Salud, Ciencia y Tecnología. 2025; 5:2144 doi: 10.56294/saludcyt20252144

REVIEW



Radiogenomics in oncology: image-genome integration for personalized medicine

Radiogenómica en oncología: integración imagen-genoma para medicina personalizada

Cinthia Katherine Galarza Galarza 1 Deltrán Lorena Bibiana Erazo Beltrán Deltrán Deltr

¹Pontificia Universidad Católica del Ecuador Sede Ambato, Escuela Ciencias de la Salud. Ambato, Ecuador.

Cite as: Galarza Galarza CK, Erazo Beltrán LB. Radiogenomics in oncology: image-genome integration for personalized medicine. Salud, Ciencia y Tecnología. 2025; 5:2144. https://doi.org/10.56294/saludcyt20252144

Submitted: 23-04-2025 Revised: 09-07-2025 Accepted: 21-09-2025 Published: 22-09-2025

Editor: Prof. Dr. William Castillo-González

Corresponding author: Cinthia Katherine Galarza Galarza

ABSTRACT

Introduction: radiogenomics, which combines medical imaging data with genomic profiling, has emerged as a key tool in precision oncology. This noninvasive approach improves the diagnosis and prognosis of tumors such as lung, rectal, glioma, and breast cancer.

Objective: a systematic review (PRISMA 2020) was conducted of studies published between 2020 and 2025, extracted from PubMed, Scopus, Web of Science, ScienceDirect, and the Cochrane Library. Of 670 articles found, 21 met the inclusion criteria.

Method: this was a systematic review following the PRISMA 2020 guidelines. Original studies, reviews, and meta-analyses published in English or Spanish were included. Searches were conducted in PubMed, Scopus, Web of Science, ScienceDirect, and the Cochrane Library.

Results: of a total of 670 articles retrieved, 21 met the inclusion criteria. Most studies demonstrated a high predictive capacity of radiogenomic models to identify mutations such as EGFR and KRAS.

Conclusions: this study underscores the need to establish multicenter protocols and robust validations to ensure their clinical applicability and consolidate their role in personalized medicine.

Keywords: Radiogenomics; Image Interpretation; Magnetic Resonance Imaging; Precision Medicine; Biomarkers; Tumor; Artificial Intelligence; Oncology.

RESUMEN

Introducción: la radiogenómica, que combina datos de imagen médica con perfiles genómicos, se ha posicionado como herramienta clave en oncología de precisión. Este enfoque no invasivo mejora el diagnóstico y pronóstico de tumores como cáncer de pulmón, recto, gliomas y mama.

Objetivo: se realizó una revisión sistemática (PRISMA 2020) de estudios publicados entre 2020 y 2025, extraídos de PubMed, Scopus, Web of Science, ScienceDirect y Cochrane Library. De 670 artículos encontrados, 21 cumplieron los criterios de inclusión.

Método: se trata de una revisión sistemática siguiendo la guía PRISMA 2020. Se incluyeron estudios originales, revisiones y metaanálisis publicados en inglés o español. Las búsquedas se realizaron en PubMed, Scopus, Web of Science, ScienceDirect y Cochrane Library.

Resultados: de un total de 670 artículos recuperados, 21 cumplieron con los criterios de inclusión. La mayoría de los estudios demostraron una alta capacidad predictiva de modelos radiogenómicos para identificar mutaciones como EGFR y KRAS.

Conclusiones: este estudio subraya la necesidad de establecer protocolos multicéntricos y validaciones robustas para garantizar su aplicabilidad clínica y consolidar su rol en la medicina personalizada.

© 2025; Los autores. Este es un artículo en acceso abierto, distribuido bajo los términos de una licencia Creative Commons (https://creativecommons.org/licenses/by/4.0) que permite el uso, distribución y reproducción en cualquier medio siempre que la obra original sea correctamente citada

²Universidad Técnica de Ambato, Carrera Medicina. Ambato, Ecuador.

ISSN: 2796-9711

Palabras clave: Radiogenómica; Interpretación de Imágenes; Resonancia Magnética; Medicina de Precisión; Biomarcadores; Tumor; Inteligencia Artificial; Oncología.

