Application of Radiomics in the Efficacy Evaluation of Transarterial Chemoembolization for Hepatocellular Carcinoma: A Systematic Review and Meta-analysis

Yingxuan Wang, Min Li, Zhe Zhang, Mingzi Gao, Liqin Zhao

Rationale and Objectives: This meta-analysis was aimed at evaluating the predictive value of radiomics in the context of transarterial chemoembolization (TACE) therapeutic response (TR) for hepatocellular carcinoma (HCC) and patients' survival status (SS) and providing favorable evidence for clinical application.

Materials and Methods: We searched for literature in which radiomics was applied to assess the TR of TACE for HCC and the affected patients' survival status across PubMed, Embase, Cochrane Library and Web of Science until Jul 12, 2023. The quality of included literature was evaluated using a radiomics quality score (RQS) approach, and a meta-analysis was conducted using Stata15.0.

Results: Twenty-four studies were included in the analysis. The meta-analysis revealed that the overall concordance-index (C-index) based on radiomics for predicting the TR and SS with TACE was 0.85 and 0.78, respectively. The combined radiomics-clinical model provided the best performance in evaluating the TR and SS associated with TACE. The C-index was 0.93 and 0.88 for TR and 0.84 and 0.80 for SS, in the training and validation sets, respectively. These values were higher than the 0.87 and 0.79 for TR and 0.79 and 0.70 for SS, respectively with the radiomics model, and 0.71 and 0.66 for TR and 0.72 and 0.66 for SS, respectively with the clinical model.

Conclusion: The radiomics prediction model for the efficacy of TACE in HCC showed a satisfactory prediction performance. The combined radiomics-clinic prediction model had the best performance.

Keywords: Hepatocellular carcinoma; Chemoembolization; Therapeutic; Radiomics; Meta-analysis.

Abbreviations: BCLC Barcelona Clinic Liver Classification, **C-index** Concordance-index, **HCC** Hepatocellular carcinoma, **OS** Overall survival, **PLC** Primary liver cancer, **ROS** Radiomics quality score, **SS** Survival status, **TR** Therapeutic response, **TACE** Transarterial chemoembolization

INTRODUCTION

Approximately 906,000 new cases of primary liver cancer (PLC) were reported in 2020 (1). Hepatocellular carcinoma (HCC) accounts for approximately 90% of PLC (2), and the associated morbidity and mortality are increasing worldwide. Different treatment options are recommended for HCC patients at different Barcelona Clinic Liver Cancer (BCLC) stages. An early-stage option can be surgical resection, with the 3- and 5-year survival rates being 87.8% and 77.2%, respectively (3). However, early HCC presents no obvious symptoms. It is usually diagnosed in the intermediate or advanced stage and when the optimal timing for surgical resection is missed.

Acad Radiol 2024; 31:273–285

From the Department of Radiology, Beijing Water Conservancy Hospital, Beijing, China (Y.W.); Department of Radiology, Beijing Hospital of Traditional Chinese Medicine, Capital Medical University, Beijing, China (M.L.); Department of Radiology, Beijing Changping Hospital of Chinese Medicine, Beijing, China (Z.Z.); Department of Radiology, Beijing Tiantan Hospital, Capital Medical University, Beijing, China (M.G., L.Z.). Received May 10, 2023; revised July 23, 2023; accepted August 2, 2023. **Address correspondence to:** L.Z. e-mail: zhaolq0129@163.com

https://doi.org/10.1016/j.acra.2023.08.001

Liver transplantation is an effective treatment for HCC (4), with a 5-year patient survival rate as high as 71% (5). Unfortunately, this option is limited by the scarcity of donated organs and the post-transplantation recurrence risk (4).

Transarterial chemoembolization (TACE) is a palliative therapy that can control tumor growth, prolong the survival of patients with unresectable HCC, and improve patients' quality of life. The 2022 BCLC guidelines first recommended TACE as the standard treatment for intermediate-stage (B) HCC (6), and it has been widely applied in clinical practice. A meta-analysis that included 101 literature pieces enrolled 10,108 HCC cases showed that the objective response rate of efficacy and survival status (SS) after TACE was 52.5%. The 1- and 5-year overall survival (OS) rates were 70.3% and 32.4%, respectively, and the median OS was 19.4 months (7). TACE can also be used as a neoadjuvant therapy before liver transplantation to achieve de-escalation or buffer therapy for liver transplantation patients. It is recommended for some advanced HCC patients with acceptable liver function accompanied by portal vein tumor thrombi (8,9). However, not all patients may benefit from TACE therapy (10), because of factors such as dual blood supply from both the hepatic artery and portal vein and collateral circulation, making complete tumor necrosis after TACE difficult, as well as a high recurrence rate. Early identification of patients with a good response to TACE may facilitate early repeat management to eliminate residual tumors or guide decision-making for subsequent treatment modalities, thereby minimizing therapy-related complications. Additionally, early identification of patients who do not respond to TACE aids in a timely transition to other therapies, such as radiofrequency ablation, surgical resection, or systemic therapy (molecular targeted therapy) (11,12). Therefore, using non-invasive means to accurately assess and predict the efficacy of TACE can guide individualized treatment and improve their OS effectively.

Radiomics is an emerging field and it can extract high-throughput image features from medical images and convert unquantifiable imaging information into precise data, allowing for quantitative analysis and data mining (13,14). It is extensively utilized in HCC management and yielded satisfactory results in the analysis of tumor genotype behavior, evaluation of therapeutic response (TR), and prediction of SS (15). In some recent studies, radiomics-based prediction models for efficacy in HCC patients were constructed, which is of great importance in assessing the TR to TACE and predicting patient SS. However, due to the lack of standard implementation guidelines, the overall effectiveness of the prediction models remains unclear, which hinders their full clinical application. The purpose of the current meta-analysis was to assess the TR to TACE and the effectiveness of the models for predicting SS in HCC patients. We also aimed to evaluate the quality of the radiomics-based methodology to provide a basis for personalized clinical management.

