Narrative Review

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Predicting post-radiotherapy dysphagia in head and neck cancer: A narrative review of emerging artificial intelligence models

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Abstract

Head and neck cancer (HNC) remains a significant global health burden, particularly due to the high incidence of treatment-related complications such as dysphagia. Post-radiotherapy dysphagia not only impairs swallowing and nutritional status but also reduces quality of life and increases healthcare utilization. Conventional diagnostic approaches to identify patients at risk are often limited by delayed detection, variability in assessment methods, and insufficient predictive accuracy. Predictive modeling, including statistical, machine learning, and deep learning approaches, has emerged as a promising strategy to anticipate dysphagia risk before or during treatment. Techniques such as radiomics, imaging-based biomarkers, and multimodal machine learning models allow for early identification of high-risk patients, thereby enabling tailored interventions and preventive strategies. The aim of this review is to map the current landscape of predictive models for post-radiotherapy dysphagia in HNC patients, highlighting methodologies, applications, and clinical implications. A comprehensive literature search was performed across PubMed, Scopus, Web of Science, and Embase databases, including studies published up to February 3, 2025. Evidence indicates that predictive models, particularly those integrating machine learning and deep learning approaches, show potential in improving accuracy and timeliness of dysphagia risk prediction. However, challenges remain, including heterogeneity of patient data, limited external validation, and barriers to clinical integration. This review highlights the potential of predictive modeling to enhance individualized care in HNC patients and emphasizes the need for standardized methodologies, multicenter validation, and real-world implementation to optimize outcomes.

Keywords: Predictive model, machine learning, head and neck cancer, dysphagia, non-communicable diseases

Introduction

Head and neck cancer (HNC) continues to pose a major global health challenge, ranking among the most common malignancies with substantial morbidity and mortality worldwide [1]. Advances in surgery, radiotherapy, and chemotherapy have significantly improved survival rates; however, these gains are frequently offset by treatment-related toxicities. One of the most debilitating late effects is dysphagia, or difficulty swallowing, which occurs in a considerable proportion of survivors [2,3]. Dysphagia after radiotherapy or chemoradiotherapy is not only a

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source of functional impairment but also a determinant of long-term prognosis, given its association with malnutrition, aspiration pneumonia, reduced treatment adherence, and diminished quality of life [4]. For some patients, swallowing dysfunction becomes chronic and irreversible, leading to lifelong dependence on enteral feeding and increased risk of complications. The mechanisms underlying post-radiotherapy dysphagia are multifactorial. Acute toxicities, such as mucositis and edema, may temporarily impair swallowing, while long-term effects arise from progressive fibrosis, neuropathy, and muscle weakness in swallowing-related structures [5]. Xerostomia from salivary gland damage further exacerbates difficulties with bolus formation and transport. Collectively, these sequelae compromise swallowing safety and efficiency, leading to aspiration, nutritional deficiencies, and psychosocial distress [6,7]. Importantly, the burden of dysphagia extends beyond physical symptoms; it affects social interaction, mental health, and overall survivorship outcomes.

Assessment of dysphagia in clinical practice relies on a combination of patient-reported measures, clinical bedside evaluations, and instrumental techniques such as videofluoroscopic swallow study (VFSS) or fiberoptic endoscopic evaluation of swallowing (FEES). While valuable, these methods largely identify dysphagia after it has developed rather than predicting which patients are at greatest risk [8]. As a result, opportunities for early preventive interventions are often missed. This reactive approach underscores the need for predictive models that can stratify patients by risk before or during treatment, enabling tailored therapy planning and proactive rehabilitation strategies. Predictive modeling in HNC has evolved considerably. Early work employed traditional statistical approaches such as logistic regression, Cox regression, and nomogram development to link clinical and dosimetric variables such as tumor site, stage, and dose-volume histograms to swallowing outcomes [2]. These methods are interpretable and widely accepted by clinicians but often oversimplify complex biological relationships. More recent studies have explored machine learning methods such as random forests, support vector machines, and gradient boosting, incorporating larger sets of features including demographics, treatment parameters, and imaging biomarkers. These models demonstrate improved predictive performance but face challenges with overfitting, data imbalance, and limited external validation [2].