INTRODUCTION

In the era of precision medicine, radiogenomics is emerging as a strategic tool in oncology, as it relates quantitative characteristics obtained from medical images to genomic profiles of the tumor. This approach allows for the description of intratumoral heterogeneity and the anticipation of molecular alterations, favoring the development of diagnostic and prognostic models with remarkable predictive power. (1,2) An example of this is the integration of tomography, resonance, and PET/CT data to predict mutations in genes such as EGFR, TP53, or KRAS, with areas under the curve (AUC) close to 0,80-0,90, supported by artificial intelligence techniques that increase prognostic stratification capacity. (3,4,5)

Despite these advances, the challenge of ensuring the reproducibility and clinical application of the models remains. Several reviews have pointed to wide methodological variability, ranging from image acquisition protocols to segmentation and feature selection. (6) Although there are validated models in neoplasms such as lung cancer or glioblastoma, few meet the criteria for multicenter standardization and reporting guidelines such as the Radiomics Quality Score (RQS), which aims to evaluate the methodological quality of radiomics and radiogenomics studies, or the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD), which establishes guidelines for the development and validation of predictive models. (7,8)

In this scenario, a gap becomes apparent: most previous reviews have focused on technical aspects or specific tumors, but there is a lack of an updated analysis that integrates the diagnostic and prognostic performance of recently published radiogenomic models, together with practical recommendations for their clinical standardization. This absence limits the possibility of translating the findings into medical practice.

The purpose of this article is precisely to critically review the evidence published between 2020 and 2025 on radiogenomic models in oncology, synthesize the findings in terms of diagnostic and prognostic performance, and propose technical recommendations that strengthen the reproducibility and clinical applicability of this approach. The aim is to contribute to the establishment of standardized protocols and to encourage collaborative research that promotes the integration of radiogenomics into personalized medicine.

METHOD

This study is a systematic review of the literature, developed in accordance with the PRISMA 2020 guidelines. Although international methodological guidelines were followed, the review could not be registered in PROSPERO, as this platform only accepts reviews with direct clinical outcomes in patients or animals, and the present study focuses on predictive radiogenomics models based on imaging and genomic data. The objective was to identify, evaluate, and synthesize the available scientific evidence on the integration of radiogenomics in personalized medicine-oriented oncology.

Inclusion and exclusion criteria

Original research articles published in English or Spanish between January 2020 and April 2025 were included, which evaluated the correlation between quantitative radiological characteristics and genomic profiles in cancer patients, as well as their application in diagnosis, prognosis, or prediction of therapeutic response. Case studies, conference abstracts, editorials, letters to the editor, narrative reviews, and systematic reviews were excluded, as the focus was on synthesizing primary evidence.

Sources of information and search strategy

The literature search was conducted between April and May 2025 in the PubMed, Scopus, Web of Science, and ScienceDirect databases. MeSH terms and related keywords were used, combined with Boolean operators. The complete search strategy was: ("radiogenomics" OR "radiogenomics" OR "radiogenomica" OR "radiogenomica" OR "radiogenomica" OR "neoplasms") AND ("oncology" OR "oncology" OR "oncología" OR "cancer" OR "tumor" OR "neoplasms") AND ("personalized medicine" OR "precision medicine" OR "personalized medicine") AND ("imaging" OR "MRI" OR "PET") AND ("genomics" OR "genómica" OR "mutation" OR "genetic profile") AND ("machine learning" OR "deep learning" OR "artificial intelligence"). In addition, the reference lists of the selected articles were reviewed to identify relevant studies not retrieved in the initial search.

Study selection

The results were exported to Zotero, and duplicates were removed. The selection was carried out in two phases: reading of titles and abstracts by two independent reviewers, followed by full-text evaluation of potentially eligible studies. Discrepancies were resolved by consensus among the authors. Agreement between

reviewers was estimated using the Kappa coefficient.

Data extraction and synthesis

A standardized template was designed for data extraction, which included: author(s), year, country, type of cancer evaluated, sample size, imaging technique used, radiogenomic analysis methodology, software or tools applied, performance metrics (AUC, accuracy, sensitivity, specificity), main findings, reported clinical utility, and limitations.

The synthesis was performed in a structured narrative format, organizing the results around three axes: (i) diagnostic performance of radiogenomic models, (ii) prognostic and predictive value in therapeutic response, and (iii) methodological and technical aspects that condition their reproducibility.

Methodological quality assessment

The quality of the prediction model studies was assessed using the TRIPOD guideline, currently considered the standard for reporting and evaluating diagnostic and prognostic predictive models, and the ROBIS tool was used for previous systematic reviews.

