Smart feeding: the role of artificial intelligence and integrated nutrition platforms in the ICU

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Purpose of review

Tremendous improvement in the use of artificial intelligence has opened new opportunities to analyze the data obtained from electronic health records and imaging. New technologies have tried to overcome obstacles to implement guidelines and recommendations. This review aims to describe the recent progress in the use of machine learning and new technologies in the field of nutrition of the critically ill.

Recent findings

Increase in data availability, ability to extract these data and analyze them using machine learning has allowed data scientists together with ICU specialists to improve nutritional screening and assessment and to predict occurrence of obstacles like enteral feeding intolerance or refeeding hypophosphatemia. In addition, new technologies can ensure nasogastric tube positioning and enteral feeding efficacy. Integrated platforms can integrate nutritional needs with most adequate prescriptions and modulate the nutritional administration according to the patient's tolerance and requirements. Analysis of continuous recording of imaging obtained from ultrasound can also predict gastric intolerance.

Summary

Using machine learning, numerous algorithms and nomograms have been suggested to predict enteral feeding intolerance but validation of these predictions is still required. New technologies integrating energy requirements and delivery of the optimal enteral feeding are very promising.

Keywords

artificial intelligence, critical illness, machine learning, personalized nutrition, technologies

INTRODUCTION

Recent reviews highlight the numerous neutral effects of prospective randomized studies exploring nutritional interventions in the intensive care [1,2]. Medical nutritional therapy procedure in critically ill patients has been a "set-and-forget" prescription for years. A more personalized approach is suggested, adapted to the time, from admission following the described acute and post-acute phases [1]. The new approach includes also a new assessment based on physiology and changing clinical conditions. Some biomarkers and clinical symptoms can guide health professionals [1]. Rapid progress in artificial intelligence (AI), as well as in medical technology, has been observed in recent years. This enables us not only to react to new clinical conditions but also to predict medical conditions and guide our prescriptions accordingly. This review presents most of the recent advances in this field and tries to integrate them.

ARTIFICIAL INTELLIGENCE APPLICATIONS IN PREDICTING NUTRITIONAL COMPLICATIONS

The prediction of nutrition-related complications has shifted from simple clinical observation to the use of complex, multivariable machine learning models. AI contributes to early detection and prevention of frequent nutrition-related adverse events [3▪▪]. This section explores the integration of AI into critical care nutrition. We examine the primary

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KEY POINTS

- Precision management utilizing advanced algorithms to enhance clinical decision-making and operational efficiency is achievable.
- Digital Health Intervention can improve muscle function in conscious patients.
- Integrated Nutritional Platforms and gastric ultrasound may improve safety and efficacy of nasogastric tube and enteral feeding.

algorithmic approaches implemented in predicting complications, detail the specific risk factors identified by these AI models, and address the process improvements facilitated by AI technologies that shift nutritional care from reactive management to proactive risk stratification and optimized resource allocation.

Artificial intelligence algorithmic approaches

Recent literature highlights a shift from static scores to dynamic ML algorithms that offer superior predictive power. Table 1 describes main aspects in studies that have developed prediction models for EFI and related nutritional outcomes in ICU patients. Researchers have transitioned from traditional statistical methods to advanced machine learning (ML) and deep learning (DL) algorithms to handle the complexity of ICU data [4]. Studies comparing multiple algorithms have identified specific models that offer superior predictive accuracy. For example, Random Forest models have demonstrated predictive

Table 1. Studies related to the use of AI for nutrition-related complications and outcomes

Study	Population	Target outcome	Algorithmic approaches, best model (bold) performance (test set)	Main key predictors
Wang *et al.* (2025)	487 ICU patients (China)	EFI	RF, LR, SVM AUC= 0.98	APACHE II, IAP, blood glucose level, use of analgesics, early enema, mechanical ventilation, use of probiotics
Raphaeli *et al.* (2023)	1584 ICU patients (Israel)	Early EFI & 90-day mortality	GB, KNN, DT, RF, LR AUC: 90-day mortality: AUC = 0.73, Early EFI: AUC = 0.71	BMI, GRV >250 ml (day 2), SOFA (day 1), APACHE II
Wang Y-X *et al.* (2023)	53 150 ICU patients (MIMIC-IV)	Enteral nutrition initiation	XGBoost, LR, SVM, DT, KNN, RF AUC = 0.89	Sepsis, SOFA score, acute kidney injury (AKI), body temperature
Choi *et al.* (2021)	806 ICU patients	Refeeding hypophosphatemia	XGBoost, LR, Ridge, Lasso AUC = 0.95	Initial serum phosphate, weight loss, creatinine, diabetes mellitus with insulin use, hemoglobin A1c, furosemide use, blood urea nitrogen, parenteral nutrition,
Pan *et al.* (2025)	409 patients with severe traumatic brain injury (STBI)	EFI	Logistic regression AUC = 0.797	MAP, mechanical ventilation, intake and output volumes, combined antibiotics
Hu *et al.* (2022)	195 Sepsis patients in ICU (China)	EFI	ANN, LR, naive Bayes, RF, GBT AUC = 0.79	Respiratory tract infection, nutrient type (peptide vs. intact), shock
Yalcin *et al.* (2025)	191 028 patients (Turkey, mixed units)	Need for nutritional therapy & type (enteral/parenteral)	DL, RF, ANN, elastic net, naive Bayes AUC = 0.744	Severe illness, reduced dietary intake, impaired nutritional status
Wang *et al.* (2023)	771 ICU patients	Early EFI risk	LR AUC = 0.880	Circulatory diagnosis, APACHE II score, AGI grade APACHE II

