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REVIEW

Artificial Intelligence in the Nutritional Management of Inflammatory Bowel Disease: A Scoping Review

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Background: Diet is closely associated with the onset, progression, and prognosis of inflammatory bowel disease (IBD). In the absence of specific dietary and nutritional guidelines, nutritional management for IBD patients is fraught with challenges and uncertainties. Existing research indicates that artificial intelligence (AI) has great potential for application in the nutritional management of patients with chronic diseases; however, current research on its use in IBD patients is limited.

Methods: This scoping review was reported in strict accordance with the PRISMA-ScR checklist. A systematic search was conducted across 11 databases, including PubMed, Web of Science, and Scopus, covering the period from the inception of each database to February 2026, focusing on studies investigating the application of AI in the nutritional management of IBD patients.

Results: Of the 4,560 records initially screened, 16 studies met the inclusion criteria. The results indicate that AI applications primarily focus on: dietary pattern recognition, such as using clustering algorithms to identify an association between plant-based diets and lower inflammation risk; treatment response prediction, with machine learning models predicting the success rate of total parenteral nutrition and achieving 90% accuracy in distinguishing between Crohn's disease and ulcerative colitis; personalized information support, where conversational AI such as ChatGPT answered nutritional questions with 83.0% accuracy, and smartphone apps can influence patients' dietary behaviors; identifying patient needs, where Natural Language Processing and Latent Dirichlet Allocation (LDA) topic modeling identified key patient concerns such as treatment experiences, dietary advice, and psychological burden. Key technologies encompass traditional machine learning, deep learning, natural language processing, and multi-omics integrated analysis. AI applications have preliminarily demonstrated the ability to reduce inflammatory markers and improve gut microbiota; fecal metabolites have been confirmed as reliable indicators of disease.

Conclusion: AI holds promise for the nutritional management of IBD and has shown preliminary success in pattern recognition, prediction of treatment efficacy, and patient empowerment. However, existing studies are often limited by small sample sizes and insufficient generalizability, and the evidence remains preliminary and heterogeneous. Future efforts should focus on large-scale studies and multidisciplinary collaboration to advance AI from proof-of-concept to clinical practice.

Keywords: inflammatory bowel disease, crohn's disease, ulcerative colitis, artificial intelligence, nutrition

Introduction

Inflammatory bowel disease (IBD), primarily comprising Crohn's disease (CD) and ulcerative colitis (UC), is a chronic, nonspecific, and recurrent inflammatory condition of the intestines,[1,2] with a global prevalence that is rising year by year.[3,4] The etiology of IBD is complex, involving interactions among multiple factors, including genetic susceptibility, environmental factors, gut microbiota dysbiosis, and abnormal immune responses.[5] Among the various environmental factors, diet is not only a potential modifiable risk factor for IBD onset but also a critical component throughout the entire disease management process.[6–8] For this reason, nutritional management plays a central role in IBD treatment. Its objectives extend beyond correcting and preventing malnutrition to directly modulating intestinal inflammation, alleviating symptoms, promoting mucosal healing, and optimizing the efficacy of pharmacological therapy through specific dietary patterns.[9–12] However, due to limited evidence, current guidelines have not yet established a dietary pattern suitable for IBD patients,[13] and traditional

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IBD nutritional management faces significant challenges. First, the effects of diet on the human body are highly individualized and influenced by multiple factors, including genetics,[14] gut microbiota composition,[15] disease phenotype,[16] and lifestyle habits.[17] The same food or dietary pattern may elicit vastly different responses in different patients. Second, traditional nutritional assessment tools, such as food frequency questionnaires and dietary diaries, often rely on patient recall, are subject to information bias, and struggle to quantify complex dietary exposures in real time and with precision.[18,19]

Furthermore, due to insufficient professional guidance and interference from non-specialized information, IBD patients face numerous nutritional issues, such as inadequate nutrient intake, avoidance of restrictive dietary behaviors, and blind adherence to dietary patterns.[20] These nutritional issues increase patients' risk of malnutrition, leading to adverse health outcomes such as increased risk of complications and surgery, prolonged hospital stays, and reduced immunity.[19] Finally, in the absence of specific dietary recommendations, nutritional management for IBD patients is fraught with challenges and uncertainty,[21,22] and some patients even develop a fear of eating.[23] Therefore, extracting meaningful and actionable dietary guidance strategies for individual patients from vast, multidimensional datasets is a task that traditional statistical methods struggle to accomplish. Artificial Intelligence (AI), particularly the rapid advancements in technologies such as machine learning (ML), deep learning (DL), computer vision (CV), and natural language processing (NLP), offer entirely new possibilities for addressing these challenges.[18]

