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Review Article

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Advancements in MRI radiomics for hepatocellular carcinoma: a narrative review

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Abstract

***Background & Aims*:** Hepatocellular carcinoma (HCC) is a major global health concern, ranking sixth among prevalent cancers worldwide and third in cancer-related deaths. Despite diagnostic advancements, prognosis remains challenging. Traditional methods rely on postoperative pathology, limiting preoperative decision-making. Radiomics offers a solution by extracting imaging data to predict outcomes before surgery, aiding personalized treatment decisions.

***Materials & Methods*:** A PubMed search spanning from May 2019 to June 2024 was conducted to identify relevant peer-reviewed articles using the keywords: "radiomics," "MRI," "hepatocellular carcinoma," "HCC," "radiomics features," "liver cancer imaging," "tumor segmentation," "treatment response," and "HCC prognosis." The search yielded a total of 850 articles. After an initial screening based on titles and abstracts, 150 full-text articles were reviewed, and 35 articles were selected for inclusion in this review. The review focused on highlighting the utility of radiomics features on MRI across various aspects of HCC management.

***Results*:** This review highlights MRI radiomics' extensive utility in managing HCC. It aids in diagnosis, treatment decision-making, and prognosis prediction by analyzing imaging data noninvasively. MRI radiomics informs differential diagnosis, histological grading, microvascular invasion assessment, gene expression prediction, therapeutic monitoring, and prognostic evaluation. Its transformative potential offers clinicians a comprehensive toolset for personalized care and improved patient outcomes in HCC management.

***Conclusion*:** MRI radiomics holds promise as a noninvasive tool for improving the diagnosis and treatment of HCC. Its ability to extract comprehensive imaging data enables clinicians to make personalized treatment decisions, potentially improving patient outcomes. Further research and clinical validation are warranted to fully integrate MRI radiomics into routine clinical practice for HCC management.

***Keywords*:** Diagnostic techniques, Hepatocellular Carcinoma, Magnetic resonance imaging, Radiomics; Microvascular invasion

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Introduction

Hepatocellular carcinoma (HCC) presents a significant global health challenge, ranking as the sixth most common cancer and the third leading cause of cancer-related mortality worldwide. Despite ongoing improvements in diagnostic techniques, the prognosis for HCC patients remains unsatisfactory. Traditional imaging modalities and certain histopathological features play crucial roles in assessing the prognosis of HCC patients (1). However, most prognostic indicators are derived from postoperative pathological examinations, limiting their utility in preoperative decision-making. Addressing this gap, radiomics emerges as a promising field by extracting high-dimensional imaging data from diverse image types to construct models for noninvasive prediction of clinical outcomes before surgery, thereby facilitating personalized treatment decisions. This narrative review is particularly important right now, as advancements in imaging technologies and data analytics are rapidly evolving. The increasing use of artificial intelligence and machine learning in radiomics offers the potential to revolutionize HCC diagnosis and treatment planning. As HCC incidence rates continue to rise globally, an updated synthesis of radiomics' role in clinical practice can provide valuable insights into improving patient outcomes and optimizing personalized treatment strategies. This comprehensive review aims to synthesize recent literature on magnetic resonance imaging (MRI) radiomics in the diagnosis and treatment of HCC. Through an extensive literature search spanning 2019 to 2024, relevant peer-reviewed articles were identified using a broad range of keywords (2). The review will elucidate the utility of radiomics features on MRI in various aspects of HCC management, including differential diagnosis, histological grading, assessment of microvascular invasion (MVI), prediction of gene expression status, evaluation of therapeutic response, and prognosis prediction.

Materials & Methods

A PubMed search was conducted from May 2019 to June 2024 to identify peer-reviewed articles on MRI radiomics in hepatocellular carcinoma (HCC). Keywords included "radiomics," "MRI," "hepatocellular carcinoma," "liver cancer imaging," and others. Of the 850 articles initially identified, 150 full texts were reviewed, and 35 were selected for inclusion in this narrative review. The review focused on the utility of MRI radiomics in HCC diagnosis, treatment decision-making, and prognosis prediction.