ANN/DL, artificial neural network/deep learning; AUC, area under the curve; EFI, enteral feeding intolerance; IAP, intra-abdominal pressure; LR, logistic regression; MAP, mean arterial pressure; RF, random forest; SOFA, sequential organ failure assessment; SVM, support vector machine.

performance (area under the curve, AUC = 0.95) superior to logistic regression and support vector machines for assessing enteral feeding intolerance (EFI) risk [5]. Similarly, gradient boosting has been reported to achieve the highest predictive value (AUC = 0.71) for early enteral nutrition failure [6], while XGBoost has been identified as the optimal model for predicting enteral nutrition initiation [7]. In the context of septic patients, deep learning models (such as multilayer feedforward ANNs) have outperformed traditional ML methods like random forest and naive Bayes in predicting EFI in septic patients [8].

To address the "black box" nature of AI and ensure clinician trust, recent research emphasizes the use of interpretability tools. SHAP (SHapley Additive exPlanations) values have been utilized to rank feature importance – identifying severe illness, severely impaired nutritional status, and ICU admission as primary predictors on whether the patient needed enteral, parenteral, or combined therapy [9▪] or risk for refeeding hypophosphatemia [10▪], while LIME (local interpretable model-agnostic explanations) has been applied to provide individualized predictions by visually displaying how specific features contribute to a patient's risk score [7]. Additionally, feature importance plots have been used to demonstrate that clinical features from the first two days of ICU admission are critical for predicting long-term outcomes and feeding failure [6]. To further enhance clinical usability, complex algorithms are frequently visualized as nomograms; for instance, dynamic nomograms based on LASSO regression have been developed to provide strong calibration and clinical utility for patients with severe traumatic brain injury [11].

Key predictors identified by artificial intelligence

A large portion of recent research (2021–2025) focuses on the development and validation of risk prediction models for enteral feeding intolerance (EFI) in critically ill patients. EFI remains a significant barrier to optimal nutritional support in the ICU, with reported incidences ranging from 32% to over 70% [4]. Defined primarily by gastrointestinal symptoms – such as high gastric residual volume (GRV), vomiting, and abdominal distension – that necessitate feeding interruptions, EFI is linked to worsened nutritional status, prolonged hospital stays, and increased 28-day mortality [12]. AI models screen hundreds of potential variables to determine which features are most indicative of intolerance. Recent systematic reviews identified a consistent set of "top-tier" predictors [13–16]. These features can be categorized into clinical severity and demographics, physiological markers, and therapeutic and nutritional interventions. Severity Scores including the APACHE II score and SOFA score are7 consistently identified as top predictors of feeding intolerance and nutrition initiation capability [4,5]. A high APACHE II score indicates a higher likelihood of intolerance [4]. Age [4], and shock [8] are also major risk factors for feeding intolerance.

Physiological markers including intra-abdominal pressure (IAP), metabolic and blood markers and organ function markers. Elevated IAP was identified a significant predictor with pressures of 15 mmHg as high-risk thresholds significantly increase intolerance risk [4]. Metabolic indicators such as hyperglycemia have been successfully incorporated into nomograms for patients with severe acute pancreatitis and neurosurgical ICU populations [13]. Moreover, acute kidney injury and body temperature variations, were identified as top-ranking factors influencing enteral nutrition decisions, providing predictive value that extends beyond traditional gastrointestinal metrics [7]. Similarly, Hu *et al.*[8] highlighted the role of systemic inflammation and metabolic instability in predicting EFI among septic patients.