AI primarily refers to the theories, methods, technologies, and application systems that use computer algorithms to simulate, extend, and expand human intelligence, thereby enabling computers to perform a range of intelligent activities such as reasoning, task execution, and autonomous response.[24] Its core capability lies in automatically learning patterns and regularities from complex, high-dimensional data and using them for prediction or classification.[25] In the medical field, the potential of AI is gradually being tapped. AI technologies such as ML, CV, and NLP are widely applied and show great promise in the field of nutritional management. Not only can they provide patients with nutritional assessments, diagnoses, and screening and prediction of nutrition-related risks,[26] but they can also offer personalized nutritional advice based on patients' nutritional and physical conditions, enabling automated, scientific nutritional management.[27] For example, using computer vision technology, AI can automatically analyze photos of food to estimate nutritional content and calories. This helps patients adjust their diets in real time.[28] Through natural language processing, AI can interpret patients' food diaries, identify unhealthy dietary habits, and provide recommendations for improvement.[29] Combined with machine learning algorithms, AI can dynamically predict potential future nutritional risks in patients. This supports early intervention and personalized prevention strategies.[30,31] Although research on AI in IBD nutritional management is increasing globally, the existing literature primarily focuses on the development of AI for specific applications, such as nutritional assessment[32] and dietary pattern exploration,[33] but few studies have classified these AI technologies or summarized their application outcomes. Therefore, this study aims to employ a scoping review methodology[34] to systematically review and synthesize the literature on the application of AI technologies in the nutritional management of IBD patients, and to conduct a comprehensive analysis of AI applications in this field, to provide valuable references for future research and clinical practice.

Materials and Methods

Defining the Research Questions

The research questions addressed in this scoping review are as follows: (1) In which scenarios is AI primarily applied in the nutritional management of patients with IBD? (2) What technologies and methods are employed by AI in the nutritional management of patients with IBD? (3) What are the main outcomes or research findings associated with the application of AI in IBD nutritional management?

Methodology

This scoping review aims to systematically summarize the current status and characteristics of AI applications in the nutritional management of adult patients with IBD. The research methodology strictly adheres to the scoping review framework proposed by Arksey and O'Malley and its core methodological principles,[34] while simultaneously following the PRISMA-ScR[35] checklist for literature retrieval to ensure the transparency and integrity of the research report. This research process comprises four core stages: systematic literature search, preliminary title/abstract screening, application of inclusion/exclusion criteria, and final comprehensive analysis.[36] Given that the primary objective of this study is to describe the characteristics of the existing literature rather than to assess the methodological quality of the included studies, we focused only on key methodological elements from the PRISMA checklist.[35] The detailed PRISMA-ScR checklist is available in Supplementary Material S1.

Search Strategy

A systematic search was conducted in PubMed, Web of Science, Embase, the Cochrane Library, CINAHL, IEEE Xplore, the Association for Computing Machinery Digital Library, SinoMed, CNKI, Wanfang Data, VIP, and other Chinese databases to identify studies on the application of AI in the nutritional management of patients with IBD. The search period extended from the inception of each database to February 2026. Boolean operators, including AND and OR, were used. The database search strategy was optimized using the following Medical Subject Headings (MeSH) terms:

"Inflammatory Bowel Disease" OR "Ulcerative Colitis" OR "Crohn's Disease";

"food" OR "nutrition" OR "recipe" OR "diet" OR "dish";

" artificial intelligence " OR "machine intelligence" OR "data mining" OR "fuzzy algorithms" OR "neural networks" OR "Bayesian networks" OR "text mining" OR "fuzzy logic" OR "knowledge representation" OR "machine learning" OR "deep learning" OR "natural language processing" OR "non-natural language processing" OR "random forests" OR "support vector machines" OR "algorithms".

During the initial screening phase, studies that did not meet the inclusion criteria were excluded based on title and abstract screening. As shown in Table S1, this process was conducted independently by three reviewers (XQ, QZ, and GZJ) to ensure transparency and reduce uncertainty in the review findings. Any disagreements during the study screening process were resolved through consultation with a fourth reviewer (JY), who helped finalize the list of included studies.

Data Extraction and Analysis

First, duplicate studies were removed using the EndNote reference management tool. Subsequently, title and abstract screening was performed independently by three reviewers (XQ, QZ, GZJ) as described in Section 2.3. Full-text eligibility was assessed independently by two of these reviewers (XQ and QZ), with any disagreements resolved by consulting the third reviewer (GZJ) and, if necessary, the fourth reviewer (JY). The PRISMA flowchart (Figure 1) illustrates the step-by-step screening process, including the identification, screening, and inclusion stages.[37] The characteristics of the included studies are summarized in three tables: Table 1 presents basic source characteristics (first author, year of publication, country, data source, and data volume); Table 2 presents technical and methodological details (first author, AI technologies, main application methods, and data types); and Table 3 presents outcomes and evaluation (first author, main research results, ethical issues, and technology stage).

Inclusion and Exclusion Criteria

Inclusion criteria were determined based on the PCC principle,[52][which considers the study population, concept, and context. Inclusion criteria: (1) Study population included patients diagnosed with IBD; (2) Research content involved the application of AI in the field of nutritional management; (3) Studies included algorithm or model development, usability evaluation, or application research; (4) Full-text articles were accessible. Exclusion criteria: (1) Studies conducted in IBD that are unrelated to AI in nutritional knowledge or dietary behavior; (2) Studies without full-text access or conference abstracts without full-text availability; (3) Literature not in Chinese or English.

