Oltre la teoria: strumenti pratici di AI per gli specialisti in nutrizione clinica

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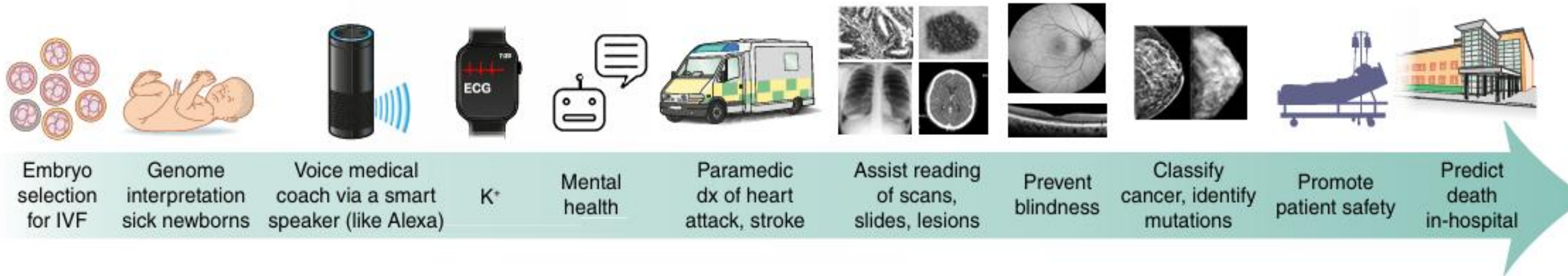
High-performance medicine: the convergence of human and artificial intelligence

*"Almost every type of clinician, ranging from specialty doctor to paramedic, will be using AI technology, and in particular **deep learning**, in the future. This largely involved pattern recognition using **deep neural networks** that can help interpret medical scans, pathology slides, skin lesions, retinal images, electro cardiograms, endoscopy, faces, and vital signs."*



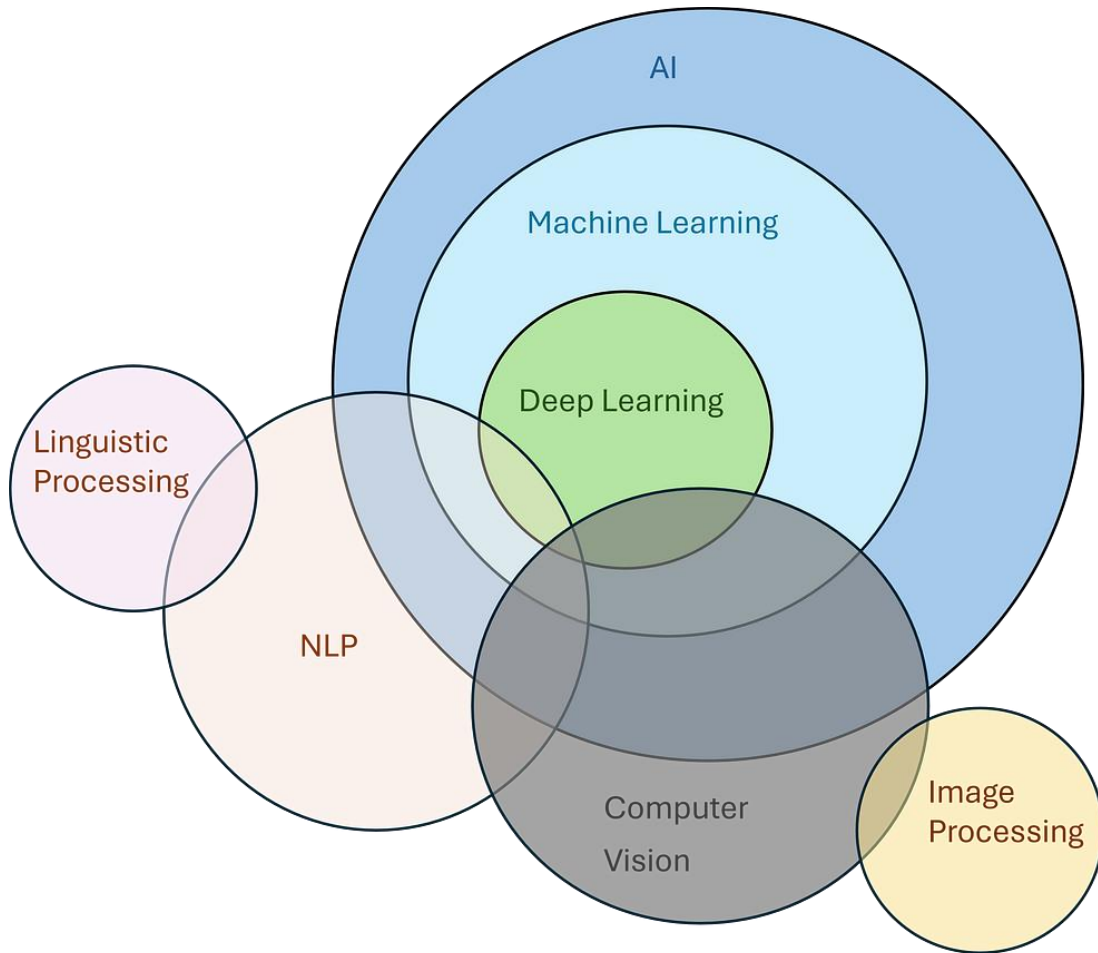
Topol EJ. Nat Med. 2019 Jan;25(1):44-56

Table 1 | Peer-reviewed publications of AI algorithms compared with doctors

Specialty	Images	Publication
Radiology/ neurology	CT head, acute neurological events	Titano et al.[27]
	CT head for brain hemorrhage	Arbabshirani et al.[19]
	CT head for trauma	Chilamkurthy et al.[20]
	CXR for metastatic lung nodules	Nam et al.[8]
	CXR for multiple findings	Singh et al.[7]
	Mammography for breast density	Lehman et al.[26]
	Wrist X-ray*	Lindsey et al.[9]
Pathology	Breast cancer	Ehteshami Bejnordi et al.[41]
	Lung cancer (+driver mutation)	Coudray et al.[33]
	Brain tumors (+methylation)	Capper et al.[45]
	Breast cancer metastases*	Steiner et al.[35]
	Breast cancer metastases	Liu et al.[34]
Dermatology	Skin cancers	Esteva et al.[47]
	Melanoma	Haenssle et al.[48]
	Skin lesions	Han et al.[49]
Ophthalmology	Diabetic retinopathy	Gulshan et al.[51]
	Diabetic retinopathy*	Abramoff et al.[31]
	Diabetic retinopathy*	Kanagasingam et al.[32]
	Congenital cataracts	Long et al.[38]
	Retinal diseases (OCT)	De Fauw et al.[56]
	Macular degeneration	Burlina et al.[52]
	Retinopathy of prematurity	Brown et al.[60]
	AMD and diabetic retinopathy	Kermany et al.[53]
Gastroenterology	Polyps at colonoscopy*	Mori et al.[36]
	Polyps at colonoscopy	Wang et al.[37]
Cardiology	Echocardiography	Madani et al.[23]
	Echocardiography	Zhang et al.[24]

Prospective studies are denoted with an asterisk.

