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Advancements in Oncological Dynamic Contrast-Enhanced Mri: A Review and Critical Analysis of Prior Studies

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ABSTRACT

Dynamic contrast-enhanced magnetic-resonance imaging(DCE-MRI) has emerged as a transformative method in oncological imaging, contributing to findings on tumor vascularity, permeability, and treatment response. This review outlines an extensive assessment of DCE-MRI implementation across various malignancies, with a specific emphasis on liver tumors, spinal metastases, and breast cancer. Through examination key pharmacokinetic parameter such as Ktrans, Ve and Kep, the article highlights their diagnostic and prognostic value in discriminating lesion types and forecasting microvascular invasion. It also delves into the integration of artificial intelligence and radiomics in optimizing the interpretability and reproducibility of DCE-MRI data. The review confronts issues related to motion artifacts, regulation, and crossplatform variability, while recommending future directions or clinical uptake and research evolution. Through this synthesis, DCE-MRI is placed as a crucial tool in precision oncology, with the extension of implementation across anatomical systems.

Key Words: Dynamic contrast-enhanced magnetic contrast resonance imaging (DCE-MRI), forward volume transfer (Ktrans), reverse constant (Kep), Computed tomography (CT) and extravascular extracellular space volume fraction (VeVe)

INTRODUCTION

An operational imaging approach, Dynamic Contrast-Enhanced Magnetic Resonance imaging (DCE-MRI) that facilitates neumarical evaluation of blood flow, tissue perfusion, and vascularity by examining signal refinement curves subsequent to contrast administration [1]. This approach records dynamic shifts in tumor vascularity permeability, often influenced by antiangiogenic therapies, delivering pivotal revelations into tumor biology and response to treatment [2]. DCE-MRI creates Pharmacokinetic variables such as the forward volume transfer (Ktrans), reverse constant (Kep), and extravascular extracellular space volume fraction (Ve), each indicating distinct elements of the tumor microenvironment and vascular behavior. These parameters facilitate monitoring of therapeutic effectiveness [3]. DCE-MRI proposes superior sensitivity than conventional MRI in recognizing subtle changes within the tumor microenvironment, leading to a significant early biomarker of treatment response [4]. This approach assists in voxel-wise calculations of perfusion characteristics, facilitating exact outlining of tumor heterogeneity and permitting personalized treatment strategies. Clinically-MRI has shown utility in multiple cancer: in hepatocellular carcinoma (HCC), it assists in assessing microvascular invasion (MVI) and distinguishing HCC from hepatic adenomas; in cervical cancers, it elevates diagnostic confidence and help avoid unnecessary radical surgeries [5]. and in soft tissue tumors, combined multiparametric analysis with diffusion imaging have diagnostic accuracy [6]. Furthermore, quantitative parameters such as Ktrans, Kvp, Ve, and add to tumor sorting and upgrade early prediction of treatment failure and recurrence risk [7]. Elevated Ktrans values are often associated with increased vascular permeability characteristic of malignant tumors, while higher Kep can reflect aggressive tumor behavior and enhanced perfusion [8,9]. Increased Ve typically indicates tumors with extensive extracellular matrix or edema, suggesting potential for aggressive spread [5]. These capabilities, such as planning and adaptive radiotherapy, enhance precision in tumor targeting [10].

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Ultrasound has a low sensitivity for early (HCC), generally varying from 60% to 70% which can significantly obstruct identification. Additionally, the results could be fluctuating due to operator-dependent factors, resulting in unpredictable findings [9]. Computed tomography (CT) demonstrates balanced specificity for HCC detection, generally between 70% and 80%. This limitation is aggravated by the risk related to ionizing radiation effects, particularly troubling patients who require frequent imaging due to high risk of reappearance [8].

Standard MRI is vulnerable to motion distortion, notably those done by patient breathing, which can compromise image quality. Furthermore, its precision declines when assessing small lesions, making it less effective in identifying early-stage HCC. DCE-MRI offers numerical analysis, such as Ktrans which reflect the measure of contrast agent transfer out of blood vessels within the extracellular medium. This parameter is vital to distinguish benign and malignant tumors which generally exhibit higher Ktrans values because of elevated vascular permeability and blood dynamics [9].

DCE-MRI offers quantitative evaluations of vascular characteristics, which are crucial for understanding tumor microenvironments and hemodynamics, thus elevating tumor characterization compared to standard MRI techniques [11]. The technique's ability to assess tumor vascularity and permeability provides insights into tumor behavior, which is key to therapeutic planning and enhancing patients result [12]. DCE-MRI can also facilitate the differentiation of malignant and benign tumors by sharing elaborated findings of tumor blood flow, which is often challenging with conventional imaging [13]. DCE-MRI can detect changes in tumor vascularity and microenvironment, providing critical insights that reduce the need for invasive biopsies in assessing response to therapy [14].

This investigation seeks to examine the reliability of (DCE-MRI) in cetegorizing benign and malignant liver tumors with precision, enhancing noninvasive diagnostic capabilities. DCE-MRI has shown potential in providing detailed predictions of microvascular invasion (MVI) and vascular encapsulation tumor clusters (VETC) in HCC, attaining the

area under the curve (AUC) of 0.85 in internal validation [9]. The integration of clinical and radiomics models in DCE - MRI can improve diagnostic performance, offering a non-surgical substitute to traditional biopsy methods. However, variability in imaging protocols and the need for standardization remain challenges that could affect the clinical application of DCE-MRI, Building upon these foundations, this review aims to objectively examine the breakthrough and clinical implementation of dynamic contrast-enhanced MRI in oncological imaging. By weaving togeather contemporary publications on DCE-MRI's diagnostic, prognostic and therapeutic tracking mchanisms involving numerous tumor categories such as liver, spinal and breast cancerous conditions.

Technical Foundation of DCE-MRI

A valuable means of evaluating tumor vascularity by quantifying how contrast agents move through tissue compartments is offered by (DCE-MRI) Dynamic contrast-enhanced MRI. Perfusion rate at which contrast material transitions from the blood flow dynamics vessels into the extracellular matrix is described through one key parameter, Ktrans (volume transfer constant), both blood flow and the permeability of vessel walls is reflected by this rate. To calculate Ktrans the TTofts model, which underpins many DCE-MRI analyses, treats tissue as two interacting compartments and uses an arterial input function. Higher tumor aggressiveness and indication of how the tumor might respond to therapies are often linked to elevated Ktrans [15,16].