Risk of Bias Assessment

Given the exploratory nature of this scoping review, a formal risk-of-bias assessment was not conducted. However, study limitations were documented where applicable.

Study Registration

This study protocol has been registered on the Open Science Framework (OSF) platform (DOI: 10.17605/OSF.IO/X85MR).

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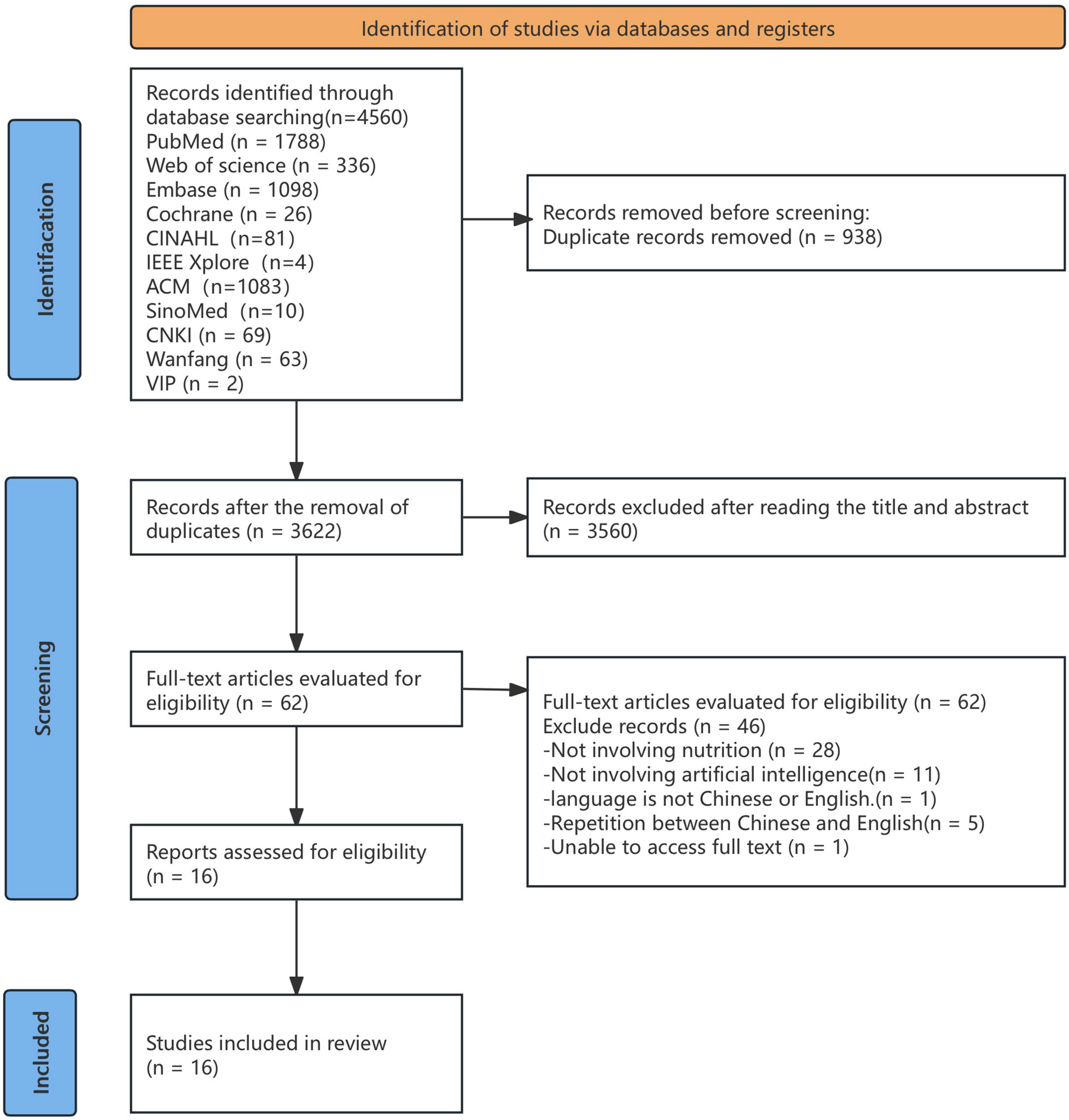

Figure 1 Flowchart for studies included in the scoping review.