The use of mechanical ventilation is a top predictor for intolerance [11]. Other influential factors include the use of vasopressors, sedative/analgesic drugs [17], and antibiotics [11]. Furthermore, Kittrell *et al.* noted that DL models have identified the type of nutrient (e.g., short-peptide vs. intact-protein formula) and the feeding delivery method (continuous vs. intermittent) as top variables [17]. In summary, there is great expansion and diversification of machine learning methodologies, with improvement in models' performance. Yet, while many models exist, they suffer from a high risk of bias due to small sample sizes and a lack of external validation across different hospital systems. Huang *et al.* and Zhou *et al.* [13,14] call for the need for external validation to ensure they work across different hospital settings. The future of the field lies in multicenter validation and the integration of real-time EHR data to create automated clinical decision support systems.

Artificial intelligence-enabled workflow improvements

The integration of AI into critical care nutrition facilitates a fundamental shift from reactive troubleshooting to proactive, precision management, utilizing advanced algorithms to enhance clinical decision-making and operational efficiency. Studies demonstrate that AI models can support the early recognition of patients at risk for intolerance, potentially preventing complications associated with feeding failure [6].

Beyond mere risk detection, these tools offer actionable guidance on specific therapeutic choices, such as determining the optimal timing for feeding initiation – identifying patients who might benefit from delayed feeding – and selecting appropriate nutrient formulations [18]. To ensure these complex insights are accessible at the point of care, researchers have translated algorithms into dynamic nomograms that allow medical staff to conveniently calculate risk probabilities using basic clinical data [11]. Furthermore, the implementation of ML-based screening tools offers the potential to optimize hospital workflows by automating risk stratification, thereby acting as decision support systems that enable dietitians to prioritize high-risk patients and allocate resources more effectively [9▪].

DIGITAL HEALTH INTERVENTIONS AND THE MUSCLE

Digital health interventions [18] were analyzed in a recent metanalysis of 11 randomized controlled trials (RCTs). AI and virtual/mixed reality were found to have a moderate strength of evidence in improving muscle mass and muscle strength in older adults with sarcopenia and could be used in the post-ICU patient suffering from severe muscle mass. Some studies employed Skype video conferencing to deliver real-time, remote-supervised resistance training implementing progression through gradual load increases. Others integrated AI technology using real-time text prompts or 3D human pose estimation for movement correction and established a phased learning process. Mixed reality (MR) technology for a 4-week cognitive-motor dual-task training, with a system that automatically adjusted difficulty based on participant performance was also studied. Exergames and health management platforms were also utilized such as Nintendo Switch exergame, where the game system automatically adjusted progression and provided gamified feedback. A comprehensive training program using home-based virtual reality (VR) combined with real-time heart rate monitoring. All these studies measured multiple sarcopenia-related outcomes, including muscle mass, strength, and physical function. The overall adherence to the interventions was good, with very high completion rates. This field seems very promising for conscious patients that can interact with the programs.

INTEGRATED NUTRITION PLATFORMS

Wide world enteral nutrition technology includes nasoenteric tubes introduced preferentially in the stomach, but also in the duodenum or the jejunum. A feeding bag is handed and connected to the feeding tube through a peristaltic pump, and delivery is continuous or intermittent [19]. This procedure has been a common practice for years but does not address many obstacles: the introduction of the nasogastric tube is blind, and the confirmation of the position of the NGT needs X-ray. The administration of the prescribed energy/protein target is impaired by patient condition and interruptions related to therapy or procedures [20] and the feeding does not recognize gastric intolerance except if patient is vomiting. Several technologies have been developed to overcome some or all the obstacles [21▪▪].

Introduction of a nasogastric tube may be associated with 13–30% misplacement [22]. The use of a camera at the tip of the nasoenteric tube has improved the possibilities to introduce the nasoenteric tube to the duodenum [23]. Electromagnetic techniques have also been developed to confirm position in the stomach and in the duodenum with satisfactory results [24]. But these techniques require trained personnel [25]. A recent study suggested integrating a biologically transparent illumination using a red light at the tip of the NGT [26]. However, this system is limited by patient limited anatomical factors and was confirmed only in 5 out of 10 volunteers.

A novel approach for placement confirmation of enteral feeding tubes has been developed using impedance. The recently FDA-cleared feeding tube (Entarik Feeding Tube, Gravitas Medical, Inc., San Francisco, CA, USA) consists of a multilumen shaft and central feeding lumen with paired impedance electrodes and temperature sensors along the distal 31 cm of the tube. The monitor integrates impedance and other physiological data via an algorithm in real-time and displays visual prompts to the clinician to assist with feeding tube placement, including an indication when the algorithm predicts the feeding tube is in the stomach. The monitor detects when the feeding tube becomes dislodged from the stomach. In 10 healthy volunteers, 60 introductions were successful and confirmed by X-ray [27]. Phase I and II detected placement and misplacement in 100% of the cases in neonate [28].