Kep (rate constant), another crucial metric, exposes how quickly the contrast agent returns from the extracellular matrix back into the bloodstream. Kep is typically computed as Ktrans divided by Ve (the volume of the extracellular space). It provides insights into the efficacy of contrast clearance and highlights differences in vascular permeability between tumor types [17,18]. As shown in Figure 1, …

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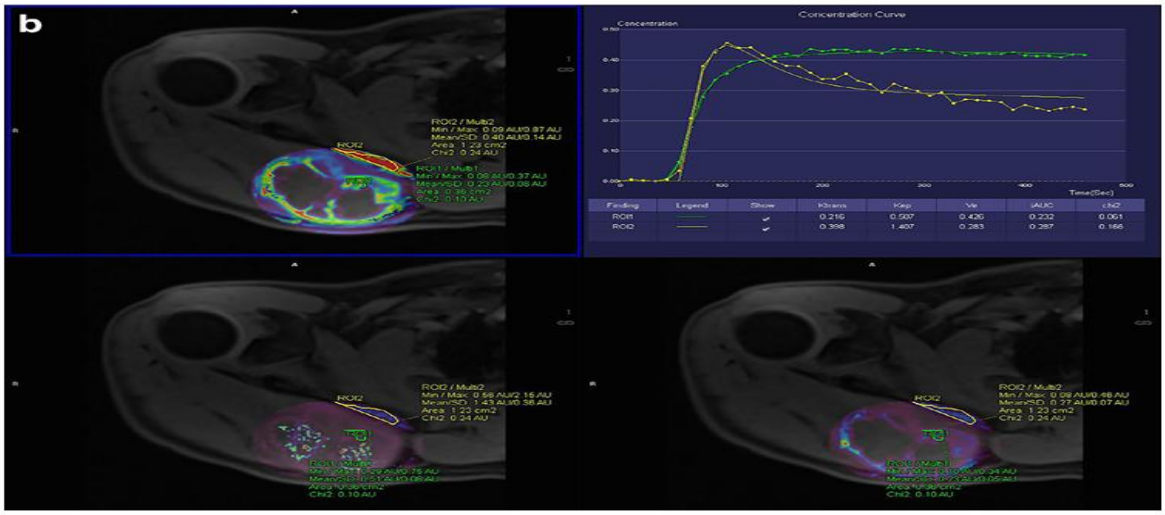


Fig 1. The values included are ktrans (0.398 min-1), Kep (1.407 min-1), Ve (0.98), and lauc observed in the ROI was labelled as type IV on the basis of tissue contrast kinetics.

$$\text{Formula: } \left\{K_{Trans} = \frac{K_{ep}.V_e}{Vp}\right\}\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The parameter Ve (extracellular volume fraction) measures the proportion of tissue volume occupied by the extracellular space. Tumors with higher Ve values have larger extracellular areas due to factors like edema or a loose extracellular matrix, features often seen in more aggressive malignancies [18,19].

$$\text{Formula: } \left\{K_{ep} = \frac{K_{Trans}}{V_e}\right\}\ldots\ldots\ldots\ldots(2)$$

Collectively, Ktrans, Kep, and Ve help assess key features of tumor biology, including angiogenic, perfusion, and vascular leakiness. High Ktrans and Kep values generally point to active tumor growth and rich blood supply, while lower levels may suggest necrosis or poor vascularization. These parameters are critical in predicting tumor behavior and potential treatment responses. Its important to note that accurate measurements of these parameters can be affected by several technical factors. Motion during imaging, especially due to breathing, can distort time-intensity data. Additionally, inconsistencies in contrast agent dosing, timing of scans, or the choice of input functions can lead to variability in results. Standardizing imaging protocols and addressing motion artifacts remain essential for reliable DCE-MRI analysis. [2,15]. As demonstrated in Figure 2

$$\text{Formula: } \left\{V_{e=}\ \frac{K_{Trans}}{K_{ep}}\right\}\ldots\ldots\ldots\ldots..(3)$$

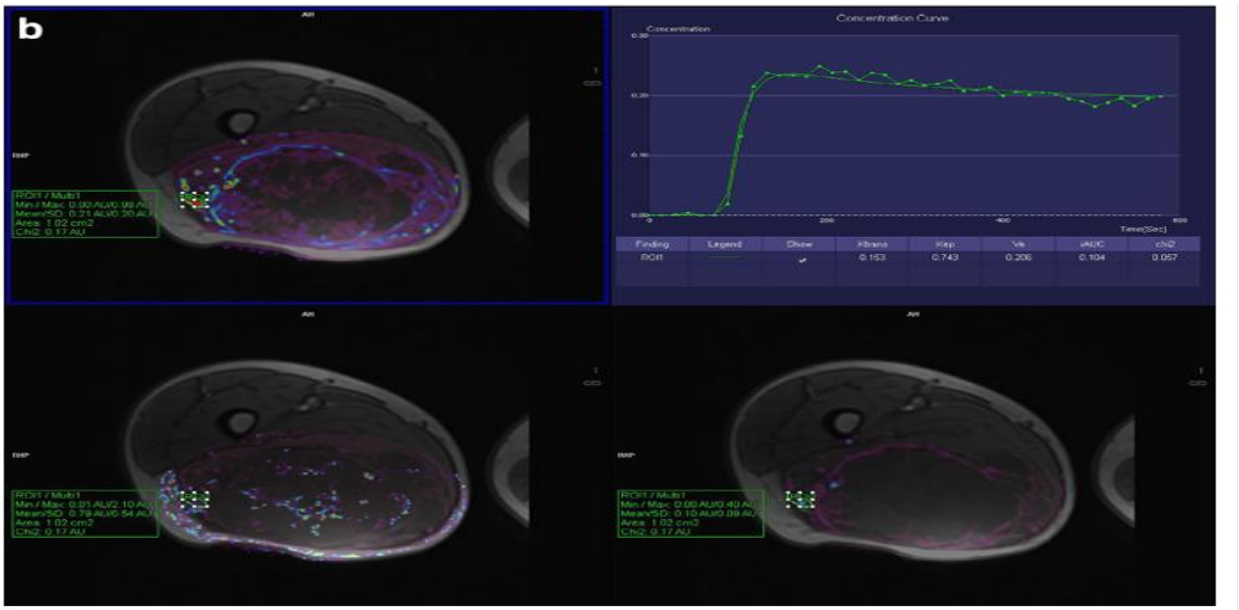


Fig 2. DCE-MRI outcomes in a 48-year-old male show low Ktrans, Kep, Ve, and iAUC values within a constrained ROI, with a type III tissue contrast concentration curve.