Artificial Intelligence, Machine Learning e oltre



L'**intelligenza artificiale (AI)** si riferisce a sistemi in grado di svolgere compiti che richiederebbero l'intelligenza umana (funzioni cognitive come il ragionamento, la previsione e la decisione).

Il **machine learning (ML)** si concentra sull'abilità dei computer di imparare autonomamente dai dati senza essere esplicitamente programmati per ogni singolo compito. Si forniscono all'algoritmo grandi quantità di dati → l'algoritmo identifica pattern ricorrenti → da questi pattern l'algoritmo costruisce un modello predittivo che può essere applicato a nuovi pazienti.

Il **deep learning (DL)** utilizza reti neurali artificiali ispirate al funzionamento del cervello umano. Si parla di reti "profonde" perché queste reti sono composte da molti strati (*layers*) di neuroni artificiali, ciascuno dei quali elabora l'informazione in modo progressivamente più complesso. Non richiede che lo specialista definisca manualmente le caratteristiche da analizzare, è il modello che "impara" quali sono le *feature* rilevanti.

- **Computer Vision (CV)** è l'applicazione del DL alle immagini (capacità dei computer di "vedere" e interpretare immagini)
- **Natural Language Processing (NLP)** è l'applicazione del DL/ML al linguaggio (capacità di leggere e interpretare il linguaggio scritto o parlato)
- **Large Language Models (LLM)** è l'evoluzione dell'NLP, modelli con miliardi di parametri addestrati su enormi quantità di testi con capacità generative (possono scrivere, riassumere, tradurre).

Perché l'AI è rilevante in nutrizione?

Theodore Armand TP et al. Nutrients. 2024 Apr 6;16(7):1073

Set personal nutrition goals

Continuous adaption of the ML models based on user feedback and health outcomes

Feedback

User Input

- Personal Information
- Health History
- Dietary Preferences
- Activity Levels
- Any existing medical conditions.

Dietary Assessment

- CNN-based models
- Pre-trained models
- ResNet, Inception
- ML for database management
- Data clustering

Food recognition

- CNN based models
- Object detection models
- YOLO (You Only Look Once)
- Faster R-CNN for real-time Food recognition

Preditive modeling for disease

- Random Forest
- Support vector machines
- Gradient Boosting
- Ensemble learning for disease risk prediction

Disease diagnosis & monitoring

- Deep neural network
- Machine learning (GBT, XGBoost)
- biomarker-based deep learning

Personalized Nutrition

- Collaborative and Content-based filtering
- NLP, and RL for Chatbots
- Genetic Algorithms
- Programming for meal plans
- Random Forest, XGBoost

Output

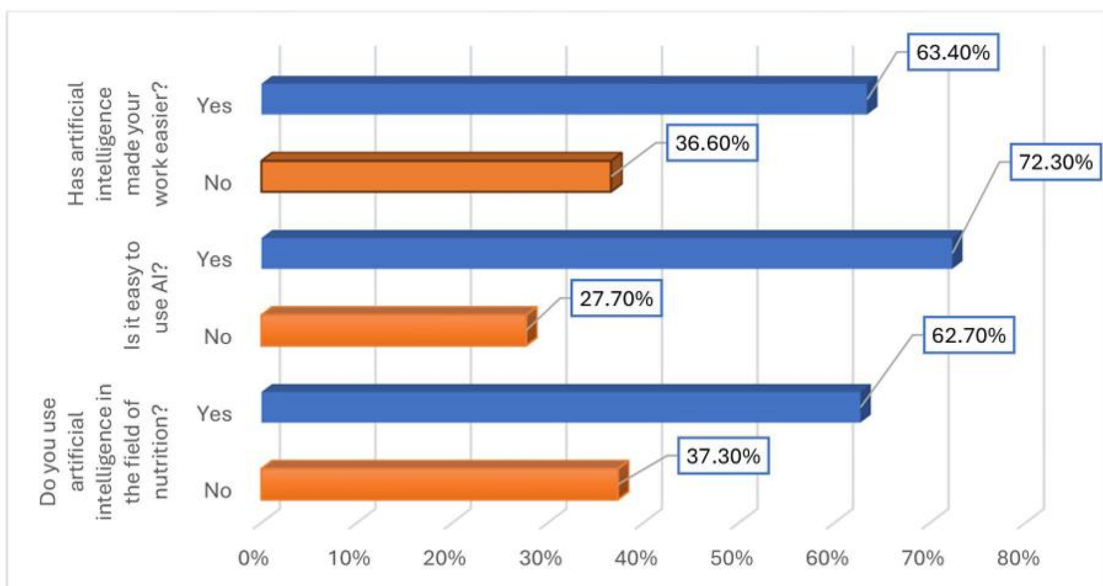
Tailored dietary and lifestyle recommendations

nutrition food deep machine learning neural dietary network intelligence artificial diabetes diet recognition personalized recommendation health assessment prediction convolutional estimation system clinical analysis biomarkers metabolomics algorithm networks language disease medicine hypertension recommender history index intake processing

L'AI permette di **collegare informazioni, individuare pattern nascosti e produrre strumenti predittivi** utili per lo screening precoce, la definizione della composizione corporea e la personalizzazione della terapia nutrizionale

Knowledge, attitude and practice of artificial intelligence among dietitians in Saudi Arabia: a cross-sectional study

