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Corresponding author:
Pratyasha Saha;
Email: axq22jnu@uea.ac.uk

Pratyasha Saha and James Holmes are Joint first authors.

From screening to prediction: rethinking malnutrition risk in primary care

Pratyasha Saha[1], James Holmes[1], Charlotte Davies[1], Alison Smith[2], Kathryn Richardson[1], Jane Skinner[1], Helen Parretti[1], Alexander MacGregor[1] and Ailsa Welch[1]

[1]University of East Anglia, UK and [2]Hertfordshire and West Essex Integrated Care Board, UK

Abstract

Despite more than 90% of cases arising in the community, malnutrition is under-recognised in UK primary care. Current screening tools such as the Malnutrition Universal Screening Tool identify malnutrition once it is already established and are inconsistently implemented. As a result, malnutrition is detected late, after functional decline and avoidable harm have already occurred. Our narrative review highlights that existing malnutrition prediction tools were largely developed in hospital populations, show variable accuracy, and have not been validated for community use. Emerging machine-learning models demonstrate feasibility but are similarly limited. We outline the urgent need for automated, data-driven prediction models drawing on routinely collected primary-care data – such as weight trajectories, comorbidities, medications, and biochemistry markers – to identify individuals at future risk of malnutrition. A proactive, electronic health record-embedded approach could shift practice from reactive diagnosis to early intervention, with the potential to improve outcomes and reduce inequalities.

Background

Malnutrition and undernutrition are highly prevalent and under-recognised in high-income countries, affecting more than three million people a year in the UK and with more than 90% of cases in the community (Russell and Elia, 2010). Malnutrition has disproportionate impacts in areas of social deprivation and in adults aged over 65 years (Dent *et al.*, 2023). Consequences are wide-ranging and include impaired wound healing, infection, hospitalization, functional decline, sarcopenia, frailty, and mortality (Saunders and Smith, 2010).

Although numerous definitions of malnutrition exist, two are widely used in clinical and research settings. The Global Leadership Initiative on Malnutrition defines malnutrition as the presence of at least one phenotypic criterion (non-volitional weight loss, low body mass index [BMI], or reduced muscle mass) and one aetiologic criterion (reduced food intake or assimilation, or inflammation/disease burden) (Barazzoni *et al.*, 2022). The National Institute for Health and Care Excellence (NICE) 2006 guidelines adopt a broader definition, defining malnutrition as a state in which a deficiency of nutrients (such as energy, protein, and vitamins and minerals) cause measurable adverse effects (on body composition, function, or clinical outcomes) (Nutrition support for adults: oral nutrition support, enteral tube feeding and parenteral nutrition Clinical guideline CG32, 2006).

In routine medical practice, malnutrition is commonly interpreted as protein-energy deficiency manifesting as weight loss, rather than micronutrient deficiency. Protein-energy malnutrition and micronutrient deficiency are distinct but overlapping clinical entities; the latter can occur without overt weight loss and may relate to poor diet quality, malabsorption, medication effects and social deprivation. Both are common in older adults, people with multiple long term conditions, frailty, and polypharmacy, and often coexist. In this review, we distinguish between these concepts while considering how future prediction models might capture features of both.

Malnutrition is often diagnosed reactively – for example after hospital admission or functional decline – representing a missed opportunity in an ageing population often living with multiple long-term conditions (Dent *et al.*, 2023). Several screening tools have been developed to identify malnutrition; however, the Malnutrition Universal Screening Tool (MUST) is currently the most widely used and promoted in the UK (Nutrition support for adults: oral nutrition support, enteral tube feeding and parenteral nutrition Clinical guideline CG32, 2006). MUST was developed by the Malnutrition Advisory Group of the British Association for Parenteral and Enteral Nutrition in 2003, combining BMI, unintentional weight loss, and acute disease, with a reported area under the receiver operator characteristic curve (AUROC) of 0.88 indicating good predictive accuracy for malnutrition (Le Thi Thanh *et al.*, 2025). MUST has been validated in hospital, community and care settings; higher MUST scores are associated with adverse outcomes such as longer hospital admissions and mortality (Saunders and Smith, 2010).

Despite these strengths, MUST and other malnutrition screening tools are essentially cross-sectional; they identify the likelihood that malnutrition is already present, but are not designed to identify future malnutrition. Moreover, implementation of screening is inconsistent. MUST is variably applied in hospitals (Schuetz *et al.*, 2021) whilst primary care uptake is low, most probably due to a combination of poor documentation of weight, limited clinician awareness, and competing consultation demands. As a result, malnutrition is still too often recognised at a late stage, when harm has already occurred and when it is difficult to reverse (Saunders and Smith, 2010).

