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REVIEW ARTICLE

The role of artificial intelligence in dietetic practice: a narrative review of current evidence and practical applications

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Background: The global nutrition landscape is shifting from population-based advice towards hyper-personalised clinical care, driven by a 'data drown' from wearable sensors and digitised health records. Artificial intelligence (AI) has emerged as a pivotal assistive technology to navigate this complexity, transitioning from a theoretical construct to a practical clinical 'co-pilot'.
Objective: This review explores the integration of AI subfields, including machine learning (ML), deep learning (DL), and natural language processing (NLP), into the nutrition care process (NCP), and the specific regulatory and ethical landscape facing South African Registered Dietitians (RDs).
Discussion: AI-driven tools enhance the NCP by improving the accuracy of dietary assessments through computer vision, automating malnutrition screening via predictive modelling and optimising high-stakes interventions such as total parenteral nutrition (TPN) in neonatal care. Additionally, the review examines emerging applications of AI in institutional food service management, including intelligent menu planning, automated procurement and food waste reduction, domains that are integral to the South African Registered Dietitian's scope of practice but have received comparatively limited attention in the literature. However, the transition to AI-augmented practice introduces risks of algorithmic bias, 'de-skilling' and AI 'hallucinations'. Within the South African context, practitioners must navigate stringent requirements set by the Health Professions Council of South Africa (HPCSA) Booklet 20 and the Protection of Personal Information Act (POPIA). The use of clinical-grade prompt engineering, such as the PCCF (Persona, Context, Constraints, and Format) framework, is presented as a vital competency to ensure medically and culturally appropriate outputs.
Conclusion: AI should be positioned as a clinical co-pilot that amplifies the impact of the dietitian rather than a substitute for professional autonomy. By maintaining a 'human-in-the-loop' approach and adhering to local regulatory frameworks, South African dietitians can leverage AI to address the nation's unique nutritional double burden and promote health equity.

Keywords : artificial intelligence, clinical dietetics, food service management, nutrition care process, precision nutrition, South Africa, therapeutic nutrition

Introduction: navigating the 'data drown'

The global nutrition landscape is undergoing a profound transformation, shifting away from traditional population-based dietary advice toward hyper-personalised clinical care.[1] This evolution is primarily driven by the 'data drown', related to the overwhelming surge of health information originating from wearable sensors, continuous glucose monitors (CGMs) and digitised food records.[2]

Historically, dietitians relied on subjective patient recalls, paper-based calculations, manual anthropometry and snapshot laboratory values.[3] However, as modernity begins to integrate into the artificial intelligence (AI) space, patients are beginning to expect actionable, data-driven insights that account for their unique biological and lifestyle variables. Without proactive integration of these technologies with everyday work, dietitians are at risk of failing to meet these expectations, losing responsiveness, efficiency and relevance in the context of patient care.[3]

AI has transitioned from a theoretical computer science construct into a pivotal assistive technology within nutrition research and clinical practice.[4,5] By leveraging high-speed computational processing, AI identifies intricate, non-linear correlations between dietary patterns and health outcomes within large-scale clinical datasets, patterns often inaccessible via traditional statistical methods. For the registered dietitian (RD), these advancements facilitate enhanced diagnostic accuracy through automation and predictive modelling, enabling a strategic shift in professional focus toward high-value, human-centric interventions: empathy, motivational interviewing and sustainable behavioural coaching.

Defining AI for the clinical practitioner

A foundational understanding of the specific AI subfields driving modern nutrition technology is essential for the effective integration of these tools into the South African clinical landscape. That said, AI and its subfields are continuously expanding, making it essential to harness a definition to avoid confusion and misunderstanding.[2] Broadly defined, AI refers to the science and engineering of creating intelligent machines and computer programs capable of performing tasks that traditionally require human intelligence, such as visual perception, reasoning, decision-making, and general problem-solving.[2,4,5] At its most fundamental level, AI includes automation and rule-based systems, which involve computers following explicit, predefined instructions to remove repetitive manual work.[5]

In a dietetic context, this is practically applied through digitised intake systems and data synchronisation across various platforms, which streamline administrative workflows by ensuring patient information is structured and verified.[4,5] Machine learning (ML), deep learning (DL), natural language processing (NLP) and large language models (LLMs) are examples of subtypes of AI.

