



Performance of a magnetic resonance imaging-based radiomics score combined with apparent diffusion coefficient in predicting hepatocellular carcinoma recurrence and disease-free survival: a retrospective cohort study

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PURPOSE

This study aimed to evaluate the prognostic value of apparent diffusion coefficient (ADC) measurements and a predefined magnetic resonance imaging (MRI)-based radiomics score for predicting early recurrence and disease-free survival (DFS) in patients with hepatocellular carcinoma (HCC) undergoing curative surgical resection.

METHODS

This retrospective study included 200 patients who underwent curative-intent resection for HCC between January 2021 and January 2025, with follow-up data reviewed through January 2026. Pre-operative multiparametric MRI examinations, including DWI, ADC maps, and dynamic contrast-enhanced sequences, were reviewed. The predefined radiomics score was derived from a validated institutional MRI-based radiomics pipeline using ADC maps and contrast-enhanced MR images. In the present cohort, the score was analyzed together with region-of-interest (ROI)-based ADC measurements as a fixed imaging biomarker, without any additional feature selection, model training, or model retraining. Early recurrence was defined as recurrence within 12 months after surgery. Univariable and multivariable logistic regression analyses were performed to identify predictors of recurrence. Prognostic performance was evaluated using receiver operating characteristic analysis, and model discrimination was compared using the DeLong test. The DFS was assessed using Kaplan–Meier and Cox proportional hazards analyses.

RESULTS

Early recurrence occurred in 66 of 200 patients (33.0%). In multivariable logistic regression analysis, tumor size [odds ratio (OR): 1.55, 95% confidence interval (CI): 1.27–1.89, $P < 0.001$], ADC (OR: 0.29, 95% CI: 0.18–0.46, $P < 0.001$), and radiomics score (OR: 4.74, 95% CI: 2.85–7.89, $P < 0.001$) were independent predictors of recurrence. The radiomics score alone achieved an area under the curve (AUC) of 0.767, whereas ADC achieved an AUC of 0.707. Combining the ADC and radiomics score significantly improved predictive performance (AUC: 0.837), outperforming both ADC alone ($P < 0.001$) and the radiomics score alone ($P = 0.008$). The full multivariable model demonstrated the highest discriminatory performance (AUC: 0.892). For survival analysis, larger tumor size, multiple lesions, lower ADC values, and higher radiomics scores were independently associated with shorter DFS. Patients classified as high-risk according to the optimal radiomics score cut-off exhibited significantly worse DFS than low-risk patients (log-rank $P < 0.001$).

CONCLUSION

Measurements of the ADC and a predefined MRI-based radiomics score provided complementary prognostic information in patients with HCC. The combined ADC–radiomics score improved prediction of early recurrence and DFS compared with either parameter alone. These findings support further validation of quantitative MRI biomarkers for non-invasive risk stratification after curative HCC resection.

CLINICAL SIGNIFICANCE

The combined assessment of ROI-based ADC measurements and a predefined MRI-based radiomics score may help refine postoperative surveillance strategies after curative HCC resection, pending validation in independent cohorts.

KEYWORDS

Apparent diffusion coefficient, disease-free survival, hepatocellular carcinoma, magnetic resonance imaging, radiomics score

Hepatocellular carcinoma (HCC) is the most common primary liver malignancy and remains one of the leading causes of cancer-related mortality worldwide. Surgical resection offers a potentially curative treatment option for selected patients; however, postoperative recurrence remains common and continues to be a major factor affecting long-term outcomes. Identifying patients at increased risk of recurrence before treatment may help optimize therapeutic decision-making and postoperative surveillance.¹

Magnetic resonance imaging (MRI) is routinely used in the evaluation of HCC and provides both morphological and functional information about tumor characteristics. Among MRI-derived parameters, diffusion-weighted imaging (DWI) and the apparent diffusion coefficient (ADC) have received increasing attention because they reflect tissue cellularity and microstructural organization. Lower ADC values have been associated with poor tumor differentiation, microvascular invasion, and aggressive biological behavior. Several studies have also reported an association between low ADC values and a higher likelihood of recurrence following curative treatment.²⁻⁵

Main points

- Early recurrence occurred in 33.0% of patients after curative surgical resection for hepatocellular carcinoma.
- Lower region-of-interest-based apparent diffusion coefficient (ADC) values and higher predefined magnetic resonance (MR) imaging-based radiomics scores were associated with early postoperative recurrence.
- The radiomics score was derived from ADC maps and contrast-enhanced MR images and was evaluated without redevelopment of the original radiomics pipeline.
- The combined ADC–radiomics score showed higher discriminatory performance than ADC or the radiomics score alone.
- Higher radiomics scores were associated with shorter disease-free survival; external validation is required before clinical implementation.