MATERIALS AND METHODS

This meta-analysis was reported in accordance with the criteria in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses published in the 2020 (PRISMA2020) statement. The study protocol has been registered with the International Platform of Registered Systematic Review and Meta-analysis Protocols (INPLASY) (INPLASY202260100; DOI number: 10.37766/inplasy2022.6.0100).

Literature Search

PubMed, Embase, Cochrane Library, and Web of Science were searched with the subject headings and free words such as "Carcinoma, Hepatocellular" (Mesh), "Radiomics" (Mesh), and "Chemoembolization, Therapeutic" (Mesh). The deadline for searching the databases was July 12, 2023. Detailed search strategies are described in Supplementary Materials.

Literature Inclusion and Exclusion Criteria

The following studies were included: (1) the language of the publication was English; (2) studies with patients clinically diagnosed as HCC and were treated with TACE; and (3) studies in which the outcome indicators of the predictive models value could be assessed directly or indirectly.

The exclusion criteria were as follows: (1) reviews, case report, conference abstracts, animal experiments, and repeated publications; (2) no predictive models to assess the TACE efficiency in HCC patients, though radiomic data were included in the study and (3) patient had received radiotherapy, chemotherapy, radio-frequency ablation, or other antitumor treatments.

Literature Screening, Information Extraction, and Quality Appraisal

Literature screening, information extraction, and quality appraisal were independently performed by two researchers (YW, ML) with over 3 years of experience in radiological diagnosis. A third researcher (LZ) assisted in reaching an agreement if there were any disagreements between the former two researchers. The data extracted included names of first authors, country, publication year, number of cases, equipment, treatment methods, prediction feature, radiomic software, feature selection, predictive model, and ROC curves.

The quality of the literature was assessed using the radiomics quality score (RQS) (16), which was used worldwide to evaluate the quality of radiomics literature. Its aim was to minimize bias and enhance the effectiveness of prediction models by establish standardized assessment criteria and reporting guidelines for radiomics research (16). It is made of a total of 16 criteria. Each criterion corresponds to a different score, depending on the degree to which the literature conforms to the criterion, and the total score ranged from −8 to 36 points. A higher score indicated a higher quality.

Statistical Methods

A meta-analysis was performed using Stata 15.0 (StataCorp LLC, College Station, TX) software. The predictive HCC efficacy model evaluated the TR to TACE and SS with TACE. Therefore, the outcome indicator used was the C-index. The inconsistency index (I^2) reflected the heterogeneity among the models. When $I^2 > 50\%$, a random-effects model was employed, and when $I^2 \leq 50\%$, a fixed-effects model was adopted to compute the combined effect index. Meanwhile, a subgroup analysis using the clinical, radiomics, and combined radiomics-clinical models were considered.

RESULTS

Overall, 1050 articles were initially retrieved. After further screening using Endnote, 488 duplicates were excluded. Then another 520 irrelevant articles were excluded by reviewing the titles, abstracts. Full texts of the remaining 42 studies were assessed for eligibility. Finally, 24 articles that satisfied the requirements were included (shown in Figure 1).

Basic Characteristics of the Included Literature

The 24 eligible articles (17–40) were published between 2019 and 2023, and all were retrospective analyses. Overall, 4191 patients were enrolled. Sixteen of the articles reported the application of CT scans. One article used both CT and MR scans (24). The remaining seven focused on MR scans. Regarding the research content, 13 (17,18,21,23,24,26,27,30,33,34,36,37,40) of the 24 articles explored the TR to TACE for HCC, nine reported SS (22,25,28,29,31,32,35,38,39), and two (19,20) focused on both TR and SS after the TACE session. Notably, five retrospective studies (20,27,31,33,38) involved data collected from multicenter clinical trials. Six of the articles (19,21,23,36,37,39) applied deep learning. The screening method of modeling variables was