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METHODOLOGY

This review was carried out using an arranged literature search framework following established narrative review methodology. Validated investigations examining dynamic contrast-enhanced MRI, pharmacokinetic modeling, and quantitative parameters such as Ktrans, Kep, Ve and Vp in lever tumor cancer were recognized by PubMed, Scopus, Google Scholar and ScienceDirect. The search included articles published from 1998 to 2025 using multiple keywords Inclusion criteria were, Studies involving DCE-MRI quantitative analysis, articles using Tofts, Extended Tofts, or advanced Pharmacokinetic models, studies recognized PK parameters with tumor grade, vascularity, or clinical efficacy. Conference abstracts, non-pharmacokinetic studies, and articles lacking quantitative assessment were excluded. Data from each study were gathered relating to methodology, PK parameters used, diagnostic efficiency, strengths, and limitations to integrate patterns, verify gaps, and showcase future research pathways.

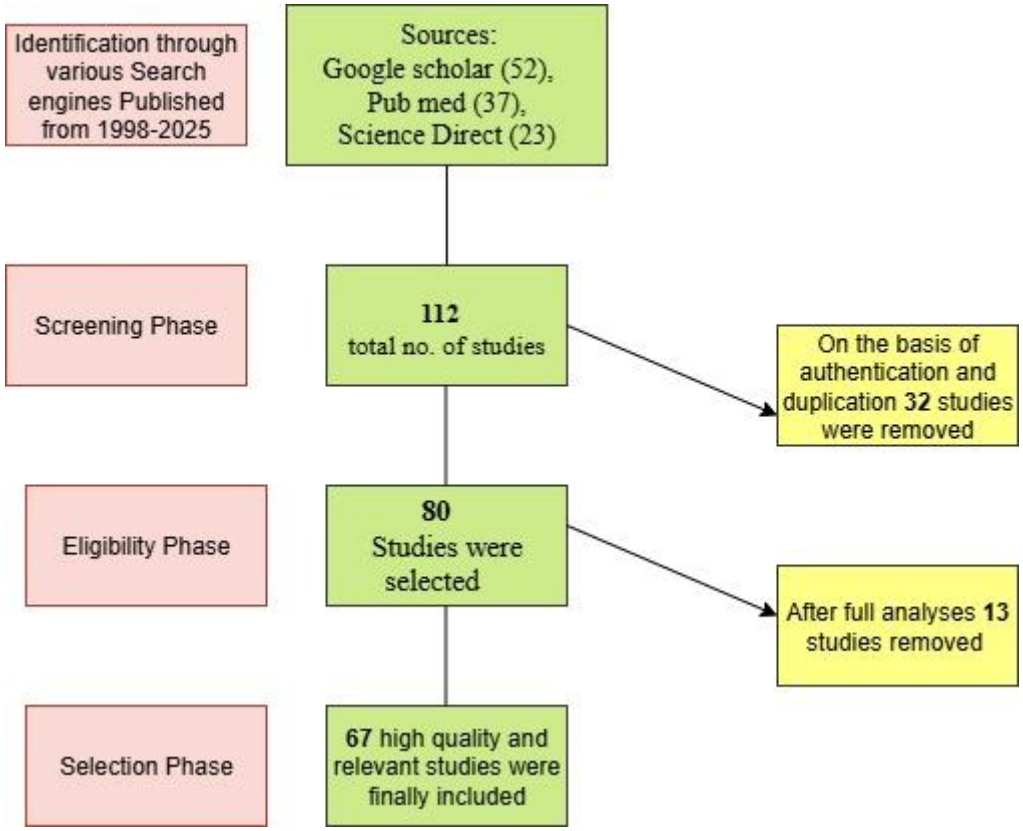


Fig 3: Representing preferred reporting items for systematic reviews and meta-analyses (PRISMA) for methodology

Diagnostic Applications of DCE-MRI

Diagnostic work of DCE-MRI in Differentiating Benign vs. Malignant Liver Lesions

In a regular clinical approach, it is rare to come across obstacles when trying to separate benign from malignant soft tissue tumors utilizing standard MRI alone, due to intersecting morphological features and signal levels [20]. Latest progress, including diffusion-weighted imaging (DWI), specifically with intravoxel incoherent motion (IVIM) structuring, has enabled improved distinction by examining water diffusion traits [21]. Parameters like the apparent diffusion coefficient (ADC), pure diffusion coefficient (D), Pseudodiffusion coefficient (D), and perfusion fraction (f) help distinguish true diffusion from perfusion-linked effects [22]. These techniques have shown capability in improving tumor profiling. Supportively, DCE-MRI relates pharmacokinetic simulating(e.g., Tofts model) to extract parameters like Ktrans, Kep, and Ve, and semi-quantitative metrics such as Iauc, providing additional operational understandings to aid in tumor separation with studies reporting significantly higher Ktrans values in HCC, reflecting its aggressive angiogenesis and greater microvascular permeability [13]. with reported area under the curve (AUC) values of 1.0 during validation and 0.8 in final test

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phases, confirming their potential for clinical application [23]. Support vector machine (SVM)-based approaches have yielded detection rate and precision around 84% and 81% respectively, in classifying liver lesions, reinforcing DCE-MRI's diagnostic value.