Alhazmi A et al. BMJ Open. 2025 Sep 30;15(9):e104230



	Fasle	Don't know	TRUE
PERSONALIZED DIET PLANNING	5.00%	11.20%	83.90%
NUTRITIONAL DATA ANALYSIS	5.00%	11.20%	83.90%
DEVELOPING HEALTHY NUTRITION PROGRAMS	3.10%	8.70%	88.20%
MEAL IMAGE ANALYSIS	5.00%	10.60%	84.40%
NUTRITION EDUCATION AND AWARENESS	7.40%	10.60%	82.00%
PATIENT HEALTH ASSESSMENT AND MONITORING	12.40%	15.50%	72.10%
DETERMINING NUTRITIONAL NEEDS	10.50%	10.60%	78.90%
IMPROVING THE EFFICIENCY OF FOOD SERVICES IN HOSPITALS	9.30%	9.30%	81.40%
RESEARCH AND DEVELOPMENT OF NEW FOOD PRODUCTS	9.30%	8.10%	82.60%
ANALYZING DIETARY HABITS AND MARKET TRENDS	9.30%	8.70%	82.00%

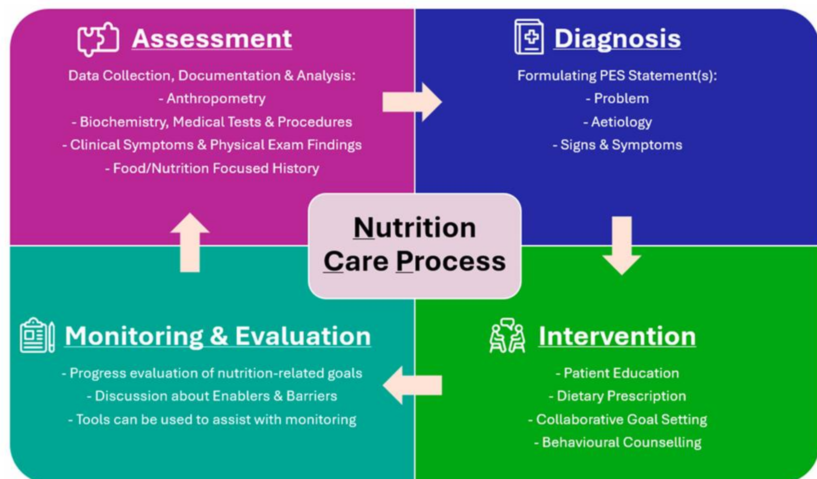
0.% 20.% 40.% 60.% 80.% 100.%

The Use of Artificial Intelligence (AI) to Support Dietetic Practice Across Primary Care: A Scoping Review of the Literature

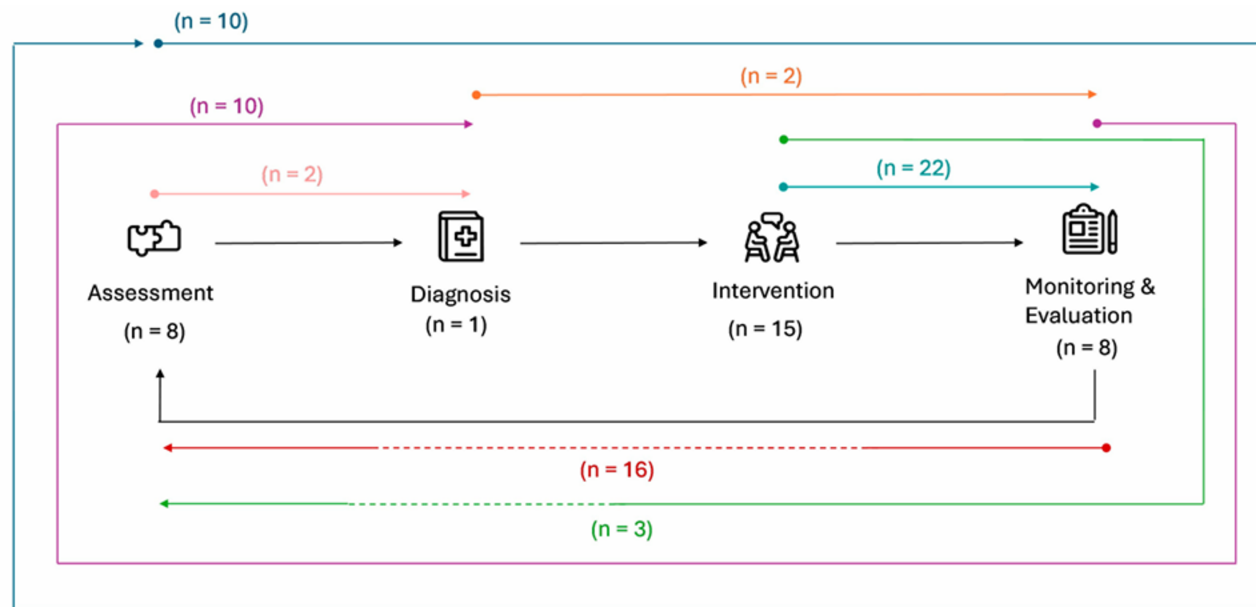
Ngo K et al. Nutrients 2025, 17(22), 3515 *[Submission received: 24 September 2025 / Published: 10 November 2025]*

2.1. Search Strategy

A preliminary pilot search of MEDLINE and IEEE was undertaken to identify articles relevant to the topic. Keywords contained in the titles, abstracts, and medical subject headings (MeSH) of articles were used to generate a search strategy which was adapted across six electronic databases: MEDLINE, Embase, PsycINFO, Scopus, IEEE, and ACM digital library. These databases were searched for peer-reviewed, original literature published from 1 January 2007 to 20 August 2024, a period during which research on the use of AI was rapidly evolving. Keywords and subject headings (including MeSH) were guided by the Population, Concept, and Context (PCC) Framework (Table 1). Key search terms included artificial intelligence, machine learning, deep learning, image recognition, generative AI, chatbots, medication nutrition therapy, nutrition care process (NCP), nutritionist/dietitian, private practice, and related synonyms. The final searches for each database are included in the Supplementary Materials (Tables S1–S5).