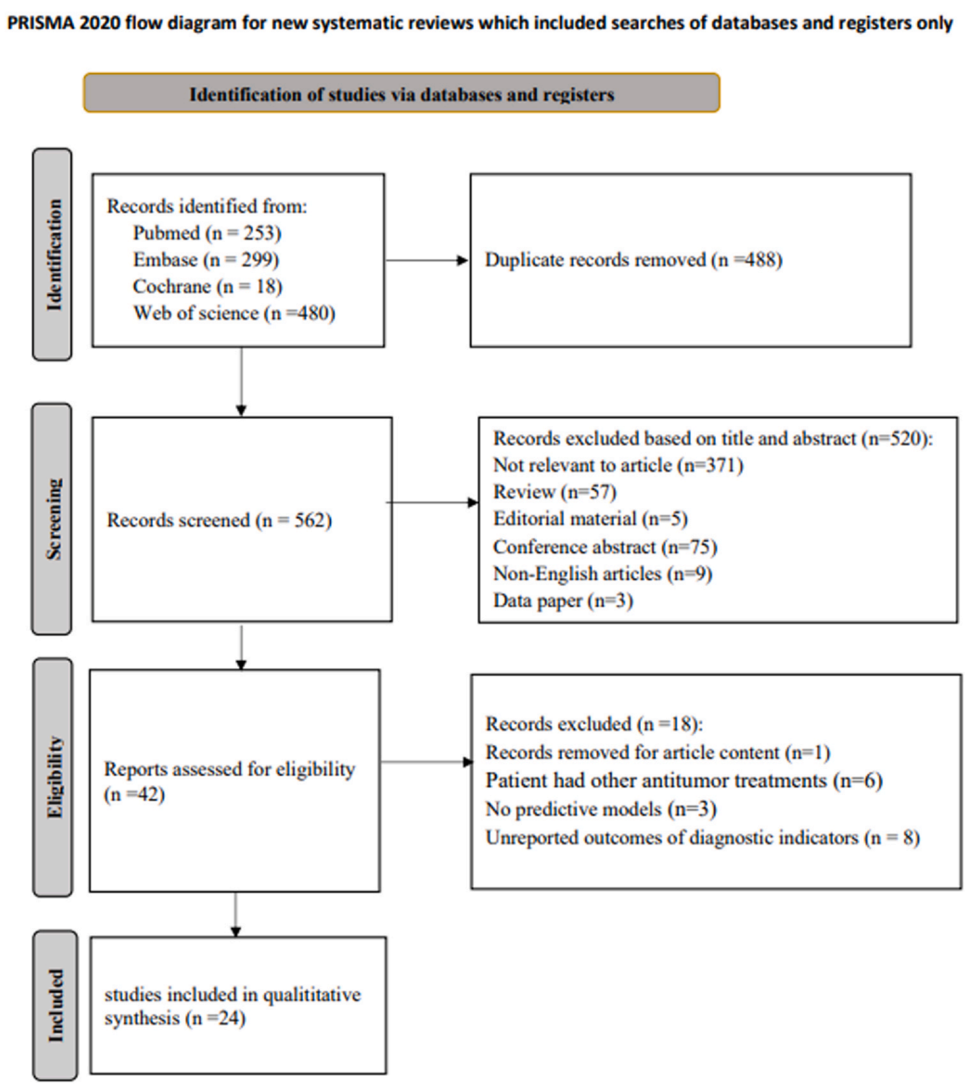

Figure 1. Literature screening flowchart.

least absolute shrinkage and selection operator (LASSO) regression, and the prediction models for TR were logistic, random forest, support vector machine, deep learning, and other diversified learning methods. Logistic regression was predominantly applied while Cox regression was adopted for SS. The basic characteristics of each study are shown in Table 1.

Quality Appraisal of the Literature

The RQS results revealed that the total score of the 24 studies ranged from seven to 23 points, with an average score of 16.92 points. The relative average score in the RQS assessment was 47.0% (range: 19.44–63.89%). Most studies reported well-documented image protocol quality and met the criteria for multiple segmentations. Feature reduction or adjustment for multiple testing and Multivariable analysis with non-radiomic features were applied to all studies. Only one study (37) did not conduct any validation, and the remaining studies performed internal validation, external validation and cross-validation. Four studies (18,26,32,40) included cost-effectiveness analyses. Fifteen studies (19,21–24,26–30,32,36,38–40) evaluated whether the model was applicable for clinical utility analysis by using decision curves. None of the studies was prospective study registered in a trial database. Two studies (23,39) were open science and data, one of which (23) applied elucidate the detect and discuss biological correlates. The scores of RQS quality assessment are shown in Table 2.

Meta-analysis Results

Prediction of Postoperative TR After TACE for HCC

The results showed that the overall C-indexes exhibited a moderate level of accuracy, with values of 0.85 and 0.78 for the training and validation sets, respectively. The combined radiomics-clinical model provided the best performance in evaluating the TR to TACE. The C-indexes of the training and validation sets were 0.93 and 0.88, respectively. The radiomics model ranked second in performance, with a C-indexes of 0.87 and 0.79 in training and validation sets, respectively. The clinical model has the poorest predictive efficiency, with a C-indexes of 0.71 and 0.66 in the training and validation sets being, respectively (Figs. 2 and 3).

Prediction of SS After TACE for HCC

The results showed that the overall C-indexes exhibited a moderate level of accuracy, with values of 0.78 and 0.72 for the training and validation sets, respectively. The combined radiomics-clinical model of HCC after TACE had the best performance, with the C-indexes of the training and validation sets being 0.84 and 0.80, respectively. Then followed by the radiomics model in the training and validation sets, with C-index of 0.79 and 0.70, respectively. The results for the SS were similar to those for the postoperative TR, with the combined radiomics-clinical model has the best prediction efficiency, and the clinical model has the poorest performance. The C-indexes of the training and validation sets were 0.72 and 0.66, respectively (Figs. 4 and 5).

DISCUSSION

Radiomics models have been used to evaluate the TR to TACE among HCC patients and their SS. Three models, the radiomics model, clinical model, and the combined radiomics-clinical model, were established in this meta-analysis.

The results showed that the combined radiomics-clinical model provided the best performance in evaluating the TR to TACE, better than that of the radiomics and clinical models. This finding was similar to the current research. Kim et al. used clinical data and radiomic features of CT images in the arterial phase to establish a prediction model for TACE efficacy among HCC patients. Studies have shown that the combined radiomics-clinical model was superior to either the radiomics or clinical model in predicting the postoperative efficacy of TACE (41). Ali Morshid et al. (42) also constructed a predictive model to evaluate the postoperative response to TACE among HCC patients. Their results showed that the accuracy of prediction was 62.9% when using the BCLC staging model alone and 74.2% when combined a deep learning model of radiomics.

Integration of radiomics and deep learning were also used to predict the treatment response to TACE in HCC. The results showed the model had notable accuracy for predicting the initial response to TACE treatment (33,37). Although some researchers assume that the predictive performance of deep learning is better than that of common single machine learning methods, more attention should be given to the selection of effective predictors, especially during the radiomics application processes. Because limited studies have been performed on the application of deep learning to establish a radiomics model in the context of TACE among HCC patients. There is a lack of data to confirm the effectiveness of deep learning in this field.