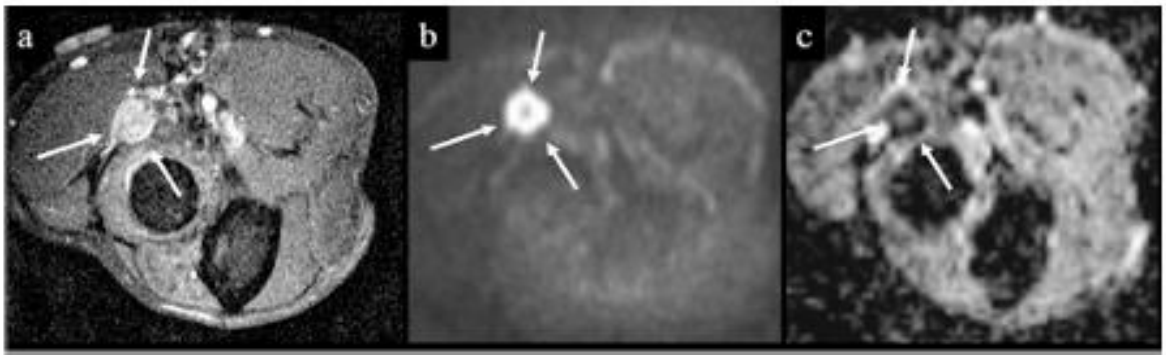
Table 1. Summary of key methodological parameters from selected studies evaluating dynamic contrast-enhanced MRI in oncologic imaging, including MRI field strength, contrast agent protocols, computational analysis tools, pharmacokinetic models, assessed dynamic variables, and pre-/post-treatment timing.

Study year	Tesla MRI	Radiologic tracer	Computational analysis	numerical analysis	Reviewed Dynamic study variables,	Duration assessment: Dynamic MRI variables
Chu et al [24] .2013.	1.5 Tesla MRI	Gd-DTPA was injected Intravenously at 0.1mmol/kg with an infusion rate of 2.5 ml	NordicICE version 2.3 (NordicNeurolab)	Tofts-based dual-compartment kinetic framework	Vp, Ktrans, AUC, PE	Pre-therapy2-115 days; post-treatment 0-187 days
Spratt et al [25, 26].	1.5 Tesla MRI	Gadolinium-DTPA was administered intravenously at 0.1 mmol/kg using volumetric flow rate at 2& e ml/s	NordicICE (Nordic Neurolab)	Tofts 2-comparment pharmaco kinetic model	Vp, Ktrans,	Fifty-seven days after -thearpy (IQR, 51-62 days).
Kumar et al. [27], 2017	1.5 Tesla MRI	Gd- contrast agent 0.1 mmol/kg at a controlled injection speed of 2-3 ml/s	NordicICE version 2.3 (NordicNeuro Lab)	Expanded dual-compartment adopted from the original Tofts approach	Vp, Ktrans	Pre and post are not specified
Lis et al. [28], 2017	1.5 Tesla MRI	The contrast agent gadolinium 0.1 mmol/kg fluid transfer unit 2.5 ml/s	NordicICE (NordicNeuro Lab) and MATLAB (Mathworks)	Toft's pharmaco kinetic model analysis	Vp, Ktrans	1 hour prior to and following therapy, as opposed to later phases (range,51-504 days)
Chen at al. [15], 2021	3T MRI	Gadopentetate dimeglumine 0.1 mmol/kg, throughput of 2 ml/s	GE ADW4.6 workstation and GenIQ software	Extended Toft's 2-compartment pharmaco kinetic model	Ktrans, Kep, Ve	1 weak prior to therapy; 1/3 months post-therapy

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Chung et al . Assessed the clinical performance of conventional MRI in distinguishing benign from malignant soft tissue tumors by assessing parameters like lesion depth, size, and signal heterogeneity. Their approach yielded a detection rate of 64%, a precision of 85%, and an overall diagnostic precision of 77%. When compared to findings from more recent studies employing multiparametric MRI, it is evident that incorporating multiple imaging parameters enhances diagnostic precision. For instance, studies report improvements in sensitivity from 71% to 81 % while maintaining constant specificity (69% to 83%) and precision [25].

Hu et al. Has proven the possibility of utilizing radiomics-based machine learning to separate benign and malignant soft tissue neoplasms. In their study, least absolute shrinkage and selection operator (LASSO) logistic regression frameworks built on apparent diffusion coefficient (ADC) traits accomplished superior diagnostic correctness (AUC=0.955, sensitivity = 83%, specificity = 100%) compared to those according to fat-suppressed T2WI attributes



ADC (μm²/sec)	D (μm²/sec)	D* (μm²/sec)	f (%)
837	881	275	133
K^{trans} (min^{-1}x10^3)	K_{ep} (min^{-1}x10^3)	V_e (%)	iAUC (%)
116	824	14	12

Fig 4: Multiparametric MRI including IVIM-DWI and DCE-MRI indicates a malignant soft tissue neoplasm, later confirmed as myeloid sarcoma. Imaging metrics such as ADC, IVIM, and perfusion parameters support the diagnosis.

(AUC = 0.75). Pattern attributes such as mean ADC, HISTO-skewness, and GLCM-associated metrics recorded slight variations in tissue heterogeneity. Significantly, benign tumors had negatively skewed ADC histograms, while malignant lesions were positively skewed due to elevated cellularity. Their application of whole-tumor volumetric division and replicable feature derivation using LIFEx software supports the methodological effectiveness of radiomics in this background. These outcomes offer convincing proof that ADC-based radiomics systems, when integrated with machine learning algorithms like LASSO, can efficiently identify tumor types, providing potential clinical decision assistance tools with high accuracy [29].

Quantitative assessment from intravoxel incoherent motion DWI (IVIM-DWI) and dynamic contrast-enhanced MRI (DCE-MRI) both suggested a malignant soft tissue neoplasm. Histopathological confirmation identified the lesion as myeloid sarcoma. Panel D summarizes the results from the multiparametric MRI analysis, including metrics such as ADC, IVIM, and perfusion-based parameters supporting the final diagnosis.

