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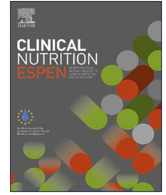

Meta-analysis

Artificial intelligence in the management of hospital malnutrition: A systematic review

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SUMMARY

Background/Aim: Hospital malnutrition is a prevalent issue affecting 30–50 % of hospitalized patients, leading to prolonged hospital stays, increased complications, and higher healthcare costs. Traditional screening methods often fail to identify malnutrition effectively. Artificial intelligence (AI) has the potential to enhance early detection, improve patient outcomes, and optimize hospital resource utilization. This systematic review aims to evaluate the effectiveness of AI-based interventions in the early identification and management of hospital malnutrition.
Methods: A systematic search was conducted across multiple databases, including PubMed, the Cochrane Library, Cumulative Index to Nursing and Allied Health Literature, and Excerpta Medica Database, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. Studies evaluating AI interventions for the detection of malnutrition in hospitalized adult patients were included. Methodological quality and risk of bias were assessed using the Joanna Briggs Institute (JBI) tools.
Results: Twelve studies met the inclusion criteria, utilizing AI algorithms such as Random Forest, Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM). AI-based models demonstrated superior accuracy compared to traditional screening methods, with area under the curve (AUC) values exceeding 90 % in several studies. These interventions improved malnutrition diagnosis rates, reduced diagnostic delays, and enhanced cost-efficiency by optimizing resource allocation and reducing hospital length of stay.
Conclusion: AI-driven approaches show strong potential for improving the detection and management of malnutrition, offering greater diagnostic accuracy and operational efficiency. Integrating AI into clinical workflows could enhance patient outcomes and generate cost savings. However, challenges such as data quality, staff training, and ethical considerations must be addressed to ensure effective implementation. Further research is needed to validate AI applications across diverse healthcare settings.
Protocol registration: This systematic review followed a protocol registered prospectively on Open Science Framework available at: 10.17605/OSF.IO/34KWU.
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1. Introduction

Hospital malnutrition is an increasingly prevalent condition in healthcare, posing a significant challenge to both patients and healthcare systems worldwide [1,2]. It affects approximately 30 %–50 % of hospitalized patients, with higher rates observed in

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medical care units and geriatric departments [3]. A significant proportion of hospitalized patients experience some form of malnutrition, which often goes undiagnosed or is insufficiently treated [4]. This condition not only adversely affects patient health but also contributes to rising healthcare costs, extended hospital stays, and an increased risk of severe complications [5,6]. The causes of hospital malnutrition are multifactorial, including clinical, therapeutic, environmental, and nutritional factors [7]. Patients with chronic illnesses, such as cancer, cardiovascular, pulmonary disease and renal diseases, as well as post-major surgery patients, elderly individuals, and those with acute conditions impairing normal food intake or nutrient absorption, are particularly at risk. Nutrition plays a fundamental role not only in the prevention of malnutrition but also as an adjuvant therapy in many diseases, enhancing treatment efficacy, improving patient outcomes, and supporting overall recovery [8–11]. Hospital malnutrition can arise from several factors, including reduced availability of nutrients, damage to vital organs that disrupt metabolism and nutrient absorption, and interventions such as pharmacological treatments or surgeries that alter normal physiological functions [12]. Furthermore, hospital-related environmental factors, such as the absence of a homelike environment or inadequate nutritional support, contribute to the onset of malnutrition [13]. When present, hospital malnutrition can lead to severe complications, including increased mortality and morbidity, prolonged hospital stays, impaired immune responses, and a heightened risk of nosocomial infections [14]. It can also delay wound healing and compromise patients' recovery capacity, increasing the likelihood of additional complications during hospitalization [15]. These consequences not only diminish patients' quality of life but also place a significant economic burden on healthcare systems, highlighting the urgent need for early identification and effective preventive strategies [16,17].

In this context, artificial intelligence (AI) technologies emerge as a promising tool to enhance healthcare management and optimize hospital processes. AI refers to a set of computational techniques that enable machines to mimic human cognitive functions such as learning, reasoning, and decision-making. In healthcare, AI systems are typically used to analyze large volumes of clinical data, support diagnostic processes, predict patient outcomes, and optimize care delivery through data-driven insights. [18]. AI can examine complex clinical variables, including vital signs, laboratory results, and diagnostic imaging, with the aim of identifying patterns that may elude human assessment [19,20]. Consequently, the use of AI in healthcare can improve diagnostic accuracy, personalize treatments based on patients' specific characteristics, and reduce overall costs by optimizing resource utilization [21]. The impact of AI in healthcare extends beyond clinical performance improvements; it also involves the reorganization of hospital processes, enabling more effective resource management, reducing medical errors, and enhancing the quality of care provided [22].

The application of AI to the management of hospital malnutrition represents one of the most promising frontiers of technology in healthcare. AI technologies can integrate and analyze various risk factors, such as body mass index (BMI), nutritional data, pre-existing diseases, and other relevant clinical information, to provide an accurate assessment of malnutrition risk [23]. Advanced AI systems can continuously monitor patients' conditions through wearable devices and sensors, collecting real-time data to detect changes in metabolism, food intake, and nutritional needs. With predictive analysis, AI can help identify at-risk patients before serious conditions develop, enabling timely, targeted interventions that prevent complications and reduce long-term costs [23,24].

Moreover, AI can support healthcare professionals in planning and implementing care interventions, optimizing resource utilization, and reducing variability in the quality of care [18]. In this context, the adoption of AI technologies not only contributes to better clinical outcomes but also reduces human errors, increases the standardization of treatments, and accelerates decision-making, ensuring that each patient receives a personalized and appropriate treatment plan [25].

Despite the many benefits, the integration of AI into the hospital setting presents several challenges. First, data quality is critical to the success of any AI system: the effectiveness of algorithms depends on the availability of accurate and complete data, which is often difficult to obtain due to technical and organizational barriers [26]. Additionally, the widespread adoption of AI requires proper training of healthcare staff and continuous supervision by clinical professionals, who must be able to interpret the results produced by algorithms and make informed decisions. There is also a need to ensure that AI systems are secure, ethical, and capable of protecting patient privacy, an essential aspect for the acceptance and adoption of these technologies [27].

Hospital malnutrition remains a significant challenge for patient health and healthcare system efficiency. With their ability to analyze large volumes of data and make evidence-based decisions, AI technologies offer great potential to improve the early diagnosis of malnutrition and optimize the management of hospital resources. The widespread adoption of AI in healthcare will likely have a substantial impact on both the effectiveness and efficiency of healthcare processes, resulting in direct benefits for patient health and the sustainability of healthcare systems [23,28].

This study aims to address the question: “Can AI improve the identification of hospital malnutrition, thereby enhancing the effectiveness and efficiency of care?” To do so, we will explore the effectiveness of AI algorithms in the early identification of hospital malnutrition, as well as their impact on the efficiency of hospital processes and the quality of care provided to patients.

2. Methods

2.1. Review methodology and protocol registration

This systematic review was reported in accordance with the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [29]. The protocol for this systematic review was registered on the Open Science Framework (OSF), DOI:10.17605/OSF.IO/34KWU.

2.2. Formulation of the research question

The research question for this review was formulated using the PICO tool [30]. The PICO framework helps structure a focused research question by addressing the following components: P = Hospitalized patients at risk of malnutrition; I = Artificial intelligence-based interventions (e.g., AI algorithms, predictive models); C = Traditional methods for identifying malnutrition (e.g., clinical assessments, standard screening tools); O = Improvement in the effectiveness and efficiency of identifying malnutrition and optimizing care.

2.3. Search strategy

A comprehensive and systematic search was conducted between October and November 2024 to identify relevant studies on the use of AI in detecting and managing malnutrition in hospitalized patients. The search was performed across key databases, including PubMed, Cochrane Library, Cumulative Index to Nursing

and Allied Health Literature (CINAHL), and Embase. To ensure a broad yet targeted scope, grey literature and hospital-specific repositories were also explored, as they often contain valuable data not included in traditional peer-reviewed publications. The search terms included "hospital malnutrition", "artificial intelligence", and their synonyms and related terms. Boolean operators (AND, OR) were strategically applied to refine the search while maintaining comprehensiveness (Tables S1–2).

During the initial screening phase, two researchers independently reviewed titles and abstracts retrieved from the database searches. Duplicates and irrelevant studies were removed using EndNote 20® software. Disagreements were resolved through discussion, and when necessary, a third researcher was consulted to provide an impartial judgment. For studies deemed relevant, full texts were obtained and assessed independently by two researchers based on predefined eligibility criteria. If consensus was not reached, the third researcher intervened to make the final decision [31].