Disease-free survival (DFS) is one of the most commonly used outcome measures in HCC studies because recurrence remains the principal determinant of long-term prognosis. Accurate estimation of recurrence risk before surgery may facilitate individualized follow-up strategies and improve patient selection for treatment. As a result, considerable effort has been directed toward the identification of imaging biomarkers capable of predicting recurrence and survival outcomes.⁶⁻⁹

Recent advances in artificial intelligence (AI) have expanded the role of medical imaging beyond visual interpretation. Radiomics allows quantitative assessment of imaging data through the extraction of large numbers of features that may reflect underlying tumor heterogeneity. Previous studies have shown that radiomics features derived from MRI can provide information regarding tumor differentiation, microvascular invasion, recurrence risk, and survival outcomes in patients with HCC.⁶⁻¹⁶

ADC maps have also become an important source for radiomics analysis. Unlike conventional ADC measurements, radiomics features extracted from ADC maps may capture spatial heterogeneity within the entire tumor and provide additional information regarding tumor biology. Several studies have suggested that ADC-based radiomics features may improve the prediction of tumor aggressiveness, histopathological characteristics, and postoperative recurrence.²⁻⁵

Despite these findings, data regarding the combined prognostic value of conventional ADC measurements and MRI-based radiomics scores remain limited. Therefore, this study aims to evaluate the prognostic value of ADC measurements and an MRI-based radiomics score for predicting early recurrence and DFS in patients with HCC undergoing curative surgical resection.

Methods

Study population

This retrospective study was approved by the Research Ethics Committee of Erzincan Binali Yildirim University (protocol number: 2026-01/03, date: 08.06.2026).

Patients who underwent curative surgical resection for HCC between January 2021 and January 2025 at the participating Erzincan Binali Yildirim University Mengücek Gazi Training and Research Hospital were reviewed. The requirement for informed consent was waived because of the retrospective design.

Ethics committee approval was obtained before data extraction and statistical analysis. No prospective patient recruitment, study-related imaging, or intervention was performed before ethics approval. Follow-up data were reviewed through January 2026, allowing assessment of 12-month early recurrence for patients without earlier documented recurrence. The study period refers to the retrospectively reviewed treatment and follow-up interval and not to prospective enrollment before ethics approval.

Initially, 287 patients were identified through the hospital information system, pathology database, and radiology archive. Patients without preoperative multiparametric liver MRI examinations ($n = 31$), patients with follow-up < 12 months ($n = 24$), patients with inadequate image quality for quantitative imaging analysis ($n = 18$), and patients with incomplete clinical data ($n = 14$) were excluded. Consequently, 200 patients were included in the final analysis (Figure 1).

All included patients underwent curative-intent surgical resection. Patients treated with ablation, liver transplantation, or systemic therapy were excluded. Clinical data were retrieved from electronic medical records. Age, sex, tumor size, lesion number, follow-up duration, recurrence status, and imaging findings were recorded.

Magnetic resonance imaging evaluation and radiomics score

Preoperative MRI examinations were performed on a 3.0-T Siemens Healthineers MAGNETOM Skyra scanner (Siemens Healthineers, Erlangen, Germany) according to a standardized institutional liver MRI protocol. The protocol included axial T1-weighted in-phase and opposed-phase imaging,

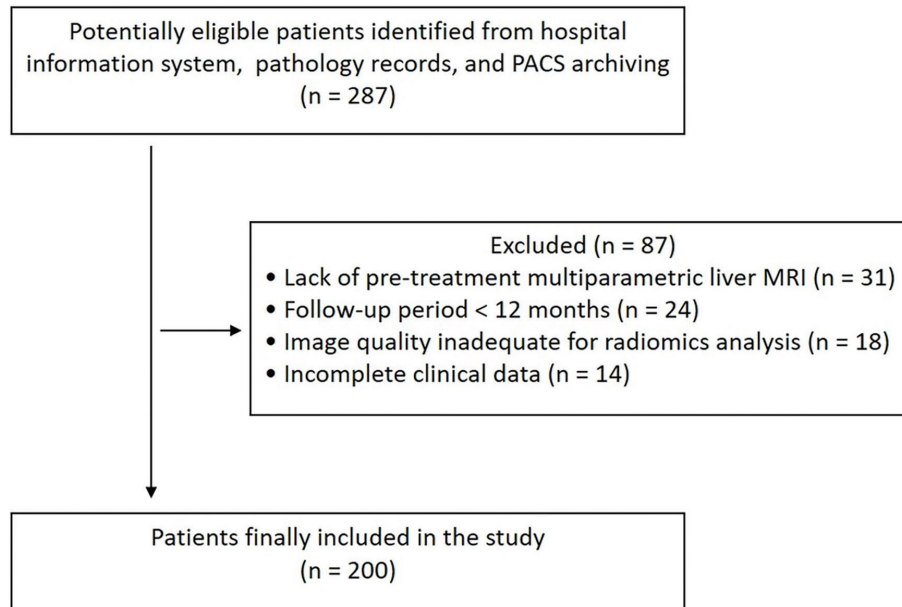


Figure 1. Flowchart of the patient recruitment and selection process. PACS, picture archiving and communication system; MRI, magnetic resonance imaging.

