classify, and analyze food items captured in images or videos [29]. Datasets such as Food-101, UEC-Food256, and Recipe1M+ provide the foundation for training these models, enabling recognition across thousands of food categories with high accuracy.

Once identified, BI tools transform the extracted visual data into quantitative nutritional insights, including calorie counts, macronutrient breakdowns, and eating frequency patterns. When integrated with Internet of Things (IoT) devices—such as smart utensils, kitchen cameras, or wearable trackers—these systems enable continuous, automated dietary logging without manual input. BI dashboards visualize the collected data, offering users and nutritionists a comprehensive overview of dietary compliance, energy balance, and consumption trends. This fusion of AI and BI thus facilitates a new era of real-time, automated nutrition analytics [34, 30].

The findings collectively demonstrate that BI acts as a cornerstone in the development of intelligent, data-centric nutrition systems. Its integration with AI allows for more accurate dietary assessment, personalized recommendations, and improved disease prevention strategies. BI's analytical and visualization capabilities transform raw nutritional data into actionable insights, supporting precision healthcare and evidence-based nutrition interventions.

Overall, BI's synergy with AI technologies signifies a pivotal advancement in digital health and nutrition research, marking the transition from traditional dietary evaluation methods to proactive, predictive, and automated nutritional intelligence systems. This evolution represents a crucial step toward achieving data-driven public health initiatives and promoting healthier, more sustainable dietary behaviors on both individual and societal levels [30].

5 | Limitations and Recommendations

Although Artificial Intelligence (AI) and Business Intelligence (BI) have shown great potential in transforming nutritional research, their development and application still face a number of data-related, methodological, and ethical limitations. The datasets most frequently used in this domain, such as Food-101, Yelp, and Protein NAP, remain limited in diversity and often contain labeling inconsistencies. Most collections represent Western dietary habits, leading to a lack of cultural generalizability. In addition, very few datasets provide longitudinal records that could reveal temporal dietary patterns and their influence on long-term health outcomes. To achieve robust and equitable performance, future initiatives should promote the construction of cross-cultural, multimodal datasets that integrate food images, nutritional composition, and user-specific variables reflecting lifestyle, culture, and physiology [28, 29, 33, 34].

From a methodological standpoint, deep-learning and transfer-learning models have achieved impressive classification accuracy for food recognition and calorie estimation; however, they still act largely as opaque systems. Their lack of interpretability reduces their acceptance in clinical or public-health contexts, where decisions must be transparent and traceable. Furthermore, such models require substantial computational resources, limiting deployment in mobile or low-resource environments. To address these gaps, researchers are encouraged to design explainable and lightweight models that balance computational efficiency with interpretability and accuracy, ensuring that clinicians and end users can understand and trust AI-generated insights [35].

Another limitation arises from the poor integration between AI algorithms and BI environments. Many current systems operate in isolation, producing results that are not easily scalable or interoperable. Establishing standardized data formats, ontology-based nutrition vocabularies, and interoperable architectures would facilitate seamless communication between analytics layers and data sources. Embedding AI prediction engines directly within BI dashboards could allow continuous data flow and enable dynamic, real-time decision-support capabilities [30, 32].

Ethical and privacy considerations further complicate the adoption of AI-based nutrition systems. Because these applications often process sensitive health and biometric data, issues such as consent, bias, and transparency become crucial. Unclear data-governance structures and potential model bias can undermine reliability and user confidence. Adopting privacy-preserving computation techniques—such as federated learning and differential privacy—while ensuring compliance with national and international health data regulations can help maintain both data protection and analytical quality [31].

To move the field forward, future research should concentrate on several practical strategies. Standardizing nutritional data taxonomies and metadata structures will enhance comparability and reproducibility. Open-access data-sharing initiatives can accelerate scientific progress and benchmarking. Implementing explainable and auditable AI frameworks will strengthen clinical trust. Integrating behavioral, cultural, and contextual variables can lead to adaptive, person-centered recommendations, while coupling BI dashboards with natural-language interfaces (e.g., ChatGPT) will make analytical tools more accessible to non-technical users. Finally, advancing AI and BI in nutrition requires close collaboration among data scientists, dietitians, healthcare professionals, and policymakers to ensure that innovation remains ethical, transparent, and inclusive [33].

In conclusion, despite notable progress, the field still faces barriers related to data diversity, model transparency, and technological interoperability. Overcoming these challenges through ethical design, data standardization, and interdisciplinary cooperation will pave the way for intelligent, explainable, and equitable AI-driven nutrition ecosystems capable of improving individual and public-health outcomes worldwide.