MRI Radiomics Workflow

MRI radiomics plays a critical role in modern HCC diagnosis and treatment by converting high-dimensional imaging data into quantitative features that can reveal tumor characteristics not visible to the human eye. By systematically integrating multiple steps, the MRI radiomics workflow facilitates the extraction of clinically meaningful data, providing a non-invasive method to assess tumor biology, predict treatment response, and improve prognostication. This workflow is particularly valuable in HCC, where early detection and precise characterization of tumor biology are paramount to guiding therapeutic decisions and improving patient outcomes. MRI radiomics involves a comprehensive workflow that integrates multiple steps, each crucial for extracting meaningful information from medical images and translating it into clinically relevant insights (3). (Figure 1)

This section will provide a comprehensive analysis of the MRI radiomics workflow, emphasizing its role in the diagnosis and treatment of HCC (4). A PubMed search was performed, covering the period from May 2019 to June 2024, using the following keywords: "radiomics," "MRI," "hepatocellular carcinoma," "HCC," "radiomics features," "liver cancer imaging," "tumor segmentation," "treatment response," and "HCC prognosis." This search resulted in 850 articles. After a preliminary review of titles and abstracts, 150 full-text articles were examined, and 35 were chosen for inclusion in this review. The focus of the review was on the application of MRI-based radiomics features in various aspects of HCC management.

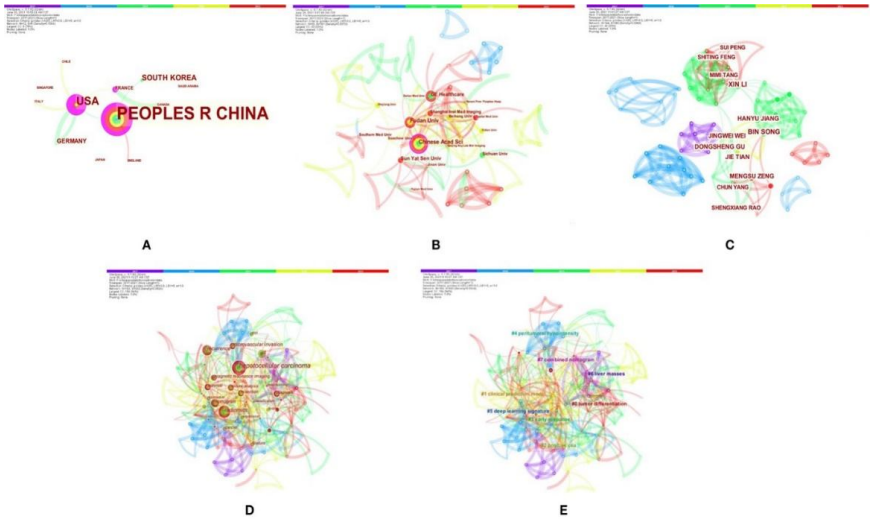

Fig. 1. Bibliometrics of magnetic resonance imaging radiomics in hepatocellular carcinoma. (A) Co-occurrence map of countries. (B) Co-occurrence map of institutions. (C) Co-occurrence map of authors. (D) Terms in theco-occurrence network. (E) Terms in theco-occurrence clusters (Front Oncol. 2021; 11: 698373 https://doi.org/10.3389/fonc.2021.698373)

Image Acquisition and Reconstruction

The MRI radiomics workflow begins with image acquisition, where high-quality imaging protocols are employed to capture detailed anatomical and functional information of the liver. Various MRI sequences, including T1-weighted, T2-weighted, diffusion-weighted imaging (DWI), and dynamic contrast-enhanced imaging, are utilized to capture different aspects of tissue characteristics (5). Parameters such as field strength, sequence type, and acquisition parameters are optimized to enhance image quality and reproducibility. Following image acquisition, data undergo reconstruction to generate digital representations of the acquired images (6). Reconstruction techniques such as Fourier transformation or iterative algorithms are employed to convert raw MRI data into interpretable images. The choice of reconstruction method can influence image resolution, signal-to-noise ratio, and overall image quality, which are critical for subsequent radiomic analysis (7).

Segmentation

Segmentation is a fundamental step in MRI radiomics, involving the delineation of regions of interest (ROIs) within the liver parenchyma and tumor lesions. Manual or semi-automated segmentation techniques are employed to outline the boundaries of anatomical structures, including the liver, tumor, and surrounding tissues. Accurate segmentation is essential for isolating relevant regions for feature extraction and minimizing variability in subsequent analyses. Advanced segmentation algorithms, such as region-growing, active contour, or deep learning-based methods, may be employed to improve accuracy and reproducibility, particularly in complex cases with heterogeneous lesions or adjacent structures (8).