Key diffusion metrics, for example, the (ADC) apparent diffusion coefficient and the diffusion coefficient (D), have demonstrated statistically appropriate differences among benign and malignant tumors [12]. While D is expected to perform ADC due to its reduced sensitivity to perfusion-related effects and improved reflection of true tissue diffusivity, receiver operating characteristic (ROC) analysis showed comparable diagnostic utility between the two (AUC values of 0.752 for ADC and 0.742 for D) [30]. These observations align with findings from Lim et al who noted significant differenciation using D but not ADC. Discrepencies may be differences in imaging technique, including Rijswijk's use of a 1.5 T scanner with limited b-values in early IVIM-DWI [13,6] Additionally, recent hypotheses propose that benign tumors might exhibit more heterogeneous or pronounced

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microcapillary perfusion than malignant ones, contributing to the lack of significant differences in D and perfusion fraction (f) between tumor types. This notion is supported by multiparametric MRI in improving soft tissue tumor evaluation while also acknowledging the limitations of perfusion-sensitive indices in certain tumor contexts [13]. Subset evaluation in the same study uncovered that IVIM-DWI was restricted in separating benign from malignant myxoid tumors because of intersecting ADC figures, resulting in extracellular matrix fluctuation[31]. Yet, DCE-MRI factors such as Ktrans and IAUC persisted significantly different even in these difficult scenarios, validating the benefit of perfusion imaging in tumors with high myxoid information. This showcases the relevance of adjusting the imaging method based on tumor structure [7].

Prediction of Microvascular invasion (MVI)

DCE-MRI combined with radiomics has advanced presurgical estimation of MVI in HCC. Models incorporating intratumorally and peritumoral features have achieved validation AUCs as high as 0.879, understanding their potential for improving surgical planning [22]. Other studies using contrast agents such as Gd-EOB-DTPA have further highlighted the role of MRI-derived radiomics in guiding clinical decisions related to MVI risk [32].

[33], Feng conducted a study and set a goal to produce and authenticate an integrated internal tumor region and tumor margin radiomics framework to forecast MVI before surgery for initial HCC cases that applied gadolinium-ethoxy benzyl-diethylenetriamine (Gd-EOB-DTPA) improved MRI. One hundred and ten HCC cases took part in this investigation. They had a presurgical and curative hepatectomy, Gd-EOB-DTPA advanced MRI analysis, and 40.0 % & 38.2% of the subjects were Microvascular invasion affirmative forecasting framework. By its precise specificity, sensitivity, and AUC, the integrated peritumoral & intratumoral radiomics model facilitated doctors in forming reliable treatment moves pre-surgery [31]. Another article by [34]. by implementation of radiomics-based nomograms for 356 cases with solitary HCC < 5cm, Microvascular Invasion, and reappearance-free survival (RFS) was estimated. During verification, it has been observed that 0.879 was the cohort AUC of the MVI nomogram by logistic regression observations and 0.920 by random forest. The median RFS of 30.5 months and >96.9 months, in corresponding order, were observed in patients with an MVI. Return was autonomously estimated by age, histologic MVI, alkaline phosphatase, and alanine aminotransferase, with an AUC of 0.654 in the RFS endorsement cohort [21]. DCE-MRI combined with radiomics has advanced the pre-surgical evaluation of MVI in HCC. Models incorporating intratumorally and peritumoral features have achieved validation AUCs as high as 0.879, understanding their potential for improving surgical planning [31]. Other studies using contrast agents such as Gd-EOB-DTPA have further highlighted the role of MRI-derived radiomics in guiding clinical decisions related to MVI risk [21].

Another study conducted by Kumar et al. In which he investigated the differentiation in duration to reappearance identification between present time MRI and DCE-MRI. Localized reappearance about 18 months prior to traditional MRI in five patients was detected by DCE-MRI (mean ± standard deviation, 6.6 ± 6.8 months) [28]. revealed that the Vp variable could identify effective reaction to therapy within 10 days post-intervention, which was likely too early than traditional MRI. DCE-MRI varies subsequent to RT could anticipate tumor reaction in less than 6 months, to evaluate the point of tumor steadiness that is approximately half the period essential by standard MRI.

DCE-MRI in other Cancers

Beyond liver cancers, DCE-MRI has been applied in breast cancer, where radiomics models based on DCE features have achieved AUCs of 0.89 for differentiating benign and malignant lesions using SVM classifiers. In cervical cancers, DCE-MRI's semi-quantitative parameters have shown strong sensitivity and specificity for malignancy detection, although some limitations persist in distinguishing among all tumor types [35].

DCE-MRI in the evaluation of spinal Metastases

Spinal metastases affect 40-70% of advanced cancer patients and are a major source of morbidity due to pain, paralysis, and vertebral fractures. Radiotherapy is a common treatment; however, conventional methods have shown limited ability to assess post-treatment MRI changes, as nearly half of lesions may appear unchanged despite clinical response. DCE-MRI has emerged as a superior modality in this context, offering kinetic

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parameters such as Ktrans, Ve, and Vp, which reflect changes in vascular permeability and interstitial fluid space. These biomarkers are highly sensitive to angiogenic and cytotoxic responses, allowing earlier detection, like RECIST. Several studies report that DCE-MRI can distinguish responders from non-responders at much earlier time points after stereotactic body radiotherapy (SBRT) or CyberKnife therapy. This has important implications for guiding timely salvage therapies and optimizing patient outcomes. However, small sample sizes remain a limiting factor in many spinal metastasis DCE studies, indicating the need for larger-scale prospective trials. [14,21]

Therapeutic Monitoring with DCE-MRI

Fluctuation in DCE-MRI criteria and Analysis of tumor outcome after Radiation Therapy

Numerous studies have explored the potential of DCE-MRI parameters particularly, Ktrans, Vp, and Ve, to monitor tumor response to radiation therapy (RT). In a study by Spratt et al.,2016 a marked reduction in ktrans was observed approximately two months following stereotactic body radiotherapy (SBRT). Specifically, up to 75% of pathologies showed a decline in mean ktrans, with some tumors demonstrating a reduction of up to 92%. Interestingly, in one patient who experienced local recurrence, ktrans values actually increased. However, due to a limited sample size, statistical comparison between responders and non-responders were not feasible. Kumar et al. provided more definitive results, reporting a significant difference in ktrans reduction among treatment effective and ineffective groups (-66% vs. -7%, p + 0.01), with no local recurrence observed in patients who achieved the more substantial ktrans drop [27].Lis et al. evaluated early responses in six patients with soial metastasis undergoing high-dose image-guided radiotherapy (HD IGRT). They found a median reduction in ktrans from 4.84 to 2.3 within one-hour post-treatment. No progression was observed during a follow-up period extending over a period of 839 days [15] Similarly, documented that responders demonstrated an average ktrans reduction of -32.6%, while non-responders demonstrated an average ktrans reduction of -32.6%, while non-responders showed a median increase of +20.4% (p + 0.001) . In contrast, (Chu et al.,2013) did not observe statistically significant changes in ktrans following RT (p = 0.48), possibly due to differences in timing or methodology [31].