A literature review was conducted following the predefined search strategy, and 21 articles were included. Screening was performed independently by two reviewers in two phases (title/abstract and full text) using a standardized form. Inter-rater agreement was quantified using Cohen's Kappa statistic, showing substantial agreement in the title/abstract phase and almost perfect agreement in the full-text reading, according to the Landis and Koch classification. Discrepancies were resolved by consensus, and when they persisted, by the opinion of a third, independent reviewer, although this was not necessary. Table 1 summarizes the records retrieved by the database and their refinement, table 2 shows the records after applying the inclusion and exclusion criteria, and the PRISMA 2020 diagram documents the complete selection flow.

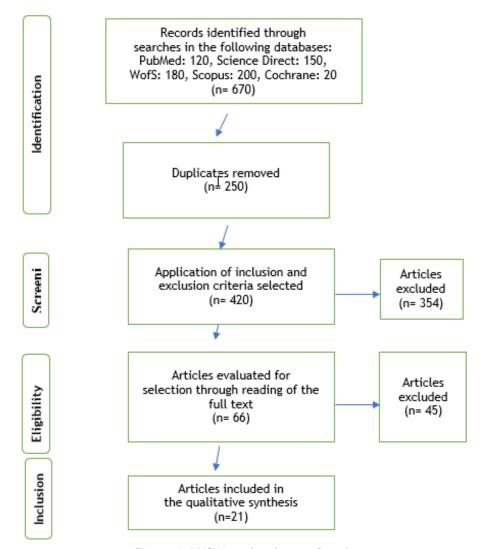


Figure 1. PRISMA study selection flow diagram

RESULTS

The search in five databases, from 2020 to 2025, retrieved 670 records. PubMed 120; Scopus 200; Web of Science 180; ScienceDirect 150; Cochrane 20. After removing 250 duplicates, 420 records were screened for title and abstract, of which 354 were excluded for not meeting the eligibility criteria. Sixty-six articles were evaluated in full text, and 45 were excluded for the following reasons: absence of radiomics-genomics integration (n=14), ineligible design (letters, editorials, or case series; n=11), non-oncological population (n=8), insufficient data or methodology (n=8), and overlap of cohorts (n=4). Consequently, 21 studies met the criteria and were included in the qualitative synthesis. The complete flow is shown in the PRISMA 2020 diagram (figure 1), and the reasons for full-text exclusion are detailed in table 2.

| Table 1. Search strategy | | | | | | | | |
|----------------------------|---------------------|-----------------------|--|--|------------------------|----------|-----------------------|--|
| Database | Documents retrieved | Duplicates removed | Unique records after deduplication | Excluded in screening (title/abstract) | Evaluated in full text | Included | Excluded at full text | |
| PubMed | 120 | 28 | 92 | 77 | 15 | 6 | 9 | |
| Scopus | 200 | 90 | 110 | 85 | 25 | 7 | 18 | |
| Web of Science | 180 | 80 | 100 | 87 | 13 | 3 | 10 | |
| ScienceDirect | 150 | 50 | 100 | 91 | 9 | 3 | 6 | |
| C o c h r a n e Library | 20 | 2 | 18 | 14 | 4 | 2 | 2 | |
| TOTAL | 670 | 250 | 420 | 354 | 66 | 21 | 45 | |

| Table 2 . Reasons for exclusion from full text (n=45) | | | | | | |
|---|----|---|--|--|--|--|
| Reason for exclusion | n | Operational criterion | | | | |
| Non-oncological population | 8 | Series on non-tumor pathology or animal models without clear translation to cancer. | | | | |
| Ineligible design (cases/letters/editorials) | 11 | Opinions, letters, case series without comparison/validation. | | | | |
| No explicit radiomics-genomics correlation | 14 | Radiomics-only or genomics-only studies without operational integration. | | | | |
| Insufficient data (incomplete metrics or methods) | 8 | No AUC/accuracy/CI; incomplete or irreproducible pipeline. | | | | |
| Duplicate cohort/overlap. | 4 | Same population reused without additional relevant analysis. | | | | |
| Total | 4 | | | | | |

DISCUSSION

The results point to tangible clinical potential when the questions are clearly established, for example, inference of mutations or prognostic stratification in specific scenarios, and when working with well-curated datasets. The heterogeneity of designs, analytical pipelines, and methodological reports conditions the comparability and robustness of the conclusions. (9,10,11)