T2-weighted imaging, DWI, and automatically generated ADC maps. In routine clinical acquisition, DWI was performed using b values of 0, 50, 400, and 800 s/mm², with slice thickness ranging from 4 to 6 mm depending on the sequence and scanner protocol. Dynamic contrast-enhanced T1-weighted imaging was also obtained, including arterial, portal venous, and delayed phases when available.

The radiomics score used in this study was a predefined MRI-based radiomics score derived from a validated institutional MRI-based radiomics pipeline using ADC maps and contrast-enhanced MRI. According to the original radiomics score derivation, whole-tumor segmentation was performed on preoperative MRI examinations using 3D Slicer software, version 5.12.0 (The Slicer Community, Boston, MA, USA), and radiomics features were extracted from ADC maps and contrast-enhanced MRI sequences. The extracted features reportedly included first-order, shape, and texture features derived from the gray-level co-occurrence matrix, gray-level run length matrix, gray-level size zone matrix, gray-level dependence matrix, and neighbouring gray-tone difference matrix. Feature selection was performed using least absolute shrinkage and selection operator regression, and eight features were retained to generate the radiomics score. As the radiomics score was already available within the study dataset, no additional image segmentation, feature extraction, feature selection, or model development was performed in the present study. The radiomics score, which incorporated both diffusion-related and contrast-enhancement-related tumor informa-

tion, was analyzed as a quantitative imaging biomarker together with ADC values for the evaluation of recurrence and DFS.

No new radiomics feature extraction, feature selection, model training, or model optimization was performed in the present cohort. The current analysis evaluated the prognostic value of the available radiomics score rather than redeveloping the original radiomics pipeline.

Image evaluation was performed retrospectively by a single radiologist (SA) experienced in abdominal MRI, who was blinded to recurrence status and survival outcomes at the time of imaging review. Because the imaging assessment was performed by a single reader, interobserver agreement was not calculated.

ADC values were measured on ADC maps using a region-of-interest (ROI)-based approach. A single ROI was placed on the section showing the largest solid viable tumor component, and the mean ADC value obtained from this ROI was used for analysis. Necrotic, hemorrhagic, cystic, and artifact-containing areas were avoided whenever identifiable. The ADC was recorded as a quantitative imaging parameter and included in the regression and survival analyses.

Non-rim arterial phase hyperenhancement was evaluated on dynamic contrast-enhanced MRI and recorded as a conventional imaging variable.

The combined ADC–radiomics score features consisted of the ADC value and radio-

tics score. For the full multivariable model, age, sex, tumor size, lesion number, ADC value, non-rim arterial phase hyperenhancement, and radiomics score were entered as candidate variables for model comparison.

Study endpoints

The primary endpoint was early recurrence, defined as intrahepatic or extrahepatic recurrence detected within 12-months after surgical resection. Recurrence was determined by reviewing follow-up imaging examinations, radiology reports, clinical records, and pathology results when available.

During follow-up, recurrence was mainly diagnosed using contrast-enhanced MRI and/or contrast-enhanced computed tomography (CT). Ultrasound, laboratory findings, and clinical follow-up were also considered when they supported the imaging diagnosis.

Imaging findings accepted as recurrence included a newly developed hepatic lesion compatible with HCC, interval growth of a suspicious lesion, newly detected intrahepatic tumor, or extrahepatic metastatic disease. Histopathological confirmation was considered when available; however, recurrence diagnosis was primarily based on characteristic follow-up imaging findings.

The secondary endpoint was DFS, defined as the interval between surgical resection and the first documented recurrence or last follow-up.

Statistical analysis

Continuous variables were expressed as mean $\pm$ standard deviation, whereas categorical variables were expressed as frequencies and percentages. ADC values and radiomics scores were standardized as z-scores before inclusion in the regression models; therefore, odds ratios (ORs) and hazard ratios (HRs) for these variables are reported per 1-standard-deviation increase. Univariable and multivariable logistic regression analyses were performed to identify independent predictors of early recurrence. Results were reported as ORs with 95% confidence intervals (CIs).

Receiver operating characteristic (ROC) analysis was performed to evaluate the predictive performance of ADC, radiomics score, the combined ADC–radiomics score, and the full multivariable model. The combined ADC–radiomics score included the ADC value and radiomics score. The full multivariable model included age, sex, tumor size, lesion number, ADC value, non-rim arterial phase hyperenhancement, and radiomics score.

Area under the ROC curve (AUC) values were compared using the DeLong test, which was used for pairwise comparison of correlated ROC curves. Bootstrap analysis was additionally performed as an internal re-sampling procedure to assess the stability of AUC estimates.

The optimal radiomics score cut-off for recurrence prediction was determined using the Youden index. Patients were subsequently stratified into low-risk and high-risk groups according to this cut-off value for Kaplan–Meier analysis.