In this meta-analysis, we also studied the SS of TACE-treated HCC patients. The results showed that the performance of the combined radiomics-clinical model was again better than that of the other two prediction models, with the radiomics model performing better than the clinical model. Jin et al. (43) predicted the possibility of extrahepatic spread or vascular invasion in patients with liver cancer after the initial TACE. Their findings indicated that the AUCs of the combined radiomics-clinical model and radiomics model were higher than those of the clinical model both in the training and validation sets. These results were similar to those of the present study. Zhang et al. (44) established an overall survival prediction model for TACE combined with sorafenib in the treatment of unresectable HCC patients based on deep learning. Their results showed that the combined clinical nomogram and deep learning signature model had a more satisfactory prediction performance compared to that of the clinical and deep learning signature model alone.

TABLE 1. Basic Characteristics of Included Studies.

First Author	Country	Publication Year	Equipment	Prediction Feature	Number of Cases	Radiomic Software	Feature Selection	Predictive Model	Reference Standard
An (17)	China	2023	CT	TR	289	Pyradiomics	LASSO	Combined	mRECIST
Bai (18)	China	2022	CT	TR	111	PyRadiomics	LASSO	C Combined	mRECIST
Bernatz (19)	Germany	2023	CT	SS + TR	61	PyRadiomics	LASSO	R C Combined	mRECIST
Chen (20)	China	2021	CT	SS + TR	473	PyRadiomics	LASSO Cox regression	C Combined	mRECIST
Chen (21)	China	2023	MRI	TR	172	PyRadiomics	LASSO	R C Combined	mRECIST
Dai (22)	China	2022	CT	SS	102	PyRadiomics	LASSO Cox regression	R C Combined	
Dai (23)	China	2023	CT	TR	38	PyRadiomics	LASSO	R C Combined	mRECIST
Fan (24)	China	2023	CT + MR (1.5T or 3.0T)	TR	92	Deep-wise software	LASSO	R Combined	LR-TR
Guo (25)	China	2021	CT	SS	94	MATLAB 2014b Python 3.6	LASSO	R C Combined	
Kong (26)	China	2021	MR	TR	99	AIK	LASSO	R C Combined	mRECIST
Kuang (27)	China	2021	MR (1.5T or 3.0T)	TR	153	AIK	LASSO	R C	mRECIST
Li (28)	China	2021	CT	SS	60	AIK	LASSO logistic regression	R Combined	
Liu A (29)	China	2022	CT	SS	70	3D Slicer software	LASSO Cox regression	R C	
Liu Q (30)	China	2022	MR	TR	140	Pyradiomics	LASSO	R C Combined	mRECIST
Meng (31)	China	2020	CT	SS	162	Pyradiomics	LASSO	R	
Niu (32)	China	2021	CT	SS	219	Pyradiomics	LASSO	R C	
Peng (33)	China	2021	CT	TR	130	Pyradiomics	LASSO	R	mRECIST1.1
Shi (34)	China	2023	CT	TR	164	3D Slicer	LASSO	R	mRECIST

TABLE 1 (Continued)

First Author	Country	Publication Year	Equipment	Prediction Feature	Number of Cases	Radiomic Software	Feature Selection	Predictive Model	Reference Standard
								Combined	
Song (35)	China	2020	MR (1.5T or 3.0T)	SS	184	AIK	LASSO	R C Combined	
Sun (36)	China	2022	CT	TR	399	Deep-wise software	LASSO	R C Combined	mRECIST
Tian (37)	China	2022	MR (1.5T or 3.1T)	TR	71	Pyradiomics	DL	R	mRECIST
Wang (38)	China	2022	CT	SS	243	PyRadiomics	LASSO logistic regression	R C Combined	
Wang (39)	China	2022	CT	SS	543	ITK-SNAP	LASSO	R C Combined	mRECIST 1.1
Zhao (40)	China	2021	MR (1.5T or 3.0T)	TR	122	AIK	LASSO	R C Combined	mRECIST1.1

AIK, artificial intelligence kit software; C, clinical model; Combined, combined radiomics-clinical model; DL, deep learning; LASSO, least absolute shrinkage and selection operator; LR-TR, liver imaging reporting and data system treatment response; mRECIST, modified response evaluation criteria in solid tumors; R, radiomics model; SS, survival status; TR, therapeutic response.

TABLE 2. RQS Quality Assessment Results of Included Studies.