2.4. Criteria and process

The inclusion criteria for this review were quantitative studies published in English that evaluated AI-based interventions for identifying or managing malnutrition in hospitalized adult patients (age ≥18 years). Studies that investigated AI algorithms, machine learning (ML) models, or predictive analytics aimed at detecting malnutrition or optimizing care pathways were included. These interventions could be compared to traditional methods like clinical judgment or screening tools. Eligible studies had to focus on adult patients hospitalized with malnutrition or at risk of malnutrition.

The exclusion criteria included secondary studies such as systematic reviews, narrative reviews, and qualitative studies, as well as studies with low methodological quality, conference abstracts, and book, or those that did not provide accessible full texts. Studies published in languages other than English, those involving pediatric populations, or those without AI-based interventions were also excluded. Additionally, studies that solely focused on nutritional screening tools without intervention or on paediatric population were excluded.

2.5. Evaluation of risk of bias and methodological quality of studies

The risk of bias and methodological quality of the included studies were independently assessed by two researchers. Discrepancies were resolved with the help of a third researcher. The Joanna Briggs Institute (JBI) Critical Appraisal Tools [32,33] were used to assess the methodological quality of the studies. These tools are widely recognized for evaluating various research designs and allow for a structured evaluation of study quality and relevance. High-quality studies were classified as those with a JBI score greater than 70 %, medium-quality studies scored between 50 % and 70 %, and low-quality studies scored below 50 % [34] (Tables S3–6).

2.6. Assessment of evidence certainty

The certainty of the evidence from individual studies was first assessed using the Oxford Centre for Evidence-Based Medicine (OCEBM) levels of evidence [35]. Evidence was categorized into five levels, with Level 1 representing the highest quality (systematic reviews of randomized controlled trials (RCTs) or well-conducted RCTs, and Level 5 representing expert opinion without empirical support. Intermediate levels (Levels 2–4) were assigned to studies such as less rigorous RCTs, single-arm trials, and observational studies, based on study design and methodological quality (Table S3–6).

Subsequently, to assess the overall certainty of the body of evidence supporting the main findings of this systematic review, the GRADE (Grading of Recommendations Assessment, Development and Evaluation) approach was applied, following the guidance provided by the Cochrane Effective Practice and Organisation of Care (EPOC) group [36].

2.7. Data extraction and synthesis

Data from the selected studies were extracted and summarized in tables, capturing key information such as the authors, year of publication, country, study design, population, type of AI intervention, study aim, results, and assessment of quality/bias. The results were presented according to the objectives of the review through a narrative synthesis and summarized in figures and tables.

3. Results

A comprehensive search across multiple databases initially retrieved 376 records: Cochrane Library (n = 34), PubMed-Medline (n = 103), CINAHL (n = 26), Embase (n = 293) and grey literature (n = 136). After removing 27 duplicates, 565 records were left for further review. A manual screening of titles eliminated 508 irrelevant articles, leaving 57 records for abstract screening. During this phase, 36 records were excluded due to irrelevance, resulting in 21 reports for eligibility assessment. Of these, nine were excluded for various reasons: secondary studies (n = 3), pediatric population (n = 2), different outcomes (n = 4). Finally, 12 studies were identified that met the inclusion criteria (Fig. 1).

3.1. Characteristics of the included studies

The studies included in this review [37–48], were conducted in various countries, including China [37,38,42,44], the United States [39,46], Taiwan [40], Austria [41], Italy [43], Spain [45], Japan [47], and Switzerland [48]. The populations analyzed consisted of hospitalized patients with conditions such as colorectal cancer, pneumonia, elderly individuals in long-term care, and surgical patients. The study samples varied in size, ranging from 308 to 8478 patients [37–47], with one study analyzing a dataset of 322 real-world meals [48]. Most studies utilized cohort designs [37,39,40,42,44,46], RCTs [38], pilot studies [41], and cross-sectional [24,43,47] or experimental designs [48]. ML models were the predominant AI interventions, with Random Forest, XGBoost, and LightGBM being the most commonly applied algorithms [37–46], followed by image recognition techniques [47] and multi-task contextual networks [48]. The outcomes evaluated across these studies included malnutrition risk identification, the effectiveness of AI in facilitating early diagnosis and intervention [39–42,45–47], and the impact on patient outcomes such as hospital stay duration and recovery [38–42,46,47]. Cost-effectiveness and operational efficiency, such as reduced diagnostic delays and improved resource allocation, were also key outcomes [38,39,41,42,45,46]. The included studies demonstrated high methodological quality, as assessed using the JBI quality appraisal tools, with an average score of 89 % (range: 75 %–100 %). The studies adhered to the standards of the Oxford Centre for Evidence-Based Medicine (OCEMB), ensuring a comprehensive evaluation and high validity of their findings. The evidence grade, ranging from 1 to 4, varied based on the study design (Table 1).

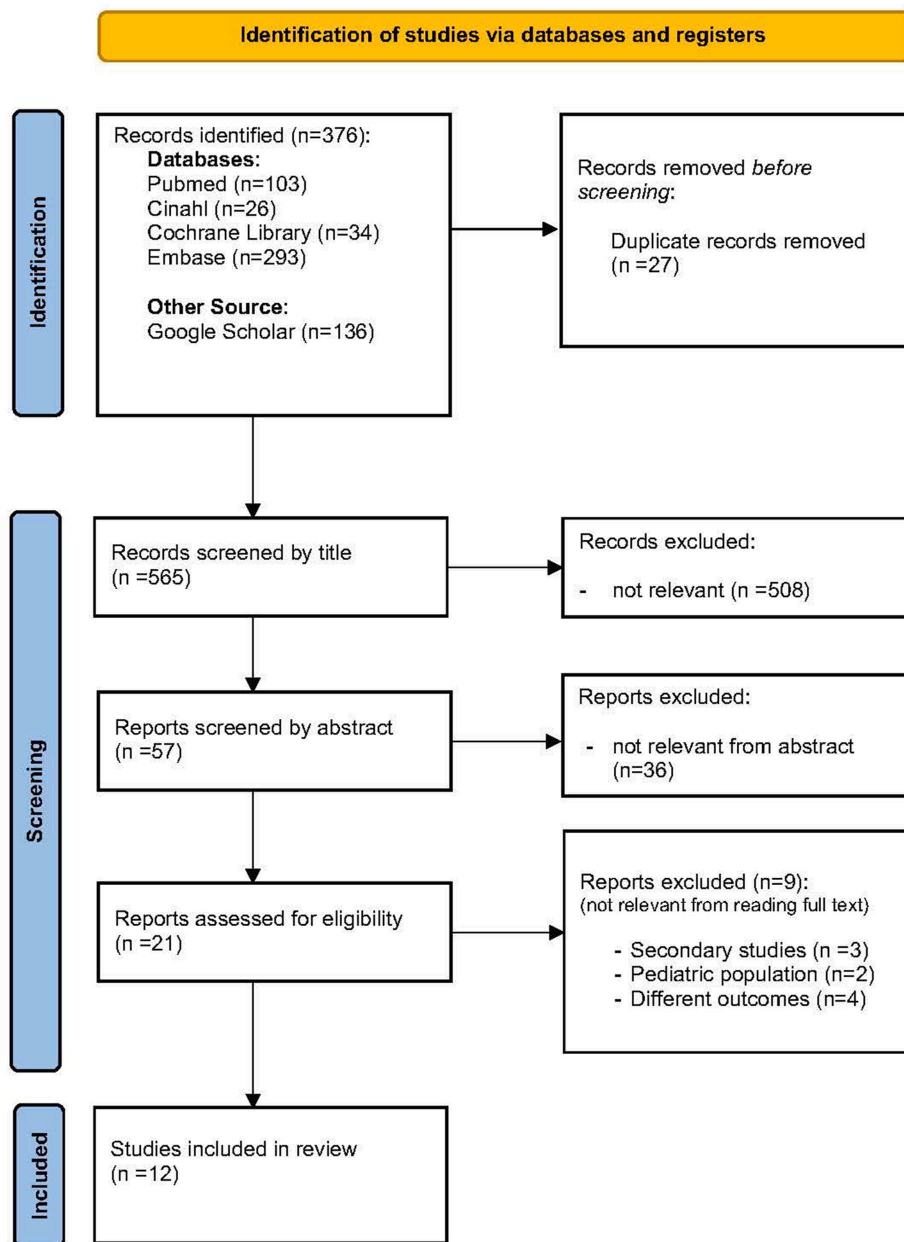

Fig. 1. PRISMA flow diagram.

3.2. Effectiveness of AI in malnutrition identification

The effectiveness of AI in identifying hospital malnutrition has been widely discussed in recent studies [39–42,45–47], which have demonstrated its superior performance compared to traditional screening tools. Various ML algorithms, including Random Forest, XGBoost, and LightGBM, have been applied to assess their accuracy in detecting malnutrition, with promising results indicating that AI models can significantly improve early malnutrition diagnosis.