Machine learning
ML serves as a critical subtype of AI, utilising statistical techniques that allow algorithms to learn from experience and patterns in data without being explicitly programmed for every specific clinical scenario.[4–6] Practically, ML models can analyse extensive datasets to identify complex, non-linear interactions and forecast outcomes, such as predicting a patient's glycaemic response to specific meal patterns or identifying significant nutritional variables linked to cardiovascular disease risk.[2,5,7]

Deep learning
DL represents a further specialised subset of ML based on artificial neural networks that mimic the synaptic connections and cognitive functions of the human brain.[5,8] This technology is essential for handling high-dimensional, multi-modal data, enabling advanced practical applications for the RD, such as identifying unique individual biochemical signatures and gut microbiome patterns to inform personalised dietary guidelines.[9] Furthermore, vision-based DL systems utilise computer vision and 3D reconstruction to automatically detect food items, estimate portion volume from single-view photographs, and predict malnutrition risk based on longitudinal patient trajectories.[2,10,11]

Natural language processing and large language models
Last, NLP and LLMs, such as ChatGPT, Google Gemini or Microsoft Copilot, emphasise the interaction between human language and computers to provide real-time, personalised education.[1,4] In everyday practice, these conversational agents can be utilised to automate clinical note-taking, interpreting session transcripts and converting them into structured medical records, reducing the administrative burden on practitioners.[1,4] These systems also offer potential for providing interactive dietary advice and simplifying complex nutritional guidelines for patients, thereby supporting behavioural 'nudging'.[12] Another example of NLP is latent Dirichlet allocation (LDA), a probabilistic generative AI model, able to uncover hidden themes, patterns and topics within large, unstructured datasets. This is particularly useful in the context of dietetics, allowing an integrated analysis of dietary patterns, disease risk and trends.[13]

Precision nutrition: redefining clinical management and nutrition surveillance through AI
The potential for AI to revolutionise the management of specific diseases, such as Type 2 diabetes mellitus (T2DM), chronic kidney disease (CKD) and cardiovascular diseases, is immense, yet it remains a domain that requires rigorous human adjudication to ensure clinical safety and efficacy.[14]

Management of type 2 diabetes mellitus
In the context of T2DM, AI models such as XGBoost are being utilised to analyse digitalised medical data to predict one-year HbA1c changes, which assists nutritional professionals in making proactive, informed decisions regarding appropriate medical nutrition therapy (MNT) interventions.[5] Furthermore, research into LLM-based AI has demonstrated a remarkable ability to generate ketogenic or Mediterranean-style meal plans that overlap with expert nutrition recommendations by over 80%.[15]

However, significant gaps persist in these AI-derived outputs.[16] These systems often neglect critical hallmarks of professional diabetes management such as precise carbohydrate counting, the specific timing of meals and snacks, and the establishment of energy deficit targets for weight loss.[16] This lack of holistic lifestyle integration is further complicated by genetic variability; for instance, variations in the TCF7L2 gene are associated with a heightened risk of T2DM and can dictate an individual's specific metabolic response to dietary carbohydrates, a level of clinical nuance that most current consumer AI models fail to capture.[9]

Applications in chronic kidney disease
In the management of chronic kidney disease (CKD), AI systems have shown promise in automating disease-stage classification and providing customised diet plans based on complex patient data.[6] Nevertheless, qualitative evaluations have highlighted a fundamental limitation in the ability of AI to resolve conflicting clinical and cultural considerations.[14] A notable example includes an AI model prioritising a patient's preference for 'Spanish cuisine' by recommending tomato-rich dishes, despite tomatoes being contraindicated in advanced renal insufficiency due to the high potassium and electrolyte content.[14] Such errors in clinical prioritisation underscore the reality that while AI can simulate a personalised recipe, it lacks the contextual judgment to prioritise a renal restriction over a cultural preference without expert human guidance.[14]

AI in hospital and disease-related malnutrition
Hospital malnutrition, particularly disease-related malnutrition (DRM), represents another critical area where AI is bridging significant gaps in current clinical practice.[11] Globally, DRM is a frequent, yet underdiagnosed, concern associated with increased morbidity, mortality and escalating healthcare costs.[11] In South Africa, the burden of malnutrition is exacerbated by socioeconomic determinants and resource constraints within the public health sector, where institutional factors such as understaffing and a lack of anthropometric equipment like stadiometers often cause nutritional risk to go unnoticed.[17] Reports indicate that in certain South African hospital samples, as many as 57% of patients meet the criteria for a malnutrition diagnosis, highlighting an urgent need for more efficient screening strategies.[17] Using AI automated tools in malnutrition poses benefits to earlier detection, limiting the development into long-term consequences.[11]