Although this review intentionally adopts a broad scope to capture the diverse landscape of AI and BI applications in nutrition, this breadth may limit the depth of technical treatment in specific areas. To address this, key methodological sections have been expanded to provide deeper analysis where required, ensuring a more balanced integration of scope and technical detail.

A focused examination of ethical considerations in AI-driven nutrition systems highlights three key dimensions: privacy, bias, and explainability. Privacy concerns arise in systems that process user images or detailed dietary logs. For example, the food-image recognition models employed in Sun et al. (2023) [15] , rely on continuous photo uploads, which introduces risks related to image storage, user identification, and cross-border data transfer. Bias is another critical issue, as several studies use culturally narrow datasets. Vasudha et al. (2024) [17] , reported near-perfect accuracy in food recognition, yet their dataset consisted largely of region-specific dishes, limiting generalizability to other populations. A similar pattern appears in Kaya et al. (2025) [21] , where chatbot-based diet-quality assessments showed inconsistent results due to variations in user profiles and dietary habits not represented in the training data. Explainability remains a significant barrier, particularly in LLM-based systems. As demonstrated by Haman (2023) [20] , AI-generated dietary recommendations can appear coherent while lacking transparent reasoning or traceable nutritional sources, making clinical validation difficult. Addressing these challenges requires privacy-preserving data pipelines, culturally diverse datasets, and the integration of explainable-AI mechanisms to ensure safe and equitable deployment of AI technologies in nutrition.

Although this review offers a structured synthesis of AI and BI applications in nutrition, several limitations must be acknowledged. The search strategy, while comprehensive, was restricted to major academic databases and English-language publications, which may have resulted in the exclusion of relevant grey literature or region-specific contributions. Differences in methodological rigor, dataset size, and evaluation protocols across the included studies also introduce a degree of heterogeneity that limits direct comparability. Furthermore, the rapid pace of development in AI, deep learning, and large language models means that new advances may have emerged after the completion of the search process. These limitations should be considered when interpreting the findings and assessing the overall scope of this review.

Explainable AI is essential for healthcare-focused nutrition systems, as clinicians require transparent and interpretable model outputs to validate recommendations and ensure patient safety. Most current models operate as black boxes, limiting clinical trust. Integrating XAI techniques—such as feature attribution or attention visualization—is therefore necessary to support reliable and accountable clinical decision-making.

6 | Conclusions and Future Work

This review demonstrates that the convergence of Artificial Intelligence (AI) and Business Intelligence (BI) has begun to redefine the field of nutritional science by introducing data-driven, adaptive, and predictive methodologies. It presents a comprehensive overview of current AI, ML, and DL technologies in nutrition. The synthesis of recent research reveals that AI techniques—particularly machine learning, deep learning, and generative models—are enabling more precise dietary assessment, personalized meal planning, and disease prediction. When integrated within BI frameworks, these algorithms transform large, unstructured datasets into actionable insights through interactive dashboards, real-time visualization, and evidence-based nutritional analytics. This integration represents a paradigm shift from traditional descriptive dietary studies to intelligent, decision-support systems capable of continuous learning and adaptation.

Despite significant progress, several critical limitations continue to hinder large-scale implementation. The scarcity of diverse, longitudinal, and culturally inclusive datasets restricts model generalizability and fairness. Many AI systems remain opaque and computationally intensive, limiting their interpretability and practical use in clinical settings. Moreover, integration between AI-driven predictive models and BI environments remains fragmented, while ethical and privacy concerns persist due to the sensitive nature of nutritional and biometric data. Addressing these challenges will require standardization of nutritional ontologies, open-access data initiatives, and interdisciplinary frameworks that link data science, healthcare, and policy development.

Although several studies demonstrate promising short-term performance, the clinical applicability of AI-based nutrition systems remains limited by the lack of long-term validation. Most models have been evaluated in controlled or small-scale settings, with few undergoing extended real-world clinical trials. As a result, claims regarding clinical integration should be interpreted cautiously until supported by multi-year evidence across diverse patient populations.

Future research should focus on building multimodal and cross-cultural datasets that integrate food images, consumption logs, metabolic biomarkers, and behavioral factors to enhance contextual accuracy. Advancements in explainable AI (XAI) will be critical for improving model transparency and trust among clinicians and end-users. Additionally, the integration of Large Language Models (LLMs) such as ChatGPT within BI systems presents promising opportunities for developing natural-language-driven nutritional analytics, enabling more accessible human–machine interaction. The application of federated learning and privacy-preserving AI could further support global collaboration without compromising data security. Ultimately, achieving scalable, ethical, and explainable AI–BI systems will pave the way for the next generation of intelligent nutrition ecosystems, empowering individuals and institutions to make informed dietary and health-related decisions based on reliable, interpretable, and inclusive data-driven intelligence.

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Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Reference

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