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# *Radiomics in Head and Neck Cancer: A Web of Science-Based Bibliometric and Visualized Analysis*

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***Abstract:*** This study is the first to employ bibliometric analysis methods to conduct a visual analysis of the literature on the application of radiomics in the field of head and neck cancer from 2014 to mid-2025. Based on 428 documents obtained from the Web of Science database, the distribution of national (regional) collaborative networks, institutions, journals and authors' contributions, as well as the evolution of keywords were visualized and analyzed using VOSviewer and CiteSpace software. 428 documents were included in the study, and the overall trend of the number of publications showed a rapid increase after 2017, and gradually stabilized after 2021. China (118 articles) and the United States (108 articles) were at the core of the field in terms of the number of publications. However, in terms of international cooperation, China lacked compared with Europe and the United States. Maastricht University (Maastricht University, Netherlands) was the institution with the most publications; Cancers (35), Scientific Reports (32) were the journals with high impact in the field; Forghani Reza (12) was the author with the most publications. In the last 10 years, the keywords “radiomics”, “head and neck cancer”, and “machine learning” have appeared more frequently. The research focus has transitioned from tumor heterogeneity characterization to local tumor control optimization, demonstrating tangible progress toward clinical implementation. To realize the full potential of these advances, two critical requirements must be addressed. First, extensive validation through multicenter prospective trials with large sample sizes is essential. Second, comprehensive standardization of radiomics protocols across all stages including image acquisition, feature extraction, and analytical processing must be established to ensure reproducibility and facilitate clinical adoption.

## 1. Introduction

Head and neck cancer (HNC) represents a critical global health challenge, characterized by highly aggressive biological behavior and ranking as the eighth most common malignancy worldwide [1]. This heterogeneous group of tumors encompasses lesions of the lips, oral cavity, larynx, nasopharynx, oropharynx, hypopharynx, and salivary glands. Current epidemiological data reveal more than 800,000 new HNC cases and over 450,000 deaths annually [2]. China bears a disproportionate burden of this disease, accounting for approximately 17.5% of global HNC cases (177,038 cases in 2020), with nasopharyngeal carcinoma comprising 46.8% of these cases [3], demonstrating the distinctive geo-epidemiological characteristics of HNC in China. Contemporary HNC management employs a multimodal therapeutic approach encompassing surgery, chemotherapy, radiotherapy, and immunotherapy. Given the anatomical complexity and functional significance of head and neck structures, radiotherapy plays an indispensable role in achieving local control while preserving critical functions and preventing locoregional recurrence and distant metastasis [4]. Over the past decade, the emergence of radiomics has catalyzed transformative advances in radiation oncology, offering unprecedented opportunities to enhance treatment precision and outcomes.

Radiomics, first conceptualized by Lambin et al. in 2012 [5], represents a paradigm shift in medical imaging analysis through high-throughput extraction of quantitative features from conventional imaging modalities including MRI, CT, and PET-CT. These features encompass textural, morphological, and wavelet-derived parameters that transform standard imaging data into high-dimensional quantitative datasets, thereby enhancing diagnostic accuracy, staging precision, treatment optimization, and prognostic stratification [6-8]. The radiomics workflow comprises four fundamental components: image acquisition and preprocessing, region-of-interest delineation, feature extraction and selection, and model construction and validation [7]. Beyond conventional imaging analysis, radiomics enables non-invasive characterization of tissue heterogeneity and demonstrates significant correlations with genomic expression profiles [9, 10]. This capability positions radiomic biomarkers as powerful tools for advancing precision oncology through individualized treatment strategies while minimizing patient burden and invasive procedures. To ensure data reproducibility and clinical translation, international regulatory bodies, including the European Organisation for Research and Treatment of Cancer (EORTC), have established standardized technical specifications for radiomics implementation, complementing existing clinical classification systems such as BI-RADS and TNM staging [11].

Bibliometric analysis represents a powerful analytical framework for systematically evaluating research landscapes through quantitative assessment of publication patterns, institutional collaborations, and thematic evolution within specific scientific domains [12]. After literature search, there is a lack of bibliometric analysis studies of radiomics in HNC in this research area. Therefore, based on the Web of Science database (2014-2025), this paper for the first time visualizes and analyzes 428 literatures in this field to clarify the current research hotspots and cutting-edge directions, and to provide certain theoretical references for clinicians' diagnosis and treatment.