Feature Extraction

Once segmented, a diverse array of quantitative imaging features is extracted from the ROIs, capturing various aspects of tumor morphology, texture, and intensity distribution. These features encompass shape-based descriptors, intensity histograms, texture matrices (e.g., gray-level co-occurrence matrix [GLCM], gray-level run-length matrix [GLRLM]), and higher-order statistical measures (e.g., fractal dimension, wavelet transform coefficients). Feature extraction is performed using specialized software platforms or custom

algorithms, ensuring robustness, reproducibility, and scalability across different imaging datasets (9).

Feature Selection

In feature selection, redundant or irrelevant features are eliminated to reduce dimensionality and enhance the predictive power of radiomic models (10). Various techniques, including statistical tests, machine learning algorithms, and dimensionality reduction methods (e.g., principal component analysis [PCA], recursive feature elimination [RFE]), are employed to identify the most informative features associated with HCC diagnosis and treatment outcomes. Feature selection strategies aim to balance model complexity with predictive performance, ensuring optimal generalization and interpretability of radiomic models.

Modeling

The selected radiomic features are utilized to develop predictive models that characterize different aspects of HCC, including diagnosis, histological grading, MVI, and treatment response (11). Machine learning algorithms such as support vector machines (SVM), random forests, logistic regression, and deep neural networks are commonly employed to build predictive models using radiomic features as input variables. These models are trained on annotated datasets, where ground truth labels (e.g., histopathological findings, treatment outcomes) are utilized to optimize model parameters and evaluate performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (12). (Figure 2).

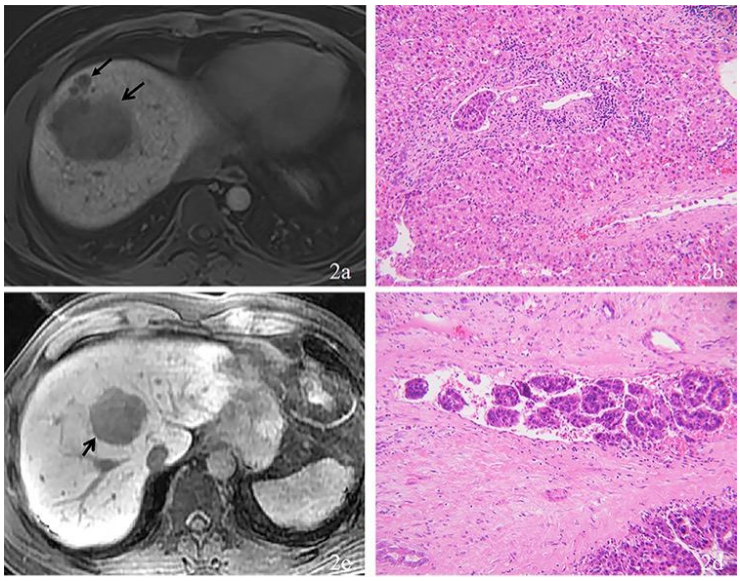

Fig. 2. Representative MRI features associated with histopathological findings. HBP images (a) for a 29-year-old male patient show peritumoral HBP hypointensity (arrow) and a satellite nodule (arrowhead). Hepatocellular carcinoma with MVI-positive was confirmed by histopathology (b). HBP images (c) for a 41-year-old male patient show a radiological capsule (arrow) without peritumoral HBP hypointensity. Hepatocellular carcinoma with MVI-positive was confirmed by histopathology (d). Abbreviations: HBP, hepatobiliary phase; MVI, MVI. https://www.dovepress.com/mri-features-for-predicting-microvascular-invasion-and-postoperative-r-peer-reviewed-fulltext-article-JHC

Model Validation

Model validation is a critical step in the MRI radiomics workflow, assessing the performance and generalizability of predictive models on independent datasets. Validation techniques such as cross-validation, bootstrapping, and external validation using unseen

patient cohorts are employed to estimate the robustness and reliability of radiomic models (13). Rigorous validation ensures that radiomic-based predictions are robust across different patient populations, imaging protocols, and scanner platforms, enhancing their clinical utility and translational potential. The MRI radiomics workflow encompasses a series of interconnected steps, from image acquisition to model validation, aimed at harnessing the rich information embedded within medical images to improve HCC diagnosis and treatment. Each step involves specialized methodologies and computational techniques, underpinned by the overarching goal of extracting actionable insights to guide personalized patient care and improve clinical outcomes in HCC management (14).