A recent study [40] utilized XGBoost and LightGBM models to predict hospital stay, mortality, and readmission rates in hospitalized pneumonia patients, achieving accuracy rates between 82 % and 92 %, and Area Under the Curve (AUC) values ranging from 0.92 to 0.99. These findings are consistent with those of Wang et al. [42], who applied ML models (XGBoost, LightGBM, and Random Forest) in a cohort of elderly patients. Their results showed AUC values exceeding 90 %, with the LightGBM model outperforming the others with an AUC of 92.1 %. This study highlighted the potential of AI not only to identify malnutrition but also to do so with a level of precision that far exceeds traditional methods.

In a similar study, Parchure et al. [39] implemented the Malnutrition Universal Screening Tool (MUST), a standardized tool for identifying adults at risk of malnutrition, in its enhanced form known as MUST-Plus, an AI-based screening tool, across six hospitals in the United States. Their study demonstrated that the AI-enhanced system significantly improved both the diagnosis and documentation of malnutrition, reducing the time required to reach a diagnosis compared to traditional methods. Additionally, another study [46], found that MUST-Plus improved sensitivity

Table 1
Characteristics of the included studies.

Authors, Year, Country	Population (n)	Study Design	Type of AI Intervention	Study Aim	Results	Quality/bias	Evidence certanly
Wu et al.[37] (2024), China	Colorectal cancer (n = 4487) Training cohort (n = 3365) Validation cohort (n = 1122)	Multicenter cohort study	ML (Random Forest)	Predicting malnutrition without weight loss data	AUC = 0.830 for malnutrition prediction	+++	1
Sun et al.[38] (2024), China	Hospitalized (n = 5763)	RCT	AI-based diagnostic system	Nutritional diagnosis	Improved cure rate and cost-effectiveness	+++	1
Parchure et al. [39] (2024), USA	Hospitalized (n = 7736)	Retrospective cohort	ML (MUST-Plus)	Malnutrition diagnosis and documentation	Improved diagnosis/ documentation rate	+++	2
Liu et al. [40] (2024), Taiwan	Hospitalized pneumonia (n = 4368)	Retrospective cohort study	ML (LightGBM, XGBoost)	Predicting hospital stay, mortality, and readmissions	Accuracy: 82–92 %, AUC: 0.92–0.99	+++	2
Kramer et al. [41] (2024), Austria	Surgical (n = 159)	Pilot study	ML (Random Forest)	Malnutrition risk prediction	Accuracy: 83.0 %, AUC: 0.833	+++	4
Wang et al. [42] (2023), China	Hospitalized elderly (n = 2660) Derivation group (n = 2128) Validation group (n = 532)	Cohort study	ML (XGBoost, LightGBM, Random Forest)	Malnutrition diagnosis	Best: LightGBM (AUC: 92.1 %), improved accuracy, sensitivity, specificity	+++	1
Di Martino et al. [43] (2023), Italy	Long term care (n = 69)	Observational study	Random Forest, Gradient Boosting, XAI	Risk prediction of malnutrition	Best models: Random Forest, Gradient Boosting; XAI methods used for interpretability.	+++	3
Ren et al. [44] (2022), China	Hospitalized elderly (over 65) (n = 2526)	Cohort study	ML (Random Forest)	Predicting in-hospital complications	Higher complication risk in GLIM diagnosed patients	+++	2
Larburu et al. [45] (2022), Spain	Hospitalized elderly (n = 998)	Observational study	ML (Random Forest, Gradient Boosting)	Malnutrition risk prediction	AUC: 0.76, 13.8 % malnutrition prevalence	+++	2
Timsina et al. [46] (2021), USA	Hospitalized (n = 8479)	Retrospective cohort	ML (Random Forest)	Malnutrition screening	MUST-Plus outperforms the original MUST in terms of: Sensitivity: 73.07 % (30 % higher than MUST) Specificity: 76.89 % (6 % higher than MUST) AUC: 83.5 % (17 % higher than MUST)	+++	2
Sakai et al. [47] (2021), Japan	Post-acute care (n = 308)	Cross-sectional study	Image recognition, ML	Screening for sarcopenic dysphagia	ROC-AUC = 0.877, PR-AUC di 0.838 good dysphagia prediction performance	+++	3
Lu et al. [48] (2020), Switzerland	Dataset of real world meals (n = 322)	Experimental study	Multi-task contextual network, few-shot learning, 3D Surface Construction algorithm	Nutrient intake estimation	Correlation >0.91 between estimated and actual intake	+++	2

AI: Artificial Intelligence; AUC: Area Under the Curve [a common metric used to evaluate the performance of classification models]; GLIM: Global Leadership Initiative on Malnutrition; PR: Precision-Recall; ML: Machine Learning; NRS-2002: Nutrition Risk Screening 2002; ROC-AUC: Receiver Operating Characteristic - Area Under the Curve [AUC of the ROC curve]; RCT: Randomized Controlled Trial; MUST: Malnutrition Universal Screening Tool; XGBoost: Extreme Gradient Boosting; LightGBM: Light Gradient Boosting Machine; XAI: Explainable Artificial Intelligence, Quality was assessed according to the JBI guidelines, using the JBI quality appraisal checklist and the method described by Sguanci et al. [32]. The level of bias risk was considered: low<50 % (+); moderate 50–70 % (++); high>70 % (+++); Certainty of evidence was assessed according to the Oxford Centre for Evidence-Based Medicine (OCEBM).

(73.07 %), specificity (76.89 %), and AUC (83.5 %) when compared to the classic MUST, further confirming the superior performance of AI in early malnutrition identification.

Kramer et al. [41] used Random Forest models for malnutrition risk prediction in surgical inpatients. The results showed that the AI model improved malnutrition diagnosis with an AUC of 0.833, confirming the utility of AI models in enhancing early malnutrition detection and enabling more efficient patient management. Moreover, some studies have also focused on using AI models to identify malnutrition in specific populations. Larburu et al. [45], used Random Forest to predict malnutrition risk in elderly women hospitalized in Spain, achieving an AUC of 0.76. Their findings indicate that even in smaller cohorts, AI models can provide crucial insights for malnutrition diagnosis. Similarly, another study [47], developed an AI-based screening tool for sarcopenic dysphagia using image recognition techniques. This model, which analyzed neck images to detect sarcopenic dysphagia, a condition linked to malnutrition, achieved a high AUC of 0.877, with a sensitivity of 87.5 % and specificity of 76.67 %. Overall, the findings from these studies [39–42,45–47], indicate that AI models, through the integration of clinical data analysis and, in some cases, image recognition techniques, offer a more accurate and timely diagnosis of malnutrition compared to conventional screening methods. These advancements hold significant potential for improving the management of hospital malnutrition, optimizing healthcare resources, and enhancing patient outcomes.

3.3. Impact of AI on hospital care and patient outcomes

The integration of AI in hospital settings has led to substantial improvements not only in the accuracy of malnutrition identification but also in the overall patient care process. By enhancing the efficiency and effectiveness of malnutrition diagnosis, AI has had a positive impact on various clinical outcomes, including patient recovery, hospitalization duration, and the reduction of malnutrition-related complications. Several studies [38–42,46,47], have highlighted the impact of AI on patient outcomes, particularly in terms of the timeliness of malnutrition diagnosis and the initiation of appropriate interventions. Parchure et al. [39], demonstrated that the implementation of MUST-Plus, an AI-based screening tool, significantly reduced the time required for diagnosing and documenting malnutrition in hospitalized patients across multiple hospitals in the United States. This reduction in diagnostic delays allowed for earlier nutritional interventions, which are critical for improving patient outcomes, particularly in complex hospitalized populations. Furthermore, a multicenter RCT conducted by Sun et al. [38], showed that an AI-based rapid nutritional diagnostic system in a multicenter, RCT led to a higher cure rate in hospitalized patients. The experimental group, which received nutritional assessments powered by AI, showed a significant increase in cure rates compared to the control group, suggesting that AI-assisted diagnosis improves clinical outcomes, likely by enabling timely interventions.

The benefits of AI in improving patient outcomes extend to specific populations as well. Liu et al. [40] applied AI models to predict hospital stay and mortality in pneumonia patients, showing that early identification of at-risk patients allowed for more focused and timely care, thus improving recovery and reducing hospital stay durations. Similarly, a previous study [46] found that AI models, such as MUST-Plus, enabled earlier referrals to dietitians, leading to a more targeted approach to malnutrition management in hospitalized patients. This improved the overall nutritional status of patients, thereby enhancing their recovery trajectory and minimizing hospital readmissions.