5863 retrieved records → 97 eligible studies



L'AI non sostituisce ma può potenziare il NCP

Esempi in nutrizione clinica

Screening del rischio di malnutrizione da dati clinici (ML complesso)

Screening del rischio di malnutrizione da dati clinici (ML semplice)

Composizione corporea opportunistica da CT (DL/CV)

Predictive model for assessing malnutrition in elderly hospitalized cancer patients: A machine learning approach

ML complesso

Duan R et al. Geriatr Nurs. 2024 Jul-Aug;58:388-398

Contesto

- Malnutrizione frequente negli anziani oncologici (prevalenza 46.4%)
- Il PG-SGA è valido ma complesso nella routine
- Serve uno screening rapido basato su dati clinici semplici (obiettivo)

Performance del modello

- 9 algoritmi ML sviluppati usando 22 variabili cliniche
- **XGBoost → AUC 0.945,** Sensibilità 0.968, Accuratezza 0.872

Variabili cliniche utili per predire la malnutrizione (LASSO + SHAP)

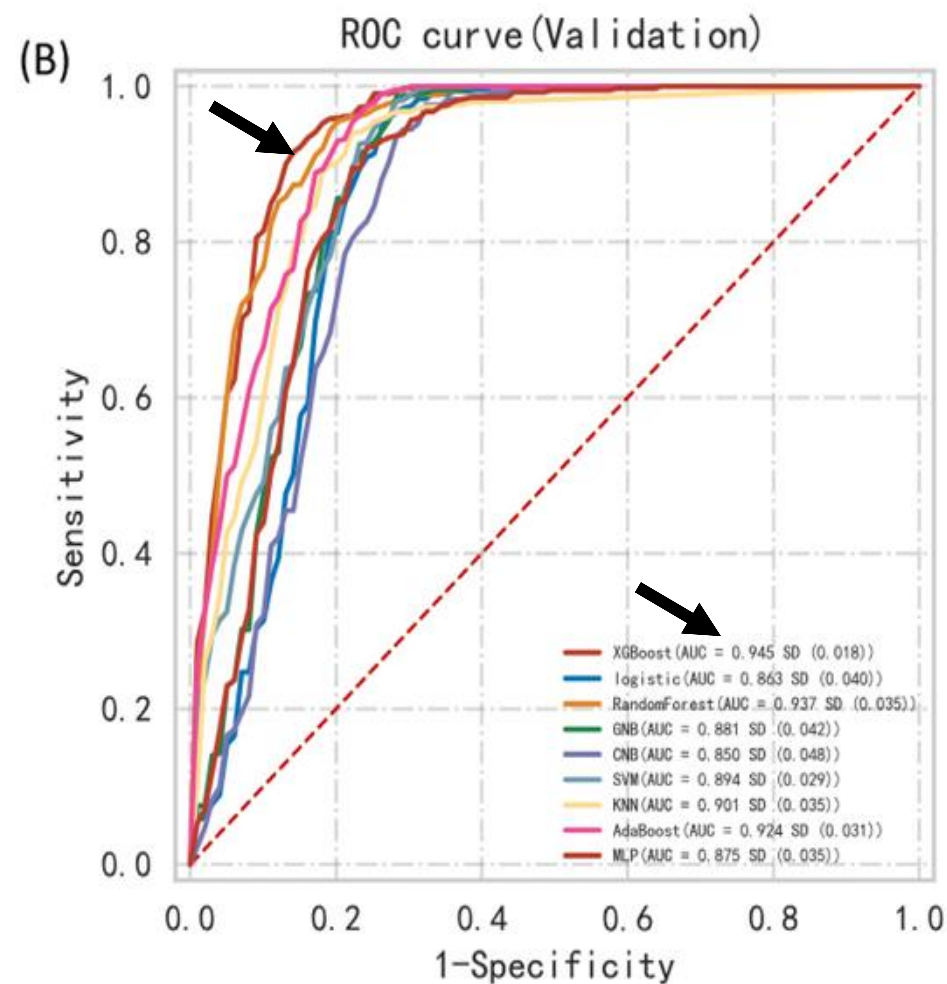
- **ADL** (*Activities of Daily Living*) – predittore più importante
- **Albumina, BMI, Età**
- SHAP rende il modello trasparente e adatto all'uso clinico

LASSO (Least Absolute Shrinkage and Selection Operator)
Metodo di regressione penalizzata che **seleziona automaticamente le variabili più rilevanti** in un modello predittivo.

SHAP (SHapley Additive exPlanations)
Metodo di **interpretabilità dei modelli di ML** basato sulla teoria dei giochi di Shapley. Serve a capire perché un modello ha fatto una certa predizione, interpretare modelli complessi (XGBoost, Random Forest, Neural Network) e identificare pattern clinici non lineari e interazioni. Aumenta la trasparenza dei modelli (*explainable* AI).

Conclusione

- Possibilità di creare screening automatici nella cartella clinica tramite ML



Malnutrition risk assessment using a machine learning-based screening tool: A multicentre retrospective cohort

Parchure P et al. J Hum Nutr Diet. 2024 Jun;37(3):622-632

ML semplice

Contesto

- Malnutrizione nei pazienti ospedalizzati ~30%
- MUST classico → identificazione subottimale del rischio nutrizionale
- Necessità di screening automatizzabile basato su EHR

MUST-Plus è un modello predittivo di ML basato su dati EHR (regressione logistica), aggiornato quotidianamente, progettato per essere integrato nel workflow dei dietisti e supportare la priorità delle valutazioni

Performance del modello (6 ospedali NYC)

- AUC: 0.76–0.85, Sensibilità: 0.63–0.80, Specificità: 0.65–0.84
- NPV: 0.87-0.92
- Usability rate RD: media 97%