Results

Basic Characteristics of Included Studies

A systematic literature search and screening process was conducted in accordance with the PRISMA statement. A total of 4,560 records were initially identified. After removal of duplicates and preliminary screening of titles and abstracts, 62 records were selected for full-text review. Of these, 46 records were excluded because they were not relevant to IBD diets, were not related to AI, were published in languages other than Chinese or English, lacked available full text, or represented duplicate Chinese and English versions of the same study.A total of 16 studies highly relevant to the research question were included. The included studies were primarily from the United States[33,38,40,42–46,50] (n=9),[33,38,40,42–46,50] China (n=3),[47–49] Romania (n=2),[32,41] Canada

Table 1 Basic Characteristics of Included Studies

First Author	Year of Publication	Country	Data Source	Data Volume
Gala M. Godoy-Brewer[38]	2025	United States	Adult IBD patients	1,067
Ricardo G. Suarez Suarez[39]	2025	Canada	PCD patients	308
Miad Boodaghidizaji[40]	2025	United States	Patients with inactive IBD	1,094
Raluca Lupusoru[41]	2025	Romania	Adult patients with refractory IBD	358
Jamil S. Samaan[42]	2025	United States	Adult IBD patients	88
Serena Onwuka[43]	2024	United States	IBD Dataset	4683
Sarah Rotondo-Trivette[44]	2024	United States	ASUC patients	151 stool images
Haider A. Naqvi[45]	2024	United States	Diet and Nutrition Questions on the UC and CD Foundation Websites	18 replies
Rubin[46]	2024	United States	Posts on the UC Forum regarding relapses, symptoms, etc.	>27,000
Blajovan B L[32]	2023	Rome Nia	Food Image Library	101000
Sun[47]	2023	China	Posts in the CD Forum	6757
Yuping Chen[48]	2023	China	CD Surgery Patients	60
He[49]	2023	China	Web of Science Core Collection	1074
Limketkai[50]	2022	United States	Adult IBD patients	691
Kaplan[33]	2022	United States	IBD patients aged 7–18 with active inflammation	54
Stemmer[51]	2022	Israel	IBD patients on Twitter Posting Tweets	4,160

Table 2 Applied Artificial Intelligence Technologies and Data Types

First Author	AI Technologies	Main Application Methods	Data Types
Gala M. Godoy-Brewer[38]	ML	Cluster analysis of dietary patterns	Clinical data, DSQ data
Ricardo G. Suarez Suarez[39]	ML	Feature selection + k-fold cross-validation	Clinical data, Laboratory test results
Miad Boodaghidizaji[40]	ML	Distinguish fecal microbiome characteristics	Laboratory test results, Fermentable soluble dietary fiber data
Raluca Lupusoru[41]	ML	Combined multi-omics and clinical biomarker analysis	Clinical data, Laboratory test results, Micronutrient data, SIBDQ, Gastrointestinal symptoms, Composite Intestinal Control Index
Jamil S. Samaan[42]	ChatGPT	Verify accuracy of nutrition-related answers	Textual data
Serena Onwuka[43]	ML + SHAP-XAI	Screen metabolites and analyze dietary correlation	Laboratory test results
Sarah Rotondo-Trivette[44]	Mobile Applications	Image analysis + statistical correlation analysis	Clinical data, Laboratory test results, Stool image data
Haider A. Naqvi[45]	Mobile Applications, BingChat, YouChat	Answer dietary management questions	Textual data
Rubin[46]	NLP	Text mining of forum posts	Textual data
Blajovan B L[32]	DNN	Food image recognition model construction	Food images, Nutritional data
Sun[47]	LDA	Topic analysis of forum posts	Textual data
Yuping Chen[48]	Smart Devices	Real-time bowel sound monitoring	Clinical data, Postoperative status data
He[49]	Bibliometrix R package	Bibliometric analysis of literatures	Textual data
Limketkai[50]	ML	K-means clustering for dietary patterns	Clinical data, Dietary intake data
Kaplan[33]	Bayesian GLM, Bayesian GLMM	Statistical analysis of patient reported outcomes	Clinical data, Laboratory test results, Dietary intake data
Stemmer[51]	NLP	Topic mining and sentiment analysis of tweets	Textual data

(n=1),[39] and Israel (n=1),[51] indicating that this topic is of interest in North America, Europe, and Asia. Data sources are diverse, including clinical patient data, social media/forum posts, public databases, and food image libraries. The volume of data varies widely, ranging from 54 cases to over 27,000 cases.

Table 3 Main Findings, Ethical Issues and Technology Stage

First Author	Main Research Results	Ethical Issues	Technology Stage
Gala M. Godoy-Brewer[38]	DSQ combined with ML can identify IBD inflammatory foods, guide dietary intervention	I	Data Analysis
Ricardo G. Suarez Suarez[39]	The model effectively predicts the success rate of EEN	I	Model Construction
Miad Boodaghidizaji[40]	ML distinguishes UC and CD via microbiome data, accuracy up to 90%	I	Model Development
Raluca Lupusoru[41]	Most patients had relieved symptoms; inflammatory markers and micronutrient status improved obviously	I	Data Analysis
Jamil S. Samaan[42]	ChatGPT-4 answered 83.0% questions correctly, 17% answers contained errors	II	Usability Validation
Serena Onwuka[43]	Fecal metabolites are better for IBD prediction and dietary correlation analysis	III	Model Development
Sarah Rotondo-Trivette[44]	Stool morphology indicators were correlated with CRP levels in ASUC patients	I	Data Analysis
Haider A. Naqvi[45]	CB-AI can give reasonable answers for most IBD dietary questions	III	Availability Validation
Rubin[46]	Forum posts mainly focused on treatment, adverse reactions and dietary advice	III	Data Analysis
Blajovan B L[32]	Food recognition system accuracy 74.6%, latency 637 ms	III	Model Development
Sun[47]	Summarized 5 core concerns of CD patients including diet and nutrition	III	Data Analysis
Yuping Chen[48]	AI bowel sound monitoring promotes earlier postoperative ONS application	III	Usability Validation
He[49]	Dietary pattern and gut microbiota are core research hotspots of IBD nutrition	II	Usability Validation
Limketkai[50]	Plant-based dietary pattern reduces the risk of active IBD symptoms	I	Data Analysis
Kaplan[33]	SCD and MSCD relieve IBD symptoms and reduce FCP levels	I	Data Analysis
Stemmer[51]	Diet-related keywords are closely associated with users' emotional sentiment	II	Data Analysis