Study ID	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	Total Score	Total Score (%)
An 2023 (17)	1	1	0	1	3	1	0	0	2	1	0	2	2	0	0	0	14	38.89
Bai 2022 (18)	1	1	0	0	3	1	0	1	1	0	0	2	2	0	1	0	13	36.11
Bernatz 2023 (19)	1	1	0	0	3	1	0	0	2	0	0	2	2	2	0	0	14	38.89
Chen 2021 (20)	1	1	0	1	3	1	0	1	2	2	0	5	2	0	0	0	19	52.78
Chen 2023 (21)	1	1	0	1	3	1	0	0	1	1	0	2	2	2	0	0	15	41.67
Dai 2022 (22)	1	1	1	1	3	1	0	1	1	2	0	2	2	2	0	0	18	50.00
Dai 2023 (23)	1	1	1	1	3	1	1	0	2	2	0	3	2	2	0	1	21	58.33
Fan 2023 (24)	1	1	0	0	3	1	0	0	2	2	0	2	2	2	0	0	16	44.44
Guo 2021 (25)	1	1	0	1	3	1	0	1	2	0	0	2	2	0	0	0	14	38.89
kong 2021 (26)	1	1	1	1	3	1	0	1	1	2	0	2	2	2	1	0	19	52.78
Kuang 2021 (27)	1	1	0	0	3	1	0	1	1	2	0	4	2	2	0	0	18	50.00
Li 2021 (28)	1	1	0	1	3	1	1	0	2	2	0	2	2	2	0	0	18	50.00
Liu A 2022 (29)	1	1	1	1	3	1	0	0	2	2	0	2	2	2	0	0	18	50.00
Liu Q 2022 (30)	1	1	1	1	3	1	0	1	2	2	0	4	2	2	0	0	21	58.33
Meng 2020 (31)	1	1	0	0	3	1	0	1	2	2	0	5	2	0	0	0	18	50.00
Niu 2021 (32)	1	1	0	1	3	1	0	1	1	2	0	3	2	2	1	0	19	52.78
Peng 2021 (33)	1	1	0	0	3	1	0	1	2	0	0	4	2	0	0	0	15	41.67
Shi 2023 (34)	1	1	0	1	3	1	0	1	2	2	0	2	2	0	0	0	16	44.44
Song 2020 (35)	1	1	0	1	3	1	0	0	2	2	0	2	2	0	0	0	15	41.67
Sun 2022 (36)	1	1	1	0	3	1	0	1	2	2	0	2	2	2	0	0	18	50.00
Tian 2022 (37)	1	1	0	1	3	1	0	1	2	0	0	-5	2	0	0	0	7	19.44
Wang 2022 (38)	1	1	1	1	3	1	1	1	2	2	0	5	2	2	0	0	23	63.89
Wang 2022 (39)	1	1	0	1	3	1	0	1	1	1	0	3	2	2	0	1	18	50.00
Zhao 2021 (40)	1	1	1	1	3	1	0	0	2	2	0	2	2	2	1	0	19	52.78

RQS, radiomics quality score; V, variation; V1, image protocol quality; V2, multiple segmentation; V3, phantom study on all scanners; V4, imaging at multiple time points, V5, feature reduction or adjustment for multiple testing; V6, multivariable analysis with non-radiomic features; V7, detect and discuss biological correlates; V8, cut off analyses; V9, discrimination statistics; V10, calibration statistics; V11, prospective study registered in a trial database; V12, validation; V13, comparison to gold standard; V14, potential clinical utility; V15, cost effectiveness analysis; V16, open science and data.

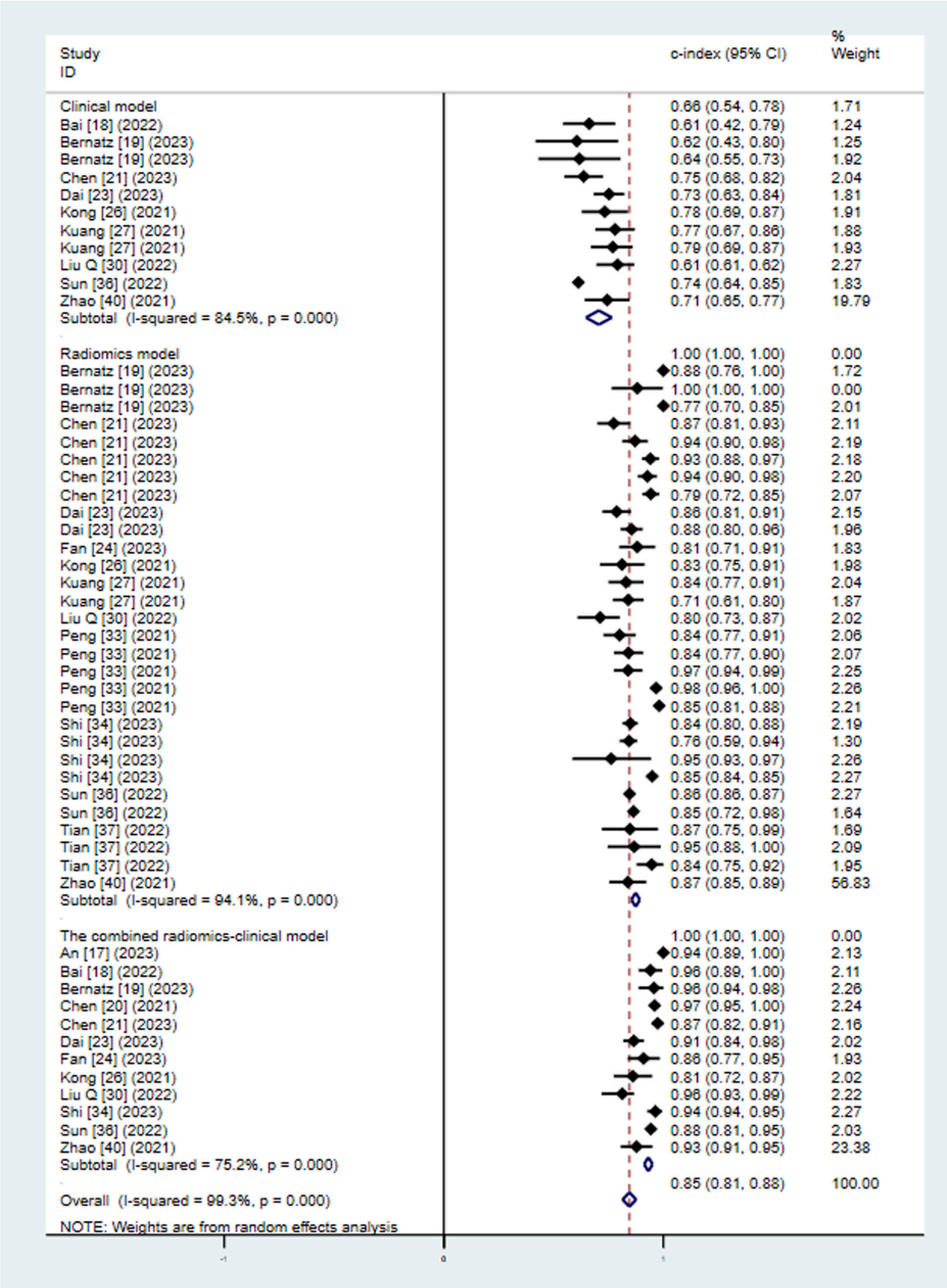

Figure 2. Forest map of radiomics to predict the therapeutic response to TACE among HCC patients in the training set. HCC, hepatocellular carcinoma; TACE, transarterial chemoembolization.