## 2. Materials and Methods

### 2.1 Data Sources

We conducted a comprehensive bibliometric analysis using the Web of Science Core Collection (WoSCC), the world's leading multidisciplinary citation database indexing over 14,400 high-impact scholarly journals [13]. The Science Citation Index Expanded (SCI-EXPANDED) within WoSCC served as our primary data source for this investigation. Our search strategy employed the topic search function with the following query: TS=("Head and neck cancer") AND ("radiomics"), including relevant synonyms and variations to ensure comprehensive literature retrieval. The search encompassed publications from January 1, 2014, through December 31, 2025, with data extraction performed on July 4, 2025. We restricted our analysis to peer-reviewed articles and reviews published in English to maintain methodological rigor and data quality. The initial search yielded 472 publications. Two independent researchers systematically reviewed titles and abstracts to assess eligibility based on predefined inclusion criteria: studies investigating head and neck cancer using radiomics methodologies. Following this screening process, 44 publications were excluded due to either lack of focus on head and neck cancer or absence of radiomics applications, resulting in a final dataset of 428 publications that met our inclusion criteria. All bibliographic data were exported in plain text format to facilitate subsequent analytical processing. Given the retrospective nature of this bibliometric study utilizing publicly available publication data, ethical approval was not required.

## 2.2 Analytical Methods

We employed a multi-faceted analytical approach to examine publication patterns and research trends within the dataset. Descriptive statistics for the top 10 countries, institutions, journals, and authors by publication output were computed using Microsoft Excel 2021. Network visualization and collaboration mapping were performed using VOSviewer software (version 1.6.20) to construct co-authorship networks among countries and individual researchers. In these network visualizations, nodes represent the analytical units (countries or authors), while connecting edges indicate collaborative relationships. Edge thickness corresponds to collaboration intensity, with thicker connections denoting stronger collaborative ties. Node connectivity reflects the breadth of international or inter-author collaborations, providing insights into the global research ecosystem surrounding radiomics in head and neck cancer. To identify emerging research frontiers and track the temporal evolution of scientific focus areas, we conducted keyword burst analysis using CiteSpace software (version 6.3.R1). This analytical approach enabled systematic detection of research topics experiencing sudden increases in attention over specific time periods, thereby revealing the dynamic progression of research priorities and emerging trends within the field.

## 3. Results

### 3.1 Annual Publication Output

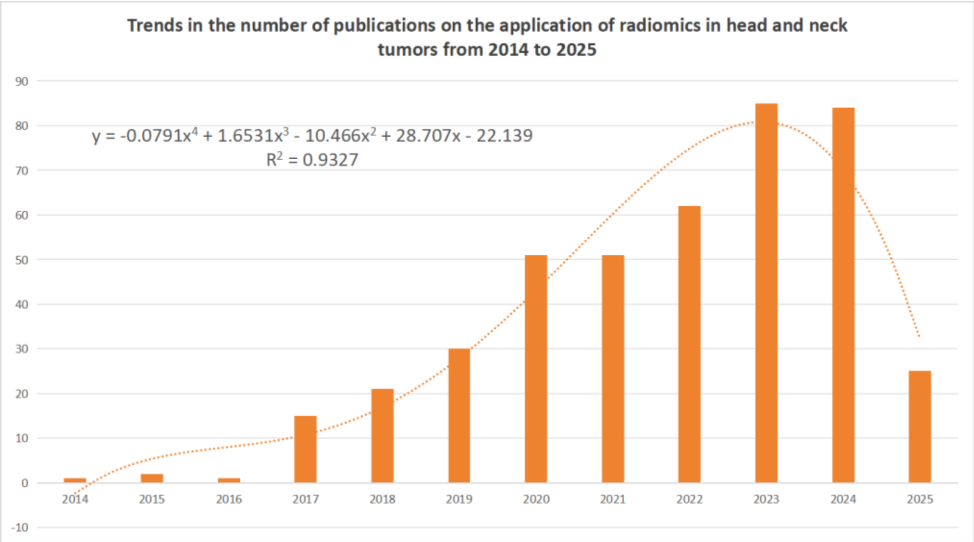



Figure 1: Trends in the number of publications on the application of radiomics in head and neck tumors from 2014 to 2025 (as of July 4, 2025).