Notes: Ethical classification: I = Institutional review; II = Ethical discussion; III = No discussion.
Abbreviations: IBD, Inflammatory Bowel Disease; PCD, Pediatric Crohn's Disease; UC, Ulcerative Colitis; CD, Crohn's Disease; ASUC, Acute Severe Ulcerative Colitis; EEN, Exclusive Enteral Nutrition; ONS, Oral Nutritional Supplementation; DSQ, Dietary Screening Questionnaire; FFQ, Food Frequency Questionnaire; SIBDQ, Short-term Inflammatory Bowel Disease Questionnaire; FCP, Fecal Calprotectin; CRP, C-reactive protein; hs-CRP, High-sensitivity C-reactive protein; ML, Machine Learning; DNN, Deep Neural Networks; NLP, Natural Language Processing; LDA, Latent Dirichlet Allocation; GLM, Generalized Linear Model; GLMM, Generalized Linear Mixed Model; SHAP, Shapley-based Additive Explanation; SCD, Special Carbohydrate Diet; MSCD, Modified Special Carbohydrate Diet; WD, Western Diet; PBD, Plant-Based Diet; CB-AI, Conformational Biasing Artificial Intelligence.

Application Scenarios of AI Technology in Nutrition Management

Across the included studies, AI technologies were primarily applied in five core scenarios: dietary pattern recognition, disease prediction, personalized support, patient sentiment analysis, and nutritional monitoring.

Dietary Pattern Recognition

Machine learning algorithms (eg, K-means clustering) were used to analyze Food Frequency Questionnaire (FFQ) data, successfully identifying specific dietary patterns (eg, plant-based diets) associated with IBD inflammatory activity. By comparing inflammatory marker levels across different clusters, these analyses provided a basis for personalized interventions.[50]

Disease Outcome Prediction

AI models demonstrated strong decision-support capabilities. For example, gradient-boosted decision trees integrated microbiome and clinical data to predict the success rate of EEN treatment.[39] In addition, microbiome data were used to distinguish UC from CD with an accuracy as high as 90%.[40]

Personalized Dietary Recommendations and Informational Support

Large language models (eg, ChatGPT-4) answered IBD dietary questions with high accuracy (83.0%).[42] Smartphone apps (eg, Dieta®) showed a positive guiding effect on dietary behaviors among specific populations (eg, male patients).[44] Furthermore, smart devices assisted in initiating postoperative oral nutritional supplementation (ONS) through real-time monitoring of bowel sounds, outperforming traditional methods.[48]

Patient Sentiment Analysis

NLP techniques, including Latent Dirichlet Allocation (LDA) topic modeling and sentiment analysis, extracted key themes and emotional trends related to treatment experiences, peer support, and diet from large-scale social media data. These approaches revealed the impact of dietary factors on quality of life.[51]

Nutritional Assessment and Monitoring

DNNs were applied to food image recognition to evaluate nutrient intake. Using the Food101 dataset, the proposed model achieved an accuracy of 74.6% with ResNet50 and EfficientNet-B0, demonstrating the feasibility of on-device AI for dietary assessment in IBD patients and providing an objective basis for remote disease monitoring.[32]