(VP) For the plasma volume parameter , Li et al, found a rapid 65.2% reduction in median Vp one-hour post-HD IGRT, a finding mirrored by Spratt et al, who documented a 58.7% decrease in spinal sarcomas post-SBRT. Chu et al. highlighted the predictive value of Vp, showing a notable changes in Vp changes among treatment effective groups (-65.66%) and ineffective groups (+145.27%+206.79%), while Kumar et al. corroborated this with a -76% versus +30% difference (p = 0.01) [30]. (VE) In contrast, this parameter showed inconsistent trends. Vellayappan's study reported no statistically significant changes in Ve values over time post-SBRT [36], found a mean increase of 161.9% on Ve five weeks post-RT. Despite this, no marked disparity were observed among effective treatment groups and non-effective groups in Ve levels or percentage changes.[37]. These findings that Ktrans and Vp are more reliable indicators of early therapeutic response to RT in liver and metastatic tumors than Ve. However, variations across studies related to timing, tumor type, and imaging protocols highlight the need for standardized methodologies to fully leverage DCE-MRI for treatment monitoring.

DCE-MRI, Gd -DTPA, gadolinium-diethylenetrimine Penta acetic acid; Vp proportion of tissue volume occupied by blood plasma; Ktrans, constant representing the movement rate among blood plasma and extracellular matrix; AUC, total signal intensity change over time; PE-maximum contrast enhancement observed; IQR, interquartile span; Ve, extravascular extracellular space volume fractions; (PS) permeability surface product; CT, RT, radiation therapy[38].

Comparative Performance of DCE-MRI

DCE-MRI offers several advantages over conventional imaging modalities. It provides higher sensitivity than ultrasound, which is known for its lower sensitivity and operator dependency [35]. Compared to CT, DCE-MRI avoids ionizing radiation and offers superior specificity [31]. Moreover, it mitigates motion artifacts seen in standard MRI and improves the detection of smaller lesions, which is crucial for early diagnosis [33]. DCE-MRI is an important tool in assessing therapeutic response. Changes in Ktrans after treatments, particularly for HCC, can reflect shifts in tumor blood flow and permeability, offering early indications of response to ablative or

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systemic therapies [34]. Significant reductions in Ktrans have been correlated with superior progression-free survival (PFS) and overall survival (OS), showcasing its prognostic value [39]. Quantitative DCE-MRI models also contribute to predicting microvascular invasion in early-stage HCC, aiding in the recognition of patients at greater vulnerability of recurrence [34]. Although data on prostate cancers are more limited, DCE-MRI is widely recognized for its broader role in monitoring vascularity and treatment responses across various tumor types [40].

Table 2. Output evaluation among FS-T2WI-based and ADC-based Rdiomics system of identifying Soft tissue Neoplasms

Parameter	--	P=0.017 (vs.FS-T2WI)
Statistical Significance Accuracy	0.750	0.955
Accuracy	70.8%	91.7%
Specificity	96.0%	100.0%
Sensitivity	55.0%	83.3%
AUC (Validation)	FS-T2WI Model	ADC-Based Model
Feature Types used	Texture features (GLCM, GLZLM) from FS-T2WI	Texture+Histogram (e.g.,HISTO-skewness) from ADC
Modeling method	LASSO- Logistic Regression	LASSO-Logistic Regression

In a straightforward analysis study, Hu et al. assessed radiomics-derived machine learning frameworks obtained from fat-suppressed T2-weighted imaging (FS-T2WI) and apparent diffusion coefficient (ADC) maps to differentiate benign and malignant soft tissue neoplasms [29]. Utilizing LASSO-logistic regression, the ADC–grounded design exhibited meaningfully superior diagnostic capability, reaching an AUC of 0.955 in the verification cohort, with a sensitivity of 83%, a specificity of 100% and overall accuracy of 91.7%. In contrast, the FS-T2WI framework generated reduced sensitivity (55%) and accuracy (70.8%), even though preserving high specificity. The variation in AUC among the models was quantitatively notable (P=0.017), highlighting the more effective identifying power of ADC extracted pattern traits. These outcomes revealed the diagnostic benefit of diffusion-based radiomics models over conventional T2-weighted imaging, specifically when volumetric examination and higher-level texture indicators are integrated. An overview of these outcomes metrics is displayed in Table 3 [29].

Advances in Radiomics, AI, and Technical Innovations

Radiomics techniques that extract detailed quantitative features from DCE-MRI have enhanced clinical decision-making. For example, models predicting microvascular invasion in HCC using DCE-MRI radiomic features have accomplished AUCs of 0.868 in the learning phase and 0.857 in confirmation sets, underscoring their diagnostic promise [41]. Although substantial progress has been made in classifying and standardizing radiomic biomarkers, there remains a noticeable lack of emphasis on the careful palining and execution of radiomic studies focused on imaging diagnostic signal breakthrough, while analyzing outcomes, many released investigations exhibit methodological errors or fall short in providing adequate methodological transparency, hindering the reader's ability to contextualize findings [42,43]. Drawing on recent collaborative experiences in radiomics research and peer review roles for journals such as Radiology, key design and statistical considerations have been identified [16]. This decision does not aim to deliver a comprehensive overview of technical radiomic

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features such as grayscale level or bin width, which are extensively reviewed elsewhere, nor does it attempt to catalog all possible sources of bias. Instead, the goal is to highlight frequent pitfalls in radiomic study design and propose practical strategies to mitigate them. By doing so, the field can move toward generating robust, reproducible, and clinically relevant outcomes capable of meaningfully advancing patient care [44].