Advanced imaging and sarcopenia detection
AI is currently transforming this landscape through models like MUST-Plus, which leverages electronic health record (EHR) data and supervised ML to accurately predict malnutrition risk by synthesising clinical assessments, physiological data and laboratory results in real-time.[11] Beyond basic screening, deep learning models (DLMs) are being applied to advanced medical imaging, such as CT scans, to achieve high segmentation accuracy for muscle tissue.[18] This allows for the early detection of sarcopenia and potentially reversible cancer cachexia in oncology patients, a task that is often too labour-intensive for manual clinical evaluation.[18]

Precision nutrition in neonatal care
The precision offered by AI extends into high-stakes environments such as the neonatal intensive care unit (NICU), where total parenteral nutrition (TPN) is a lifesaving but error-prone intervention.[19] The TPN2.0 algorithm, trained on a decade of EHR data, has demonstrated the ability to standardise TPN compositions with a precision level comparable to human experts.[19] In blinded clinical studies, physicians rated these AI-guided formulas higher than current best practices, and the model was able to identify infants at elevated risk for morbidities, including

necrotising enterocolitis and sepsis, earlier and more consistently than traditional methods.[19] These advancements suggest that while the 'human touch' of the RD remains irreplaceable for behaviour change, AI acts as an essential 'co-pilot' for the mass data synthesis and complex calculations required for modern clinical precision.

Integrating AI across the nutrition care process

The nutrition care process (NCP) serves as the standardised framework for critical thinking and evidence-based practice, ensuring that dietetic interventions are systematic, measurable and patient-centred. AI now serves as a comprehensive clinical support tool integrated across all stages of the NCP,[9] fundamentally transforming each stage of this process to provide RDs with a sophisticated clinical co-pilot capable of navigating the escalating volume and complexity of patient data.

Nutrition assessment

Dietary assessment remains a cornerstone of the NCP, yet traditional methods are frequently compromised by significant recall bias and systematic reporting errors.[5] AI is transforming this phase by synthesising complex datasets from multiple sources, including nutrigenomics, metabolomics and longitudinal EHR trajectories, to identify physiological patterns often imperceptible to manual analysis.[9]

Central to this shift are vision-based AI tools, such as goFOOD™ 2.0, NutrifyAI and Bitesnap, which utilise computer vision and DL to identify food items and estimate portion sizes directly from photographs.[10] Specifically, systems employing advanced convolutional neural networks, such as YOLOv8, have achieved food recognition accuracies of approximately 80%, while specialised vision transformer models have reached classification accuracies as high as 88.97%.[6,10] Beyond image recognition, LLMs like ChatGPT have demonstrated clinical utility. Recent evaluations show that LLM-generated energy estimations fall within 10% of United States Department of Agriculture (USDA) benchmarks in 66.4% of cases.[20] By providing immediate, objective dietary insights, these technologies significantly reduce the administrative burden on the clinician and the subjective bias inherent in patient self-reporting.

Nutrition diagnosis

For nutrition diagnosis, automated screening systems such as the MUST-Plus model utilise ML to predict risk with higher precision than traditional paper-based questionnaires.[11] While LLMs can be prompted to draft diagnostic statements, current research cautions that they often produce incomplete Problem, Etiology, and Signs/Symptoms (PES) statements, frequently missing standardised diagnostic terminology or failing to prioritise clinical urgency over patient preference.[14]

Nutrition intervention

In the nutrition intervention phase, AI-driven recommendation engines can generate personalised daily meal plans that align with specific global standards or specialised patterns, such as the DASH or Mediterranean diets.[15,16] Furthermore, AI transcription and scribing tools like Heidi Health or Docy allow clinicians to convert verbal consultations directly into structured medical records.[8] This automation enables RDs to remain fully present during the patient encounter, diverting cognitive energy away from manual entry and towards motivational interviewing and therapeutic engagement.[4]

Nutrition monitoring and evaluation

Finally, during monitoring and evaluation, the integration of wearables and mobile sensors enables 'dynamic surveillance', allowing the RD to observe real-time physiological responses, such as blood glucose or heart rate changes, and adapt therapeutic interventions based on the patient's evolving biological needs.[5] This continuous feedback loop ensures that the intervention remains efficacious and responsive to the patient's real-world environment.[21]

Practical applications of AI in dietetic practice

By shifting the professional burden from manual data management toward high-level clinical synthesis, AI may empower practitioners to optimise diagnostic precision, while refocusing on the human-centric pillars of care: empathy, relational ethics and behavioural change.[6] The following subsections present practical AI applications across the four recognised domains of the South African registered dietitian's scope of practice: therapeutic nutrition, food service management, community nutrition and nutrition research, with documentation and administrative support functioning as an enabler across all domains.