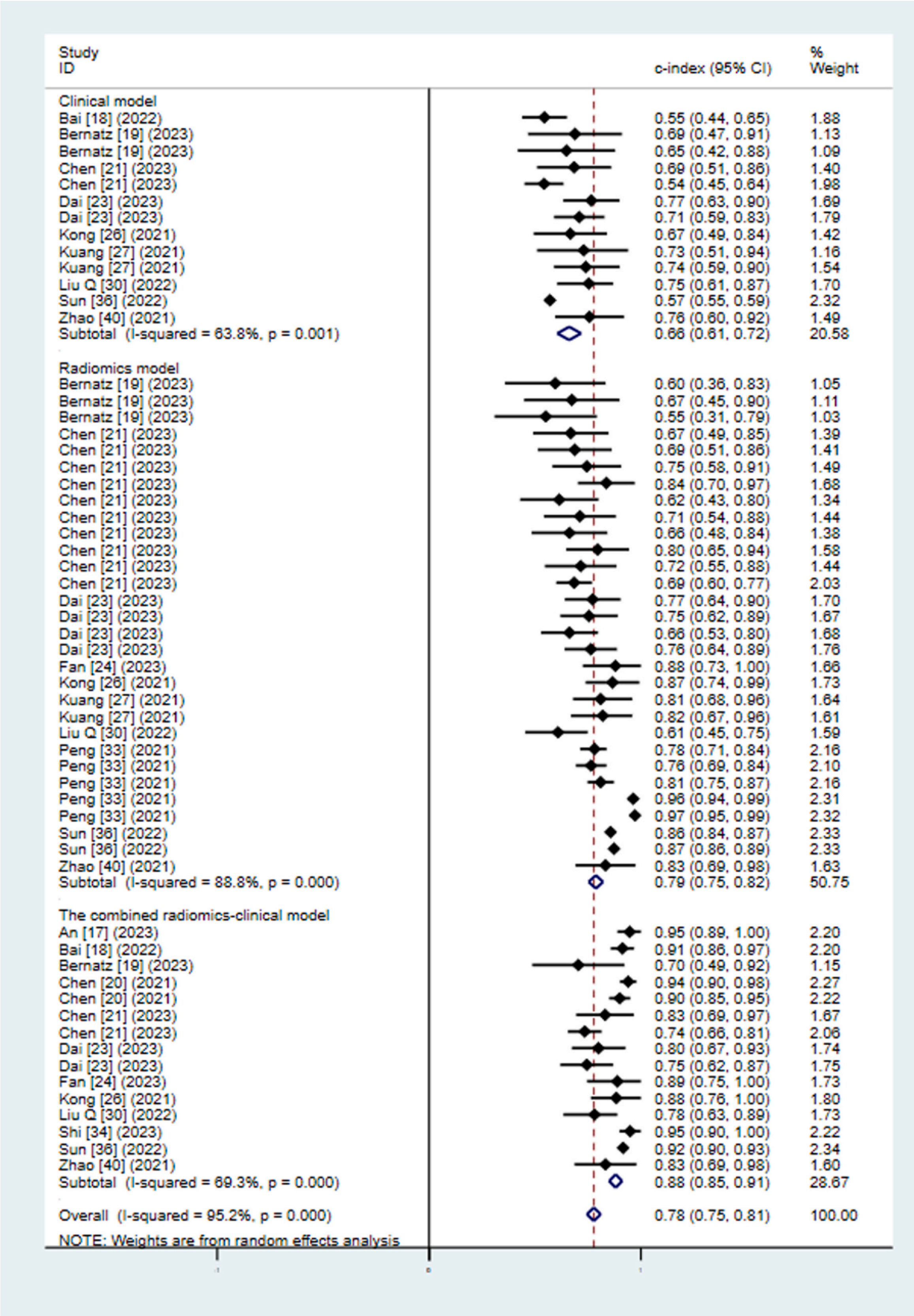

Figure 3. Forest map of radiomics to predict the therapeutic response to TACE among HCC patients in the validation set. HCC, hepatocellular carcinoma; TACE, transarterial chemoembolization.