DFS was evaluated using Kaplan–Meier analysis and compared with the log-rank test. Univariable and multivariable Cox proportional hazards regression analyses were performed to identify independent predictors of DFS. HRs with 95% CIs were reported. Statistical significance was defined as a two-sided *p* value of <0.05 .

Results

A total of 200 patients with HCC were included in the study. Early recurrence occurred in 66 patients (33.0%), whereas 134 patients (67.0%) remained recurrence-free during follow-up. Patients with recurrence demonstrated significantly larger tumors, lower ADC values, and higher radiomics scores than those without recurrence (Table 1).

In univariable logistic regression analysis, tumor size (OR: 1.24, 95% CI: 1.08–1.43, $P = 0.003$), standardized ADC (OR: 0.47, 95% CI: 0.33–0.65, $P < 0.001$), and standardized radiomics score (OR: 3.05, 95% CI: 2.08–4.46, $P < 0.001$) were significantly associated with recurrence. In multivariable analysis, tumor

size (OR: 1.55, 95% CI: 1.27–1.89, $P < 0.001$), standardized ADC (OR: 0.29, 95% CI: 0.18–0.46, $P < 0.001$), and standardized radiomics score (OR: 4.74, 95% CI: 2.85–7.89, $P < 0.001$) remained independent predictors of recurrence. Multiple lesions demonstrated a borderline association with recurrence (OR: 2.16, 95% CI: 0.94–4.93, $P = 0.068$) (Table 2).

In Cox proportional hazards analysis, larger tumor size (HR: 1.28, 95% CI: 1.13–1.45, $P < 0.001$), multiple lesions (HR: 1.68, 95% CI: 1.02–2.76, $P = 0.041$), lower ADC values (HR: 0.52, 95% CI: 0.40–0.68, $P < 0.001$), and higher radiomics scores (HR: 2.55, 95% CI: 1.89–3.44, $P < 0.001$) were independently associated with shorter DFS (Table 3).

ROC analysis yielded an AUC of 0.707 for ADC and 0.767 for the radiomics score. Combining ADC and the radiomics score improved the predictive performance, achieving an AUC of 0.837, and the full multivariable model demonstrated the highest discriminatory performance (AUC: 0.892) (Table 4 and Figure 2). DeLong analysis showed that the combined ADC–radiomics score significantly outperformed ADC alone (AUC: 0.837 vs. 0.707, $P < 0.001$) and the radiomics score alone (AUC: 0.837 vs. 0.767, $P = 0.008$). The full model also demonstrated significantly higher discriminatory performance than the combined ADC–radiomics score (AUC: 0.892 vs. 0.837, $P = 0.001$). No significant difference

Table 1. Baseline characteristics according to recurrence status

Variable	Overall (n = 200)	No recurrence (n = 134)	Recurrence (n = 66)	<i>P</i> value
Age, years	60.13 $\pm$ 12.00	59.68 $\pm$ 11.85	61.06 $\pm$ 12.34	0.452
Tumor size, cm	5.45 $\pm$ 2.22	5.11 $\pm$ 2.27	6.12 $\pm$ 1.96	0.001
ADC	1.11 $\pm$ 0.23	1.16 $\pm$ 0.22	1.00 $\pm$ 0.22	< 0.001
Radiomics score	0.59 $\pm$ 0.22	0.53 $\pm$ 0.21	0.73 $\pm$ 0.17	< 0.001
DFS, months	20.86 $\pm$ 8.28	24.22 $\pm$ 7.06	14.03 $\pm$ 6.09	< 0.001
Male sex	98 (49.0%)	65 (48.5%)	33 (50.0%)	0.962
Multiple lesions (≥ 2)	101 (50.5%)	66 (49.3%)	35 (53.0%)	0.725
Non-rim APHE-positive	109 (54.5%)	75 (56.0%)	34 (51.5%)	0.657

ADC, apparent diffusion coefficient; APHE, arterial phase hyperenhancement; DFS, disease-free survival.

Table 2. Multivariable logistic regression

Variable	Univariable OR (95% CI)	Univariable <i>P</i> value	Multivariable OR (95% CI)	Multivariable <i>P</i> value
Age (per year)	1.01 (0.99–1.04)	0.443	0.99 (0.96–1.03)	0.671
Male sex (vs. female)	1.06 (0.59–1.92)	0.843	1.72 (0.78–3.85)	0.183
Tumor size (per cm)	1.24 (1.08–1.43)	0.003	1.55 (1.27–1.89)	< 0.001
Multiple lesions (vs. single)	1.16 (0.64–2.10)	0.616	2.16 (0.94–4.93)	0.068
ADC (per SD increase)	0.47 (0.33–0.65)	< 0.001	0.29 (0.18–0.46)	< 0.001
Non-rim APHE-positive	0.84 (0.46–1.51)	0.552	1.16 (0.51–2.63)	0.727
Radiomics score (per SD increase)	3.05 (2.08–4.46)	< 0.001	4.74 (2.85–7.89)	< 0.001

ADC and radiomics score are reported per 1-standard-deviation increase. ADC, apparent diffusion coefficient; APHE, arterial phase hyperenhancement; OR, odds ratio; CI, confidence interval; SD, standard deviation.

was observed between the ADC and radiomics score alone ($P = 0.307$) (Table 5).