Clinical documentation and administrative relief

In modern healthcare settings, administrative duties can consume up to a quarter of a practitioner's working hours, often leading to significant administrative fatigue.[8] This burden is increasingly alleviated through intake automation and digital synchronisation using South African-relevant platforms such as Bookem, Kalix and Practice Better. Furthermore, AI-driven scribing and transcription tools like Heidi Health, Otter.ai, Wonder and Docy can convert verbal consultations into structured medical records, within the Assessment, Diagnosis, Intervention, Monitoring, and Evaluation (ADIME) format.[8] Beyond simple transcription, advanced NLP models are able to interpret and summarise these clinical conversations, achieving similarity rates to manual documentation as high as 87.5%.[4] This automation enables RDs to remain fully present during the patient encounter, diverting cognitive energy away from manual entry and towards motivational interviewing and therapeutic engagement.[4]

AI in therapeutic nutrition practice

AI is demonstrating increasing utility across the breadth of therapeutic nutrition practice, from precision metabolic management in high-acuity clinical settings to personalised behavioural coaching in outpatient and community-based care.

AI is facilitating a significant shift toward precision medicine in high-stakes clinical environments, such as the NICU, where TPN is a critical but subjective and error-prone therapy.[19] The TPN2.0 algorithm, developed using a decade of longitudinal EHR data, has demonstrated the ability to standardise TPN compositions with a precision level comparable to expert neonatologists, achieving a Pearson's correlation of 0.94.[19] In blinded studies, physicians rated TPN2.0 formulas as superior to current best practices, largely because the system can identify infants at elevated risk of complications, such as mortality (78%), necrotising enterocolitis (73%) and bronchopulmonary dysplasia (71%), much earlier than traditional screening methods.[19] This precision mitigates the risks associated with subjective administration and optimises nutrient delivery during the most vulnerable stages of life.[19]

Behavioural nudging and coaching

To support long-term adherence to therapeutic lifestyle modifications, nutritional professionals are increasingly employing AI virtual coaches such as Paola, eTRIP and GlucoGoalie.[12] These systems use conversational agents to provide 24/7 'behavioural nudging', offering real-time feedback on portion sizes and physical activity goals.[12] Clinical evaluations show that daily interaction with these AI-assisted platforms significantly increases the likelihood of a patient achieving their weight management objectives.[22] For example, participants using these tools have demonstrated clinically significant results, including weight loss ranging from −0.8 kg to over 13% of baseline bodyweight, alongside measurable reductions in waist circumference over 12-week intervention periods.[12]

AI in institutional food service management

Beyond direct patient care, AI holds considerable potential for transforming institutional food service management (FSM), an area that falls squarely within the South African registered dietitian's scope of practice yet has received comparatively limited attention in the published literature on AI and nutrition.[5] In resource-constrained public health settings, dietitians are frequently required to oversee the planning, procurement and nutritional adequacy of meals for large patient populations, often with limited administrative support. AI-driven menu planning systems, such as the Menu Information and Knowledge Acquisition System (MIKAS), represent an early but instructive example of how knowledge-based models can automate the construction of nutritionally complete menus by leveraging incremental learning from expert dietitian input.[23] More contemporary ML-based approaches are now capable of simultaneously optimising menus against multiple competing constraints, including nutrient targets, therapeutic dietary restrictions, patient preferences and institutional procurement budgets, a level of multi-variable optimisation that is highly relevant to the South African hospital context.[24]

AI is also being applied to the operational dimensions of food service, including predictive inventory management, automated procurement scheduling and food waste quantification.[4] By analysing historical meal uptake data, patient census records and supply chain variables, predictive algorithms are capable of substantially reducing food wastage in hospital settings, a meaningful consideration given that food waste represents a significant financial and environmental burden within the South African public health system.[26] Furthermore, computer vision systems have demonstrated the capacity to monitor tray return data in real time, detecting patterns of poor oral intake at a population level and flagging at-risk patients for prioritised dietetic review.[2] Although many of these FSM applications remain in developmental or pilot phases, their trajectory suggests that AI will increasingly serve as an operational co-pilot for the food service dietitian, automating routine logistical functions while enabling practitioners to redirect their expertise toward therapeutic and quality assurance roles.