Kramer et al. [41], also observed that AI tools helped identify malnutrition risks early in surgical patients, leading to more efficient preoperative and postoperative care. By improving the early detection of malnutrition-related complications, AI helped to mitigate issues such as delayed wound healing and infection, which are common in malnourished patients. In the same context, Sakai et al. [47], highlighted how AI-based image recognition technology used to identify sarcopenic dysphagia, often associated with malnutrition, allowed healthcare providers to intervene earlier, preventing further complications such as aspiration pneumonia, which could lead to prolonged hospitalization and worse recovery outcomes. Moreover, the impact of AI on patient care extends beyond the direct medical benefits. Wang et al. [42] demonstrated that AI models could predict malnutrition in elderly patients with a high degree of accuracy, enabling more efficient use of healthcare resources. By identifying at-risk patients earlier, hospitals could allocate resources more effectively, ensuring that interventions were timely and appropriate, thus preventing unnecessary costs associated with malnutrition-related complications.

3.4. Cost efficiency and economic impact of AI-based malnutrition screening

The integration of AI into malnutrition screening processes represents not only a clinical advancement but also a significant opportunity for healthcare systems to optimize costs and improve economic outcomes. As healthcare providers strive to balance quality care with cost-effectiveness, AI presents a promising solution by enhancing the efficiency of malnutrition detection and intervention. By enabling early identification of malnutrition, AI-driven systems can prevent the progression of malnutrition-related complications, thereby reducing hospitalization costs, minimizing resource consumption, and lowering the overall economic burden on healthcare systems.

A study by Sun et al. [38] investigated the economic benefits of an AI-based rapid nutritional diagnostic system in a multicenter RCT, revealing that the experimental group, which received AI-powered nutritional assessments, achieved a higher cure rate compared to the control group. The economic evaluation indicated that the AI intervention incurred a relatively low incremental cost while significantly improving clinical outcomes. The incremental cost-effectiveness ratio (ICER) was favorable, suggesting that AI-driven malnutrition screening is both cost-effective and economically beneficial in hospital care. Similarly, Parchure et al. [39] examined the economic impact of AI in malnutrition diagnosis by implementing the MUST-Plus AI tool across six hospitals in the United States. Their findings showed that integrating AI into clinical workflows reduced the time required for malnutrition diagnosis, leading to earlier interventions. This not only improved patient outcomes but also contributed to shorter hospital stays and lower costs associated with managing malnutrition-related complications. The study underscored that AI can generate both direct and indirect cost savings by preventing the escalation of malnutrition-related health issues, thus optimizing hospital resource utilization. Similarly, Timsina et al. [46] also found that AI-based models like MUST-Plus enhanced the operational efficiency of dietitians by enabling timely referrals of high-risk patients. This reduced the need for costly reactive interventions and prevented the progression of severe malnutrition-related complications. The study concluded that early AI-driven diagnosis significantly reduces healthcare costs by facilitating preventive interventions, thereby minimizing the incidence of prolonged and expensive malnutrition-associated treatments. In a cohort study, Wang et al. [42], evaluated the cost-effectiveness of AI models in a cohort of elderly patients at risk of malnutrition. Their study

demonstrated that AI-assisted screening allowed for more efficient use of healthcare resources, enabling hospitals to prioritize care for patients most at risk of malnutrition. This not only improved patient outcomes but also resulted in cost savings through better allocation of hospital resources, avoiding unnecessary treatments for patients who were not at risk. A recent study [41], examined the economic impact of AI in surgical patients and found that early detection of malnutrition using AI models led to fewer complications, such as delayed wound healing and infections. This reduction in complications resulted in shorter hospital stays and lower overall treatment costs. The cost-effectiveness analysis showed that AI implementation provided substantial savings compared to traditional screening methods, further emphasizing the financial benefits of AI integration into clinical practice. Lastly, Larburu et al. [45], demonstrated that AI-driven malnutrition risk prediction, using Random Forest models, contributed to more efficient hospital resource management in elderly women hospitalized in Spain. By reducing the need for extensive clinical evaluations and facilitating earlier interventions, the study highlighted that AI technologies can optimize hospital expenditures while maintaining high-quality care. A graphical summary of the results is shown in Fig. 2.

3.5. Risk of bias and methodological limitations

Although all included studies underwent critical appraisal using the JBI tools and were generally classified as of moderate to high quality, several recurrent methodological limitations were identified, which may affect the interpretation of the findings. A major concern across multiple studies was selection bias, particularly due to the retrospective design and convenience sampling [37,39–43]. Most datasets were drawn from single centers or highly selected populations, limiting the generalizability of the ML models to broader or more diverse clinical settings.

Furthermore, confounding variables were often not adequately controlled, especially when models were trained and tested on non-randomized data without appropriate adjustment for clinical complexity or comorbid conditions [37,38,43,48]. Some studies lacked clear reporting on the handling of missing data, and imputation strategies were inconsistently applied or omitted altogether, potentially introducing systematic bias in the model training phase [39,41,46].

Another critical limitation was the lack of external validation. While most models demonstrated good performance in internal testing (e.g., cross-validation or hold-out sets), very few studies validated their algorithms in independent cohorts [44–46]. This raises concerns about overfitting and the actual predictive power of these models in real-world settings.

Additionally, variations in malnutrition definitions and diagnostic criteria (e.g., GLIM, NRS-2002, or institutional standards) and outcome measures (e.g., nutritional status, clinical deterioration, or survival) complicate the comparison across studies. The heterogeneity in predictors, model architectures (e.g., Random Forest, neural networks, Support Vector Machines), and performance metrics (e.g., AUC, accuracy, F1 score) further adds complexity and may obscure true effect estimates [37,45,47,48].

Taken together, these methodological limitations indicate that, although AI holds substantial promise for the assessment of malnutrition, the findings should be interpreted with caution. The reported effectiveness of AI-based tools may be overestimated, and their applicability to heterogeneous hospital populations remains uncertain. Future research should prioritize multicenter study designs, prospective validation, rigorous bias mitigation strategies, and transparent methodological reporting to improve the credibility and applicability of the evidence base. Overall, these limitations highlight the need for cautious interpretation of the current evidence and underscore the importance of robust bias assessment in evaluating the strength and certainty of findings in AI-based malnutrition prediction models. A summary of the key

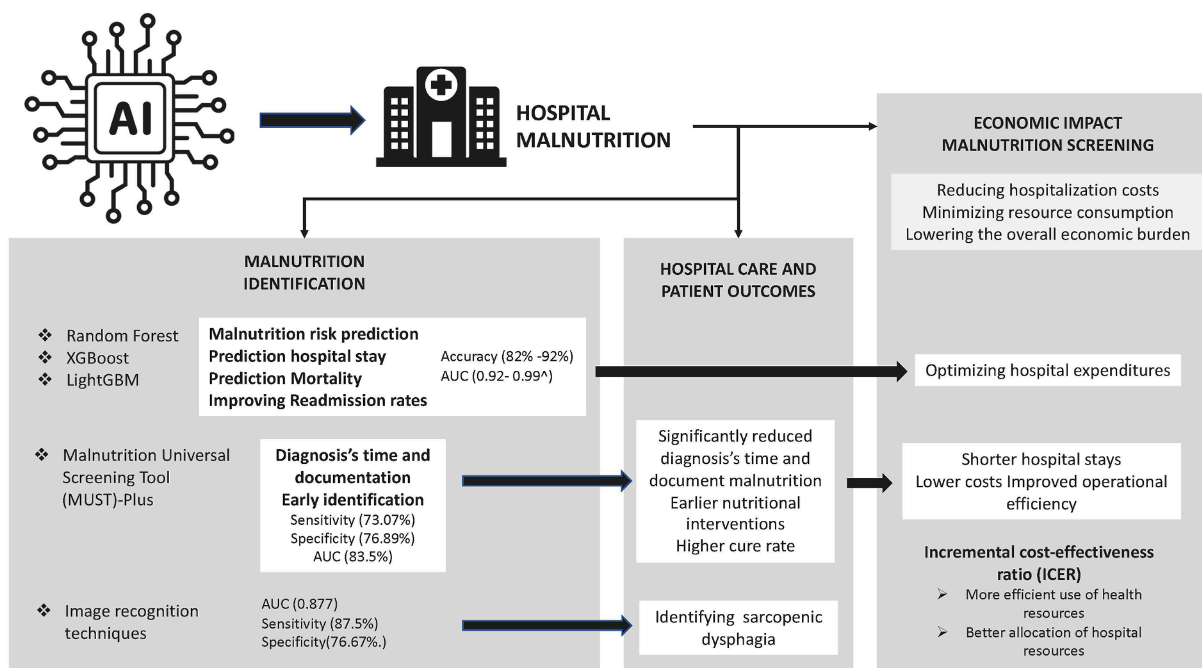

Fig. 2. Artificial intelligence in the management of hospital Malnutrition
AI: Artificial Intelligence; AUC: Area Under the Curve; MUST: Malnutrition Universal Screening Tool; XGBoost: Extreme Gradient Boosting; LightGBM: Light Gradient Boosting Machine; ICER: Incremental Cost.effectiveness Ratio.

methodological limitations identified across the included studies is presented in Table 2.