Major AI Technologies and Methods Applied

The AI technologies applied across the included studies were diverse and encompassed multiple branches of machine learning. Traditional machine learning algorithms were the most widely used and were primarily applied to classification, regression, and clustering tasks. Classification and regression: Including Random Forests (RF), Support Vector Machines (SVM), XGBoost, LightGBM, and LASSO regression. These algorithms are commonly used to build predictive models[39,43] (eg, predicting EEN success rates) and to identify important features (eg, through feature selection). Cluster Analysis: K-means clustering is a commonly used method for identifying patient dietary patterns.[50] Probabilistic Models: Bayesian generalized linear models (GLMs) and generalized linear mixed models (GLMMs) are used to analyze patient-reported outcome data to evaluate treatment efficacy.[33] Deep Learning Algorithms: These demonstrate advantages when processing images and complex text data. DNNs are primarily used to build food image recognition models.[32] NLP is a core technology for processing and analyzing text data, including topic modeling (LDA), sentiment analysis, and keyword extraction.[46,51] Large Language Models and Conversational AI: Represented by the ChatGPT series (including GPT-4, Bing Chat, and YouChat), research has focused on evaluating their accuracy, comprehensiveness, and reproducibility in providing IBD nutritional information.[42,45] Multi-omics Integration and Explainable AI: Multi-omics Analysis: The NostraBiome platform is a prime example; by integrating metagenomic, metabolomic, transcriptomic, and clinical biomarker data and employing supervised ML (Gradient-Boosted Decision Trees) for comprehensive analysis, it provides patients with personalized microbiome and nutritional guidance. Lupusoru R et al[41] found that fecal metabolites provide more reliable disease-prediction models than plasma metabolites. Explainable AI (XAI): A study employed a method based on Shapley additive explanations (SHAP) to interpret the predictions of ML classifiers, thereby enhancing the model's transparency and credibility.[43] Bibliometric Analysis Tools: The Bibliometrix R package was used to perform frequency analysis, network analysis, and geographical visualization of the literature in this field, revealing research hotspots (such as fatty acids and gut microbiota) and emerging trends.[49]

Key Findings and Effects of AI Applications

The application of AI in IBD nutritional management has preliminarily demonstrated its value and potential. Key research findings include: Feasibility of personalized dietary guidance: AI-based dietary screening tools (eg, DSQ) and predictive models can effectively identify inflammation-associated foods, providing practical tools for dietary assessment, guidance, and monitoring in clinical practice.[38] A study by Raluca Lupusoru et al[41] showed that, under AI guidance, the stool frequency of 358 participants decreased significantly, acute symptoms and rectal bleeding were alleviated in most patients, and over 70% of patients reported a "significant improvement" in their overall condition. Concurrently, inflammatory biomarkers (high-sensitivity C-reactive protein, fecal calprotectin) and micronutrient deficiencies (iron, zinc) improved, and beneficial gut microbiota (eg, Faecalibacterium prausnitzii, Bifidobacterium longum, and Akkermansia muciniphila) increased significantly. Comparison of the Efficacy of Specific Dietary Regimens: AI analysis provides data support for the efficacy of specific dietary regimens. The study found that the Special Carbohydrate Diet (SCD) and the Modified Special Carbohydrate Diet (MSCD) were superior to a standard diet in improving symptoms and reducing fecal calprotectin levels, with the SCD showing more pronounced effects.[33] Unraveling the complex relationship between diet, microbiota, and host metabolism: Through multi-omics analysis, studies have confirmed the significant impact of IBD on the interactions between gut microbial metabolites and diet. Diet-related metabolites in feces demonstrated stronger and more population-specific disease associations than plasma metabolites, offering a new perspective for a deeper understanding of IBD pathogenesis.[43] The Role of AI Tools in Patient Education and Behavior Change: Conversational AI can provide appropriate nutritional information to the majority of patients.[45] Meanwhile, observational studies indicate that certain patient groups (such as men and Black patients) are more likely to adopt AI-driven dietary recommendations,[44] suggesting that AI tools are subtly influencing patient behavior and are expected to drive the development of more precise and dynamic nutritional management models.

Discussion

From Macro-Level Pattern Recognition to Micro-Level Mechanism Exploration: AI Deepens Understanding of the "IBD Diet"

The overall landscape of AI applications in IBD nutritional management, including the core technologies, main application scenarios, key findings, and future directions, is summarized in Figure 2.The review found that the application of AI is reshaping our understanding of dietary management for IBD on two levels. At the macro level, through machine learning clustering algorithms, researchers can identify dietary patterns associated with different levels of inflammation risk (eg, plant-based diets vs Western diets) from complex dietary data.[50] This approach addresses the limitations of traditional studies that focus on individual nutrients or foods and more effectively reflects the holistic and complex nature of real-world dietary patterns. It also provides stronger evidence for the development of generalizable dietary guidelines. At the micro level, multi-omics integration platforms such as NostraBiome combine AI with metagenomic and metabolomic data, not only validating the effects of specific dietary patterns on gut microbiota and inflammatory markers,[41] but also revealing the unique value of fecal metabolites as predictors of disease.[43] This suggests that future nutritional interventions may no longer be limited to "what to eat," but will instead focus on "how ingested food is metabolized by an individual's gut microbiota," thereby achieving truly personalized nutrition.