Impatto clinico

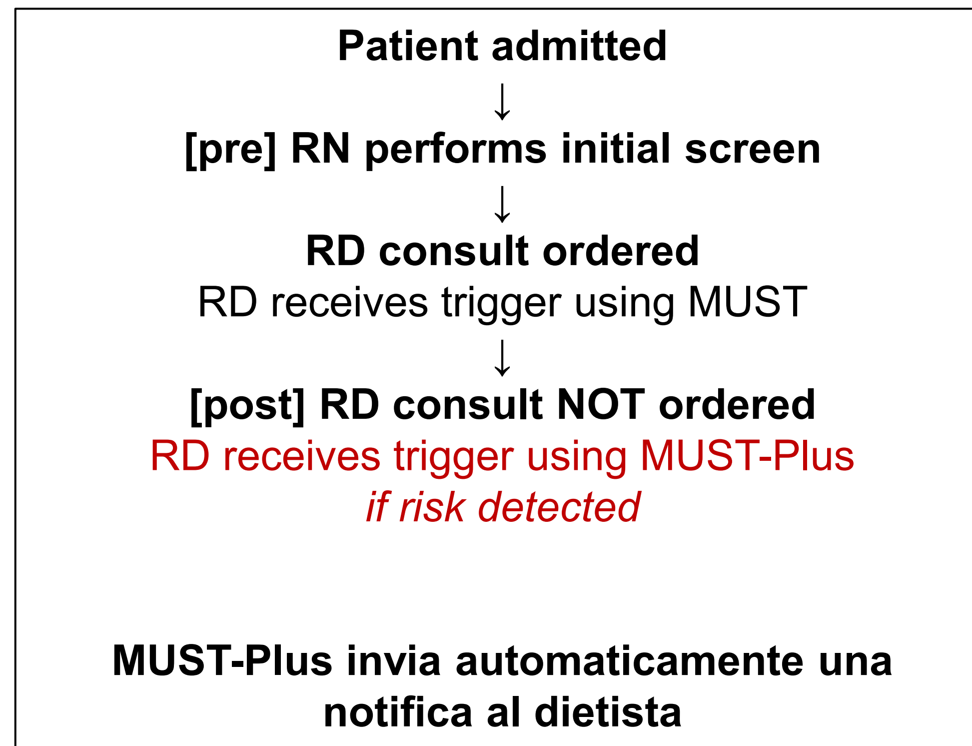
- Migliorata l'identificazione di malnutrizione: 7% → 10%

Ridotto il lag diagnosi:

- Diagnosi entro 24 h: 5% → 22%
- Diagnosi oltre 48 h: 66% → 50%

Conclusione

MUST-Plus migliora screening (intercetta pazienti a rischio che altrimenti sarebbero persi) e diagnosi precoce senza complicare il workflow dei dietisti



RD: registered dietitian
RN: registered nurse

Predicting malnutrition in gastric cancer patients using computed tomography(CT) deep learning features and clinical data

DL/CV

Huang W et al. Clin Nutr. 2024 Mar;43(3):881-891

Contesto
- Malnutrizione frequente nel cancro gastrico (~45%)
- NRS-2002 utile ma non sempre sufficiente
- La CT-L3 contiene informazioni sulla massa muscolare

Approccio DL
- Segmentazione psoas a livello L3 → ROI standard
- DL (ResNet50) per estrazione automatica delle *feature* muscolari
- Selezione delle feature più informative (PCA + LASSO)
- Costruzione modelli ML (11 algoritmi testati)

Dati clinici predittori indipendenti di malnutrizione (multivariata)
BMI (OR 0.569), Linfociti (OR 0.638), Albumina (OR 0.924)

Modello solo *feature* immagini
- **AUC test = 0.769,** Accuratezza = 0.734, Sensibilità = 0.795, Specificità = 0.680

Mixed model: *deep features* + (BMI + albumina + linfociti)
- **AUC test = 0.857,** Accuratezza = 0.861, Specificità = 0.780, Sensibilità = 0.818
- Buon accordo con criteri GLIM (k = 0.647)

Impatto clinico
- Predice rischio nutrizionale da CT già disponibili (uso opportunistico)
- Potenziale integrazione del DL nel workflow radiologico–nutrizionale per identificare automaticamente i pazienti a rischio nutrizionale

ResNet50
Rete neurale convoluzionale profonda (CNN) composta da 50 strati, parte della famiglia **Residual Networks (ResNet)**. Estrae **feature ad alta complessità** da immagini, è usata per classificazione, segmentazione, feature embedding, transfer learning. Si usa come **feature extractor**: da TAC, RM, ecografie ricava centinaia/migliaia di caratteristiche "profonde" non osservabili clinicamente.

PCA (Principal Component Analysis)
Tecnica statistica di **riduzione della dimensionalità** che trasforma variabili correlate (cliniche, antropometriche, imaging) in un numero minore di **componenti principali** che catturano la massima varianza possibile dei dati. Riduce il numero di variabili mantenendo l'informazione chiave e **visualizza pattern complessi** (cluster, fenotipi).

Chi fa cosa nell'AI clinica

Bioinformatico / Data Scientist / Ingegnere

- Progetta, sviluppa e addestra gli algoritmi
- Pulizia dati, *feature engineering*, scelta dell'architettura, validazione tecnica
- Costruisce pipeline e integrazione nei sistemi informatici
- Produce output quantitativi

Clinico (Dietista / Medico / Infermiere)

- Capisce le basi (AI ≠ ML ≠ DL)
- Sa leggere gli output (ad es. AUC, sensibilità, *feature importance*)
- Collabora con bioinformatici/IT per adattare modelli al contesto locale (dataset, popolazione)
- Valida clinicamente confrontando l'output AI con la valutazione nutrizionale reale
- Usa i risultati per decidere (l'AI non sostituisce il giudizio clinico)

Clinical AI Physician [Mahajan A et al. Lancet Reg Health Am. 2025 Oct 25;51:101280]

- Figura dedicata alla supervisione dell'AI in medicina
- Ponte tra bioinformatici/ingegneri e clinici (traduce output tecnici in decisioni sicure)
- Competenze: *validation literacy, bias assessment, drift surveillance*
- Garantisce sicurezza, aggiornamento e appropriatezza dei modelli

Relazione tra esseri umani e AI nella pratica clinica

Topol EJ. Nat Med. 2019 Jan;25(1):44-56

Human driver monitors environment			System monitors environment		
0 No automation The absence of any assistive features such as adaptive cruise control.	1 Driver assistance Systems that help drivers maintain speed or stay in lane but leave the driver in control.	2 Partial automation The combination of automatic speed and steering control—for example, cruise control and lane keeping.	3 Conditional automation Automated systems that drive and monitor the environment but rely on a human driver for backup.	4 High automation Automated systems that do everything—no human backup required—but only in limited circumstances.	5 Full automation The true electronic chauffeur: retains full vehicle control, needs no human backup, and drives in all conditions.