MRI Radiomics will explore the role of MRI radiomics in the differential diagnosis of HCC, particularly in distinguishing HCC from other hepatic lesions such as hepatic adenomas, focal nodular hyperplasia (FNH), and hepatic metastases. This review discusses the specific radiomics features utilized and their diagnostic accuracy compared to traditional imaging methods (15).

Histological Grading and Microvascular Invasion Assessment

Histological grading and the assessment of MVI are paramount in determining prognosis and guiding treatment decisions in HCC. This section delves into the utility of MRI radiomics in predicting histological grade and MVI status noninvasively. Moreover, it explores the correlation between radiomics features and histopathological findings, elucidating their implications for treatment stratification and prognostic assessment (16). Histological grading, particularly through the Edmondson-Steiner classification, is critical for predicting HCC outcomes. Higher-grade tumors often correlate with poorer prognosis and a more aggressive disease course. However, this traditional method has limitations, such as requiring invasive biopsies and potential variability between observers. MRI radiomics offers an alternative by providing a noninvasive way to predict tumor grade preoperatively. This approach could improve treatment planning by offering a more consistent and less invasive assessment. Radiomics analysis of preoperative MRI scans can predict histological grade by extracting quantitative features that reflect the tumor's biological characteristics. These features include metrics such as texture, shape, and intensity, which can help differentiate between well-differentiated and poorly differentiated tumors. For instance, poorly differentiated tumors tend to display higher heterogeneity and irregular margins, both of which can be captured in MRI images. These radiomic markers provide detailed insights into tumor architecture, offering useful information for treatment decisions.

Predicting Histological Grade

Histological grading of HCC is essential for determining tumor aggressiveness and guiding treatment strategies. Traditionally, histological grade is assessed using the Edmondson-Steiner grading system based on architectural and cytological features observed on histopathological specimens (17). However, obtaining histological samples for grading requires invasive procedures such as biopsy or surgical resection, which may not always be feasible, especially in cases of multifocal or diffuse disease. MRI radiomics offers a noninvasive approach to predicting histological grade by extracting quantitative imaging features from preoperative MRI scans. Radiomic features derived from T1-weighted, T2-weighted, and diffusion-weighted imaging sequences capture intrinsic tumor characteristics, including shape, texture, and intensity variations. Studies have demonstrated correlations between radiomics features and histopathological grade, with higher-grade tumors exhibiting distinct radiomic signatures characterized by increased heterogeneity, irregular margins, and altered intensity patterns. Radiomics-based predictive models integrating multiple imaging modalities and clinical parameters have shown promise in accurately stratifying HCC patients into different histological grade categories. These models enable clinicians to preoperatively assess tumor aggressiveness and tailor treatment strategies accordingly, such as selecting candidates for

neoadjuvant therapy or aggressive surgical resection (18).

Assessing Microvascular Invasion

MVI is a strong predictor of tumor recurrence and poor prognosis in HCC patients undergoing curative resection. The presence of MVI indicates tumor invasion into small hepatic vessels, signifying a more aggressive tumor phenotype and a higher likelihood of tumor dissemination (19). Histological assessment of MVI requires microscopic examination of surgical specimens, which may not always capture the extent of vascular invasion accurately. MRI radiomics provides a noninvasive means of assessing MVI status by capturing subtle imaging features associated with vascular invasion. Radiomic features derived from dynamic contrast-enhanced MRI sequences, such as enhancement patterns, washout kinetics, and vascular permeability parameters, reflect the underlying vascular architecture and tumor microenvironment characteristics (20). Specific radiomic features, such as texture analysis and shape characteristics, have proven effective in distinguishing between MVI-positive and MVI-negative tumors. MVI-positive tumors often exhibit irregular enhancement patterns, heterogeneous texture, and altered perfusion kinetics, which can be used to predict MVI status preoperatively. Radiomics-based predictive models integrating MRI radiomics features with clinical variables have shown promise in predicting MVI status preoperatively. These models enable risk stratification of HCC patients based on their likelihood of harboring MVI-positive tumors, facilitating treatment planning and prognostic assessment (21). Patients identified as high-risk for MVI may benefit from adjuvant therapies or intensified surveillance protocols postoperatively to mitigate the risk of tumor recurrence and improve long-term outcomes. Radiogenomics, a burgeoning field at the intersection of radiomics and genomics, holds immense potential for advancing precision medicine in hepatocellular carcinoma (HCC). By integrating radiomics data derived from medical imaging with genomic information obtained from molecular profiling techniques, radiogenomics seeks to elucidate the molecular underpinnings of tumor heterogeneity and predict gene expression patterns and molecular subtypes of HCC. This section delves into recent advancements in MRI radiogenomics and its implications for precision medicine in HCC (22).