The optimal radiomics score cut-off determined using the Youden index was 0.62. A median-based cut-off (0.595) was additionally evaluated and yielded a similar patient distribution; however, the Youden-derived threshold was selected for subsequent survival analyses because it maximized the discrimination between recurrence and non-recurrence. Using this threshold, 97 patients were classified as high-risk and 103 as low-risk. Recurrence occurred in 56 of 97 patients (57.7%) in the high-risk group and in 10 of 103 patients (9.7%) in the low-risk group (Table 6).

Kaplan–Meier analysis demonstrated significantly poorer DFS in the high-risk group than in the low-risk group (log-rank $P < 0.001$) (Figure 3).

Discussion

HCC, the most common primary malignancy of the liver worldwide, remains a major global health concern. Imaging modalities play a central role in the surveillance, diagnosis, and treatment monitoring of HCC; however, the limitations of current screening methods, particularly in the detection of early-stage tumors, have increased interest in AI-assisted imaging approaches.^{1,10}

AI applications have been increasingly utilized in various aspects of imaging-based HCC assessment, including lesion detection, segmentation, characterization, and classi-

fication. In particular, radiomics enables the quantitative analysis of tumor heterogeneity, providing valuable insights into tumor biology, treatment response, and prognosis. When integrated with clinical and laboratory data, radiomics represents a promising approach that may facilitate the development of personalized treatment strategies.^{10,11}

Systematic reviews, meta-analyses, and multicenter studies reported in the literature have demonstrated that radiomics-based models show promising results in the diagnosis, recurrence prediction, and prognostic assessment of HCC. In a systematic review evaluating Liver Imaging Reporting and Data System (LI-RADS)-based lesion classification, high diagnostic performance was reported for differentiating benign from malignant lesions. However, important limitations were highlighted, including the inclusion of predominantly typical HCC cases, the lack of evaluation across all LI-RADS categories, and the absence of external validation in most studies.^{10,11,17–19}

Furthermore, multicenter studies have demonstrated that MRI-based radiomics, particularly when combined with machine learning or deep learning approaches, can non-invasively predict HCC tumor differentiation with good diagnostic performance.^{12,13}

Recent studies have further shown that radiomics approaches derived from deep learning-enhanced MRI images may improve the prediction of HCC histopathological grade compared with conventional imaging, highlighting the potential of radiomics for

assessing tumor aggressiveness. Moreover, systematic reviews have supported the prognostic value of radiomics features for survival prediction, while emphasizing the need for prospective studies and robust external validation before widespread clinical implementation.¹⁴

A meta-analysis including 49 studies reported that radiomics approaches outperformed traditional clinical models in predicting HCC recurrence, with MRI-based models showing particularly favorable results. The highest predictive performance was achieved by models that combined radiomics features with clinical data.⁶ Similarly, a recent meta-analysis demonstrated that MRI-based radiomics approaches achieved high performance in predicting both recurrence and microvascular invasion, reaching AUC values of 0.83 and 0.87, respectively, in validation cohorts.⁷

Accumulating evidence suggests that radiomics- and deep learning-based models provide valuable prognostic information in HCC, enabling the prediction of postoperative recurrence, DFS, and overall survival. Both CT- and MRI-derived radiomics features have demonstrated independent prognostic value, and predictive performance appears to improve further when imaging biomarkers are integrated with clinical and radiological variables. These models have shown promising results across different treatment settings, including hepatic resection, liver transplantation, and transarterial chemoembolization, and may outperform conventional prognostic approaches.^{8,9,15,16,20,21}

Table 3. Cox proportional hazards analysis for disease-free survival

Variable	Univariable HR (95% CI)	Univariable P value	Multivariable HR (95% CI)	Multivariable P value
Age (per year)	1.01 (0.99–1.03)	0.341	1.00 (0.98–1.02)	0.835
Male sex (vs. female)	1.04 (0.64–1.68)	0.882	1.29 (0.79–2.12)	0.315
Tumor size (per cm)	1.18 (1.05–1.32)	0.004	1.28 (1.13–1.45)	< 0.001
Multiple lesions (vs. single)	1.12 (0.69–1.81)	0.649	1.68 (1.02–2.76)	0.041
ADC (per SD increase)	0.58 (0.45–0.75)	< 0.001	0.52 (0.40–0.68)	< 0.001
Non-rim APHE-positive	0.80 (0.49–1.29)	0.359	0.97 (0.59–1.59)	0.898
Radiomics score (per SD increase)	2.32 (1.75–3.09)	< 0.001	2.55 (1.89–3.44)	< 0.001

ADC and radiomics score are reported per 1-standard-deviation increase. ADC, apparent diffusion coefficient; APHE, arterial phase hyperenhancement; HR, hazard ratio; CI, confidence interval; SD, standard deviation.