There is therefore a need for longitudinal predictive tools capable of identifying people at future risk of malnutrition before features including weight loss or functional decline become evident. This is particularly important in primary care, where malnutrition often first develops and where preventative interventions are likely to be most effective. Current evidence that early community malnutrition detection improves hard endpoints such as hospitalization and mortality remain limited. Nutritional interventions have been shown to improve selected outcomes. A meta-analysis of oral nutritional supplementation in community settings reported fewer medical complications, including infections, impaired wound healing and pressure ulcers (Cawood *et al.*, 2023), but evidence on cost-effectiveness remains incomplete (Thomson *et al.*, 2022). Improving prediction has the potential to support better targeting of interventions, but its impact on clinical outcomes and cost-effectiveness will require further evaluation.

Existing malnutrition prediction tools

Given the need for additional predictive tools to identify malnutrition, we performed a targeted narrative review of all published literature up to 01/09/2025. Papers were selected through targeted searches of PubMed, Google Scholar and relevant reference lists, prioritizing studies of malnutrition screening or prediction tools. The review identified few studies on malnutrition prediction tools, mostly derived from hospital populations.

The most extensively validated predictive scoring system is the Geriatric Nutritional Risk Index (GNRI) (Bouillanne *et al.*, 2005). The GNRI is calculated with a formula incorporating weight and albumin [(1.489 × albumin [g/L]) + (41.7 × weight [Kg]/ideal body weight[Kg])] and was developed in a hospitalized population of adults aged ≥65 years. It reflects a prognostic 'nutrition-related risk', defined as the likelihood that a person will experience complications (infections and bedsores), with cut-offs that stratify the risk of adverse outcomes (<82 = major, 82–92 = moderate, 92–98 = low). Validation studies demonstrate a sensitivity of the GNRI tool from 66–95% and specificity between 55–92% (Sanayei *et al.*, 2021). The aim of the GNRI was to overcome limitations specific to older populations, including recall bias for weight, by utilizing ideal body weight and albumin as predictors. The original paper demonstrated a graded increase in mortality risk in GNRI categories, from those at low risk (OR 5.6 [95% CI: 1.2, 26.6]) to major risk (OR 29 [95% CI: 5.2, 161.4]). GNRI has additionally been applied across a wide range of conditions, including cardiovascular disease and cognitive impairment, reflecting its simplicity and prognostic utility (Qin *et al.*, 2025). However, its reliance on weight and albumin may underestimate malnutrition or undernutrition in overweight populations. Similar tools in smaller populations that use an estimate of nutritional status to predict the risk of adverse outcomes include the prognostic nutritional index in patients with solid tumours (combines albumin and lymphocyte counts) (Kollu *et al.*, 2024); the mNUTRIC in critically ill patients (incorporates IL-6 measurements) (Kollu *et al.*, 2024); and the CONUT score in hospitalized patients (using albumin, cholesterol and lymphocyte counts) (Rossi *et al.*, 2025).

Lee *et al.* (2021) investigated whether combining the GNRI with the Charlson Comorbidity Index (CCI) improved prognostic accuracy in elderly patients with diffuse large B cell lymphoma (Lee *et al.*, 2021). Adding GNRI to CCI significantly increased the AUROC for survival prediction (0.73; 95% CI: 0.69–0.78) when compared with CCI alone (0.64; 95% CI: 0.59–0.69). This underscores that nutritional status and multimorbidity indices can enhance prognostic models for survival prediction. However, this tool has a focus on a hospitalized population with a specific haematological condition, with limited relevance to primary care and community settings.

A broader population-based approach to identifying malnutrition was taken by Truijen *et al.* (2021) who analysed the UK National Diet and Nutrition Survey of individuals aged ≥50 years (Truijen *et al.*, 2021). Using routine biochemical tests (including haemoglobin, ferritin, and CRP), in addition to established malnutrition indicators such as low BMI and low protein intake, the authors developed a model predicting micronutrient deficiency (including zinc, vitamins B6 and B12). Its predictive model achieved an AUROC (0.79; 95% CI: 0.76–0.81), with 66% sensitivity and 78% specificity for poor nutritional status. This study represents an important step towards community-level prediction, demonstrating the potential of routinely collected biochemical data to identify nutritional risk in older adults. It also highlights the conceptual distinction between predicting protein-energy malnutrition and predicting micronutrient deficiency, demonstrating that these two outcomes may require different predictors, thresholds and interventions.

The use of artificial intelligence (AI) technologies and machine-learning (ML) approaches are beginning to be explored in malnutrition research, with a recent systematic literature review finding that most studies use supervised random forests (Janssen *et al.*, 2024), which are a type of ML model that builds multiple decision trees to improve prediction accuracy; the review also noted that malnutrition prediction remains under-researched. Illustrative examples include prediction of malnutrition-based anaemia (often occurring secondary to iron, folate or vitamin B12 deficiency): for example one study of 438 geriatric outpatients which achieved 85.4% accuracy (Göl *et al.*, 2025). ML models have also been tested in critically ill adult populations with an Extreme Gradient Boosting (XGBoost) model, a high-performance decision-tree–based algorithm, predicting malnutrition using variables such as BMI, neutrophil count and magnesium, resulting in an AUROC of 0.88 (95% CI 0.86–0.91) (Liu *et al.*, 2025). These studies demonstrate the feasibility of AI-driven malnutrition prediction, whilst also highlighting the lack of models developed or validated in primary care and community settings, where most malnutrition arises.