AI as a Bridge Between Clinical Endpoints and Patients' Daily Experiences

Traditional IBD nutrition research has largely focused on clinical endpoints (such as disease activity indices and inflammatory markers). This review finds that AI, particularly NLP technology, is expanding the research perspective to patients' daily lives. By mining vast amounts of text from social media and forums,[46,47,51] researchers can capture patients' most genuine concerns (such as worries about specific foods or a desire for peer support), emotional fluctuations, and unmet needs in real time and at low cost. The integration of patient-reported data with clinical data provides a foundation for a patient-centered, full-cycle care model. For example, the identification of food-related keywords

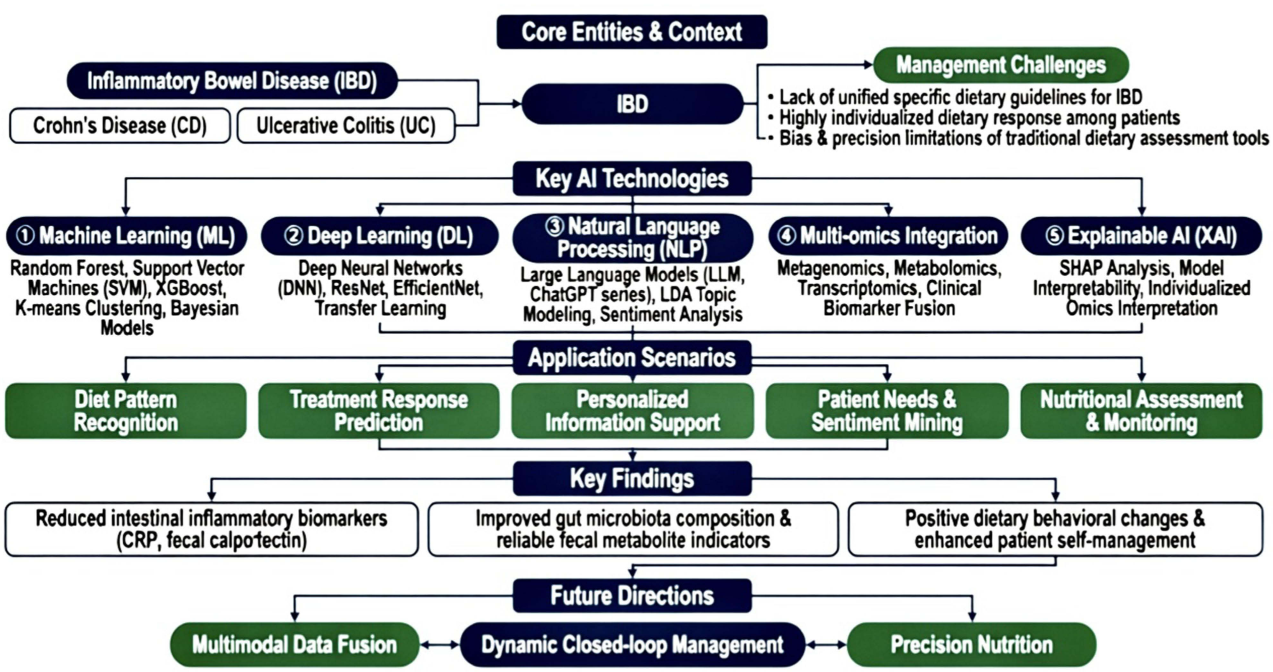

Figure 2 Conceptual framework of AI applications in the nutritional management of IBD.

associated with negative emotions not only reflects patients' dietary concerns but may also indicate potential disease triggers, thereby providing new opportunities for clinical communication and health education.

Opportunities and Challenges of Conversational AI in Patient Empowerment

The emergence of large language models such as ChatGPT has provided patients with an immediate and convenient channel for accessing nutritional information. This review indicates that these models demonstrate a certain degree of accuracy and comprehensiveness in answering IBD-related nutritional questions[45] and are expected to serve as a valuable supplement to traditional medical consultations. Particularly in settings with relatively scarce medical resources, they can effectively enhance patients' self-management capabilities. However, the inadequate or outdated responses identified in the studies (17% in this review) also pose a challenge that cannot be ignored. Inaccurate information may mislead patients and lead to adverse consequences. Therefore, ensuring that medical information generated by chatbot-based AI (CB-AI) remains accurate and up-to-date, while clearly positioning it as a supplement rather than a substitute for professional medical decision-making, is a key challenge for future applications.

AI-Driven Behavior Change and Digital Health Equity

One included study found significant differences in the adoption of AI dietary recommendations among patients of different genders and races (with higher adoption rates among men and Black patients).[44] This phenomenon warrants careful consideration. On the one hand, it confirms that AI tools can influence patients' real-world behavior, offering hope of bridging the gap between standardized guidelines and individualized practice. On the other hand, it also serves as a wake-up call: the training data for AI algorithms, the design of user interfaces, and the selection of dissemination channels may inadvertently exacerbate or introduce new health inequities. Future research and applications must prioritize equity in digital health to ensure that AI-based nutrition tools benefit all IBD patient populations, rather than just specific subgroups.

Limitations of Existing Research and Future Prospects

Several important limitations of the current evidence base should be explicitly acknowledged. First, only 16 studies met the inclusion criteria, indicating that research at the intersection of AI, nutrition, and IBD remains at a very early stage. Second, the included studies were highly heterogeneous in terms of study design, including cross-sectional, retrospective, and proof-of-concept studies; AI technologies, including CNNs, random forests, NLP, and LLMs; data sources, including food images, dietary records, social media data, and electronic health records; and clinical contexts, including remission, active disease, and post-surgical settings. Third, none of the included studies performed external validation of their AI models, and no prospective or interventional studies were identified. Consequently, the current evidence should be interpreted as a preliminary mapping of an emerging research field, rather than as definitive evidence of the effectiveness of AI in improving nutritional management or clinical outcomes in IBD.