Table 4. Bootstrap analysis of AUC estimates

Model	AUC	Model 1	Model 2	Bootstrap approx. P value
ADC	0.707	ADC	Radiomics	0.315
Radiomics	0.767	ADC	ADC + radiomics score	< 0.001
ADC + radiomics score	0.837	Radiomics	ADC + radiomics score	0.009
Full model	0.892	ADC + radiomics score	Full model	< 0.001

ADC, apparent diffusion coefficient; AUC, area under the receiver operating characteristic curve.

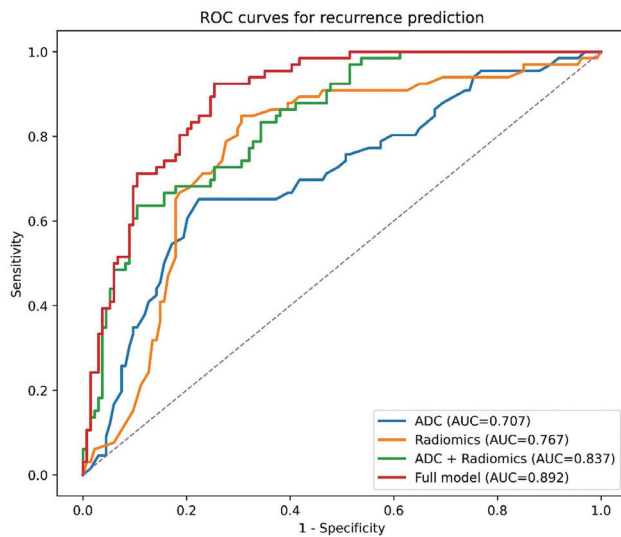


Figure 2. Receiver operating characteristic curves for recurrence prediction. ROC, Receiver operating characteristic; AUC, area under the curve; ADC, apparent diffusion coefficient.

Table 5. DeLong analysis

Model 1	Model 2	AUC 1	AUC 2	DeLong P value
ADC	Radiomics score	0.707	0.767	0.307
ADC	ADC + radiomics score	0.707	0.837	< 0.001
Radiomics score	ADC + radiomics score	0.767	0.837	0.008
ADC + radiomics score	Full model	0.837	0.892	0.001
ADC	Full model	0.707	0.892	< 0.001
Radiomics score	Full model	0.767	0.892	< 0.001

ADC, apparent diffusion coefficient; AUC, area under the receiver operating characteristic curve.

Table 6. Youden-derived radiomics score cut-off

Cut-off method	Cut-off value	High-risk n	Low-risk n	High-risk recurrence	Low-risk recurrence
Youden-derived ROC cut-off	0.620	97	103	56 (57.7%)	10 (9.7%)
Median cut-off	0.595	100	100	56 (56.0%)	10 (10.0%)

The Youden-derived threshold was internally derived in the study cohort. ROC, receiver operating characteristic.

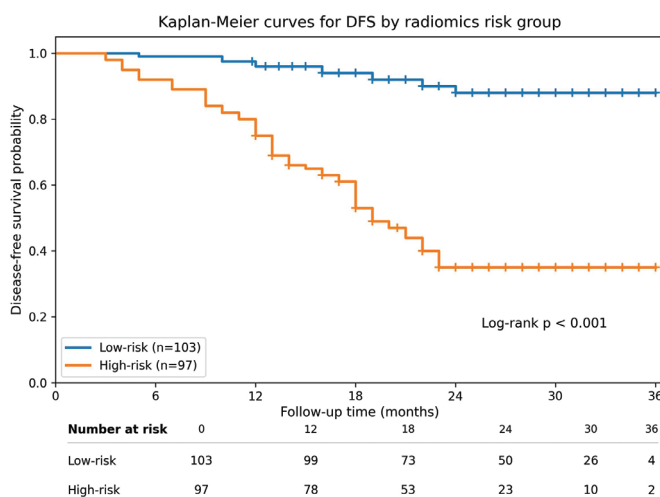


Figure 3. Kaplan-Meier curves for disease-free survival according to the radiomics risk group. Patients were stratified according to the Youden-derived radiomics score cut-off of 0.62; log-rank $P < 0.001$. DFS, disease-free survival. DFS, disease-free survival.

The potential of radiomics features derived from ADC maps to reflect the biological behavior of HCC has been investigated in several studies.