The distribution of the annual number of publications related to HNC in the field of radiomics is shown in Figure 1 (2014-2025): the number of publications is gradually increasing. The publication situation can be divided into three periods: 1. Initial exploration period (2014~2016): the annual publication volume in this period is less than 1.3 articles/year, indicating that radiomics was still in the stage of technological exploration at that time. 2. Rapid development period (2017~2020): the publication volume in the last year of this period (2020) reaches 51, which is an increase of 240% compared with that in 2017 (15 articles), thus showing that more high-quality studies emerge in this period. 3. Mature development platform period (2021~2025): the annual average number of articles in the first four years of this period steadily increases to about 70.5 articles (the highest value occurs in 2023, 85 articles).

### 3.2 Publishing Countries

Table 1: Top 10 most influential countries in the field of radiomics research for head and neck cancer

| rank | countries | documents | citations | average citation |
|---|---|---|---|---|
| 1 | China | 118 | 31973 | 31.85 |
| 2 | USA | 108 | 7825 | 62.60 |
| 3 | Italy | 62 | 2553 | 77.36 |
| 4 | Canada | 53 | 397 | 15.88 |
| 5 | Netherlands | 45 | 271 | 13.55 |
| 6 | Germany | 38 | 1457 | 76.68 |
| 7 | the United Kingdom | 23 | 1890 | 99.47 |
| 8 | France | 20 | 1172 | 65.11 |
| 9 | Switzerland | 20 | 612 | 36.00 |
| 10 | Japan | 19 | 396 | 28.29 |

This study analyzed 49 countries (regions) in this field, and the top three countries (regions) in terms of the number of publications were China (118), the United States (108) and Italy (62) (Table 1). Although China ranked first in terms of the number of articles published, there was still a gap between the breadth and density of China's academic cooperation with the international community and that of the European and American countries (Figure 2). At present, global cooperation shows localized group cooperation and has not formed a large cooperation network.

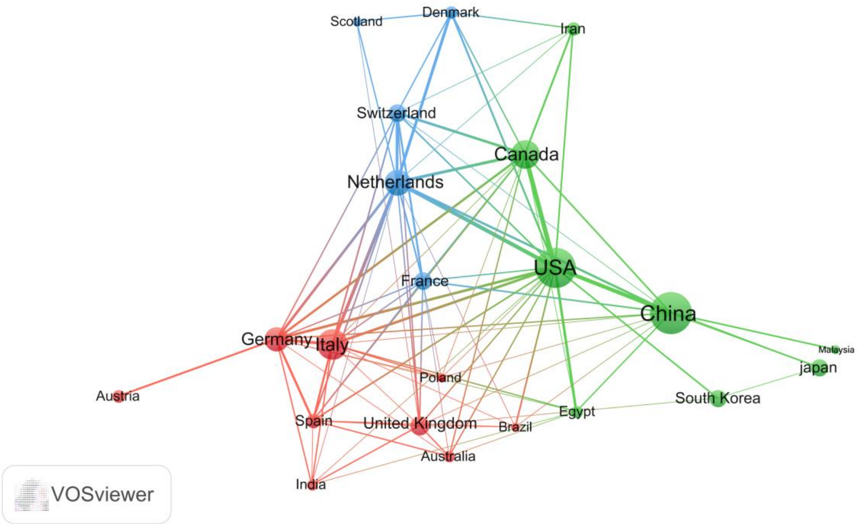



Figure 2: Country contribution map based on article output

### 3.3 Publishing Institutions

As shown in Table 2, among the statistical literature, Maastricht University (Netherlands), University of Milan (Italy), and Harvard Medical School (USA) ranked 1st (22 articles), 2nd (21 articles), and 3rd (18 articles) in terms of the number of publications, respectively. In addition, Shanghai Jiao Tong University (China) is the only Asian institution on the list with the 8th place. About 90% of the high-yield institutions are from high-income countries, indicating that the investment of substantial resources in research is a major determinant of output.