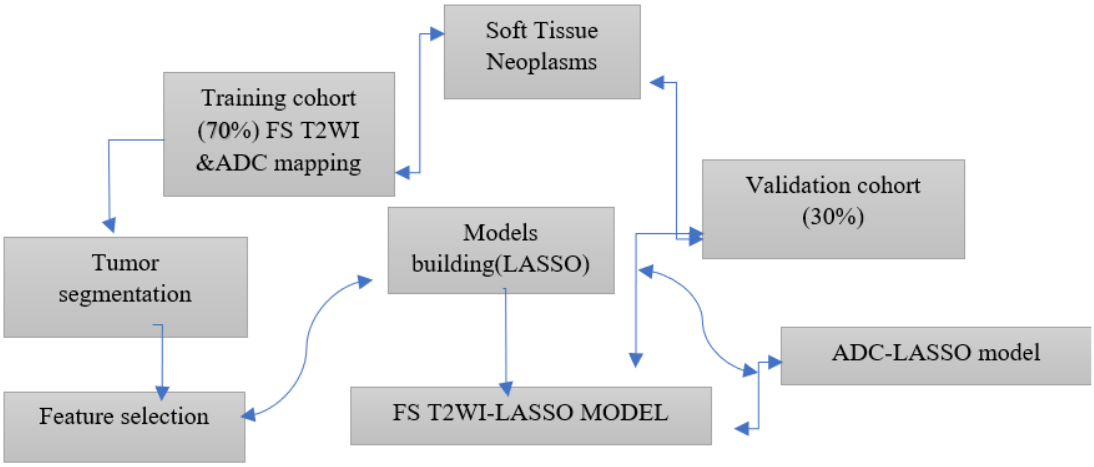


Fig 5: Flowchart of radiomics and machine learning.

Radiomics demands a huge quantity of superior-quality information for assessment. Easily, such databases are not accessible. Most of the existing data collections are retrospective and hence do not have sufficient data on the applicability of outcomes. There is a requirement for prospective data collection. The association between diverse radiomic traits can be acquired by segmentation. Furthermore, the rapid evolution of automated techniques retrieving extensive-scale numerical attributes from medical imaging has led to a significant surge in radiomics-related publications .

Furthermore, the rapid evolution of automated techniques retrieving extensive-scale numerical attributes from medical imaging has led to a significant surge in radiomics-related publications [45]. These studies often aim to leverage combinations of imaging features for tasks such as disease diagnosis, prognosis, therapy planning, or other decision-support functions. Rdiomics refers not to the features themselves, ranging from conventional metrics like Hounsfield units to more complex textural and machine-learned parameters [46]. Despite its promise, a critical concern is that only a minor fraction of these measurable visual diagnostics achieve clinical translation. To date, no high-throughput radiomic signature has gained widespread clinical adoption. This underscores the importance of recognizing potential methodological barriers, including variability in study designs. Identifying and overcoming these hidden challenges is essential to realizing the full clinical potential of radiomics [47].

Although its capabilities, radiomics has not yet attained broad clinical incorporation. Moskowitz et al. Note that no high-processing-rate radiomic patterns are presently in standard clinical use. This lack of implementation is mostly credited to irregular confirmation, a lack of normalization, and the existence of unsettled technical and statistical biases.

Moskowitz et al recognize that many radiomic research efforts are subject to structured biases that weaken applicability. Frequent challenges involve bias when imaging elements are also used to determine outcomes, verification bias due to targeted selection of validated cases, and spectrum bias when study cohorts do not represent the wider clinical population. The picking of images to be employed, both for preparation and confirming a radiomics framework, needs to be evaluated. Certain results, such as histologic diagnosis, are merely analyzed for a group of cases, based in part on medical analysis of imaging outcomes. Constraining the research to these patient image results in validiation bias (Table 1,) which is a data absence issue that might produce production of sensitivity that are too inflated predictions, of specificity that are too low, or in rare scenarios, lack of capacity in a straightforward manner predict sensitivity and specificity. A distinct study design

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has been recommended to prevent this bias, and there are numerous approaches put forward to bias-adjustment ways when validation bias is considered inevitable [48].

Excessive fitting continues to be a major challenge in radiomics simulation. It happens when models are fitted too closely to specific datasets, detecting noise rather than the true signal, thus lowering general reliability. This issue, combined with uncorrected multiple testing where hundreds of features are explored without proper statistical safeguards, frequently inflates performance metrics, as highlighted by Moskowitz et al Feature values in radiomics are highly sensitive to image acquisition parameters, scanner types, and segmentation approaches. Moskowitz et al. emphasize that even identical features extracted from the same anatomical region can vary significantly across platforms or acquisition protocols, undermining reproducibility and cross-institutional comparability. To ensure clinical relevance and reproducibility, rigorous study design and transparent reporting are essential. As recommended by Moskowitz et al., adherence to guidelines such as STARD for diagnostic accuracy, TRIPOD for prediction modeling, and REMARK for tumor markers can improve the quality of radiomic research and facilitate eventual clinical adoption.