Discussion

More than two decades after the 2002 Royal College of Physicians editorial 'Nutrition and patients: a doctor's responsibility' set out recommendations to embed identification of malnutrition in clinical practice, progress remains limited (Kopelman and

Lennard-Jones, 2002). There are few available tools to predict future malnutrition, and none have been developed or validated in primary care. Studies based in hospital settings and specific populations give valuable insights, suggesting that many routinely collected predictors, including anthropometric measurements, clinical biochemistry, demographic factors and comorbidity indices, have the potential to be accurate predictors for micronutrient deficiency, undernutrition and malnutrition. Advances in health informatics and electronic health records (EHR) now offer an opportunity to develop automated prediction models, with the electronic frailty index and the QRISK tool as examples, providing a successful precedent for EHR-linked tools that passively stratify risk using routine coded data.

We recognize that developing predictive models for primary care must overcome several practical barriers and would need to be formally validated. Firstly, missing body weight data are a major challenge and longitudinal weight trajectories are often incomplete. Secondly, consultation time is limited, and clinicians may experience 'tool fatigue' from multiple risk assessments. Thirdly, malnutrition coding is heterogenous, complicating case ascertainment and validation. An ideal prediction tool would draw on multiple variables rather than rely on single biomarkers, such as the GNRI, which relies on albumin. Protein-energy malnutrition and micronutrient deficiency should also not be treated as interchangeable outcomes, although they often overlap in vulnerable populations. Micronutrient deficiency detection may require additional biochemical predictors. A future primary care model may require either a composite approach or separate linked predictions that distinguish between the two.

These barriers argue strongly for the development of an automated malnutrition prediction tool, that can trigger targeted follow-up. A predictive model could integrate features including weight history, comorbidities, demographic factors, polypharmacy, and routine laboratory tests alongside micronutrient markers if available. Such models would need to be rigorously tested for fit and accuracy, with consideration of unintended consequences - over-identification could increase referrals to dietetic services, whereas under-identification could perpetuate inequalities. Other potential harms include the medicalization of normal or transient weight fluctuations (Kale and Korenstein, 2018), patient anxiety, inappropriate micronutrient supplementation, and further complexity for people already experiencing polypharmacy (Atak Tel *et al*., 2023; Campos *et al*., 2024).

Embedding predictive risk scores into primary care EHR systems would allow opportunistic case-finding at medication reviews, long-term condition reviews and flu vaccination visits, aligning with NICE guidance and minimizing additional clinician burden. As prediction tools without an actionable clinical pathway may increase workload without improving outcomes, implementation should have clear thresholds, agreed actions for each threshold, clarity on who is responsible for responding to alerts, and appropriate training (Neame *et al*., 2019). For example, a low-risk alert may prompt repeat weight measurement from a practice nurse, and a high-risk alert may justify a dietetic referral by a GP or a medication review by a pharmacist. Earlier identification of malnutrition is only beneficial if the health system can offer these timely and proportionate interventions with sufficient local capacity to respond. Nutritional risk identification must also link to practical social support, as social determinants often drive the effects of nutritional interventions (Odoms-Young *et al*., 2024).

Model validation is also an important consideration (Goldstein *et al*., 2017). Deriving models in large databases such as the Clinical Practice Research Datalink is attractive, but single-dataset development risks overfitting and limited transportability. Ethnic, socioeconomic, and regional variation also require careful attention: malnutrition phenotypes may differ across groups, BMI cutoffs vary by ethnicity, and micronutrient deficiencies cluster differently by deprivation status. Without consideration for this in their design, malnutrition prediction models could inadvertently widen existing health inequalities through underrepresentation or algorithmic bias (Perets *et al*., 2025). Robust model development will require meaningful patient and public involvement, alongside deliberate strategies to address digital exclusion, language barriers, health literacy, and equitable access. Implementation should also include transparent communication with patients about how routinely collected data are used, proportionate governance, and safeguards against unnecessary surveillance of vulnerable groups.

Conclusion

Malnutrition remains underdiagnosed in primary care and community settings in the UK, and is often diagnosed late after adverse outcomes have occurred. Whilst current screening tools are useful, they are inconsistently implemented in clinical practice and lack impactful predictive power. Developing automated, data-driven predictive models from large UK primary care datasets, that integrate anthropometry, comorbidity indices, and routine biochemistry, offers a promising route to improve malnutrition prevention. Such models, co-designed with patients and tested for real-world usability, could enable a shift from reactive diagnosis to proactive prevention. Future tools should not assume benefit; they must be linked to clear clinical pathways, evaluated prospectively for clinical benefit, for cost-effectiveness, unintended harms and equity across diverse populations. Earlier detection of malnutrition has the potential to improve health outcomes, reduce health inequalities, and deliver significant savings for the NHS.

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