Table 2: Top 10 most influential institutions in the field of radiomics research for head and neck cancer

| rank | countries | documents | citations | average citation |
|---|---|---|---|---|
| 1 | Maastricht University | 22 | 5165 | 234.77 |
| 2 | University of Milan | 21 | 329 | 15.67 |
| 3 | Harvard Medical School | 18 | 1061 | 58.94 |
| 4 | University of Texas MD Anderson Cancer Center | 17 | 688 | 40.47 |
| 5 | University of Toronto | 17 | 4306 | 253.29 |
| 6 | McGill University | 16 | 928 | 58.00 |
| 7 | German Cancer Research Center | 14 | 686 | 49.00 |
| 8 | Shanghai Jiao Tong University | 13 | 210 | 16.15 |
| 9 | Vrije Universiteit Amsterdam | 13 | 4211 | 323.92 |
| 10 | Polytechnic University of Milan | 12 | 162 | 13.50 |

### 3.4 Publishing Journals

As shown in Table 3, the journals with the most articles were Cancers, Scientific Reports, and Frontiers in Oncology, with 35, 32, and 25 articles, respectively; Scientific Reports had the most citations, with 1,593 citations, and was the journal with greater impact.

Table 3: Top 10 most influential journals in the field of radiomics research for head and neck cancer

| rank | journals | documents | citations | average citation | countries |
|---|---|---|---|---|---|
| 1 | Cancers | 35 | 362 | 10.34 | Switzerland |
| 2 | Scientific Reports | 32 | 1593 | 49.78 | the UK |
| 3 | Frontiers in Oncology | 25 | 789 | 31.56 | Switzerland |
| 4 | European Radiology | 20 | 484 | 24.20 | Germany |
| 5 | Radiotherapy and Oncology | 12 | 483 | 40.25 | Switzerland |
| 6 | Diagnostics | 12 | 173 | 14.42 | the US |
| 7 | Medical Physics | 12 | 137 | 11.42 | the UK |
| 8 | Oral Oncology | 10 | 263 | 26.30 | the UK |
| 9 | Head and Neck-journal for the Sciences and Specialties of the head and | 9 | 132 | 14.67 | the US |
| 10 | European Journal of Nuclear Medicine and Molecular Imaging | 8 | 169 | 21.13 | Germany |

### 3.5 Publishing Authors

As shown in Table 4, the top four authors in terms of the number of publications are Forghani Reza (12), Leemans C. René (11), Calareso Giuseppina and Licitra Lisa (both 10). The author with the 2nd highest number of publications, Leemans C. René, has the highest centrality index value in the collaborative network shown in Figure 3, indicating that he is currently one of the most important members of the field.

Table 4: Top 10 most influential authors in the field of radiomics research for head and neck cancer

| rank | authors | documents | Citations | average citation |
|---|---|---|---|---|
| 1 | Forghani, Reza | 12 | 272 | 22.67 |
| 2 | Leemans, C. René | 11 | 3907 | 355.18 |
| 3 | Calareso, Giuseppina | 10 | 166 | 16.60 |
| 4 | Licitra, Lisa | 10 | 155 | 15.50 |
| 5 | Aerts, Hugo J. W. L. | 9 | 4738 | 526.44 |
| 6 | Lambin, Philippe | 9 | 4373 | 485.89 |
| 7 | Guckenberger, Matthias | 9 | 685 | 76.11 |
| 8 | fFuller, Clifton D. | 9 | 420 | 46.67 |
| 9 | Castelijns, Jonas A. | 9 | 188 | 20.89 |
| 10 | De Graaf, Pim | 9 | 155 | 17.22 |