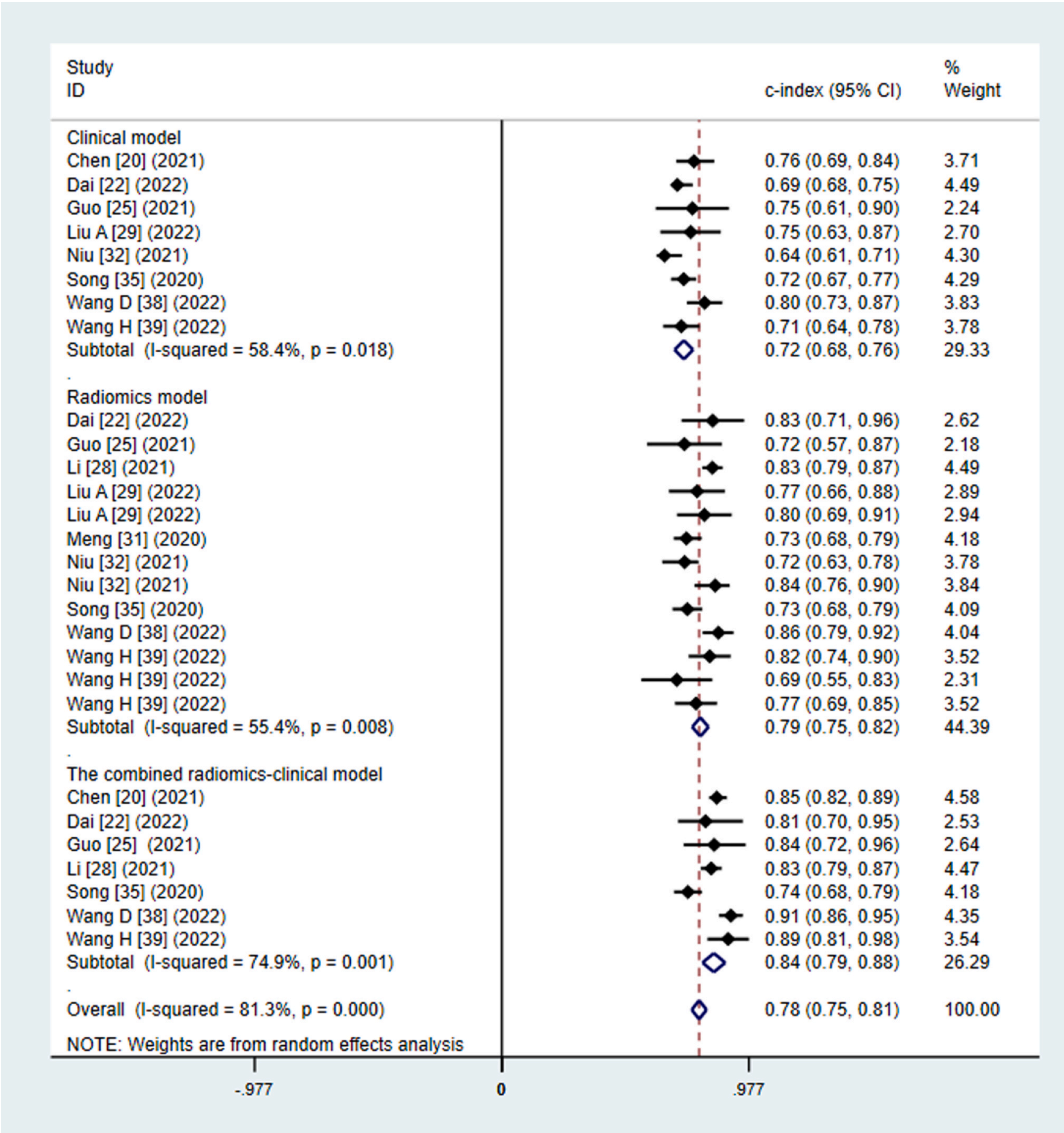

Figure 4. Forest map of radiomics to predict the survival status of TACE-treated HCC patients in the training set. HCC, hepatocellular carcinoma; TACE, transarterial chemoembolization.

RQS is a rigorous quality rating scale for evaluating the performance of a radiomics-based design. We evaluated the methodological quality by using the RQS method in our meta-analysis. Our results showed that the average RQS was 16.92 (47.0% of the total score). The average score on RQS was 4.9–10.83 in the previous systematic reviews on radiomics studies (45–49). Our results were slightly better than those of previous research, but did not reach a higher level. Detect and discuss biological correlates, prospective study registered in a trial database, and open science and data are important components in the assessment of RQS. However, they were rarely applied in the literature included in our study. In addition, validation and cost effectiveness analysis are crucial for the assessment of RQS quality, which could effectively help acquire information (50). However, only five studies used multicenter validation (20,27,31,33,38) and four