3.6. Study heterogeneity and generalizability

To address the heterogeneity observed among the included studies, we conducted a qualitative synthesis based on study designs, population, and AI approach. The included studies showed substantial heterogeneity in terms of design, populations, AI models, clinical settings, and outcome measures. As outlined in Table 1, they encompassed a RCT [38], observational studies [43,45], retrospective cohort studies [39,40,46], prospective cohort studies [37,42,44], a cross sectional study [47], and experimental approaches [48] with varied populations (e.g., elderly, surgical, oncologic patients) and different AI approaches (e.g., random forest, LightGBM, neural networks, image-based systems).

This clinical and methodological variability complicates direct comparisons and limits the generalizability of findings. Differences in malnutrition definitions and outcome metrics further hinder consistent synthesis. Recognizing this heterogeneity is essential to accurately interpret the evidence and identify where AI tools may be most appropriately applied in clinical nutrition settings.

3.7. Certainty of evidence based on GRADE

To assess the overall certainty of the evidence supporting the main findings of this systematic review, we applied the GRADE approach [36]. Five outcomes were identified as critical for both clinical and organizational decision-making in the context of artificial intelligence applied to hospital malnutrition. These outcomes included diagnostic accuracy, sensitivity, specificity, the clinical impact on nutritional status, and time to diagnosis. For each outcome, the certainty of evidence was assessed across the five standard GRADE domains: risk of bias, inconsistency, indirectness, imprecision, and publication bias (Table 3 and Table S7). The included studies were mostly observational, with significant heterogeneity in terms of AI models used, study populations, data sources, and definitions of outcomes. These methodological and contextual differences, along with frequent limitations such as retrospective design, lack of blinding, and absence of external validation, contributed to the downgrading of several domains across outcomes.

Table 2
Summary of identified biases and methodological issues summary of identified biases and methodological issues.

Study (Author, Country, Year)	Identifical Bias
Di Martino et al., Italy, 2023 [43]; Liu et al., China, 2024 [40]	Selection bias, confounding
Kramer et al., USA, 2022 [41]; Ren et al., China, 2022 [44]	Selection bias, missing data
Larburu et al., Spain, 2022 [45]	Selection bias, lack of external validation, diagnostic variability
Sakai et al., Japan, 2021 [47]	Selection bias, confounding bias, diagnostic variability
Wu et al., China, 2024 [37]	Confounding bias, diagnostic variability
Sun et al., China, 2024 [38]	Confounding bias
Wang et al., China, 2023 [42]	Missing data, lack of external validation
Parchure et al., USA, 2024 [39]	Lack of external validation, diagnostic variability
Timsina et al., USA, 2021 [46]	Diagnostic variability, missing data
Lu et al., China, 2020 [48]	Selection bias, confounding bias, lack of external validation

4. Discussion

Given these methodological constraints, the findings should be interpreted in light of the limitations discussed above. This systematic review aimed to examine the role of AI in the identification of hospital malnutrition, assessing how the use of advanced algorithms can help improve the effectiveness of early diagnoses, optimize hospital processes, and enhance the quality of care provided to patients. The findings of this review demonstrate that AI plays a crucial role in the early detection of hospital malnutrition, significantly enhancing the efficacy and timeliness of diagnosis compared to traditional screening methods. In particular, advanced ML algorithms, such as XGBoost, LightGBM, and Random Forest, have exhibited superior performance, with AUC values frequently exceeding 90 % [40,42], confirming the precision and reliability of AI models in identifying patients at risk of malnutrition. Moreover, our review highlights that the integration of AI-based tools, such as MUST-Plus, not only accelerates the diagnostic process but also enhances documentation accuracy and improves the sensitivity of nutritional assessments [39,46]. Studies conducted across diverse patient populations, including elderly and surgical patients, further demonstrate that AI-assisted tools contribute to more accurate malnutrition diagnoses, with AUC values ranging between 0.833 and 0.92 [39–42,45-47]. These findings suggest that the adoption of AI models optimizes care pathways, reducing complications associated with malnutrition, such as delayed wound healing and infections [41,47]. Furthermore, AI-driven approaches have a positive impact on hospital resource management and healthcare costs. The early identification of at-risk patients, combined with timely nutritional interventions, has contributed to shorter hospital stays, reduced readmission rates, and lower costs associated with malnutrition-related complications [38–42,46]. For instance, the integration of MUST-Plus into clinical workflows improved the sensitivity (73.07 %) and specificity (76.89 %) of diagnoses, achieving an AUC of 83.5 % compared to traditional methods [46]. Recent studies [38,39,42] have demonstrated that AI-based systems offer a cost-effective solution, providing a favorable cost-effectiveness ratio while contributing to more efficient hospital resource utilization. Early identification and timely management of at-risk patients reduced malnutrition-related complications and optimized the quality of care. These results highlight the potential of AI not only to enhance malnutrition diagnosis and management but also to promote more effective use of hospital resources, thereby improving patient clinical outcomes and the overall efficiency of healthcare systems. The findings of our review are consistent with previous research exploring the role of AI in the diagnosis and management of hospital malnutrition. For instance, a recent study [49] highlighted that, despite over 90 % of AI models developed for malnutrition detection demonstrating high accuracy, their clinical application remains limited. This aligns with our data, which confirm the superiority of ML algorithms, such as Random Forest and LightGBM, in improving the early diagnosis of malnutrition [39,42], while also emphasizing the need for greater integration into clinical workflows. Furthermore, another study [50] highlighted AI's potential to analyze large volumes of clinical data to identify patients at risk of malnutrition. Similarly, the study conducted by Liu et al. [40] employed ML models, including LightGBM and XGBoost, to predict hospital stay duration, mortality, and readmission rates in pneumonia patients, achieving AUC values between 0.92 and 0.99. These findings align with ours, demonstrating that AI provides effective tools for timely diagnosis, ultimately improving clinical outcomes and optimizing healthcare resource utilization. Notably, recent studies have shown remarkable performance of ML algorithms, with AUC values ranging from

Table 3
GRADE evidence profile.

Outcome	Study (Year)	RoB	Inconsistency	Indirectness	Imprecision	Publication Bias	Final Quality
Diagnostic accuracy (AUC)	Parchure et al. (2023) [44]; Ren et al. (2023) [45]; Liu et al. (2023) [36]; Larburu et al. (2023) [47]; Lu et al. (2022) [37]; Sun et al. (2022) [38]; Wang et al. (2022) [39]; Wu et al. (2021) [40]; Sakai et al. (2021) [41]; Timsina et al. (2020) [42]	Downgrade (retrospective, no blinding)	No downgrade (direction consistent)	No downgrade	Downgrade (small samples, wide CI)	Not downgraded	●●●○
Sensitivity	Parchure et al. (2023) [44]; Liu et al. (2023) [36]; Lu et al. (2022) [37]; Wu et al. (2021) [40]; Sakai et al. (2021) [41]; Timsina et al. (2020) [42]	Downgrade (no external validation)	No downgrade (range acceptable)	Downgrade (selective samples)	No downgrade	Not downgraded	●●○○
Specificity	Parchure et al. (2023) [44]; Liu et al. (2023) [36]; Lu et al. (2022) [37]; Wu et al. (2021) [40]; Sakai et al. (2021) [41]; Timsina et al. (2020) [42]	Downgrade (missing data, no blinding)	Downgrade (range 70–88 %)	No downgrade	No downgrade	Not downgraded	●○○○
Nutritional status impact	Di Martino et al. (2023) [43]; Sun et al. (2022) [38]; Kramer et al. (2021) [46]	Downgrade (no control group, unclear methods)	No downgrade (consistent direction)	Downgrade (proxy indicators)	Downgrade (very small samples)	Not downgraded	●●○○
Time to diagnosis	Larburu et al. (2023) [47]; Sun et al. (2022) [38]	Downgrade (no comparator, retrospective)	No downgrade	No downgrade	Downgrade (qualitative only)	Not downgraded	●●●○

Visual summary of GRADE certainty ratings across the five key outcomes assessed in the review. Certainty was graded as High (●●●●), Moderate (●●●○), Low (●●○○), or Very Low (●○○○), according to the GRADE Working Group recommendations. AUC. Area Under the Curve.