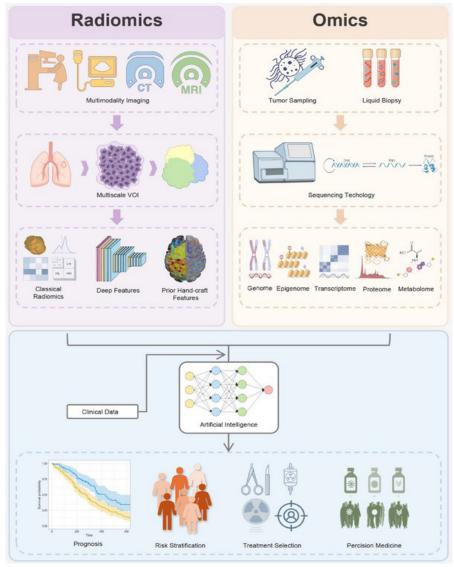
When examining studies by tumor location and imaging modality, a relatively consistent pattern is observed in lung cancer: CT-based models, with or without PET/CT, aimed at predicting point mutations and stratifying risk tend to report moderate to high performance. In neuro-oncology, multiparametric magnetic resonance imaging approaches have proven helpful for molecular classification and have shown more variable results when the objective is purely prognostic. In other, more common tumors such as breast, liver, and head and neck, the signal is more heterogeneous. There are reports with acceptable discriminatory capacity in specific tasks; however, the frequency of external validations is lower, and the dispersion of metrics is greater. The most commonly reported performance measures have been area under the curve (AUC), accuracy, and sensitivity/ specificity. (1,2,3,15)

A cross-sectional reading of these metrics suggests that performance improves when radiogenomic descriptors are combined with simple, easily accessible clinical variables such as age, stage, or treatment, as opposed to the image alone. Even so, the inter-study variation resulting from preprocessing, segmentation, selection, and stability of functions and validation strategies currently prevents us from affirming the consistent superiority of one technique or modality over another beyond specific examinations, such as chest CT for epidermal growth receptor or multiparametric MRI for molecular signatures in gliomas. (16,17)

Clinical extrapolation remains very limited. The area under the curve is high, but these values cannot be sustained without calibration or external validation, whether geographical or temporal. According to RQS,

segmentation and clinical justification are usually well described, but external validation, stability testing, impact/cost assessment, and code/data availability are lacking. With TRIPOD, there are repeated gaps in sample size, missing data, calibration, and reclassification, and little reporting of temporal/geographic validations. In PROBAST, biases due to participant selection, non-standardized predictors (equipment dependence), and analyses with risk of overfitting predominate.⁽¹⁰⁾ Where there was harmonization and standardization of image flow and functions, performance was more stable; when calibration was lacking and there was only internal validation, high metrics with little generalization appeared. This is in line with already known barriers: small samples, heterogeneity of pipelines, lack of pre-registration, and lack of reproducible code.

In practice, radiogenomics complements, but does not replace, biopsy: it helps prioritize molecular testing, anticipate alterations, and stratify treatment. To move forward, it is necessary to standardize the acquisition/extraction of results, continue using TRIPOD, evaluate bias with PROBAST, and incorporate external validation, calibration, and clinical utility. (11,12) In addition, code and functionality dictionaries should be shared and harmonization applied in order to improve reproducibility. Its clinical adoption requires multicenter validation, explicit calibration, pipeline harmonization, and transparent reporting.



Sourse: information obtained from He et al. (14)

Figure 2. Schematic diagram illustrating the integration of radiomics with omics data for precision cancer care

The first step is to collect data, including images and biological samples. From these resources, various dimensions of radiomic characteristics and molecular signatures of cancers are extracted and refined. Finally, radiomic and omic data are interconnected and integrated using advanced artificial intelligence algorithms to build accurate clinical prediction models.