AI in community nutrition and nutrition research

The application of AI extends beyond the individual patient encounter into the domains of community nutrition and nutrition research, both of which form core elements of the South African dietitian's scope of practice. Population-level surveillance, public health nutrition monitoring, the prediction of nutrition-related disease trends and the management of food security challenges are addressed in detail in the following section. The academic and research applications of AI, including its implications for nutrition research methodology, evidence synthesis and academic integrity, are similarly discussed therein.

Beyond the individual: system-level implications of AI in nutrition

Application and use of AI reaches beyond precise nutrition and patient health, harnessing potential for widespread public health nutrition research, nutrition-related disease surveillance and transformations in the nutrition-related economic landscape.

Enhanced population surveillance and disease prediction

Public health nutrition surveillance is well known to be time consuming and error prone, relying on manual data collection and analysis.[2] The implementation of AI facilitates data accessibility beyond traditional manual collection methods, allowing for the integration of multi-dimensional datasets from wearables and EHRs.[2,24] Multi-dimensional data from wearable devices, mobile dietary assessment tools, EHRs and large-scale population databases can be integrated and analysed, harnessing the potential to monitor risks and trends in non-communicable diseases (NCDs), predict dietary behaviours of populations, optimise resource allocation to critical areas, determine efficient nutritional interventions based on global stratification and inform on nutrition-related concerns through the use of chatbots and messaging apps such as WhatsApp.[25] AI holds potential for utilisation in food security, monitoring global food supply chains and predicting climate-related disruptions, thus improving timely intervention.[24] Despite these benefits, ethical challenges, risk of bias and data privacy may need to be addressed prior to the use of AI in public health. Also, many studies are small-scale, with need for more long-term cohorts and mixed-method studies prior to AI being implemented in public health and economic policies.[26]

Economic scalability of AI-supported nutrition services

The global economic burden of nutrition-related health-costs is rising.[27] Obesity, a nutrition-related disease, is estimated to cost $2 trillion annually, 3% of the global gross domestic product. Future predictions indicate that, if not addressed, costs will double in the next decade, and reach $18 trillion by 2060.[28]

Through the use of AI in the provision of nutrition services, healthcare costs can be significantly reduced. A systematic review on 24 studies found that AI implementation in healthcare could reduced by 5–10%. This is due to the benefits of inefficiency reduction, clinical note automation, diagnostic time reductions and administrative functioning. Administrative function in particular is a high-cost, low-clinical risk task, and through AI integration, cost- and time efficiencies improve.[26]

Navigating ethical, regulatory and professional challenges in dietetics

As AI transitions from a theoretical novelty to a practical clinical tool, the dietetic profession faces a complex array of challenges that extend beyond simple technical accuracy to encompass deep-seated professional, ethical and legal concerns.[4] A central and pervasive anxiety remains the perceived threat of professional displacement. However, current evidence strongly supports a model of human–AI augmentation rather than substitution.[1] While AI systems possess an unparalleled capacity to manage the modern 'data drown', synthesising information from wearables, biochemical markers and longitudinal records with a speed and complexity unmatched by human cognitive functions, AI remains fundamentally limited in its inability to form the authentic human bonds essential for therapeutic success.[5] Machines lack the empathy, emotional intelligence and contextual judgment required for effective motivational interviewing and the nuanced navigation of a patient's lived experience.[21] Consequently, a task-shifting paradigm is emerging where AI acts as a sophisticated 'co-pilot', managing administrative burdens and complex data processing, thereby liberating the RD to focus on the uniquely human aspects of clinical decision-making and long-term behaviour change.[1]

Risks of de-skilling and algorithmic errors

An over-reliance on automated systems carries the significant risk of 'de-skilling' the healthcare workforce.[8] If practitioners defer critical reasoning to algorithms without active adjudication, there is a legitimate concern that independent diagnostic abilities and clinical vigilance may begin to erode over time.[8] This is particularly dangerous when considering that AI remains prone to 'hallucinations': the generation of highly confident but entirely erroneous statements.[14] In safety-critical nutritional management, such as allergen identification or the calculation of micronutrient targets for complex comorbidities, the failure of AI to recognise specific clinical contraindications may lead to harmful patient outcomes.[16]