Deep learning approaches have further advanced the field by enabling automated feature extraction from medical images such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) [9]. Radiomics combined with convolutional neural networks allows high-dimensional analysis of tissue structure, dose distribution, and treatment-induced changes, offering powerful tools for outcome prediction. However, these models are data-intensive and often criticized for their "black-box" nature, which limits interpretability and clinical trust [10]. Emerging hybrid strategies aim to overcome these challenges. Radiomics integrated with machine learning classifiers, or multi-omics approaches that combine genomic, proteomic, and imaging data, are increasingly being investigated to refine patient-specific risk models. In parallel, explainable artificial intelligence (AI) is being developed to improve model transparency and clinician acceptance by elucidating how predictions are generated. These innovations hold promise for moving predictive modeling closer to real-world implementation [11].

Despite progress, significant gaps remain. A major limitation is the lack of standardized definitions and outcome measures for dysphagia, which complicates cross-study comparisons. Imaging and treatment planning variability, heterogeneous datasets, and small sample sizes further hinder reproducibility and generalizability. Most studies are retrospective and single-institutional, highlighting the need for multicenter collaborations and prospective validation [2]. Ethical and regulatory issues related to clinical AI deployment particularly around patient privacy and accountability also require careful consideration. This narrative review aims to synthesize current evidence on predictive modeling approaches for post-radiotherapy dysphagia in HNC patients. We discuss the clinical relevance and pathophysiological basis of dysphagia, summarize predictive models from traditional statistics to machine learning and deep learning, and highlight emerging hybrid methods. We also examine current challenges and gaps in the literature and propose future directions, including the integration of explainable AI, multicenter standardized datasets, and interdisciplinary collaboration. By consolidating current knowledge, this review seeks to inform ongoing research and support the development of clinically applicable predictive tools to reduce the burden of dysphagia and improve quality of life for HNC survivors.

Methods

This review was conducted with a narrative synthesis approach, aiming to map and summarize existing evidence on predictive models for post-radiotherapy dysphagia in patients with HNC. A scoping framework was used to comprehensively capture the breadth of predictive methodologies, including traditional statistical models, machine learning, deep learning, and hybrid approaches, without restricting inclusion based on study design or outcome heterogeneity.

A literature search was performed across PubMed, Scopus, Web of Science, and Embase to identify relevant studies published up to February 3, 2025. The search strategy combined Medical Subject Headings (MeSH) and free-text terms related to HNC, radiotherapy, dysphagia, and predictive modeling. Key search terms included: "head and neck cancer," "radiotherapy," "dysphagia," "predictive model," "risk prediction," "machine learning," "artificial intelligence," and "deep learning".

All retrieved records were independently screened based on titles and abstracts, followed by full-text review. The findings were synthesized narratively. No formal risk-of-bias assessment was performed, consistent with the objectives of the review.

Pathophysiology and clinical impact of post-radiotherapy dysphagia

Post-radiotherapy dysphagia in HNC patients is the result of multiple, often overlapping, pathophysiological mechanisms that progressively impair swallowing function. Radiation-induced mucosal injury is among the earliest complications, characterized by acute inflammation, edema, and ulceration that cause odynophagia and compromise normal bolus passage. Over time, chronic tissue remodeling and fibrosis develop, leading to reduced elasticity of pharyngeal and laryngeal structures and impaired opening of the upper esophageal sphincter. Salivary gland damage produces xerostomia, which diminishes lubrication of food and predisposes patients to bolus stasis and prolonged oral transit. Neuropathy, resulting from radiation-induced damage to cranial nerves and neural pathways, further disrupts the complex sensorimotor coordination of swallowing, while progressive muscle weakness reduces the strength of pharyngeal contraction [12]. Clinically, patients often present with symptoms ranging from mild swallowing difficulty to severe aspiration, with a heightened risk of aspiration pneumonia. Malnutrition and unintentional weight loss are common sequelae, which not only reduce overall physical resilience but also negatively affect treatment tolerance and recovery [13]. Dysphagia also profoundly impacts patients' psychosocial well-being, as difficulty with eating and drinking interferes with social interaction, autonomy, and quality of life. The long-term consequences of post-radiotherapy dysphagia are particularly significant. A subset of patients may become dependent on percutaneous endoscopic gastrostomy tubes for long-term nutritional support, which can further decrease functional swallowing use and exacerbate disuse atrophy. Treatment interruptions or modifications may be required in patients with severe nutritional deficits, undermining oncologic outcomes. Moreover, the chronic nature of radiation-induced tissue injury means that dysphagia may not only persist but also worsen over years, contributing to increased morbidity and even mortality due to recurrent aspiration events [14]. Thus, post-radiotherapy dysphagia represents a multifaceted complication that extends well beyond swallowing impairment, posing critical challenges to survivorship care in HNC patients [2].