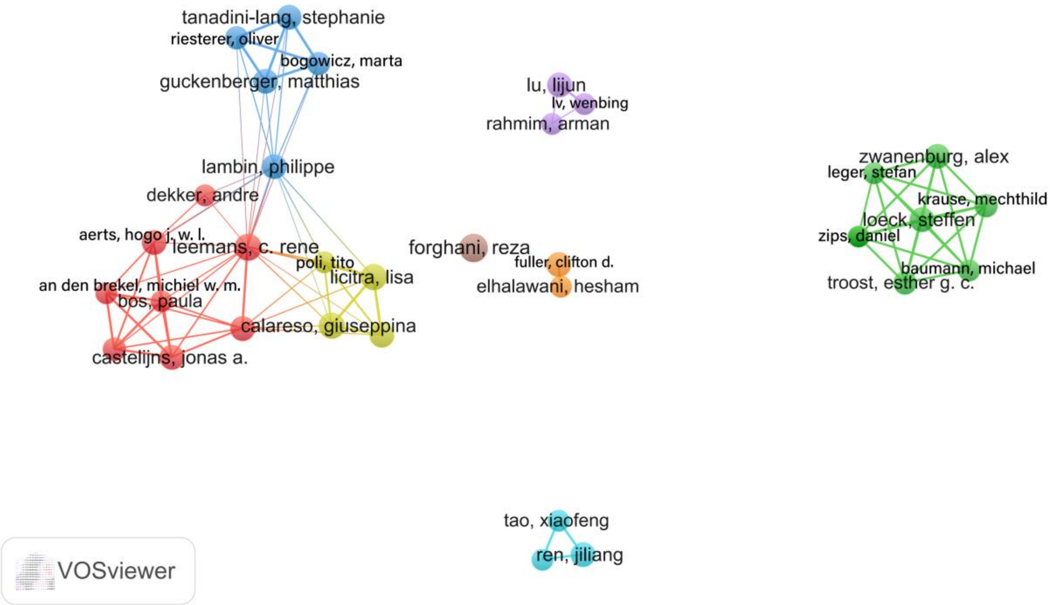



Figure 3: Visualization of the author contribution network

### 3.6 Keyword Analysis

Keywords often demonstrate what is hot in a research area. This study uses VOSviewer software to visualize and analyze keyword co-occurrences, demonstrating multiple applications of these keywords in this research area. For example, radiomics standardizes quantitative features (e.g., texture, shape, wavelet features) through PET-CT, CT, MRI and other imaging data, and machine learning improves clinical diagnosis and prognosis through screening image features and important model building, and the two work together to promote the process of precision radiotherapy and individualized treatment. As shown in Figure 4A, the high-frequency keywords that appeared in the past 10 years mainly include: "radiomics", "head and neck cancer", "machine learning", "cancer", "survival", "prediction", "images", "texture analysis", "radiotherapy" and "features". The evolution of keywords over time in Figure 4B shows that keywords such as "deep learning", "diagnosis" and "artificial intelligence" are emerging as hot topics in academia since 2022. The results of the keyword emergence analysis (Figure 5) reveal that “texture analysis” has the longest duration as a research hotspot, while “heterogeneity” has the most significant emergence intensity (intensity value = 4.8). In addition, “tumor volume” and “local tumor control” are emergent signals that have attracted the attention of scholars in recent years and have become the focus of current research.

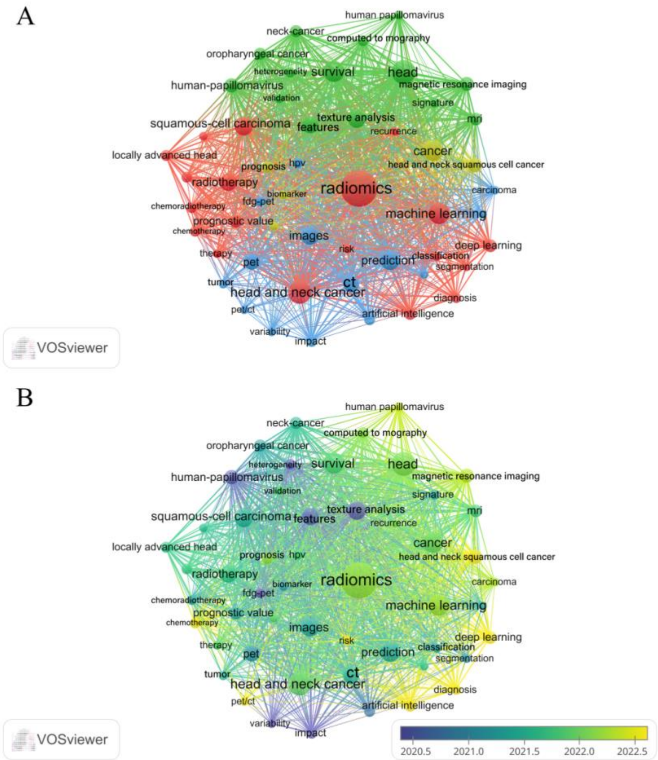
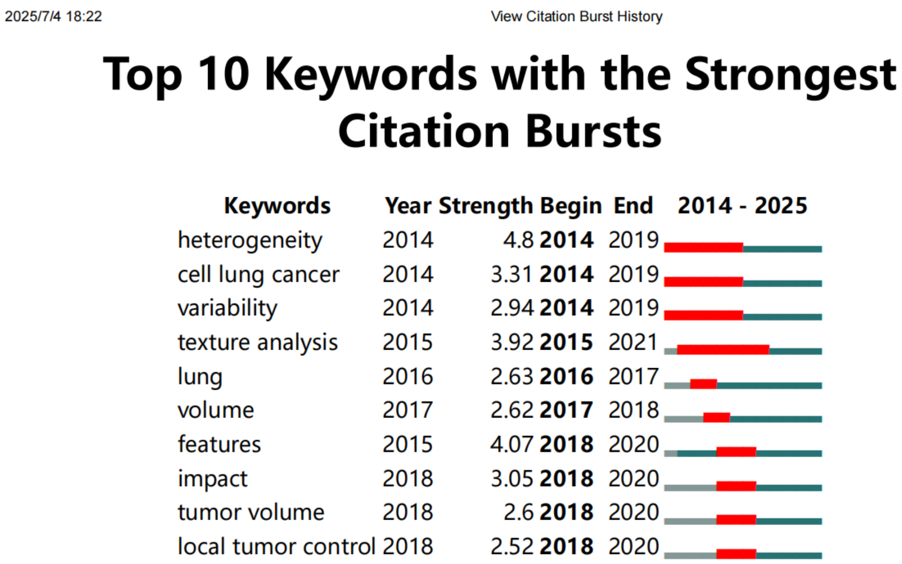