Beyond its diagnostic potential, radiogenomics allows the construction of spatial and contextual maps that relate tumor biology to its microenvironment, opening up new perspectives for more precise therapeutic

interventions. In line with this, radiomics enables the extraction of quantitative information from medical images and the linking of this information to molecular profiles, thereby improving diagnosis and personalized medicine. These advanced techniques transform images into clinically relevant data, optimizing tumor characterization, therapeutic prediction, and the monitoring of oncological diseases without the need for invasive interventions.⁽¹⁸⁾

Despite all the benefits, its large-scale implementation in clinical practice still requires overcoming barriers related to system interoperability and external validation of the models developed, among other challenges, such as the need for standardization in the acquisition and processing of medical images, since technical variability between equipment and protocols can affect the reproducibility of findings. (13) Likewise, the validation of predictive models in diverse populations and heterogeneous clinical contexts is essential to ensure their universal applicability and avoid biases that limit their use. From an ethical perspective, dilemmas arise regarding the privacy of biomedical data and the protection of patients' genetic identities, especially when large-scale image and genomic information databases are integrated. The adoption of advanced technologies poses the risk of deepening inequalities in access to personalized health services, which requires clear policies to ensure equity and distributive justice in their implementation. (14,19,20,21)

| Table 3. Review articles | | | | | | | | |
|---|--|---|--|--|--|--|--|--|
| Article name | Publication date and authors | Methodology and objective | Conclusions and recommendations | | | | | |
| The era of radiogenomics in precision medicine: an emerging approach to support diagnosis, treatment decisions, and prognostication in oncology | 2020 - Shui et al. ⁽¹⁾ | with the aim of synthesizing the integration of radiomic and genomic data in the context of precision on cology. The methodology included the collection and preprocessing of medical images and molecular profiles, the segmentation of tumor regions, and the extraction of quantitative features through radiomics techniques. Subsequently, machine learning algorithms were applied to construct predictive models for diagnosis, prognosis, and | quantitative data from medical images, combined with clinical and genomic profiles in open databases, consolidates radiogenomics as a solid link between | | | | | |
| Radiogenomics in rectal cancer: an emerging approach for personalized m e d i c i n e . | 2023 - O'Sullivan et al. ⁽¹⁵⁾ | systematic review based on the PRISMA 2020 guidelines, with the aim of analyzing contemporary applications of radiogenomics in the management of rectal cancer. The methodology included a structured | Radiogenomics shows high potential in predicting therapeutic response in rectal cancer by combining structural image information with molecular characteristics of the tumor. This | | | | | |

phenotypes: current knowledge future perspectives in cancer diagnosis

aim of synthesizing the current potential for outcomes evaluated were extracted. This validation. data transparency in methodology, and multicenter design, which allowed for a critical evaluation of the scientific rigor of the included studies.

PET radiogenomics 2025 - Filippi et al. (4) The study was designed as a The combination of radiomic data and imaging systematic review, developed under obtained by PET with genomic the PRISMA guidelines, with the information has shown significant improving evidence on the application of PET- characterization, particularly in terms based radiogenomics in oncology. An of predicting specific mutations such as exhaustive search was conducted in EGFR or KRAS. This approach allows for a databases such as PubMed, Scopus, and more accurate assessment of the tumor's Web of Science, including publications biological profile, thus contributing up to October 31, 2024. Original to the personalization of treatment. studies integrating radiomic and It is important to consider the limited genomic analysis in human populations methodological quality of many of were selected, and variables related to the studies included, marked by tumor type, radiopharmaceutical used, a lack of external validation, the segmentation methods, statistical use of retrospective designs, and strategies applied, and clinical poor standardization of workflows. situation compromises The methodological quality of each reproducibility of the findings and hinders study was assessed using the Radiomics their clinical application, underscoring Quality Score (RQS 2.0) scale, the urgent need for prospective, considering criteria such as external multicenter studies with rigorously reproducibility, structured methodological protocols.

machine learning in musculoskeletal oncology care and combined with transcriptomic, prediction of relevant create a multimodal profile. To handle procedures, promoting safer Multimodal fusion enabled generation of

In tegration of radiomic and genomic radiogenomics and solution and genomic and genomic land genomics and solution integrate medical imaging data data using artificial intelligence tools and genomic profiles in the context represents a promising strategy for musculoskeletal oncology, improving the diagnosis and molecular Radiomic variables were extracted characterization of musculoskeletal from different imaging techniques tumors. This approach allows the epigenetic, and mutational data to alterations without the need for invasive the high dimensionality of the data, more efficient personalized medicine. reduction techniques such as LASSO Despite the demonstrated potential and PCA were applied, and then of the multimodal models developed, regression and classification models their clinical implementation still faces were used to construct predictors significant challenges, such as workflow of tumor molecular characteristics. standardization, the need for robust the databases, and external validation in "virtual biopsies" large cohorts. Therefore, it is concluded using artificial intelligence, with that future research should focus on the aim of detecting key mutations improving reproducibility and developing and guiding therapeutic decisions. collaborative protocols to facilitate their adoption in oncology medical practice.