In the diagnostic setting, a study involving 83 patients with HCC and 46 patients with intrahepatic cholangiocarcinoma reported that machine learning models based on radiomics features extracted from ADC maps achieved high accuracy in differentiating the two tumor types and maintained robust performance in an external validation cohort.²

In a study including 51 patients histopathologically confirmed with HCC, ADC-based texture features were found to be significantly associated with the Ki-67 proliferation index and tumor-stroma ratio, whereas no significant correlation was observed with tumor grade or inflammatory cell infiltration.³

With regard to histological grading, a study including 171 HCC lesions demonstrated that the addition of radiomics features derived from ADC maps and venous-phase enhancement maps significantly improved the prediction of tumor differentiation grade.⁴ Similarly, in patients with solitary HCC, whole-tumor ADC-based radiomics analyses outperformed single-slice ADC measurements, and the highest performance for early recurrence prediction was achieved using combined models integrating clinical-radiological and radiomics features (AUC: 0.85–0.88).⁵

Collectively, these findings indicate that ADC-based radiomics analyses have considerable potential not only for tumor characterization but also for the prediction of histopathological features, biological aggressiveness, and clinical outcomes.

The present findings are in line with previous work suggesting that quantitative MRI biomarkers may provide prognostic information in HCC. In this cohort, both ROI-based ADC and the predefined MRI-based radiomics score remained associated with early recurrence. Their combination improved model discrimination compared with either parameter alone, indicating that diffusion restriction and radiomics-based tumor characterization may capture partly complementary aspects of tumor biology.

The association between higher radiomics scores and shorter DFS supports the potential role of MRI-based quantitative assessment in postoperative risk stratification. However, these findings should be interpreted in the context of the retrospective

single-center design, the absence of external validation, and the fact that the radiomics score was not redeveloped in the current cohort.

Nevertheless, several technical challenges may limit the widespread clinical implementation of ADC-based radiomics analyses. In a reproducibility study conducted in patients with HCC, radiomics features demonstrated acceptable repeatability when acquired using the same MRI system; however, reproducibility decreased substantially across different MRI platforms. The authors further reported that T1-weighted images yielded more stable radiomics features, whereas T2-weighted images and, in particular, ADC-derived parameters were more susceptible to variations in imaging protocols and scanner characteristics.²²

Although interobserver agreement ranged from moderate to excellent, variability related to manual segmentation could not be eliminated. Consequently, the literature emphasized the need for standardized imaging protocols and the development of automated segmentation methods to improve the robustness of radiomics analyses.²³

Overall, MRI-based radiomics features demonstrate good repeatability when assessed on the same scanner and by different observers; however, reproducibility across different MRI systems remains limited. These findings highlight the importance of technical standardization and external validation in multicenter and multi-platform radiomics studies and underscore their necessity for improving the generalizability of ADC-based radiomics features across different institutions.

Our study has some limitations. First, this was a retrospective study conducted at a single institution, which may limit the generalizability of the findings. Second, although the radiomics score was available for all patients, radiomics feature extraction and model development were not performed within the present cohort. The radiomics score was a predefined MRI-based variable derived from ADC maps and contrast-enhanced MR images; therefore, the original segmentation process, feature extraction steps, feature selection method, and model construction could not be fully re-evaluated in this retrospective analysis. Third, external validation was not available. In addition, the Youden-derived radiomics score cut-off was determined and tested within the same cohort, which may have led to an optimistic separation of DFS

curves. The imaging assessment was performed by a single reader, and interobserver agreement was not evaluated. Several pathological variables strongly associated with HCC recurrence, including microvascular invasion, tumor differentiation grade, capsule invasion, and surgical margin status, were not incorporated into the predictive models. Therefore, the independent value of imaging biomarkers should be interpreted with caution and confirmed in independent cohorts, including detailed pathological variables.

In conclusion, ROI-based ADC measurements and a predefined MRI-based radiomics score were independently associated with early recurrence and DFS after curative resection of HCC. The combined ADC–radiomics score showed better predictive performance than either parameter alone. These findings suggest that quantitative MRI biomarkers may contribute to preoperative risk assessment and postoperative surveillance planning, but external validation in larger multicenter cohorts is needed before routine clinical implementation.

Footnotes

Conflict of interest disclosure

Sonay Aydın, MD, serves as Section Editor for Diagnostic and Interventional Radiology. He had no involvement in the peer-review of this article and had no access to information regarding its peer-review. The other authors declared no conflicts of interest.

References

- Llovet JM, Kelley RK, Villanueva A, et al. Hepatocellular carcinoma. *Nat Rev Dis Primers*. 2021;7(1):6. [Crossref]
- Zhang Y, Yin X, Guo B, Yang H, Huang Z. Interpretable ADC-based radiomics models for differentiating hepatocellular carcinoma and intrahepatic cholangiocarcinoma. *Front Oncol*. 2026;16:1681920. [Crossref]
- Meyer HJ, Potratz J, Jechorek D, Schramm KI, Borggrefe J, Surov A. Association between diffusion-weighted imaging and tumor matrix in liver cancer: a cross-sectional study. *Transl Cancer Res*. 2025;14(3):1516-1525. [Crossref]
- Ameli S, Venkatesh BA, Shaghghi M, et al. Role of MRI-derived radiomics features in determining degree of tumor differentiation of hepatocellular carcinoma. *Diagnostics (Basel)*. 2022;12(10):2386. [Crossref]
- Wang L, Feng B, Wang S, et al. Diagnostic value of whole-tumor apparent diffusion coefficient map radiomics analysis in predicting

early recurrence of solitary hepatocellular carcinoma ≤ 5 cm. *Abdom Radiol (NY)*. 2022;47:3290-3300. [Crossref]