0.76 [45] to 0.99 [40]. Similarly, a study [51] on predictive models for falls in elderly Chinese individuals demonstrated that AI can serve as an effective tool for health risk prevention and targeted intervention strategies, further reinforcing the role of these innovative technologies in clinical practice. In a compelling example of AI application in surgical settings, a study [52] analyzing 4046 posterior spinal fusions demonstrated the effectiveness of Deep Neural Networks in predicting post-operative surgical site infections (SSI). The model achieved an AUC of 0.775, with a positive predictive value (PPV) of 92.56 % and a negative predictive value (NPV) of 98.45 %. Notably, the study identified key risk factors such as congestive heart failure and chronic pulmonary failure, while also revealing protective factors, including minimally invasive surgery approaches. Similarly, a study [53] applied ML algorithms to predict the risk of pressure injuries in critically ill surgical patients, analyzing data from 6376 patients using the Random Forest method. The model achieved an AUC of 0.79 for both stage 1+ and stage 2+ pressure injuries, demonstrating that AI can effectively utilize electronic health record (EHR) data without requiring additional assessments from healthcare staff. These results further validate the role of ML in clinical decision-making and risk assessment, highlighting its potential to improve patient care. Remaining in the surgical field, a systematic review study [54] analyzed nine studies on the application of ML in managing surgical wounds, including cardiothoracic surgeries, cesarean sections, colectomies, burns, laparotomies, and minimally invasive procedures. ML proved effective in assessing SSI and classifying wounds, with algorithms such as Support Vector Machine (SVM) and Convolutional Neural Network (CNN) achieving high precision, and ANN reaching 96 % accuracy in facial plastic surgery. These studies [51–54] collectively underscore the growing impact of AI not only in nutritional risk assessment but also in broader clinical risk evaluation, further demonstrating its potential to enhance patient management in hospital settings. Additionally, the economic burden of malnutrition on healthcare systems is considerable, as it is often associated with longer hospital stays, increased complications, and higher readmission rates, ultimately leading to increased healthcare costs [55–57].

In line with these findings, a study by Raphaeli et al., [58] demonstrated that AI models applied in oncology could serve as the first layer in a comprehensive nutritional therapy workflow, providing healthcare professionals with advanced tools to better assess malnutrition risks and enhance therapeutic precision. Similarly, the study conducted by Papathanail I et al., [59] proposed an AI system for estimating nutritional intake through meal image analysis. This methodology aligns with the findings of Lu et al. [48], who achieved correlations exceeding 0.91 between estimated and actual intake using deep learning techniques. Another study by Besculides M. et al., [60] focused on MUST-Plus, showed interesting parallels with the study by Timsina et al. [46], which demonstrated that this tool significantly outperforms the traditional MUST in terms of sensitivity (+30 %), specificity (+6 %), and AUC (+17 %). This underscores the importance of integrating such systems into clinical workflows, as also highlighted by Sun et al. [38], who documented improvements in cure rates and cost efficiency. Finally, another study conducted by Sharma et al. [57] highlighted how AI can significantly improve the diagnosis of malnutrition compared to traditional methods. This aligns with the results obtained by Timsina et al. [46] and Wang et al. [42], who demonstrated a notable increase in sensitivity (+30 %), specificity (+6 %), and accuracy (AUC greater than 83.5 %) through the use of AI-based tools such as MUST-Plus. A central aspect of

this study [61] was the focus on hospitalized patients with nutritional deficiencies, a feature shared with other studies [42,44]. These studies explored the risk of nutritional complications in elderly and vulnerable patients, emphasizing the importance of AI in improving care for these populations.

4.1. Limitations

While several studies included in this analysis demonstrate adequate quality and provide valuable insights, it is important to acknowledge certain limitations in the existing literature. Notably, the body of evidence is constrained by the relatively small number of included studies and substantial heterogeneity in study designs, populations, and outcome measures. Additionally, some studies are based on retrospective data collection, lack external validation, and report findings with limited generalizability. These limitations may affect the overall interpretation of the evidence and highlight the need for further research employing more rigorous, standardized, and prospective methodologies to enhance the reliability and applicability of AI-driven malnutrition screening in clinical practice.

A formal assessment of publication bias was not conducted, owing to the substantial heterogeneity in outcome measures and the absence of sufficiently comparable quantitative data across the included studies. Nonetheless, the increasing momentum surrounding AI research and the potential for selective publication of positive findings may have contributed to publication bias within the available evidence base.

4.2. Implications for clinical practice

The findings of this systematic review highlight that advanced AI algorithms, such as XGBoost and Random Forest, enable the early identification of malnutrition risk, significantly improving the sensitivity and specificity of diagnoses compared to traditional methods. Integrating AI-based tools, such as the MUST-Plus, into clinical workflows accelerates diagnostic processes, optimizes hospital resource utilization, and reduces complications, including infections and delayed wound healing.

Furthermore, timely identification of at-risk patients, combined with targeted nutritional interventions, has been shown to shorten hospital stays, lower readmission rates, and reduce associated healthcare costs. These benefits underscore the potential of AI to enhance healthcare resource management, streamline care pathways, and support sustainable healthcare, ultimately improving outcomes for both patients and healthcare systems [62–64]. The implementation of AI in clinical practice holds promising prospects, not only for enhancing clinical outcomes and enabling early risk detection, but also for contributing to a more efficient use of healthcare resources. When complemented by emerging technologies such as the Internet of Things (IoT), which enable continuous and remote patient monitoring, these innovations collectively support the evolution toward a more responsive and data-driven model of care [65]. To further support clinical implementation, it is essential to consider how AI tools can be effectively embedded into routine workflows. A potential integration of AI into malnutrition screening involves embedding predictive models within EHRs to automatically flag at-risk patients based on clinical data, as demonstrated by the MUST-Plus tool, which achieved over 90 % provider acceptance and improved diagnostic timeliness. However, implementation may face barriers such as poor workflow integration, limited explainability (XAI), lack of training, and clinician mistrust. Facilitators include early stakeholder involvement, interpretable outputs, and seamless integration into clinical routines [66,67].

5. Conclusion

This systematic review highlights the significant potential of AI in enhancing the early diagnosis and management of hospital malnutrition. ML models such as XGBoost, LightGBM, and Random Forest have shown exceptional promise in the timely identification of at-risk patients, outperforming traditional methods. The integration of AI-driven tools, such as MUST-Plus, not only accelerates the diagnostic process but also enhances the sensitivity and specificity of nutritional assessments, leading to more efficient resource management and a reduction in malnutrition-related complications. Furthermore, early identification of at-risk patients, coupled with prompt nutritional interventions, has resulted in notable reductions in hospital stays, readmission rates, and costs associated with managing complications.

The findings suggest that AI significantly improves early malnutrition diagnosis, optimizes healthcare resources, and reduces costs, all while positively impacting clinical outcomes. However, while further research is necessary to address existing methodological limitations and improve the integration of AI models into routine clinical practice, the results indicate that AI adoption can greatly enhance the quality of care and the overall efficiency of healthcare systems. Specifically, AI not only provides an advantage in early malnutrition detection and management but also contributes to optimizing resource allocation, reducing healthcare costs, and improving patient outcomes. Therefore, the integration of AI into healthcare systems presents a pivotal opportunity for the future of healthcare, supporting more efficient, personalized, and data-driven approaches to patient management.

Credit statement

SM: Conceptualization, Methodology, Writing Original Draft, Review &; Editing, Investigation; GF: Writing Original Draft, Review &; Editing; DL: Review &; Editing, Data Analysis; GC: Writing Original Draft, Review &; Editing; FP: Methodology, Visualization; SMP: review &; Editing; MS: Conceptualization, Methodology, Writing Original Draft, Review &; Editing, Visualization; SM and GF provided an equal contribution as first author in drafting the manuscript; MS and SMP contributed equally as last author. All authors read and approved the final manuscript.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author, upon reasonable request.

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

The authors confirm that all data presented in this manuscript are original and derived from independent analysis. AI tools were employed solely during the final stage of manuscript preparation to assist with language refinement and structural editing. No AI-generated content contributed to data interpretation, analysis, or the formulation of the study's conclusions.

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Conflicts of interest

The authors declare no potential conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clnesp.2025.10.002.

References

[1] Zhang T, Sulo S, Drawert S. EE326 malnutrition prevalence and economic burden among US hospitalized older adult patients with and without COVID-19. Value Health 2023 Jun;26(6):S119. https://doi.org/10.1016/j.jval.2023.03.627.

[2] Cass AR, Charlton KE. Prevalence of hospital-acquired malnutrition and modifiable determinants of nutritional deterioration during inpatient admissions: a systematic review of the evidence. J Hum Nutr Diet 2022 Dec;35 (6):1043–58. https://doi.org/10.1111/jhn.13009.

[3] Starace E, De Pasquale G, Morenghi E, Crippa C, Matteucci S, Pieri G, et al. Hospital malnutrition in the medicine and neurology departments: a complex challenge. Nutrients 2023;15(24):5061. https://doi.org/10.3390/nu15245061.

[4] Volkert D, Saeglitz C, Gueldenzoph H, Sieber CC, Stehle P. Undiagnosed malnutrition and nutrition-related problems in geriatric patients. J Nutr Health Aging 2010 May;14(5):387–92. https://doi.org/10.1007/s12603-010-0085-y.