Humans and machine doctors

0	1	2	3	4	5
				Unlikely	

Livello 3
I sistemi analizzano e propongono risultati ma serve sempre supervisione clinica per validare, interpretare e decidere

Livello 0-1-2
L’AI supporta il clinico con analisi di dati, immagini e automazioni semplici ma il controllo resta umano

nature medicine

Review article https://doi.org/10.1038/s41591-025-03983-2

Generative artificial intelligence in medicine

Received: 2 April 2025

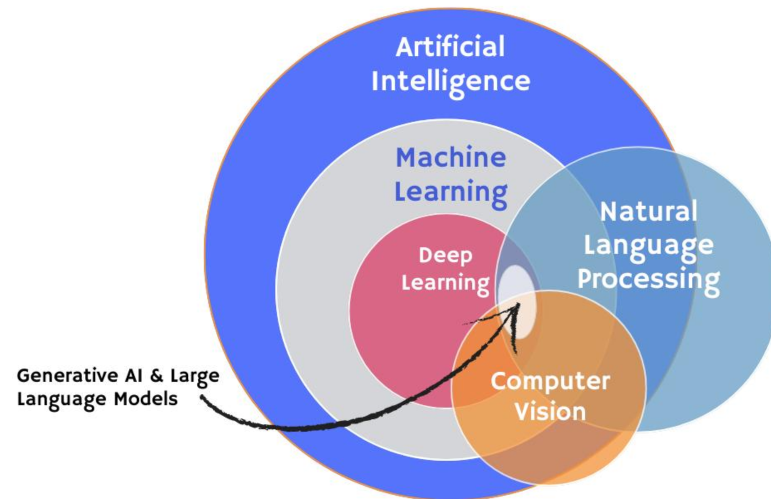
Accepted: 27 August 2025

Published online: 6 October 2025

Zhen Ling Teo[1,2,15], Arun James Thirunavukarasu[3,15], Kabilan Elangovan[1,2], Haoran Cheng[1,4], Prasanth Moova[1,2], Brian Soetikno[5], Christopher Nielsen[6], Andreas Pollreisz[1,7], Darren Shu Jeng Ting[1,4,8,9,10], Robert J. T. Morris[11,12], Nigam H. Shah[13], Curtis P. Langlotz[14] & Daniel Shu Wei Ting[1,2,5]

Generative artificial intelligence (GAI) can automate a growing number of biomedical tasks, ranging from clinical decision support to design and

and discuss validation approaches using specific examples to illustrate challenges and opportunities for further work.



- La Generative AI è un **sottoinsieme di DL e NLP**, nasce dall'evoluzione dei modelli linguistici
- Il suo potenziale è la **capacità di interfacciarsi con l'operatore**, imparando ad usare il nostro linguaggio
- La **Generative AI** è la parte dell'AI capace non solo di analizzare dati ma anche di **generare contenuti** (testo, immagini, suoni)
- Sta rapidamente entrando nella pratica clinica, **automatizzando** un numero crescente di attività: **dall'analisi della documentazione clinica alla produzione di immagini sintetiche, fino al supporto decisionale.** Aiuta a sintetizzare informazioni complesse, estrarre dati, scrivere report e collegare tra loro segnali clinici che da soli richiederebbero molto tempo.
- Rispetto al DL tradizionale che richiedeva database enormi, **i modelli generativi funzionano anche con dataset più piccoli e specifici**

Artificial intelligence (AI) in nutrition: A case-based comparison of generative AI models

Hurt RT et.al. Nutr Clin Pract. 2025 Nov 6

I Large Language Models ragionano come uno specialista?

TABLE 2 Assessment of four AI tools by five nutrition experts.

Questions		ChatGPT, mean (SD)	Copilot, mean (SD)	Gemini, mean (SD)	OpenEvidence, mean (SD)
1	AI tool response missing recommendations that the experts thought of?	3.000 (0.400)	3.520 (0.867)	2.880 (0.576)	3.160 (0.623)
2	Clarity of recommendations	3.920 (0.268)	3.720 (0.303)	4.160 (0.261)	3.660 (0.467)
3	Insights that the AI tool provided that experts did not consider	1.600 (0.245)	1.840 (0.329)	1.400 (0.283)	1.760 (0.167)
4	Overall satisfaction with the AI tool	3.360 (0.358)	3.080 (0.795)	3.840 (0.410)	3.360 (0.329)
5	Quality of evidence cited	3.240 (0.623)	3.360 (0.817)	3.040 (0.767)	3.280 (0.593)
6	Relevance of the response to the case	3.840 (0.329)	3.480 (0.901)	4.040 (0.297)	3.760 (0.261)
7	The likelihood of experts following recommendations from the AI tool	3.440 (0.590)	3.200 (0.883)	3.720 (0.303)	3.480 (0.482)
8	The usefulness of recommendations provided by the AI tool	3.480 (0.415)	3.160 (0.910)	3.800 (0.374)	3.360 (0.555)

- **SI**, LLMs replicano il ragionamento di specialisti quando ricevono una domanda chiara e specifica
- **NO**, al momento non offrono strategie rivoluzionarie o intuizioni cliniche inaspettate

Investigation and Assessment of AI's Role in Nutrition—An Updated Narrative Review of the Evidence

Kassem H et al. Nutrients. 2025 Jan 5;17(1):190

2. Materials and Methods

A comprehensive literature search was conducted across three databases: PubMed, Google Scholar, Scopus, Web of Science, and EBSCO. This search covered publications from 2003 to 2024 and included terms related to AI and nutrition, such as "artificial intelligence", "machine learning", "deep learning", "dietary assessment", "nutritional analysis", "clinical nutrition", "nutrition education", and "personalized nutrition". Boolean operators (AND, OR) were utilized to refine the search results. Additionally, extra records were identified by tracking the citations of the included studies.

Table 2. Summary of AI techniques, applications, implementation status, and limitations in nutrition.

AI Technique	Applications	Implementation Status	Limitations
Machine learning (ML)	Personalized nutrition, dietary pattern recognition	Partially implemented	Bias in training data
Deep learning (DL)	Nutrient composition estimation, image-based food tracking	Experimental phase	Requires large datasets
Natural language processing (NLP)	AI chatbots for dietary advice	Partially implemented	Accuracy of advice
Wearable sensors	Calorie tracking, real-time monitoring	Partially implemented	Limited availability of continuous glucose monitors
AI-Powered apps	Diet tracking and recommendations	Partially implemented	Accuracy and privacy concerns

Investigation and Assessment of AI's Role in Nutrition—An Updated Narrative Review of the Evidence

Kassem H et al. Nutrients. 2025 Jan 5;17(1):190

Table 1. AI techniques in personalized nutrition and diet planning.