The utility of AI in clinical practice is dependent on the quality of the practitioner's input, a skill known as prompt engineering.[16] The components of the PCCF (Persona, Context, Constraints, and Format) framework are derived from the foundational principles of prompt engineering for healthcare.[29] The PCCF framework is a clinical-grade prompt engineering strategy designed to minimise AI 'hallucinations' and ensure that outputs are medically and culturally appropriate for the South African context. While general prompting relies on simple queries, this framework forces AI to operate within the established boundaries of the dietetic profession.

Table 1 provides three distinct examples for each pillar of the framework, illustrating how to shift from general requests to precise clinical instructions.

The 'human-in-the-loop' and verification mandate

To mitigate these risks, current evidence emphasises that the RDs must remain the 'human-in-the-loop', serving as the final clinical validator for all automated outputs.[21] This oversight is professionally essential given the documented inaccuracies in quantitative AI outputs. For example, while LLMs like ChatGPT demonstrate promising consistency with an average 3.3% coefficient of variation for energy intake, nearly 97% of its energy estimations fall within only a 40% margin of error compared with standard USDA benchmarks.[20] Consequently, dietitians are mandated to verify all AI-generated calculations to ensure they meet the rigorous accuracy standards required for safe MNT.[30]

Mitigating algorithmic bias and promoting health equity

The issue of algorithmic bias remains a profound ethical concern that South African RDs must proactively mitigate to prevent the widening of healthcare inequalities.[21] Because many AI models are trained on historical datasets that are skewed toward Western, high-income populations, there may be a lack of representative understanding of diverse dietary patterns and unique biological traits.[1] For example, training data featuring individuals of European or North American ancestry may lead to recommendations that are clinically inappropriate for local populations.[21] A specific illustration of this bias involves individuals of West African ancestry who are often genetically more salt-sensitive and at higher risk of hypertension. AI trained on a non-diverse population may fail to prioritise the low-sodium guidelines recommended for this group, thereby exacerbating existing health disparities.[21]

The South African regulatory landscape

In the South African context, RDs must navigate the stringent regulatory and ethical landscape defined by the HPCSA and the Protection of Personal Information Act (POPIA).[30] The HPCSA's recent release of Booklet 20 (2025) provides a crucial framework for the ethical integration of AI, stipulating that these tools must strictly serve an assistive role to enhance human intelligence.[30] One of the most significant mandates within these guidelines is the requirement for professional competency, which dictates that practitioners may only utilise AI tools within their established areas of expertise and cannot use technology to compensate for personal knowledge gaps. Furthermore, the RD must maintain absolute clinical authority, remaining legally and professionally liable for the final decision on patient care regardless of the digital assistance employed.[30] Accountability for errors is a cornerstone of this guidance, and practitioners are mandated to provide transparent disclosure to patients whenever AI has meaningfully shaped a diagnosis or treatment plan.[30]

Data security and POPIA compliance

Complementing these professional standards is the legal requirement for POPIA compliance, which classifies health data as 'special personal information'.[30] This designation necessitates that RDs obtain explicit, informed patient consent for data processing and maintain robust, high-security storage protocols.[30] A significant risk in modern practice involves the inadvertent sharing of identifiable patient-specific information on open, public AI platforms, such as the free version of ChatGPT, which may constitute a profound breach of patient confidentiality and legal duty.[21] Practitioners must ensure that any AI system utilised for patient records or clinical analysis is technically robust, reproducible and compliant with both cybersecurity standards and the requirements of the South African Health Products Regulatory Authority (SAHPRA).[30]

Academic integrity and future professional training

The integration of AI extends into the pedagogical foundations of the next generation of nutrition professionals.[1] There is an imperative to incorporate AI literacy and digital fluency into university curricula, enabling students to critically evaluate algorithmic outputs and comprehend the underlying mechanisms of technology-assisted care.[1] However, this shift necessitates a robust evolution of academic integrity frameworks.