- Jin J, Jiang Y, Zhao YL, Huang PT. Radiomics-based machine learning to predict the recurrence of hepatocellular carcinoma: a systematic review and meta-analysis. *Acad Radiol*. 2024;31(2):467-479. [Crossref]
- Maung ST, Tangkijvanich P, Chaiteerakij R. Magnetic resonance imaging radiomics for predicting hepatocellular carcinoma recurrence following resection or ablation: a systematic review and meta-analysis. *Abdom Radiol (NY)*. 2026;51(4):1834-1853. [Crossref]
- Gong XQ, Tao YY, Wu YK, et al. Progress of MRI radiomics in hepatocellular carcinoma. *Front Oncol*. 2021;11:698373. [Crossref]
- Zhao Y, Wu J, Zhang Q, et al. Radiomics analysis based on multiparametric MRI for predicting early recurrence in hepatocellular carcinoma after partial hepatectomy. *J Magn Reson Imaging*. 2021;53(4):1066-1079. [Crossref]
- Ronot M, Calderaro J. Incorporating artificial intelligence into imaging for surveillance and diagnosis of liver cancer: Innovations, challenges, and clinical translation. *Hepatology*. 2026. [Crossref]
- Lewis S, Hectors S, Taouli B. Radiomics of hepatocellular carcinoma. *Abdom Radiol (NY)*. 2021;46(1):111-123. [Crossref]
- Wu M, Jin M, Huang S, Yang X, et al. Radiomics-driven machine learning models for noninvasive prediction of pathological differentiation in hepatocellular carcinoma: insights from multisequence magnetic resonance imaging (MRI). *Clin Radiol*. 2025;92:107160. [Crossref]
- Wu K, Zhu Z, Xu D, et al. Gd-EOB-DTPA-enhanced MRI radiomics and deep learning models for predicting the pathological differentiation degree in hepatocellular carcinoma. *Eur J Radiol*. 2026;194:112487. [Crossref]
- Jia F, Wu B, Wang Z, et al. Deep learning 3D super-resolution radiomics model based on Gd-enhanced MRI for improving preoperative prediction of HCC pathological grading. *Abdom Radiol (NY)*. 2026;51(2):682-693. [Crossref]
- He Y, Hu B, Zhu C, et al. A novel multimodal radiomics model for predicting prognosis of resected hepatocellular carcinoma. *Front Oncol*. 2022;12:745258. [Crossref]
- Zhang J, Liu X, Zhang H, et al. Texture analysis based on preoperative magnetic resonance imaging (MRI) and conventional MRI features for predicting the early recurrence of single hepatocellular carcinoma after hepatectomy. *Acad Radiol*. 2019;26(9):1164-1173. [Crossref]
- Liu X, Elbanan MG, Luna A, et al. Radiomics in abdominopelvic solid-organ oncologic imaging: current status. *AJR Am J Roentgenol*. 2022;219(6):985-995. [Crossref]

18. Wu Y, White GM, Cornelius T, et al. Deep learning LI-RADS grading system based on contrast enhanced multiphase MRI for differentiation between LR-3 and LR-4/LR-5 liver tumors. *Ann Transl Med.* 2020;8(11):701. [\[Crossref\]](#)
19. Harding-Theobald E, Louissaint J, Maraj B, et al. Systematic review: radiomics for the diagnosis and prognosis of hepatocellular carcinoma. *Aliment Pharmacol Ther.* 2021;54(7):890-901. [\[Crossref\]](#)
20. Wei X, Xiao J, Liu Y, et al. Survival prediction and treatment decisions in hepatocellular carcinoma: a deep learning-based radiomics approach. *Br J Hosp Med (Lond).* 2026;87(1):50380. [\[Crossref\]](#)
21. Schindler P, von Beauvais P, Hoffmann E, et al. Combining radiomics and imaging biomarkers with clinical variables for the prediction of HCC recurrence after liver transplantation. *Liver Transpl.* 2025;31(10):1226-1237. [\[Crossref\]](#)
22. Carbonell G, Kennedy P, Bane O, et al. Precision of MRI radiomics features in the liver and hepatocellular carcinoma. *Eur Radiol.* 2022;32(3):2030-2040. [\[Crossref\]](#)
23. Zwanenburg A, Vallières M, Abdalah MA, et al. The image biomarker standardization initiative: standardized quantitative radiomics for high-throughput image-based phenotyping. *Radiology.* 2020;295(2):328-338. [\[Crossref\]](#)