Beyond these field-wide limitations, several specific challenges warrant further attention. Most of the included studies were single-center studies with small sample sizes, which limits the generalizability of AI models to broader populations. Future large-scale, multicenter, prospective studies are needed to validate model stability and reliability. In addition, heterogeneity in AI technologies, data types, and outcome measures precludes direct comparisons across studies or meta-analyses; therefore, the field should gradually establish core data standards and a set of key outcome measures. With regard to AI explainability, although some studies incorporated methods such as SHAP, most models, particularly deep learning models, remain "black boxes," which may hinder clinical trust. Future research should strengthen the use of explainable AI (XAI) to ensure that decision-making logic is understandable to clinicians. Finally, AI-based personalized dietary recommendations raise ethical and regulatory concerns, including data privacy, algorithmic bias, and liability, particularly when patients receive direct advice from conversational AI systems, such as CB-AI. Defining liability and ensuring safety are therefore urgent issues that require further discussion.

Looking ahead, the application of AI in IBD nutritional management is likely to evolve in the following directions: (1) Multimodal integration – combining clinical data, omics data, digital phenotypes (dietary images, bowel sounds, activity levels), and patient-reported data to build comprehensive personalized decision support systems; (2) Dynamic closed-loop management – shifting from static assessments to real-time monitoring via wearable devices and smart applications, enabling dynamic adjustments; (3) Precision nutritional intervention – leveraging multi-omic analysis to develop effective nutritional prescriptions for specific patient subgroups, including precise carbohydrate adjustments; and (4) Clinical decision support tools – integrating rigorously validated AI models into clinical workflows as auxiliary tools for physicians, not as substitutes.

Strengths and Limitations

The strengths of this study are primarily reflected in the following aspects. First, this review focuses on the emerging field of AI in the nutritional management of IBD. Methodologically, it strictly adheres to the PRISMA-ScR statement and the Arksey and O'Malley framework, and the study protocol was pre-registered on the OSF platform, thereby enhancing the rigor and reproducibility of the review process. Second, this study goes beyond the limitations of individual technologies or isolated application scenarios by systematically classifying and integrating 16 studies across multiple dimensions, including technology type, application scenario, data source, and research stage. It identifies five core application scenarios: dietary pattern recognition, treatment outcome prediction, personalized support, patient perspective analysis, and nutritional monitoring. It also systematically summarizes the application of AI technologies, including machine learning, deep learning, natural language processing, large language models, and multi-omics integration. In terms of results presentation, this study emphasizes an in-depth exploration of clinically relevant outcomes. Specifically, it summarizes preliminary evidence regarding the potential effects of AI-based approaches in reducing inflammatory markers, improving gut microbiota, and optimizing postoperative nutritional management. Particular attention is also given to the unique value of fecal metabolites as disease-related indicators, which may provide new insights for subsequent mechanistic research. Finally, based on the synthesis of existing evidence, this study identifies several areas that warrant further exploration, including model generalizability and interpretability, as well as data ethics and regulatory frameworks. To address these issues, we propose future directions such as multimodal data fusion, dynamic closed-loop management, and precision nutritional interventions, thereby providing guidance for future research in this field.

This review has several limitations. First, as a scoping review, it aimed to map the overall landscape of the research rather than to assess the methodological quality of individual studies; therefore, a formal risk-of-bias assessment of the included studies was not conducted. Second, although the search strategy was designed to be comprehensive, unpublished studies or studies published in languages other than Chinese or English may have been omitted. Finally, because this field is evolving rapidly, some of the most recent research findings may not have been captured.

Conclusion

In summary, the application of AI in the nutritional management of IBD represents a dynamic and emerging area of research. Current evidence suggests that AI technologies have considerable potential to identify personalized dietary patterns, predict treatment outcomes, capture patients' real-world needs, and support self-management. However, this field still faces several challenges, including small sample sizes, limited model generalizability, poor interpretability, and underdeveloped ethical and regulatory frameworks. Future research should focus on multimodal data fusion, prospective interventional trials, strengthening explainable AI (XAI) research, and establishing appropriate ethical and regulatory frameworks to facilitate the translation of AI technologies from proof-of-concept studies into clinical practice, with the ultimate goal of improving the nutritional status and quality of life of patients with IBD. Specifically, future research should prioritize prospective, externally validated AI models that measure clinically relevant nutritional outcomes, such as remission rates and nutritional status biomarkers, in IBD populations, using standardized reporting guidelines such as CONSORT-AI.

Data Sharing Statement

Data available in a publicly accessible repository.

Acknowledgments

No formal effect measures were used, as this is a scoping review focused on mapping existing evidence. No data conversions or handling of missing statistics were performed, as this was a scoping review.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declare no conflicts of interest.

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