[5] Wong A, Huang Y, Banks MD, Sowa PM, Bauer JD. A cost-consequence analysis of nutritional interventions used in hospital settings for older adults with or at risk of malnutrition. Healthcare (Basel) 2024 May 17;12(10):1041. https://doi.org/10.3390/healthcare12101041.

[6] Lim SL, Ong KC, Chan YH, Loke WC, Ferguson M, Daniels L. Malnutrition and its impact on cost of hospitalization, length of stay, readmission and 3-year mortality. Clin Nutr 2012 Jun;31(3):345–50. https://doi.org/10.1016/j.clnu.011.11.001.

[7] Norman K, Haß U, Pirlich M. Malnutrition in older adults-recent advances and remaining challenges. Nutrients 2021 Aug 12;13(8):2764. https://doi.org/10.3390/nu13082764.

[8] Pellegrinelli A, Mancin S, Brolese A, Marcucci S, Roat O, Morenghi E, et al. Impact of preoperative malnutrition on patients with pancreatic neoplasms post-duodenopancreatectomy: a retrospective cohort study. Nutrients 2024 Jun 12;16(12):1839. https://doi.org/10.3390/nu16121839.

[9] Ostrowska J, Sulz I, Tarantino S, Hiesmayr M, Szostak-Węgierek D. Hospital malnutrition, nutritional risk factors, and elements of nutritional care in Europe: comparison of Polish results with all European countries participating in the nDay survey. Nutrients 2021 Jan 18;13(1):263. https://doi.org/10.3390/nu13010263.

[10] D'Almeida CA, Peres WAF, de Pinho NB, Martucci RB, Rodrigues VD, Ramalho A. Prevalence of malnutrition in older hospitalized cancer patients: a multicenter and multiregional study. J Nutr Health Aging 2020;24(2): 166–71. https://doi.org/10.1007/s12603-020-1309-4.

[11] Mancin S, Mazzoleni B. Probiotics as adjuvant therapy in the treatment of allergic rhinitis. Res J Pharm Technol 2023;16(5):2393–8. https://doi.org/10.52711/0974-360X.2023.00394.

[12] Purnamasari D, Bunawan NC, Suseno D, Rinaldi I, Dillon DH. In-hospital malnutrition among adult patients in a national referral hospital in Indonesia. Nutr Res Pract 2023 Apr;17(2):218–27. https://doi.org/10.4162/nrp.2023.17.2.218.

[13] Barker LA, Gout BS, Crowe TC. Hospital malnutrition: prevalence, identification and impact on patients and the healthcare system. Int J Environ Res Publ Health 2011;8(2):514–27. https://doi.org/10.3390/ijerph8020514.

[14] Schuetz P, Seres D, Lobo DN, Gomes F, Kaegi-Braun N, Stanga Z. Management of disease-related malnutrition for patients being treated in hospital. Lancet 2021 Nov 20;398(10314):1927–38. https://doi.org/10.1016/S0140-6736(21)01451-3.

[15] Demarest-Litchford M, Munoz N, Strange N, Casirati A, Cereda E. The impact of malnutrition on skin integrity and wound healing. Adv Skin Wound Care 2024 Mar 1;37(3):126–35. https://doi.org/10.1097/ASW.0000000000000107.

[16] Inciong JFB, Chaudhary A, Hsu HS, Joshi R, Seo JM, Trung LV, et al. Economic burden of hospital malnutrition: a cost-of-illness model. Clin Nutr ESPEN 2022 Apr;48:342–50. https://doi.org/10.1016/j.clnesp.2022.01.020.

[17] Verdu-Rotellar JM, Calero E, Duran J, Navas E, Alonso S, Argemí N, et al. Impact of malnutrition on the quality of life in older patients with advanced heart failure: a cohort study. Rev Clin Esp (Barc) 2024 Feb;224(2):105–13. https://doi.org/10.1016/j.rceng.2024.01.005.

[18] Al Kuwaiti A, Nazer K, Al-Reedy A, Al-Shehri S, Al-Muhanna A, Subbarayalu AV, et al. A review of the role of artificial intelligence in healthcare. J Pers Med 2023 Jun 5;13(6):951. https://doi.org/10.3390/jpm13060951.

[19] Al-Antari MA. Artificial intelligence for medical diagnostics-existing and future AI technology. Diagnostics (Basel) 2023 Feb 12;13(4):688. https://doi.org/10.3390/diagnostics13040688.

[20] Vistisen ST, Johnson AEW, Scheeren TWL. Predicting vital sign deterioration with artificial intelligence or machine learning. J Clin Monit Comput 2019 Dec;33(6):949–51. https://doi.org/10.1007/s10877-019-00343-7.

[21] Krishnan G, Singh S, Pathania M, Gosavi S, Abhishek S, Parchani A, et al. Artificial intelligence in clinical medicine: catalyzing a sustainable global healthcare paradigm. Front Artif Intell 2023 Aug 29;6:1227091. https://doi.org/10.3389/frai.2023.1227091.

[22] Maleki Varnosfaderani S, Forouzanfar M. The role of AI in hospitals and clinics: transforming healthcare in the 21st century. Bioengineering (Basel) 2024 Mar 29;11(4):337. https://doi.org/10.3390/bioengineering11040337.

[23] Singer P, Robinson E, Raphaeli O. The future of artificial intelligence in clinical nutrition. Curr Opin Clin Nutr Metab Care 2024 Mar 1;27(2):200–6. https://doi.org/10.1097/MCO.0000000000000977.

[24] Zheng J, Wang J, Shen J, An R. Artificial intelligence applications to measure food and nutrient intakes: scoping review. J Med Internet Res 2024 Nov 28;26:e54557. https://doi.org/10.2196/54557.

[25] Choudhury A, Asan O. Role of artificial intelligence in patient safety outcomes: systematic literature review. JMIR Med Inform 2020 Jul 24;8(7): e18599. https://doi.org/10.2196/18599.

[26] Ranjbar A, Ravn J. Data quality in healthcare for the purpose of artificial intelligence: a case study on ECG digitalization. Stud Health Technol Inform 2023 Jun 29;305:471–4. https://doi.org/10.3233/SHTI230534.

[27] Tang L, Li J, Fantus S. Medical artificial intelligence ethics: a systematic review of empirical studies. Digit Health 2023 Jul 6;9:20552076231186064. https://doi.org/10.1177/20552076231186064.

[28] Bond A, Mccay K, Lal S. Artificial intelligence & clinical nutrition: what the future might have in store. Clin Nutr ESPEN 2023 Oct;57:542–9. https://doi.org/10.1016/j.clnesp.2023.07.082.

[29] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021 Mar 29;372:n71. https://doi.org/10.1136/bmj.n71.

[30] Brown D. A review of the PubMed PICO tool: using evidence-based practice in health education. Health Promot Pract 2020 Jul;21(4):496–8. https://doi.org/10.1177/1524839919893361.

[31] Sguanci M, Mancin S, Piredda M, De Marinis MG. Protocol for conducting a systematic review on diagnostic accuracy in clinical research. MethodsX 2024 Jan 20;12:102569. https://doi.org/10.1016/j.mex.2024.102569.

[32] Barker TH, Stone JC, Sears K, Klugar M, Tufanaru C, Leonardi-Bee J, et al. The revised JBI critical appraisal tool for the assessment of risk of bias for randomized controlled trials. JBI Evid Synth 2023;21(3):494–506.

[33] Moola S, Munn Z, Tufanaru C, Aromataris E, Sears K, Sfetcu R, et al. Chapter 7: systematic reviews of etiology and risk. In: Aromataris E, Munn Z, editors. JBI manual for evidence synthesis. JBI; 2020. https://synthesismanual.jbi.global.

[34] Sguanci M, Ferrara G, Palomares SM, Parozzi M, Godino L, Gazineo D, et al. Dysgeusia and chronic kidney disease: a scoping review. J Ren Nutr 2024 Sep;34(5):374–90. https://doi.org/10.1053/j.jrn.2024.04.005.

[35] Howick J, Chalmers I, Glasziou G, Greenhalgh T, Heneghan C, Liberati A. Explanation of the 2011 Oxford Centre for evidence-based medicine (OCEBM) levels of evidence. Oxford Centre for Evidence-Based Medicine; 2011 [available at: https://www.cebm.ox.ac.uk/resources/levels-of-evidence/ocebm-levels-of-evidence.

[36] Guyatt GH, Oxman AD, Akl EA, Kunz R, Vist G, Brozek J, et al. GRADE guidelines: 1. Introduction – GRADE evidence profiles and summary of findings tables. J Clin Epidemiol 2011 Apr;64(4):383–94. https://doi.org/10.1016/j.jclinepi.2010.04.026.

[37] Wu T, Xu H, Li W, Shi H, Song C. The potential of machine learning models to identify malnutrition diagnosed by GLIM combined with NRS-2002 in colorectal cancer patients without weight loss information. Clin Nutr 2024;43(5): 1151–61. https://doi.org/10.1016/j.clnu.2024.04.001.