Author and Year	AI Technique	Description
Maher et al., 2020 [17]	Natural language processing (NLP)	AI chatbots provide personalized dietary recommendations through natural language conversations. They guide users with portion size suggestions, physical activity goals, and dietary modifications.
Varshney et al., 2023 [18]	Machine learning (ML)	Uses data to generate personalized nutrition recommendations, identify dietary patterns and monitor food intake and nutrients composition
Abdullah et al., 2022 [21]	Deep learning (DL)	Based on artificial neural networks, it identifies unique features within datasets And helps in prediction of the nutrients relationship to humans, which will aid in creating individulaized diets
Niszczota and Rybicka, 2023 [23]	Apps like ChatGPT (limited implementation)	ChatGPT was evaluated for generating dietary recommendations. Meals created by ChatGPT were aligned with dietary guidelines, while inaccuracies in energy calculation and food allergens detection were observed
Agne and Gedrich, 2024 [24]		A comparison of ChatGPT's recommendations with the Food4Me algorithm revealed errors in linking macronutrient and micronutrient intakes with specific foods
Kim et al., 2024 [25]		A study comparing ChatGPT-generated diet plans to weight-loss diet plans used in clinic settings found that AI-generated diets closely matched the utilized clinical plans

Table 3. Application of AI in clinical nutrition.

Author and Year	AI Technique	Description
Bond et al., 2023 [44]	Deep learning (DL)	Deep learning (DL) allows for rapid muscle mass evaluations through CT imaging, (currently implemented in research settings and some clinical centers) predicts early enteral nutrition needs for ICU patients, (still requires more large-scale validation studies before widespread clinical adoption), and verifies nasogastric tube (NGT) placement with chest X-rays (being actively used in many hospitals)
	Machine learning (ML)	Assess the risk of refeeding syndrome, (currently experimental/research phase) while wearable devices monitor hydration (partially implemented), and detect infections in patients on home parenteral support (primarily experimental)
	AI-integrated smart toilets	Monitor bowel movements, detect blood in the stool, and measure stool or stoma output, providing valuable data for managing hydration and fluid balance. (Primarily experimental/prototype phase)
Janssen et al., 2024 [45]	Machine learning (ML)	Predict the likelihood and severity of adverse drug reactions based on factors like circulatory system diseases and parenteral nutrition in critically ill neonates. (Partially implemented in specialized centers)
	Machine learning (ML)	Identifying malnutrition in cancer patients shows moderate agreement with established tools like the Patient-Generated Subjective Global Assessment. (Currently in transitional phase between experimental and implemented)
	Advanced AI-assisted radiological imaging	Integrating malnutrition screening can enhance the detection of sarcopenia and accurate risk identification. (Partially implemented in clinical settings)

Review

Artificial Intelligence in Nutrition and Dietetics: A Comprehensive Review of Current Research

Panayotova GG. Healthcare (Basel). 2025 Oct 14;13(20):2579

2. Materials and Methods

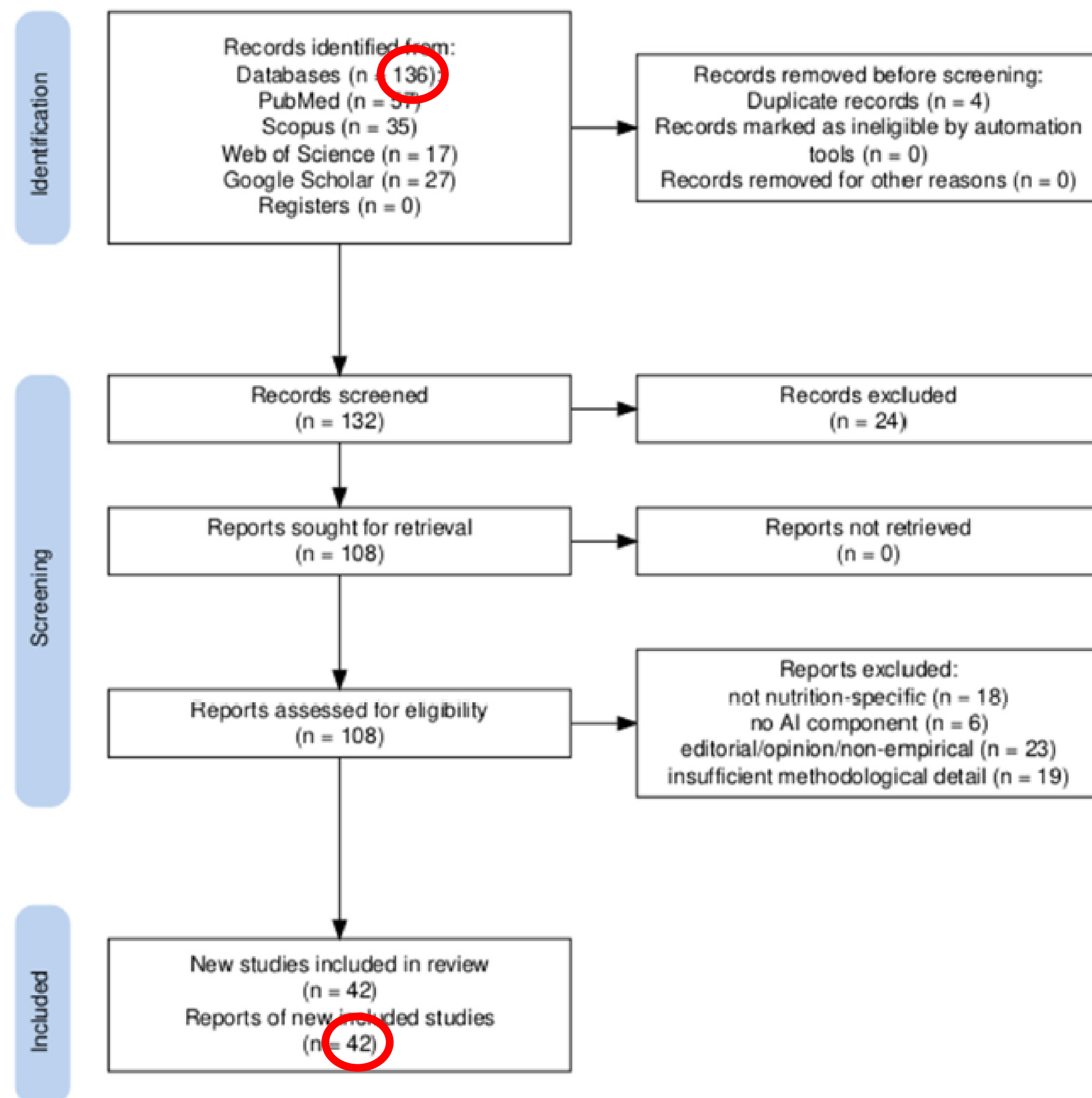
2.1. Objective and Scope

The primary objective of this review is to systematically examine and critically synthesize peer-reviewed academic literature on the current applications of AI in nutrition and dietetics. The scope encompasses a wide range of use cases, including:

- AI-driven dietary assessment and food recognition;
- Personalized nutrition planning and metabolic prediction;
- Clinical decision support in chronic disease contexts;
- Generative AI and conversational agents in patient education;
- Mobile health applications and remote coaching;
- Ethical, regulatory, and professional practice considerations.

2.2. Search Strategy

A comprehensive literature search was conducted across several scientific databases, including PubMed, Scopus, Web of Science, and Google Scholar. The search spanned publications from January 2020 to July 2025, ensuring the inclusion of recent developments in AI and its integration with nutrition science. Representative search terms included "Artificial Intelligence", "Machine Learning", "Deep Learning", "Natural Language Processing", "Large Language Models", combined with "Nutrition", "Dietetics", "Dietary Assessment", "Personalized Nutrition", "Diet Planning", "Malnutrition", "Virtual Health Coaching", and "Nutrition Education".



Review

Artificial Intelligence in Nutrition and Dietetics: A Comprehensive Review of Current Research

Panayotova GG. Healthcare (Basel). 2025 Oct 14;13(20):2579

Table 1. Overview of AI techniques used in nutrition and dietetics (methods-oriented summary).

AI Technique	Application Area	Examples	Strengths	Limitations
Machine Learning (ML)	Dietary assessment, predictive modeling	Prediction of nutrient intake patterns; risk stratification for T2DM/obesity	Learns from large datasets, identifies hidden patterns, adaptable to diverse contexts	Requires large, high-quality datasets; risk of bias from training data
Deep Learning (DL)	Food image recognition, portion estimation	CNN-based food recognition apps (e.g., FoodAI, DietCam)	High accuracy in visual classification; reduces self-report errors	Limited generalizability; depends on food image databases
Natural Language Processing (NLP)	Conversational agents, dietary advice	Chatbots simulating dietitians; LLM-based nutrition Q&A	Enables real-time dialogue, supports education, improves accessibility	Challenges in ensuring accuracy, potential for misinformation
Large Language Models (LLMs)	Virtual coaching, education, health literacy	ChatGPT-based nutrition assistants, personalized diet advice	Generates tailored responses, scalable, user-friendly	Explainability issues, prone to hallucinations, ethical concerns
Reinforcement Learning (RL)	Behavior change support, personalized recommendations	Adaptive diet plans based on user adherence	Learns dynamically from user feedback, supports habit formation	Computationally intensive; limited testing in nutrition contexts
Hybrid Models (ML + Sensors/IoT)	Continuous monitoring, precision nutrition	Wearables integrating HRV, glucose, activity with AI-driven diet feedback	Combines physiological + behavioral data; supports real-time personalized nutrition	Data privacy issues; requires interoperability of devices
Generative AI	Food innovation, flavor design	AI-assisted flavor compound generation, recipe development	Creative potential; accelerates product development in sensory science	Early stage; limited validation of consumer acceptance

Review

Artificial Intelligence in Nutrition and Dietetics: A Comprehensive Review of Current Research

Panayotova GG. Healthcare (Basel). 2025 Oct 14;13(20):2579

Theme	Key Issues	Implications for Practice
Bias in Training Data	Underrepresentation of certain populations, cultural food diversity not captured	Risk of inaccurate or inequitable recommendations for minority and low-income groups
Transparency & Explainability	Black-box nature of deep learning and LLMs	Reduced trust among clinicians and patients; difficulty in verifying recommendations
Data Privacy & Security	Sensitive dietary, medical, and biometric data at risk	Potential breaches of GDPR/HIPAA compliance; erosion of patient trust
Professional Roles	Concerns that AI might replace dietitians	Threat to professional identity; fear of devaluation of expertise
Task-Shifting	Delegation of routine tasks to AI systems	Risk of oversimplifying complex patient cases
Education & Training Needs	Lack of digital/AI literacy among dietitians and nutritionists	Risk of misuse or over-reliance on AI systems
Accountability & Liability	Ambiguity about responsibility when AI advice causes harm	Legal and ethical uncertainty for clinicians and institutions
Equity in Access	Limited availability in low- and middle-income countries	Risk of widening global health disparities

Etica e AI

- **AI deve essere sempre sotto controllo umano**
- Trasparenza e spiegabilità non sono optional
- Sicurezza, privacy e equità devono guidare lo sviluppo
- I modelli attuali violano spesso le leggi esistenti (ad es. GDPR)
- Le Big Tech sono dominanti, servono alternative pubbliche
- I LMMs devono essere regolamentati come dispositivi medici quando usati
- Monitoraggio continuo obbligatorio (drift, errori, bias)
- Governance internazionale per evitare disuguaglianze globali

Conclusioni

- **L'AI è già parte della nutrizione clinica:** ML e DL stanno potenziando la previsione del rischio nutrizionale e clinico, l'analisi della composizione corporea, la personalizzazione della dieta e il riconoscimento automatico degli alimenti. Le applicazioni disponibili sono già promettenti.

- **La sua integrazione nei sistemi clinici è inevitabile** ma richiede qualità dei dati, interoperabilità, mitigazione dei *bias* e solide basi etiche e regolatorie.

- **È necessaria una validazione rigorosa:** trasparenza dei modelli, inclusione di popolazioni diverse, verifiche periodiche delle prestazioni e supervisione clinica costante sono essenziali per garantire sicurezza ed equità.

- **L'AI è uno strumento, non un sostituto del clinico:** funziona come *decision support*, *early warning system* e acceleratore dell'efficienza. **La decisione finale rimane umana e richiede nuove competenze di AI *literacy*.**

Grazie per l'attenzione