bridging the gap between imaging and genomics

Radiogenomics: 2024 - Vivacqua et al. (16) The study was designed as a Radiogenomics is establishing itself as a radiogenomics in the resolution medical images and profiles features (radiomics) using artificial the clinical implementation identified, and technical advances, current challenges, and potential areas for future research were evaluated.

comprehensive narrative review key tool for precision medicine, enabling to analyze the current state of non-invasive correlation between tumor context phenotypic characteristics precision oncology. Relevant in medical images and underlying scientific information was compiled molecular alterations. This approach by combining the analysis of high-facilitates the prediction of genomic relevant to genomic data derived from tumor prognosis, and therapeutic selection, profiles. A methodological framework contributing to more personalized and was described that includes the high efficient decision-making in oncology. quantitative extraction of image Despite its transformative potential, intelligence techniques, together with radiogenomics still faces significant systematic integration with omic data limitations, such as the lack of such as genetic, transcriptomic, and standardization in image acquisition and proteomic sequences. Specific clinical processing, the scarcity of prospective applications in solid tumors (such as multicenter studies, and the need for breast, lung, and glioma) were then external validation of predictive models.

in prognostic models for lung cancer. Despite the potential value

Imaging genomics 2025 - Gou et al. (13) Systematic review with bibliometric Research in oncological radiogenomics of cancer: bibliometric analysis and review

methodologies.

NF1 genotype and imaging phenotype on whole-body MRI: NF1 radiogenomics

Correlation between 2020 - Lui et al. (21) Twenty-nine patients diagnosed This preliminary study shows a significant 59 image features were extracted in using a proprietary volumetric analysis platform (3DQI). A radiomic heatmap was constructed to explore associations between image features and mutation domains/types, both at the tumor level and per patient. Linear mixed-effects models and oneway analysis of variance (ANOVA) were applied to compare the similarity of radiomic profiles within and between different genetic mutation groups.

The prognostic value 2024 - Jiang et al. (3) The study was conducted as a systematic The combination of radiomic features review according to PRISMA guidelines extracted from computed tomography and was pre-registered in PROSPERO (CT) with genomic data significantly (CRD42023472571). A comprehensive improves the predictive capacity search was conducted in key databases of prognostic models in lung cancer such as PubMed, Embase, Web of patients, outperforming unimodal Science, and Cochrane Library, up approaches. This integration allows for to May 13, 2024, using predefined a more accurate assessment of tumor inclusion criteria to identify research behavior, favoring risk stratification and combining radiomics and genomics personalized clinical decision-making. Methodological quality was assessed radiogenomic models, their clinical using the radiomics quality score (RQS) applicability is still limited by the and the PROBAST tool for risk of bias. low methodological quality of several Finally, the AUC and C-index values studies, heterogeneity in segmentation of the radiogenomic models were and data extraction methods, and analyzed and compared with those of limited external validation. These the unimodal models, highlighting the findings underscore the need for superior performance of the former. prospective, standardized, multicenter studies to more robustly translate this emerging approach into clinical practice.

> analysis, focusing on the field of has grown exponentially over the radiogenomics applied to cancer. last decade, revealing a consolidated A structured search was conducted interest in integrating medical imaging in the PubMed, Embase, and Web characteristics with genomic data to of Science databases up to July improve the diagnosis, prognosis, and 2024, using controlled terms and therapeutic personalization of cancer. combinations such as "radiogenomics" Despite methodological advances in and "cancer." The selection of studies the use of artificial intelligence and was performed independently by radiomics tools to extract complex two researchers, applying inclusion features from medical images, the criteria that restricted the articles to heterogeneity of the approaches used original research in humans, published and the lack of standardization of in English, and using radiogenomics workflows represent an obstacle to Subsequently, a the consolidation of radiogenomics detailed data extraction was carried as a clinical tool. It is concluded that ou , and finally a bibliometric future research should focus on the analysis was integrated using the multicenter validation of predictive Bibliometrix and VOSviewer packages, models , database interoperability, which allowed mapping publication and the development of consistent collaboration networks, methodological frameworks that allow and citation patterns in the area. radiogenomicknowledge to be effectively translated into the healthcare setting.