Recent Advancements in MRI Radiogenomics

In recent years, significant strides have been made in MRI radiogenomics, leveraging advances in imaging technology and genomic profiling techniques to unravel the intricate relationship between imaging phenotypes and underlying molecular alterations in HCC. By harnessing the wealth of information encoded within medical images, radiogenomic studies have identified imaging features that correlate with specific genetic mutations, signaling pathways, and molecular subtypes of HCC (22). For instance, radiomic features derived from multiparametric MRI sequences, including T1-weighted, T2-weighted, diffusion-weighted, and dynamic contrast-enhanced imaging, have been linked to genetic alterations such as TP53 mutations, CTNNB1 mutations, and MYC amplifications in HCC (23). These radiogenomic associations provide insights into the biological characteristics and tumor behavior associated with specific genomic alterations, facilitating the development of personalized treatment strategies tailored to individual patient profiles (24).

Implications for Precision Medicine

The predictive value of radiomics features for gene expression patterns holds profound implications for precision medicine in HCC. By noninvasively assessing tumor biology and molecular heterogeneity, radiogenomic models can inform treatment decisions and stratify patients based on their likelihood of responding to targeted therapies and immunotherapy (25). For instance, radiogenomic signatures predictive of activation of the Wnt/β-catenin pathway or dysregulation of the PI3K/AKT/mTOR pathway may identify patients suitable for therapies directed against these pathways, such as beta-catenin inhibitors or mTOR inhibitors. Additionally, radiomic features associated with immune cell infiltration, tumor immune evasion mechanisms, and immune checkpoint molecule expression can guide the selection of patients who may

benefit from immune checkpoint inhibitors (ICIs) or combination immunotherapy regimens. These radiogenomic biomarkers can also aid in patient stratification for clinical trials, enabling the identification of cohorts most likely to benefit from novel therapeutic interventions. This approach enhances the success rate of precision medicine strategies in HCC (26). By integrating radiomics data with genomic information, radiogenomics offers significant potential to optimize treatment outcomes, improve patient survival, and advance personalized medicine in HCC management. Through this synergy, radiogenomics facilitates more tailored and effective treatment approaches, paving the way for enhanced patient care in liver cancer.

Prediction of Treatment Response and Prognosis

MRI radiomics has emerged as a promising tool for predicting treatment response and prognosis in HCC patients, offering insights that can guide personalized therapeutic strategies and improve patient outcomes. This section explores recent studies on the predictive value of radiomics features for response to locoregional therapies such as transarterial chemoembolization (TACE) and surgical resection. Additionally, it will explore the prognostic implications of radiomics-based models in predicting recurrence and overall survival outcomes (27).

Prediction of Treatment Response

TACE is a widely used locoregional therapy for unresectable HCC, designed to deliver chemotherapy agents directly to the tumor while inducing ischemia through embolization of hepatic artery branches. MRI radiomics has shown significant promise in predicting treatment response to TACE, enabling clinicians to identify patients likely to benefit from this intervention and tailor treatment plans accordingly (28). Recent studies have demonstrated the utility of radiomics-based models in predicting tumor response to TACE, with radiomic features derived from pre-TACE MRI scans serving as predictive biomarkers. These features encompass a wide range of morphological, textural, and intensity-based characteristics, reflecting underlying tumor biology and heterogeneity (29). By quantifying spatial and temporal variations in tumor phenotypes, radiomics models stratify patients into different risk groups based on their likelihood of achieving complete or partial response, stable disease, or disease progression following TACE (Figure 3). Radiomics-based predictive models can incorporate clinical variables such as tumor size, alpha-fetoprotein (AFP) levels, and liver function parameters to enhance predictive accuracy and clinical utility. Integrating multimodal data from MRI, laboratory tests, and clinical variables enables comprehensive risk stratification and personalized treatment planning, optimizing therapeutic outcomes while minimizing treatment-related complications (30).