Table 3. Repeated contributors of deviation and Bias in Radiomic studies

Type (Study design)	Description
Spectrum bias (Ransohoff et al.,) [49].	Study are not fully representative of the population of interest Example; model developed using only extreme cases(eg, very sick and/or very healthy idividuals)
Verfication bias (Begg et al.,1988) [50].	Analysis only includes cases where the outcomes is axcertained, which is nonrepresentative subset of the population of interest Example: Only including patients with biopsies where the decision to biopsy to determined based on imaging.
Incorporation bias (Zhou et al.,2002) [51].	Final result uses data from the images beings examined, Example; Predicting the outcomes from CT images where the outcome is defined by radiologists from CT imaging.
Software variability (Fornacon et al.,2020) [52].	Feature measurement of the same region of interest in the same scan can give different results Example; custom designed attributes, computed on a distinct platform, or with a different version of the same software, can have different values despite compliance with accepted standards.
Operator variability (Pavic et al., 2018) [53].	Manual or semiautomated segmentation affects feature measurement Example Inter-and intraoperator variablility exists in manual contours; this variability is also influenced by the disease site and existing clinical contour guidelines .
Bias due to overfitting (Hawkins et al.,2004) [54].	Model captures spurious association in the training data, in addition to assosciation that would be replicated in similar data sets. Example A model captures random variation (Noise) in the training data and appears to perform well but does not work well in independent validation data.
Bias from exclusion of indeterminate or missing feature data (Begg et al.,) [50].	Ignoring images with missing features measurements in analyses might result in to biased assessments of the charecteristics and the algorithims performance, as well as decreased generalizability of the algorithim .

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Optimistic Performance bias (Harrell et al.,1996) [55].	Evaluating the algorithims on the same data that was used to build or optimize the algorithim.

To overcome these challenges, recent efforts have focused on improving study design, quality control, and transparency in radiomics research. A robust radiomics study must incorporate sound feature selection, appropriate modeling methodology, and comprehensive validation. Feature selection should be data-driven, incorporating dimensionality reduction techniques to eliminate non-robust or redundant variables. Modeling often relies on a single machine learning technique, but the use of multiple algorithms can enhance generalizability. Crucially, the validation process should include discrimination and calibration metrics, supported by bootstrapping or cross-validation to reduce sampling bias [56]. To standardize methodological rigor, the radiomics quality score (RQS) was developed, guiding researchers to report protocols, QA procedures, and justification for model decisions. RQS also encourages full transparency in prediction model development, complementing frameworks like TRIPOD, which mandate complete and unbiased reporting of multi-variable prediction models. These frameworks are essential for reducing bias, improving replicability, and facilitating the clinical adoption of radiomics-based tools [57].

DISCUSSION

(DCE-MRI) Dynamic contrast-enhanced MRI continues to gain traction as a powerful imaging modality for non invasively assessing liver tumors, offering insights into perfusion dynamics, vascular permeability, and extracellular volume. Its strength lies in the ability to acquire images continuously, often during free-breathing, with motion corrected reconstruction that achieves high temporal resolution typically within 6-second intervals [15]. Commercially available post-processing tools facilitate this process by incorporating motion correction algorithms with adjustable translational and reproducibility [58]. Quantitative pharmacokinetic parameters derived from DCE-MRI, including Ktrans, Kep, and Ve, serve as critical indicators of tumor behavior and treatment response. These metrics are estimated on a voxel-wise framework utilizing constrained nonlinear modeling methods, often supported by models that account for additional variables such as arterial and venous plasma flow, extracellular volume, and delay times. Such modeling techniques, using Lavenberg-Marquardt optimization, are reinforced with constraints to maintain physiologic plausibility [59].

In clinical settings, these parameters offer significant diagnostic values, with evidence showing that they can detect therapeutic effects, recurrence, or treatment failures earlier than conventional imaging techniques. For example, post-radiotherapy reductions in ktrans and Vp have consistently been observed among treatment responders, suggesting a correlation between these perfusion metrics and therapeutic efficacy [60]. Despite these benefits, several challenges hinder DCE-MRI's universal adoption. Tumor heterogeneity, inconsistent imaging follow-ups, and technical complexity can affect parameter reliability [61]. Additionally, achieving diagnostically sufficient image quality can be cumbersome, often requiring repeat contrast-enhanced scans, adding burden to both patients and healthcare workflows. Nevertheless, DCE-MRI remains an essential tool, especially when paired with systematic statistical evaluation and interobserver agreement. Its potential for early response prediction and precision monitoring reaffirms its emerging role in oncology imaging, although alignment and refinement of imaging parameters remain areas for ongoing development [47].

The advanced clinical utility of Dynamic Contrast-enhanced-MRI in liver cancer, upcoming research should target many key areas. Standardization of parameters and acquisition protocols is essential to reassure routine use of DCE-MRI metrics, particularly for distinguishing between liver pathologies like (HCC) hepatocellular carcinoma and (HCA) hepatocellular adenoma. Longitudinal studies tracking DCE-MRI parameter changes over time could offer precious insights into tumor progression and treatment response, supporting the development of predictive models for patients' outcomes. Integrating functional MRI techniques alongside DCE-MRI could enhance spatial mapping of liver function and inform more personalized treatment plans [13]. Technical innovations, including advanced K-space undersampling, golden-angle sampling, and training radiologists without excessive use of contrast agents [12]. There is also growing interest in deep learning frameworks to

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improve parameter estimation accuracy and reduce computational demands, thereby enhancing diagnostic confidence [13]. Developing cost-effective solutions, such as streamlined protocols and affordable contrast agents, alongside telemedicine integration protocols, DCE-MRI accessibility, especially in low-resource settings [62]. These research directions aim to enhance both the diagnostic power and clinical practicality of DCE-MRI in liver cancer care.

CONCLUSION

Recent reviews consistently highlight the substantial diagnostic significance of Dynamic Contrast Enhanced Magnetic Resonance Imaging in the diagnosis, observation, and characterization of liver tumors. DCE-MRI has proven more effective than standard methods of imaging modalities in categorizing benign from malignant liver lesions, evaluating microvascular invasion, and assessing treatment response. The quantitative parameters it provides, such as Ktrans, Kep, and Ve, offer critical insights into tumor vascularity and permeability that supports more informed clinical decision-making. Although challenges like protocols variability, motion, artifacts, and limited standardization remain, the integration of radiomics and artificial intelligence with DCE-MRI is seen as a promising direction for improving diagnostic accuracy and patient outcomes. As ongoing research continues to address these limitations, DCE-MRI is likely to make a highly demanding, vital contribution to personalized liver cancer care.

Ethical Statement

None of the authors have conducted any research on humans or animals for this paper.

Conflicts of Interest

The authors declare no conflicts of interest related to this work.

Data Availability Statement

Since this study did not create or analyse any new data, data sharing is not applicable to this article.

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Author Contribution Statement

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