A recent platform designed for mechanically ventilated enterally fed patients has been tested (smART+, ART MEDICAL, Israel) [29]. It includes a CO_2 sensor and flow meter deriving resting energy expenditure from VCO_2 measurement. Its accuracy has been recently being evaluated in comparison to the Q-NRG (Cosmed, Italy) and shows a clinically acceptable bias of –140 kcal, a RMSE of 203.0 kcal/day [95% confidence interval (CI): 171.7–235.1] and a significant superiority to predictive equations (Unpublished Data). Once energy requirements are determined, a hub allows the physician to choose the most adequate enteral formula according to the hospital availability, the nonnutritional calories received by the patient and the protein requirements. A nasogastric tube equipped with impedance sensors allows a safe placement of the nasogastric tube. The system is alarming in case the NGT is out of position and enteral feeding is stopped. The impedance sensors can detect minor and massive reflux and in the last case will stop the enteral feeding process and allow an active residual release of the gastric content to a bag. In case of prolonged interruption related to the patient gastrointestinal intolerance or related to diagnostic or procedure actions, the platform can evaluate the energy/protein deficit and program automatically compensation to reach the daily nutritional target.

A single center study [29] comparing this platform to a standard of care procedure found a significant advantage in feeding efficacy during all the days of the early, late period of the acute phase and in the postacute phase. This feeding efficacy was close to 90% while much lower in the control group. The use of metoclopramide has significantly decreased. Overfeeding was almost never encountered. The prevention of overfeeding may improve outcome [2], including decrease in inflammation, infection rate, hyperglycemia and insulin resistance and decrease in ICU stay. This decrease in length of stay was observed in the Kagan study [29]. The presence of impedance sensors continuously informing the physician of the presence of refluxes is unique (see Fig. 1). A deep analysis of all the detected refluxes [30] reveals that on the 35,000 refluxes detected in all the patients, 20,000 are very short (below 3 s) and less than 10% are inducing an active residual release of more than 240 ml. The 9145 minor refluxes involving only the lower sensors had a duration of 33 ± 161 s and discharged very small ARR (1.2 ± 4.9 g). The 4865 massive refluxes were detected by sensors Z5 and Z6 for 90 ± 345 s but had also a low mean ARR. These numbers suggest that gastrointestinal intolerance is much more modulated by the analysis of the intensity of the reflux than by the collection of the gastric residual volume, a parameter that has been considered as obsolete by some authors [31]. Ten patients have been analyzed after extubation, but still being with the NGT equipped with sensors in place. Most of these patients were receiving High Flow Nasal Cannula oxygen therapy. The sensors detected more refluxes during HFNC than during mechanical ventilation. Three hours prior extubation the mean ARR was 4.1 ml/h compared to 14.03 ml/h on HFNC ($P < 0.004$), suggesting that HFNC may expose the recently extubated patient to increased risk of aspiration [32].

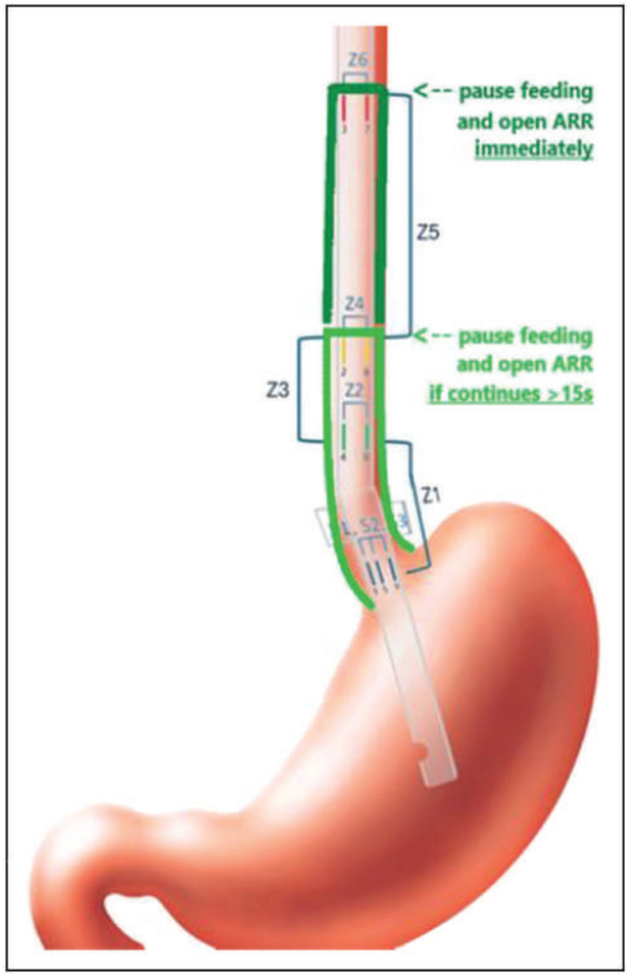

FIGURE 1. Sensors positioning in the smART+ nasogastric tube. From Singer P and Setton E [21■■] with permission.