Traditional plagiarism declarations, which focused on the unauthorised use of peer-authored text, must be modernised to include explicit disclosures regarding the use of generative AI (GenAI). In alignment with the HPCSA guidelines,[30] both students and practitioners must adopt ethical declarations when AI is utilised for data synthesis or content organisation. Such disclosures reinforce the principle that the human practitioner, whether a student in training or a private practicing dietitian, retains ultimate responsibility for the interpretive accuracy,

Table 1: The PCCF framework: tabulated examples for dietetic practice

Pillar	Description	Example 1: Acute care	Example 2: Private practice	Example 3: Public health
Persona	Assigns a professional identity and 'area of expertise' to the AI	'Act as a clinical ICU dietitian specialising in metabolic support and refeeding syndrome'	'Act as a specialist South African private practice dietitian with expertise in paediatric food allergies'	'Act as a community nutritionist focusing on food security and stunting in rural South African districts'
Context	Provides the necessary patient markers, clinical status and health goals	'The patient is a 65-year-old female in the ICU, post-prolonged fasting, with low serum phosphate and potassium'	'The patient is a 4-year-old male with a confirmed shellfish and tree nut allergy, exhibiting poor growth and selective eating'	'I am working with a household of 6 in an informal settlement with limited electricity and a reliance on maize-based staples'
Constraints	Establishes clinical guardrails, cultural restrictions and safety exclusions	'Exclude all enteral fibre formulas; ensure protein does not exceed 12 g/kg in the first 24 hours'	'Do not suggest any processed snacks; recipes must be nut-free and use ingredients found in major SA retailers'	'Recommendations must be low-cost; avoid recipes requiring long boiling times due to fuel constraints'
Format	Specifies the required structure for the final professional end-product	'Generate an ADIME note suitable for a hospital electronic health record'	'Prepare for me a 3-day meal plan in a table format for me to present to his mother, along with a grocery list'	'Provide a bulleted list of 5 educational talking points in simplified English for a caregiver handout'

clinical validity and ethical application of the information presented.

The following may be adapted for student assignments, corporate presentations, or formal clinical literature reviews:

- For academic submissions (students): 'I hereby declare that GenAI tools [specify tool, e.g. ChatGPT-4] were utilised in the preparation of this work. I confirm that all clinical interpretations, literature syntheses, and final conclusions are my own, and I remain fully accountable for the accuracy and integrity of the content.'
- For corporate presentations (private practice): 'Portions of the data visualisation and content organisation in this presentation were assisted by AI. All nutritional recommendations and evidence-based insights have been independently verified by a RD to ensure compliance with South African clinical guidelines and HPCSA ethical standards.'
- For consulting projects: 'This technical report utilised AI-assisted search and synthesis protocols to manage large datasets. However, the selection of source material, the critical appraisal of evidence, and the resulting professional recommendations were conducted manually by the author to ensure clinical relevance and scientific rigour.'
- Short-form disclaimer (footnote/slide footer): 'AI-assisted content: All outputs have been professionally audited for clinical accuracy and original thought by the undersigned RD.'

Conclusion: the future of the digital dietitian

AI represents an opportunity to redefine the boundaries of clinical nutrition and scale the impact of nutritional professionals in South Africa. While AI can process data at speeds unmatched by humans, its true value lies in a task-shifting model where the machine handles menial administrative and computational burdens, thereby liberating the practitioner to perform the uniquely human roles of empathy, cultural adaptation and motivational interviewing.[1,21]

Realising this potential requires a transition from passive adoption to proactive, evidence-based stewardship. Clinicians must act as critical evaluators of AI-generated outputs, manually verifying the correctness, clinical relevance and appropriateness of all information before it is communicated to the client. In alignment with the clinical authority and professional vigilance mandated by the Health Professions Council of South Africa (HPCSA), the professional remains ultimately responsible for every dietary prescription and intervention. Consequently, any technological error or 'hallucination' does not absolve the practitioner of accountability. Professional liability for patient outcomes cannot be delegated to an algorithm, and the practitioner must be prepared to defend the clinical validity of every automated insight employed.

By mastering emerging technical competencies, such as prompt engineering, and ensuring rigorous compliance with the Protection of Personal Information Act (POPIA), South African practitioners can transform contemporary data saturation into a robust vehicle for precision care.

Ultimately, AI should be positioned not as a challenge to professional autonomy, but as a clinical co-pilot that amplifies dietetic impact across the continuum of nutrition care. By leveraging these technologies to enhance precision, efficiency and scalability, the profession is better equipped to address South Africa's unique nutritional double burden. In this context, AI serves as a catalyst for health equity, ensuring that evidence-based nutrition care is recognised and delivered as a fundamental human right for all South Africans.

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