Current approaches to dysphagia assessment

Current assessment of dysphagia in HNC patients relies on a combination of clinical and instrumental methods, each offering unique advantages but also notable limitations. Clinical evaluations often begin with bedside swallowing assessments, in which clinicians observe the patient's ability to swallow different consistencies of food and liquid. These assessments are frequently supplemented by patient-reported outcome measures, such as the MD Anderson Dysphagia Inventory (MDADI), which capture the functional and psychosocial impact of swallowing difficulties from the patient's perspective [15]. While these tools are relatively easy to administer and provide important insights into daily functioning, they may lack sensitivity in detecting subclinical or early-stage dysphagia [15].

To achieve a more detailed understanding of swallowing physiology, instrumental evaluations are considered the gold standard. The VFSS provides dynamic radiographic visualization of the swallowing process, allowing for objective identification of aspiration, residue, and impaired bolus transit. Similarly, FEES enables direct visualization of pharyngeal and laryngeal structures during swallowing. These methods have been invaluable in advancing the clinical management of dysphagia, as they provide objective data that inform rehabilitation strategies and treatment adjustments [16].

Despite their utility, current assessment approaches face important limitations. Both VFSS and FEES are resource-intensive, requiring specialized equipment, trained personnel, and in the case of VFSS, exposure to ionizing radiation. Moreover, access to these tools can be limited in resource-constrained healthcare systems, leading to underdiagnosis or delayed intervention. Clinical assessments, while more accessible, are often subjective and may vary based on clinician expertise and patient compliance. Importantly, many patients present with advanced symptoms, meaning current methods often detect dysphagia only after significant functional impairment has occurred [16]. These limitations highlight the rationale for developing predictive modeling approaches. By leveraging machine learning and AI to analyze clinical, imaging, and treatment-related data, predictive models offer the potential to identify patients at high risk of dysphagia before overt symptoms appear.

Predictive modelling approaches

Traditional statistical models

Traditional statistical models have long been the foundation for outcome prediction in oncology, including post-radiotherapy dysphagia. Commonly used approaches such as logistic regression, Cox proportional hazards regression, and nomograms have provided clinicians with interpretable and clinically acceptable tools to estimate risk. These models typically integrate input features such as tumor site and stage, patient demographics, comorbidities, dose-volume histograms, and specific radiation doses to organs-at-risk involved in swallowing (e.g., pharyngeal constrictor muscles, larynx, and esophagus) [17,18]. The strength of these methods lies in their transparency and ease of interpretation; clinicians can readily understand the contribution of each variable to the overall risk, which facilitates trust and clinical adoption [2,17,18]. Furthermore, nomograms derived from regression models have been used in clinical decision-making to personalize radiotherapy plans and counsel patients about potential functional outcomes [19]. However, the limitations of statistical models are increasingly evident in the modern era of high-dimensional data. Their underlying assumption of linearity and proportional hazards may oversimplify complex biological interactions, and they are often unable to capture nonlinear relationships between multiple clinical, dosimetric, and imaging variables [18,20]. As a result, while traditional models remain widely accepted, they may lack robustness and predictive accuracy when faced with the multifactorial and nonlinear nature of treatment-induced toxicities such as dysphagia [20].