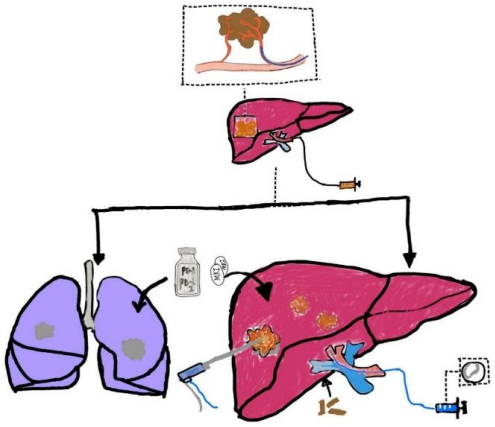

Fig. 3. Shows transarterial chemoembolization

Prognostic Implications

In addition to predicting treatment response, MRI radiomics has demonstrated prognostic value in predicting recurrence and overall survival outcomes in HCC patients. Radiomics-based models can integrate preoperative imaging features, histopathological parameters, and clinical variables to develop prognostic signatures that stratify patients into different risk categories based on their likelihood of disease recurrence and long-term survival (31). Studies show that radiomics features derived from preoperative MRI scans hold prognostic significance in predicting recurrence-free survival (RFS), overall survival (OS), and disease-specific survival (DSS) following surgical resection of HCC (32). By capturing intratumoral heterogeneity, vascularity, and tumor microenvironment characteristics, radiomics models identify high-risk patients who may benefit from adjuvant therapies or intensified postoperative surveillance strategies. Moreover, radiomics-based prognostic models facilitate personalized risk assessment and treatment decision-making, enabling clinicians to tailor follow-up protocols and therapeutic interventions based on individual patient profiles. By integrating radiomics data with clinical parameters and histopathological findings, multidisciplinary teams can optimize patient management strategies, ultimately improving long-term outcomes for HCC patients (33).

Challenges and Future Directions

MRI radiomics holds immense promise for revolutionizing the diagnosis and treatment of HCC. However, its widespread clinical application is hindered by several challenges and limitations, including issues related to data standardization, analytical methodologies, and study design (34). This section also explores future directions in MRI radiomics research aimed at overcoming these obstacles and unlocking its full potential (35).

Data Standardization

One of the primary challenges in MRI radiomics is the lack of standardized imaging protocols and data acquisition techniques. Variability in imaging parameters, such as field strength, sequence type, and acquisition parameters, can introduce inconsistencies in radiomic features, limiting the reproducibility and generalizability of radiomics models (36). To address this challenge, efforts are underway to establish standardized imaging protocols and data acquisition guidelines for HCC imaging studies (37). Collaborative initiatives involving radiologists, physicists, and clinicians aim to define consensus protocols that ensure uniformity across imaging platforms and facilitate data harmonization for multicenter studies. Standardization of segmentation protocols is also essential to ensure consistent delineation of regions of interest (ROIs) within MRI images. Variability in segmentation algorithms and interobserver variability can impact the reliability and accuracy of radiomic features, compromising the robustness of radiomics models. Harmonization of segmentation methodologies and the development of automated segmentation algorithms are critical steps toward overcoming this challenge and enhancing the reproducibility of radiomics analyses (38).

Analytical Methodologies

The analytical methodologies employed in MRI radiomics pose another challenge, particularly regarding feature extraction, selection, and model development. The choice of radiomic features and machine learning algorithms can influence the predictive performance and interpretability of radiomics models. However, there is a lack of consensus on the optimal feature selection techniques and machine learning algorithms for HCC radiomics studies. To address this challenge, comparative studies evaluating different feature extraction methods and machine learning algorithms are needed to identify the most robust and clinically relevant approaches (39). Additionally, advancements in deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), hold promise for capturing complex spatial and temporal relationships within MRI images, potentially improving the predictive accuracy of radiomics models (40).