> with neurofibromatosis type 1 (NF1) correlation between germline mutations and germline mutations previously in the NF1 gene and patterns of radiomic identified by targeted next-generation features of neurofibromas assessed sequencing were selected. Based by whole-body magnetic resonance on previous whole-body magnetic imaging. The findings support the resonance imaging (WBMRI) studies, existence of a radiogenomic link between 218 neurofibromas (97 discrete and the NF1 genotype and the imaging 121 plexiform) were analyzed using phenotype, reinforcing the potential a coronal STIR sequence. Each tumor of radiogenomics as a non-invasive was segmented individually, and tool for molecular characterization neurofibromatosis type

The integration of radiological and genomic data promises to transform contemporary oncology by enabling more precise, dynamic medicine tailored to each patient's individual characteristics. Radiogenomics is expected to play a crucial role in clinical decision-making, from initial diagnosis to the selection of targeted therapies and monitoring of therapeutic response, with the potential to improve clinical outcomes and patients' quality of life. In addition, radiogenomics could contribute to the discovery of new prognostic and predictive biomarkers, driving translational research and encouraging the design of more efficient and personalized clinical trials. In the long term, the incorporation of this discipline into digital health platforms and its linkage with other omics, such as transcriptomics and proteomics, could consolidate a comprehensive approach to tumor biology that transcends the current limits of cancer diagnosis and treatment. This scenario, although promising, requires sustained investment and commitment to research, technological infrastructure, and the training of professionals capable of interpreting and integrating the complexity of the multidimensional data that radiogenomics provides.

CONCLUSION

The synthesis of the 21 studies shows consistent signals in two specific scenarios: lung cancer with CT to infer mutations, especially with EGFR/KRAS, and gliomas with multiparametric MRI for molecular classification, with quantified performance ranging from moderate to high in internal validations and variable results in other locations. The integration of imaging with clinical variables tends to outperform unimodal models, but clinical extrapolation is limited by poor external validation, lack of calibration, and workflow heterogeneity.

Overall methodological quality remains low to moderate: RQS scores are affected by the absence of external validation and stability analysis; TRIPOD scores show persistent gaps in sample size, handling of missing data, and calibration reporting; and, according to PROBAST, the risk of bias is concentrated in participant selection, definition of predictors, and analysis with potential overfitting. This highlights precise operational needs for translation based on harmonizing, acquiring, segmenting, and standardizing functionality.

Radiogenomics, in its current state, complements, rather than replaces, biopsy, where molecular testing is prioritized, anticipating alterations of therapeutic interest and supporting stratification in defined contexts. To consolidate its clinical adoption, a prospective, multicenter agenda is required, with the publication of code and functionality dictionaries, harmonization procedures, and interoperable repositories, so that the observed performance translates into real, reproducible utility in oncology practice.

REFERENCES

- 1. Shui L, Ren H, Yang X, Li J, Chen Z, Yi C, et al. The era of radiogenomics in precision medicine: an emerging approach to support diagnosis, treatment decisions, and prognostication in oncology. Front Oncol. 2020;10:570465. doi:10.3389/fonc.2020.570465.
- 2. Lambin P, et al. Radiogenomics: bridging imaging and genomics. MedComm. 2024; 5(3):e372. doi:10.1002/mco2.722.
- 3. Jiang Y, Gao C, Shao Y, Lou X, Hua M, Lin J. The prognostic value of radiogenomics using CT in patients with lung cancer: a systematic review. Insights Imaging. 2024;15:259. doi:10.1186/s13244-024-01831-4.
- 4. Filippi M, Muoio B, Giannini V, et al. PET radiogenomics and imaging phenotypes: current knowledge and future perspectives in cancer diagnosis. Eur J Nucl Med Mol Imaging. 2025; 52(1):1-12. doi:10.1007/s00259-024-06579-6.
- 5. Kumar R, Sporn K, Khanna A, et al. Integrating radiogenomics and machine learning in musculoskeletal oncology care. Diagnostics (Basel). 2025; 15(11):1377. doi:10.3390/diagnostics15111377.
- 6. Wen Z, Sun L, Zhao P, et al. Insights into PET-based radiogenomics in oncology. Eur J Nucl Med Mol Imaging. 2025; 52(3):345-60. doi:10.1007/s00259-025-07262-7.
- 7. Gao X, et al. External validation of a CT-based radiogenomics model for EGFR mutation in lung cancer. Acad Radiol. 2025. doi:10.1016/j.acra.2025.01.001.
- 8. Rios Velazquez E, et al. A review of radiomics and genomics applications in cancers. Radiother Oncol. 2022; 160:210-220. doi:10.1186/s13014-022-02192-2.
- 9. Peters MDJ, Godfrey C, McInerney P, Munn Z, Tricco AC, Khalil H. Scoping Reviews. In: Aromataris E, Lockwood C, Porritt K, Pilla B, Jordan Z, editors. JBI Manual for Evidence Synthesis. JBI; 2024. 2020. https://

synthesismanual.jbi.global. doi:10.46658/JBIMES-24-09.