Figure 4A: Keyword co-occurrence network visualization

Figure 4B: Overlay visualization of the keyword co-occurrence network




| Keywords | Year | Strength | Begin | End | 2014 - 2025 |
|---|---|---|---|---|---|
| heterogeneity | 2014 | 4.8 | **2014** | 2019 | |
| cell lung cancer | 2014 | 3.31 | **2014** | 2019 | |
| variability | 2014 | 2.94 | **2014** | 2019 | |
| texture analysis | 2015 | 3.92 | **2015** | 2021 | |
| lung | 2016 | 2.63 | **2016** | 2017 | |
| volume | 2017 | 2.62 | **2017** | 2018 | |
| features | 2015 | 4.07 | **2018** | 2020 | |
| impact | 2018 | 3.05 | **2018** | 2020 | |
| tumor volume | 2018 | 2.6 | **2018** | 2020 | |
| local tumor control | 2018 | 2.52 | **2018** | 2020 | |

Figure 5: Top 10 keywords with the strongest citation bursts

## 4. Discussion

Based on bibliometric analysis of 428 publications, radiomics research in head and neck cancer has shifted from tumor heterogeneity to local tumor control (Figure 5), which intuitively reflects the current application scenario of in-depth clinical diagnosis and treatment of radiomics.

Research stage distribution: Start-up period (2014-2016): the annual number of articles <1.3, the reason is mainly because the radiomics technology is not mature enough, coupled with some multimodal images have not been unified standards [14]; high-speed growth period (2017-2020): the number of articles in 2020 was 51, compared with the number of articles in 2017, an increase of 240%. 240% growth in 2020, due to (1) technological breakthroughs: deep learning (DL) feature extraction algorithms to further improve the model generalization ability [15, 16], to promote the clinical application of imaging genomics; (2) clinical needs: use of parotid Delta imaging genomics features to quantify the changes in the course of radiotherapy treatment and predict the risk of severe dry mouth at 12 months post-radiotherapy [17]; Data integration: the large number of multiple single-center studies in academia regarding the use of radiomics in HNC [18-20]. Platform period (2021-2025): the average annual number of publications in the first 4 years (2021-2024) is 70.5, which is about 64.7% higher than that in the starting year (2021), with a significantly weakened growth momentum, and the overall platform is running at a high level; this indicates that the core of the research has shifted from technology validation to clinical application in the early stage. There is an urgent need to conduct prospective studies to further improve the quality level of evidence.