Study Design

Many MRI radiomics studies are retrospective in nature, limiting their ability to establish causal relationships and generalize findings to broader patient populations. Prospective cohort studies with standardized imaging protocols and longitudinal follow-up are needed to validate the predictive performance of radiomics models in real-world clinical settings. Furthermore, multicenter collaborations and external validation studies are essential to assess the generalizability and robustness of radiomics-based predictions across different patient cohorts and imaging platforms (41).

Discussion

MRI radiomics in HCC offers exciting potential to transform HCC diagnosis and treatment. By harnessing advanced imaging techniques and computational analysis, radiomics provides a noninvasive means to predict critical factors such as histological grade and MVI, guiding personalized treatment strategies. However, challenges in standardizing imaging protocols and analytical methodologies underscore the importance of collaborative efforts among researchers, clinicians, and imaging experts. Establishing standardized protocols and validating radiomics models across different research settings are essential steps toward overcoming these challenges and accelerating the translation of radiomics into clinical practice. The integration of multi-omics data with radiomics presents an exciting opportunity to advance precision medicine in HCC. By combining imaging data with genetic, transcriptomic, and proteomic information, tailored treatment approaches can be developed to address the molecular characteristics of individual tumors. Lastly, prospective clinical trials with longitudinal follow-up are crucial for confirming the clinical utility of radiomics in guiding treatment decisions and improving patient outcomes. These trials not only assess the predictive power of radiomics models in real-world clinical settings but also identify any limitations or challenges that need to be addressed before radiomics can be widely adopted in routine clinical practice.

Future Directions

Despite these challenges, MRI radiomics holds significant potential for advancing personalized medicine in HCC. To realize this potential, several future directions can be explored: (a) Integration of Multi-Omics Data: Integrating radiomics data with genomics, transcriptomics, and proteomics data can provide comprehensive insights into the molecular landscape of HCC, enabling the development of multimodal predictive models that capture the heterogeneity of the disease and guide targeted therapeutic interventions.(b) Development of Standardized Protocols: Establishing standardized imaging and segmentation protocols for MRI radiomics studies is crucial to ensure consistency and reproducibility across different research centers. Collaborative efforts to define consensus guidelines and quality control measures will enhance the reliability and comparability of radiomics analyses. (c) Validation in Prospective Clinical Trials: Prospective clinical trials are needed to validate the clinical utility of MRI radiomics-based models in guiding treatment decisions and improving patient outcomes. These trials should incorporate standardized imaging protocols, longitudinal follow-up, and comprehensive outcome assessments to assess the prognostic and predictive value of radiomics features in real-world clinical practice.

Conclusion

MRI radiomics revolutionizes HCC diagnosis and treatment by decoding tumor biology and guiding personalized therapies. Despite challenges like standardization and data access, ongoing research aims to integrate radiomics into routine clinical practice. However, several limitations must be acknowledged, including variability in imaging protocols across institutions, limited large-scale datasets for validation, and the lack of consensus on feature selection methods. These factors may impact reproducibility and the generalizability of findings. Further multicenter studies and collaborative efforts are essential to overcome these barriers. Nonetheless, with its potential to enhance

patient outcomes through tailored treatments, MRI radiomics heralds a new era of precision oncology in HCC management.

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Ethical statement

This review article was based on comprehensive searches of various medical databases, with data collection spanning from May 2019 to June 2024. The study was approved by the Institutional Ethics Committee, ZJU4H (ID No: ZJU4H00198986). The authors confirm that the review adheres to ethical guidelines, utilizing studies exclusively from peer-reviewed journals that comply with established ethical standards.

Data availability

The supporting data of this study is always obtainable on request from the corresponding author.

Conflict of interest

The authors declare that there are no obvious or potential conflicts of interest related to the publication of this study.

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Author Contribution

Conceptualization: Sakarie Mustafe Hidig, Data curation: Sakarie Mustafe Hidig, Hannan Samatar, Fidele Kakule Kitaghenda, Mohamed Abdifatah Mohamed. Methodology: Sakarie Mustafe Hidig, Hannan Samatar, Fidele Kakule Kitaghenda, Mohamed Abdifatah Mohamed. Visualization: Sakarie Mustafe Hidig. Writing – original draft: Sakarie Mustafe Hidig. Writing – review & editing: All authors.

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