Machine learning methods

Machine learning approaches have emerged as a powerful alternative to traditional regression-based models, offering greater flexibility in handling complex and nonlinear relationships [21,22]. Algorithms such as random forests, support vector machines, and gradient boosting have been applied to predict post-radiotherapy dysphagia with promising results [23]. These methods can incorporate a broader range of input features, including demographic data, tumor characteristics, treatment-related parameters such as detailed radiation dose distributions, and imaging biomarkers extracted through radiomics [22,23]. Reported outcomes across studies often include performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve, with machine learning models frequently outperforming conventional statistical approaches [23,24]. The strength of machine learning lies in its ability to detect subtle patterns and interactions within high-dimensional data that may not be apparent with regression models [21,22]. However, challenges remain. Many studies are limited by small sample sizes, leading to risks of overfitting and poor generalizability [21,24]. Data imbalance, where non-dysphagia cases vastly outnumber dysphagia cases, further complicates model training and may bias predictions [23]. Additionally, the lack of external validation across multicenter datasets limits confidence in their clinical utility [21,24]. Despite these limitations, machine learning methods represent an important step toward more accurate and individualized prediction of dysphagia, bridging the gap between simplistic statistical models and highly complex deep-learning approaches.

Deep learning approaches

Deep learning represents the most advanced frontier in predictive modeling for post-radiotherapy dysphagia, leveraging neural network architectures to automatically learn features from raw clinical and imaging data [21,25]. In particular, the integration of radiomics with deep neural networks has allowed researchers to extract high-dimensional quantitative features from CT, MRI, or PET scans, capturing subtle changes in tissue density, texture, and morphology that may be associated with dysphagia risk [22,25,26]. Convolutional neural networks have been employed for tasks such as automated segmentation of organs-at-risk and prediction of functional outcomes based on dose distribution maps and imaging data [25,27]. The key advantage of deep learning lies in its ability to handle large, complex datasets and identify intricate patterns without the need for manual feature engineering [22]. This capacity makes it especially suited for modeling the heterogeneous effects of radiation therapy across different anatomical and functional structures. However, deep learning approaches are not without challenges. They are inherently data-hungry, requiring large, well-annotated datasets for robust training—something that is often lacking in the context of relatively rare and heterogeneous complications like post-radiotherapy dysphagia [26,27]. Furthermore, the "black-box" nature of deep neural networks raises concerns about interpretability, making it difficult for clinicians to fully trust and adopt their predictions without additional explainability frameworks [22,27]. Despite these hurdles, the potential of deep learning to revolutionize predictive modeling is substantial, particularly as larger multicenter datasets and explainable AI tools become more available [25-27].

Hybrid approaches

In recent years, research has increasingly moved toward hybrid and integrative approaches that go beyond the use of a single data modality or algorithm. One prominent example is the combination of radiomics with machine learning or deep learning methods. Radiomics involves extracting high-dimensional quantitative features from standard imaging modalities such as CT, MRI, or PET, capturing subtle changes in tissue texture, intensity, and spatial heterogeneity that may not be visually appreciable by clinicians [9,22,30]. These imaging-derived biomarkers can then be used as inputs for machine learning classifiers such as random forests or support vector machines, or for deep learning networks that automatically learn feature hierarchies [28,30]. This combination allows predictive models to capture the complex relationships between radiation dose distribution, tissue-level changes, and the subsequent risk of functional impairment like dysphagia. For example, models that integrate dose-volume histograms with radiomic features of swallowing structures have shown improved performance over models using dose metrics alone [22,28].

Another emerging frontier is multi-omics integration, which seeks to combine genomics, transcriptomics, proteomics, and radiomics data into a unified predictive framework [29,31]. The rationale is that radiotherapy-induced toxicities such as dysphagia are not solely driven by mechanical or dose-related factors but also by underlying patient-specific biological susceptibilities. For instance, genetic variations in DNA repair pathways, inflammatory markers, or fibrosis-related genes may predispose some individuals to greater tissue damage and long-term swallowing dysfunction [29]. By integrating these molecular profiles with imaging and clinical data, researchers aim to build more holistic and personalized risk models. Multi-omics approaches can also help identify novel biomarkers of radiation toxicity and open new avenues for precision oncology, where treatment plans can be tailored not only to tumor control but also to minimizing functional morbidity [29,32].