[38] Sun MY, Wang Y, Zheng T, Wang X, Lin F, Zheng LY, et al. Health economic evaluation of an artificial intelligence (AI)-based rapid nutritional diagnostic system for hospitalized patients: a multicenter, randomized controlled trial. Clin Nutr 2024;43(10):2327–35. https://doi.org/10.1016/j.clnu.2024.08.030.

[39] Parchure P, Besculides M, Zhan S, Zhan S, Cheng FY, Timsina P, et al. Malnutrition risk assessment using a machine learning-based screening tool: a multicenter retrospective cohort. J Hum Nutr Diet 2024;37:622–32. https://doi.org/10.1111/jhn.13286.

[40] Liu MY, Sung MY, Liu CF. Machine learning to predict the risk of malnutrition in hospitalized patients with pneumonia and analysis of related prognostic factor. Stud Health Technol Inform 2024;316:717–8. https://doi.org/10.3233/SHTI240514.

[41] Kramer D, Jauk S, Veeranki S, Schrempf M, Traub J, Jugel E, et al. Machine learning-based prediction of malnutrition in surgical in-patients: a validation pilot study. Stud Health Technol Inform 2024;313:156–7. https://doi.org/10.3233/SHTI240029.

[42] Wang X, Yang F, Zhu M, Cui H, Li J, Wei Y, et al. Development and assessment of assisted diagnosis models using machine learning for identifying elderly patients with malnutrition: cohort study. J Med Internet Res 2023;25: e42435. https://doi.org/10.2196/42435.

[43] Di Martino C, Delmastro F, Dolciotti C. Explainable AI for malnutrition risk prediction from m-Health and clinical data. 2023. p. 100429. https://doi.org/10.1016/j.smhl.2023.100429.

[44] Ren SS, Zhu MW, Zhang KW, Chen BW, Yang C, Xiao R, et al. Machine learning-based prediction of in-hospital complications in elderly patients using GLIM-, SGA-, and ESPEN 2015-diagnosed malnutrition as a factor. Nutrients 2022;14(15):3035. https://doi.org/10.3390/nu14153035.

[45] Larburu N, Artola G, Kerexeta J, Caballero M, Ollo B, Lando CM. Key factors and AI-based risk prediction of malnutrition in hospitalized older women. Geriatrics 2022;7:105. https://doi.org/10.3390/geriatrics7050105.

[46] Timsina P, Joshi HN, Cheng F, Kersch I, Wilson S, Colgan C, et al. MUST-Plus: a machine learning classifier that improves malnutrition screening in acute care facilities. J Am Coll Nutr 2021;40(1):3–12. https://doi.org/10.1080/07315724.2020.1774821.
[47] Sakai K, Gilmour S, Hoshino E, Nakayama E, Momosaki R, Sakata N, et al. A machine learning-based screening test for sarcopenic dysphagia using image recognition. Nutrients 2021;13(11):4009. https://doi.org/10.3390/nu13114009.
[48] Lu Y, Stathopoulou T, Vasiloglou MF, Christodoulidis S, Stanga Z, Mougiakakou S. An artificial intelligence-based system to assess nutrient intake for hospitalised patients. IEEE Trans Multimed 2020;23:1136–47. https://doi.org/10.1109/TMM.2020.2993948.
[49] Janssen SMW, Bouzembrak Y, Tekinerdogan B. Artificial intelligence in malnutrition: a systematic literature review. Adv Nutr 2024;15(9):100264. https://doi.org/10.1016/j.advnut.2024.100264.
[50] Ma W, Cai B, Wang Y, Sun MW, Lu CD, Jian H. Artificial intelligence driven malnutrition diagnostic model for patients with acute abdomen based on GLIM criteria: a cross-sectional research protocol. BMJ Open 2024;14(3): e077734. https://doi.org/10.1136/bmjopen-2023-077734.
[51] Chen X, He L, Shi K, Wu Y, Lin S, Fang Y. Interpretable machine learning for fall prediction among older adults in China. Am K Prev Med 2023;65(4): 579–86. https://doi.org/10.1016/j.amepre.2023.04.006.
[52] Hopkins BS, Mazmudar A, Driscoll C, Svet M, Goergen J, Kelsten M, et al. Using artificial intelligence (AI) to predict postoperative surgical site infection: a retrospective cohort of 4046 posterior spinal fusions. Clin Neurol Neurosurg 2020;192:105718. https://doi.org/10.1016/j.clineuro.2020.105718.
[53] Alderden J, Pepper AG, Wilson A, Whitney JD, Richardson S, Butcher R, et al. Predicting pressure injury in critical care patients: a machine-learning model. Am J Crit Care 2018;27(6):461–8. https://doi.org/10.4037/ajcc2018525.
[54] Zhang H, Zhao J, Farzan R, Otaghvar HA. Risk predictions of surgical wound complications based on a machine learning algorithm: a systematic review. Int Wound J 2024;21(1):e14665. https://doi.org/10.1111/iwj.14665.
[55] Russell CA. The impact of malnutrition on healthcare costs and economic considerations for the use of oral nutritional supplements. Clin Nutr Suppl 2007;2:25–32. https://doi.org/10.1016/j.clnu.2007.04.002.
[56] Freijer K, Tan SS, Koopmanschap MA, Meijers JMM, Halfens RJG, Nuijten MJC. The economic costs of disease related malnutrition. Clin Nutr 2013;32: 136–41. https://doi.org/10.1016/j.clnu.2012.06.009.
[57] Lim SL, Ong KCB, Chan YH, Loke WC, Ferguson M, Daniels L. Malnutrition and its impact on cost of hospitalization, length of stay, readmission and 3-year mortality. Clin Nutr 2012;31:345–50. https://doi.org/10.1016/j.clnu.2011.11.001.
[58] Raphaeli O, Singer P. Towards personalized nutritional treatment for malnutrition using machine learning-based screening tools. Clin Nutr 2021;40(10):5249–51. https://doi.org/10.1016/j.clnu.2021.08.013.
[59] Papathanail I, Brühlmann J, Vasiloglou MF, Stathopoulou T, Exadaktylos AK, Stanga Z, et al. Evaluation of a novel artificial intelligence system to monitor and assess energy and macronutrient intake in hospitalised older patients. Nutrients 2021;13(12):4539. https://doi.org/10.3390/nu13124539.
[60] Beculides M, Mazumdar M, Phlegar S, Freeman R, Wilson S, Joshi H, et al. Implementing a machine learning screening tool for malnutrition: insights from qualitative research applicable to other machine learning–based clinical decision support systems. JMIR Form Res 2023;7:e42262. https://doi.org/10.2196/42262.
[61] Sharma V, Sharma V, Khan A, Wassmer DJ, Schoenholtz MD, Hontecillas R, et al. Malnutrition, health and the role of machine learning in clinical setting. Front Nutr 2020;7:44. https://doi.org/10.3389/fnut.2020.00044.
[62] Sguanci M, Palomares SM, Cangelosi G, Petrelli F, Sandri E, Ferrara G, Mancin S. Artificial intelligence in the management of malnutrition in cancer patients: a systematic review. Adv Nutr 2025 Jul;16(7):100438. https://doi.org/10.1016/j.advnut.2025.100438.
[63] Palomares SM, Ferrara G, Sguanci M, Gazineo D, Godino L, Palmisano A, et al. The impact of artificial intelligence technologies on nutritional care in patients with chronic kidney disease: a systematic review. J Ren Nutr 2025 Jun 28. https://doi.org/10.1053/j.jrn.2025.06.002. S1051-2276(25)00126-8.
[64] Sacchini F, Mancin S, Cangelosi G, Palomares SM, Caggianelli G, Gravante F, et al. The role of artificial intelligence in diabetic retinopathy screening in type 1 diabetes: a systematic review. J Diabetes Complications 2025 Oct;39 (10):109139. https://doi.org/10.1016/j.jdiacomp.2025.109139.
[65] Sguanci M, Mancin S, Gazzelloni A, Diamanti O, Ferrara G, Morales Palomares S, et al. The internet of things in the nutritional management of patients with chronic neurological cognitive impairment: a scoping review. Healthcare (Basel) 2024 Dec 25;13(1):23. https://doi.org/10.3390/healthcare13010023.
[66] Hassan M, Kushniruk A, Borycki E. Barriers to and facilitators of artificial intelligence adoption in health care: scoping review. JMIR Human Factors 2024;11:e48633. https://doi.org/10.2196/48633.
[67] Ahmed MI, Spooner B, Isherwood J, Lane M, Orrock E, Dennison A. A systematic review of the barriers to the implementation of artificial intelligence in healthcare. Cureus 2023;15(10):e46454. https://doi.org/10.7759/cureus.46454.