- 10. Navarrete IG, Yaqub M. A radiogenomics pipeline for lung nodules segmentation and prediction of EGFR mutation status from CT scans. arXiv. 2022. arXiv:2211.06620.
- 11. Gu J, Zhao Z, Zeng Z, Wang Y, Qiu Z, Veeravalli B, et al. Multi-phase cross-modal learning for noninvasive gene mutation prediction in hepatocellular carcinoma. arXiv. 2020. arXiv:2005.04069.
- 12. Ismail M, Correa R, Bera K, Verma R, Bamashmos AS, Beig N, et al. Spatial-and-context aware (SpACe) "virtual biopsy" radiogenomic maps to target tumor mutational status on structural MRI. arXiv. 2020. arXiv:2006.09878.
- 13. Gou J, Cheng J, Zhang Y. Imaging genomics of cancer: a bibliometric analysis and review. Cancer Imaging. 2025;25(24). doi:10.1186/s40644-025-00841-9.
- 14. He W, Huang W, Zhang L, Wu X, Zhang S, Zhang B. Radiogenomics: bridging the gap between imaging and genomics for precision oncology. MedComm (Beijing). 2024; 5(9):e722. doi:10.1002/mco2.722.
- 15. O'Sullivan NJ, Carroll D, Creamer D, Joyce MR. Radiogenomics in rectal cancer: an emerging approach for personalized medicine. Cancers (Basel). 2023; 15(12):3042. doi:10.3390/cancers15123042.
- 16. Vivacqua G, Latorre A, Suppa A, Nardi M, Pietracupa S, Mancinelli R, et al. Radiogenomics: bridging the gap between imaging and genomics. MedComm. 2024; 5(3):e372. doi:10.1002/mco2.722.
- 17. Beig N, Bera K, Tiwari P. Introduction to radiomics and radiogenomics in neuro-oncology: implications and challenges. Neurooncol Adv. 2020; 2(S4):v3-iv14. doi:10.1093/noajnl/vdaa148.
- 18. Zeng S, Wang XL, Yang H. Radiomics and radiogenomics: extracting more information from medical images for the diagnosis and prognostic prediction of ovarian cancer. Mil Med Res. 2024; 11:77. doi:10.1186/s40779-024-00580-1.
- 19. Perillo T, De Giorgi M, Papace UM, Serino A, Cuocolo R, Manto A. Current role of machine learning and radiogenomics in precision neuro-oncology. Explor Target Antitumor Ther. 2023; 4:545-55. doi:10.37349/etat.2023.00151.
- 20. Scarborough JA, Scott JG. Translation of precision medicine research into biomarker-informed care in radiation oncology. Semin Radiat Oncol. 2022; 32(1):42-53. doi:10.1016/j.semradonc.2021.09.001.
- 21. Liu Y, Jordan JT, Bredella MA, Erdin S, et al. Correlation between NF1 genotype and imaging phenotype on whole-body MRI: NF1 radiogenomics. Neurology. 2020; 94(24):e2521-e2531. doi:10.1212/WNL.0000000000009490.

FUNDING

The authors did not receive funding for the development of this research.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTION

Conceptualization: Cinthia Katherine Galarza Galarza.

Data curation: Cinthia Katherine Galarza Galarza.

Formal analysis: Cinthia Katherine Galarza Galarza.

Research: Cinthia Katherine Galarza Galarza and Lorena Bibiana Erazo Beltrán.

Methodology: Lorena Bibiana Erazo Beltrán.

Project management: Cinthia Katherine Galarza Galarza and Lorena Bibiana Erazo Beltrán.

Resources: Cinthia Katherine Galarza Galarza. Supervision: Cinthia Katherine Galarza Galarza. Validation: Lorena Bibiana Erazo Beltrán. Visualization: Lorena Bibiana Erazo Beltrán.

Writing - original draft: Lorena Bibiana Erazo Beltrán. Writing - review and editing: Cinthia Katherine Galarza Galarza.