In a post hoc analysis of the main study [33], from the 313 hospitalization days, 280 days were obtained with at least 12 h of recording. Interruption occurred 20% of the days (4.5 h). 19.8% of the interruption time was related to patients GIT intolerance (a total mean of 75 min) while 80.2% was related to diagnostic or therapeutic interruptions (total mean of 196 min). However, the feeding efficacy remained 89.3% during the study period. Nutritional therapy close to 100% of the target was reached in 176 days (63%) of the included patients. These findings confirmed the results of others. A comparative table of the described smART+ platform with the standard therapy is presented (Table 2 from 21).

Ultrasound is used as POCUS to confirm nasogastric tube position but also to determine gastric emptying [34■]. Continuous evaluation of the gastric content in a dynamic time monitoring way, can allow GRV calculation by determining the antral cross-sectional area (CSA). A calculated ultrasound gastric CSA cut-off $\geq 9.27\,\text{cm}^2$ (sensitivity 100%,

Table 2. Studies related to the use of AI for monitoring nutritional support

Study	Core technology/ methodology	Application in clinical care	Key findings & implications
Klarich *et al.* (2022)	Heuristic evaluation of human factors	Smart infusion pump interface	Usability issues in pump design; highlights the importance of human–machine interface to avoid errors
Drudi *et al.* (2024)	Reinforcement learning (RL)	Dynamic treatment optimization	RL models can process cardiorespiratory features to suggest "optimal" clinical actions, paving the way for closed-loop titration
Wang & Hsu (2023)	Wearable IoT & cloud computing	Long-term patient monitoring	Integrates sensor data (HR, SpO_2, activity) with AI to provide continuous health inspection in care environments, reducing manual nursing load

AI, artificial intelligence; IoT, Internet of Things.

specificity 87%) and a USG gastric volume ≥111.594 ml (sensitivity 100%, a specificity 92%) can predict aspiration [35]. This technology has even been improved using artificial intelligence [36], obtaining automatic measurements of gastric antrum volume using algorithms. The volume of the gastric content varies over time; therefore, the CSA area can be presented as a line. This line indicates the level of gastric volume content over time. This tool may predict gastric intolerance [37]. After enteral nutrition initiation, this technique of evaluation of GRV may be an excellent predictor of feeding intolerance.

MONITORING NUTRITIONAL SUPPORT

Monitoring nutritional support in critical care have evolved from manual oversight to AI-driven clinical decision-support systems (CDSS) that enables dynamic real-time adaptation of feeding treatment and prioritize both safety and precision [38▪]. One of the key drivers to this transition is the integration of smart infusion pumps, which improved the delivery of parenteral nutrition and fluids, while stressing the importance of heuristic evaluation of human factors to reduce the risk of programming errors [39]. Beyond hardware, the introduction of reinforcement learning (RL) models offers a pathway toward "closed loop" nutritional management, where algorithms can suggest optimal treatment strategies by processing complex cardiorespiratory and metabolic features in real-time [40]. This is further supported by the deployment of Internet of Things (IoT) systems and wearable sensors, which facilitate continuous, long-term monitoring of patient status, ensuring that nutritional interventions are adjusted dynamically as physiological needs shift [41]. Overall, the implementation of such AI-driven monitoring tools provides improved means to track patient status and to ensure nutritional recovery that the started in critical care continues through long-term rehabilitation. Table 2 shows the key findings of these studies.

CONCLUSION

Daily practice of medical nutrition therapy is changing. Precision Nutrition can be achieved through Data using as an example, an effective EFI prediction that will require a combination of clinical phenotypes (BMI, age, SOFA), observational markers (GRV, diarrhea), and emerging sensors (impedance, POCUS). The integration of these findings into Electronic Health Records will facilitate real-time risk assessment and proactive feeding adjustments. Clusters will be determined to adapt to the prescription of enteral or parenteral nutrition and will improve the prescription performances. Technologies will be able to perform better than health professionals so often victim of the work overload.

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