Analysis of the global collaboration network (Figure 2) reveals significant disparities in international research engagement despite China's leading publication output of 118 articles. While China demonstrates the highest productivity, its international collaborative networks remain underdeveloped compared to European and North American research ecosystems. This limited international engagement may reflect both insufficient collaborative infrastructure and fundamental differences in regional disease epidemiology. Notably, China accounts for 46.8% of global nasopharyngeal carcinoma incidence, whereas European and North American populations predominantly present with oropharyngeal carcinomas [3, 21], potentially driving divergent research priorities and methodological approaches. European and North American institutions have prioritized methodological innovation in radiomics applications. Maastricht University demonstrated the efficacy of integrating clinical data with radiogenomic features, achieving remarkable predictive performance for head and neck cancer with excellent generalizability across diverse patient populations. This integrated approach shows considerable promise as a screening tool for high-risk population identification [22]. Similarly, Harvard Medical School identified 440 quantitative imaging features spanning intensity, morphological, and textural parameters with robust predictive capabilities across 1,019 patients with lung and head and neck cancers. These features correlate with tumor heterogeneity and gene expression patterns, offering potential to reduce diagnostic costs, minimize patient burden, and enhance clinical decision-making precision [9]. Current collaborative patterns exhibit pronounced regional clustering, limiting the global validation and scalability of promising radiomics models. Several significant predictive models, including those for radiation-induced temporal lobe necrosis, remain confined to single-center or regional validation studies and lack large-scale, multi-population verification [23, 24]. Consequently, international research cooperation and exchange are imperative to promote the widespread use of radiomics in clinical practice.

Keyword analysis reveals research hotspots and emerging frontiers. The transition from "heterogeneity" to "local tumor control" in keyword bursts reflects the shift from "fundamental feature research" toward "clinical optimization strategies." Keyword analysis demonstrates "machine learning" ranking third in co-occurrence frequency with sustained high relevance, while "deep learning" has emerged prominently since 2022. These technologies demonstrate complementary roles in HNC clinical research: traditional machine learning employs empirical knowledge for manual feature extraction, advantageous in small-sample studies (such as predicting cervical lymph node metastasis in 400 tongue squamous cell carcinoma patients) [25], whereas deep learning is based on a large amount of data and information, and completes the complex spatial modeling through autonomous learning, which integrates clinical data, radiomics features, and medical images through multimodal fusion to enhance model reproducibility and clinical applicability in HNC diagnosis, treatment, and prognostic assessment [22, 26]. Traditional machine learning and deep learning models demonstrate excellent complementarity within this domain. However, deep learning models continue facing "black box" limitations with insufficient interpretability [27].

In addition, it can also be seen that “diagnosis” and “artificial intelligence” are the research areas that have been paid attention to by scholars in recent years, and the diagnostic value of radiomics is gradually developing into a research hotspot. High-order textural features (wavelet transformation characteristics) from CT/MRI imaging enable detection of microscopic lesions [28] and prediction of cervical lymph node metastasis in head and neck squamous cell carcinoma [25]. Marco Bologna's team successfully evaluated different clinical endpoints in non-endemic nasopharyngeal carcinoma patients using MRI radiomics features [29]. From another perspective, radiomics and artificial intelligence demonstrate synergistic effects: traditional radiomics + AI = deep learning radiomics (DLR). Clinical factor-assisted deep learning radiomics nomogram models (DLRN) achieved EGFR mutation status prediction AUCs of 0.901 and 0.875 in training and testing cohorts of head and neck squamous cell carcinoma patients, respectively [20]. Future research must address multicenter validation challenges to facilitate successful research-to-clinical translation.

## 5. Conclusions

For the first time, through the method of bibliometrics, three important findings in the field of radiomics of head and neck tumors were explored. They are as follows: (1) The top three countries in terms of the output of articles on radiomics of HNC are China, the United States, and Italy. However, China lags behind Europe and the United States in terms of international cooperation; (2) The research direction has gradually shifted from the extraction of original basic features (such as heterogeneity, etc.) to the dynamic optimization aimed at local tumor control in clinical practice; (3) Deep learning combined with traditional models is better than using deep learning alone or traditional models alone in breaking through the limitations of small sample data. This conclusion directly determines that multi-center independent verification and the establishment of strict standardized procedures (such as IBSI) are necessary to truly achieve successful clinical transformation, providing an important decision-making reference framework for the practice of precise radiotherapy for HNC.

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