The application of explainable AI represents an essential step toward clinical translation. Traditional machine learning and especially deep learning models are often criticized as "black-box" systems, where predictions are generated without transparent reasoning [33]. This lack of interpretability limits clinician trust and adoption in real-world practice, particularly in sensitive fields such as oncology and geriatrics. Explainable AI techniques, such as feature importance analysis, Shapley additive explanations (SHAP), or saliency maps in imaging, aim to reveal which variables or image regions most strongly influenced the model's prediction [10,34]. By providing this level of transparency, explainable AI helps bridge the gap between algorithmic predictions and clinical decision-making, making it easier for oncologists and speech-language pathologists to understand why a patient is considered at high risk of dysphagia and how preventive strategies might be tailored. These hybrid approaches reflect the ongoing paradigm shift in predictive modeling: from single-modality, hypothesis-driven models to integrated, data-rich, and interpretable frameworks [10,35]. While challenges remain including the need for large multicenter datasets, harmonization of imaging and molecular data, and standardized validation pipelines these innovations hold significant promise for improving early identification of at-risk patients, guiding proactive interventions, and ultimately reducing the burden of post-radiotherapy dysphagia in HNC survivors [10,35,36].

Challenges and gaps in the literature

Despite promising progress, several key challenges continue to hinder the development and clinical translation of predictive models for post-radiotherapy dysphagia in HNC patients. A major limitation lies in the lack of standardized definitions and outcome measures for dysphagia. Different studies employ varying clinical endpoints ranging from patient-reported questionnaires, VFSS, or feeding tube dependency which making it difficult to compare results or pool data across cohorts. Similarly, variability in imaging protocols and treatment planning techniques introduces inconsistencies in extracted radiomic features or dose-volume metrics, which can compromise the generalizability of predictive models. Another barrier is data heterogeneity and imbalance, where the number of patients with severe dysphagia is often much smaller than those without, leading to skewed datasets that bias algorithms and limit sensitivity in detecting high-risk individuals. Furthermore, while advanced machine learning and deep learning methods offer powerful predictive capabilities, their limited interpretability raises concerns about clinical trust and accountability. Clinicians are often reluctant to adopt tools that cannot clearly explain the rationale behind their predictions, especially when these predictions may directly influence treatment decisions. Lastly, ethical and regulatory considerations pose additional hurdles, including issues of patient privacy in handling sensitive clinical and imaging data, the need for transparency in algorithm development, and the lack of clear regulatory frameworks for AI deployment in oncology. Collectively, these challenges highlight the gap between methodological innovation and practical implementation in clinical care.

Future directions

Addressing those challenges will require a multi-faceted strategy that emphasizes both methodological rigor and clinical applicability. One critical step is the creation of large, multicenter standardized datasets, which would help harmonize outcome measures, imaging protocols, and clinical annotations. Such datasets would improve the robustness of predictive models and enable external validation across diverse populations. Another key direction is the integration of explainable AI frameworks to improve interpretability and clinician trust. Techniques such as feature attribution, heatmaps, or Shapley value analysis can provide insights into which clinical, imaging, or biological factors most strongly drive model predictions. Furthermore, prospective validation in real-world clinical settings is necessary to assess the true utility of predictive tools beyond retrospective research environments. Emerging technologies, such as wearable devices and digital health platforms, also offer exciting opportunities for longitudinal monitoring of swallowing function, enabling models to be continuously updated with real-time data. Finally, success in this field will depend heavily on interdisciplinary collaboration, bringing together oncologists, radiologists, speech-language pathologists, rehabilitation specialists, and AI researchers. Such collaboration can ensure that predictive models are not only technically sound but also clinically meaningful, user-friendly, and seamlessly integrated into existing workflows.

Conclusion

Predictive modeling represents a promising frontier for the early identification of patients at risk of post-radiotherapy dysphagia in HNC. By leveraging advances in radiomics, machine learning, and multi-omics integration, researchers have begun to build tools that can anticipate swallowing dysfunction before it becomes clinically apparent. Current evidence is encouraging, but remains fragmented due to small, heterogeneous datasets, lack of standardization, and limited prospective validation. To move from research to routine practice, future efforts must focus on building larger standardized datasets, applying explainable AI for greater transparency, and performing real-world clinical validation. With these advances, predictive models could eventually support more personalized treatment planning, allow for proactive interventions, and reduce the long-term morbidity associated with HNC therapy.

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Competing interests

The authors declare no competing interests.

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Underlying data

All underlying data have been presented in this article.

Declaration of artificial intelligence use

We hereby confirm that no artificial intelligence (AI) tools or methodologies were utilized at any stage of this study, including during data collection, analysis, visualization, or manuscript preparation. All work presented in this study was conducted manually by the authors without the assistance of AI-based tools or systems.

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