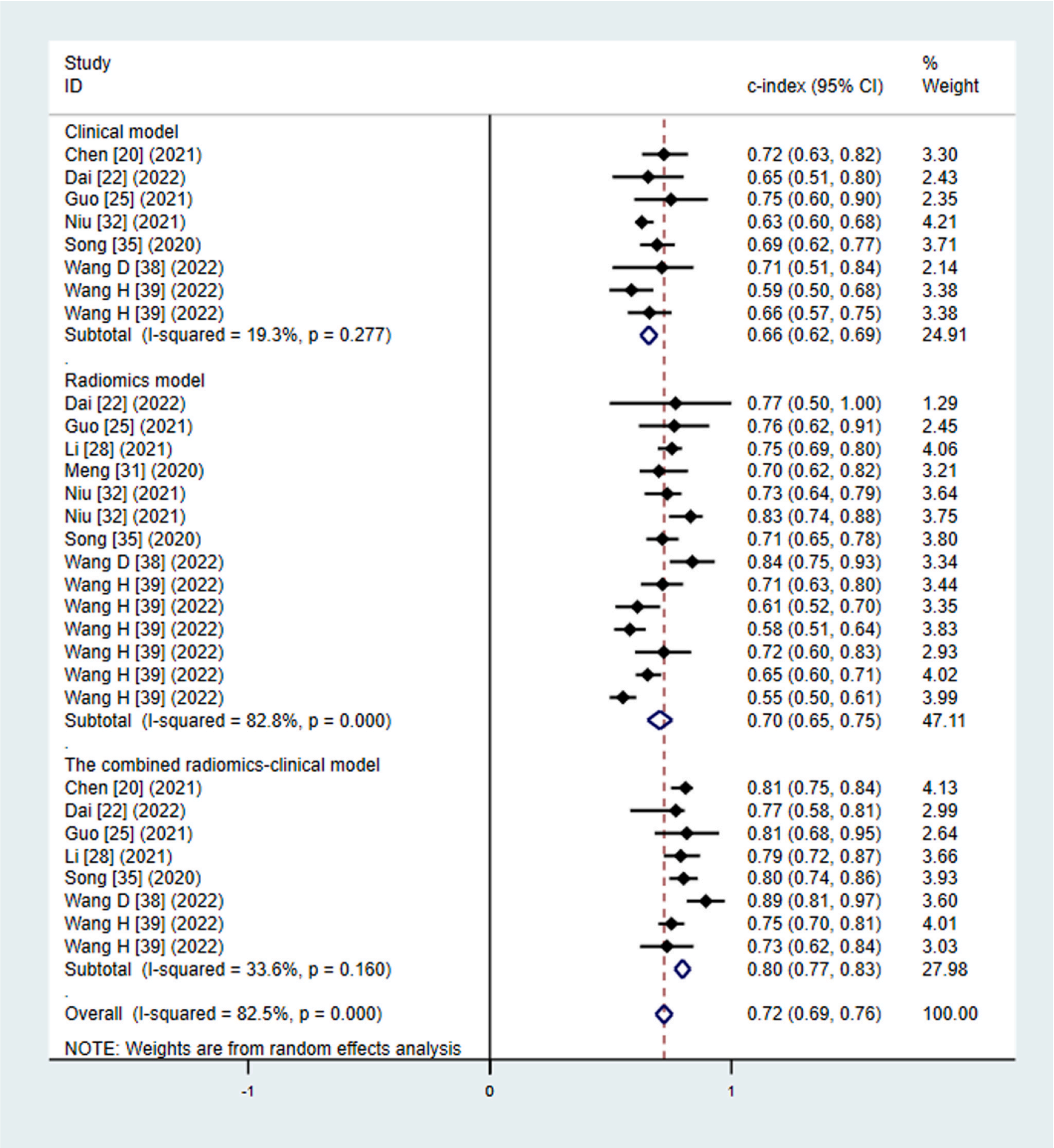

Figure 5. Forest map of radiomics to predict the survival status of TACE-treated HCC patients in the validation set. HCC, hepatocellular carcinoma; TACE, transarterial chemoembolization.

studies underwent cost effectiveness analysis (18,26,32,40). The RQS tool should be continuously updated to be more widely used in radiomics-associated research (51,52).

New progress has been made in the field of radiomics with regard to the diagnosis, evaluation of growth pattern of tumor blood vessels and vascular micro invasion of HCC (53–56), prognosis after surgical treatment (57,58), and complications after TACE treatment (59). However, there are relatively few studies on the response to TACE among HCC patients and their SS. Our study makes up for the lack of radiomics in HCC research to some extent.

Our study has several limitations. (1) The scanning parameters were not unified in the absence of standards for image acquisition and post-processing. Different software used for radiomics analysis also caused certain errors in the delineation of the region of interest. (2) Most of the studies were single-center, retrospective studies with relatively small sample sizes. (3) The TACE techniques, such as conventional TACE (cTACE) or drug-eluting beads TACE was not mentioned in most of the included studies. (4) Radiomics research requires multidisciplinary collaboration. Many algorithms were inconsistent during the process of data processing, and the verification methods were not completely unified.

Although there are major challenges to the application of radiomics in clinical settings, its prospect is worth looking forward to with the development of artificial intelligence. The combined radiomics-clinical model will yield greater value in evaluating the efficacy of TACE in HCC patients and guiding clinical decision-making. In the future, a large number of unified prospective studies are needed to confirm the efficacy of TACE among HCC patients and predicting patient survival based on radiomics prediction models.

DECLARATION OF COMPETING INTEREST

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Liqin Zhao reports was provided by National Natural Science Foundation of China (No. 82072003).

ACKNOWLEDGMENTS

This work was supported by a grant from the National Natural Science Foundation of China (No. 82072003). The study protocol has been registered with the International Platform of Registered Systematic Review and Meta-analysis Protocols (INPLASY) (INPLASY202260100; DOI number: 10.37766/inplasy2022.6.0100). The authors wish to thank Dr. Shanshan Wu for her technical supports. Dr. Jianying Li for his English expression advice during the drafting of this manuscript.

AUTHOR CONTRIBUTIONS

LZ and YW contributed to the study design and the original protocol. YW, ML, ZZ, and MG collected and analyzed the data. YW, ML, MG, and LZ interpreted the data. YW wrote the manuscript. LZ, ML, MG, and ZZ revised the manuscript. All the authors have reviewed the final version of the manuscript and approved it for publication.

APPENDIX A. SUPPORTING MATERIAL

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.acra.2023.08.001.

REFERENCES

1. Sung H, Jemal A, Bray F, et al. Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: Cancer J Clin 2021; 71(3):209–249.
2. Pagano D, Khouzam S, Magro B, et al. How important is the role of iterative liver direct surgery in patients with hepatocellular carcinoma for a transplant center located in an area with a low rate of deceased donation? Front Oncol 2022; 12:929607.
3. Wang JH, Chen CL, Lu SN, et al. Survival comparison between surgical resection and radiofrequency ablation for patients in BCLC very early/early stage hepatocellular carcinoma. J Hepatol 2012; 56(2):412–418.
4. Sapisochin G, Bruix J. Liver transplantation for hepatocellular carcinoma: outcomes and novel surgical approaches. Nat Rev Gastroenterol Hepatol 2017; 14(4):203–217.
5. Adam R, Karam V, Delvart V, et al. Evolution of indications and results of liver transplantation in Europe. A report from the European Liver Transplant Registry (ELTR). J Hepatol 2012; 57(3):675–688.
6. Reig M, Mazzaferro V, Salem R, et al. BCLC strategy for prognosis prediction and treatment recommendation: the 2022 update. J Hepatol 2022; 76(3):681–693.
7. Lencioni R, de Baere T, Soulen MC, et al. Lipiodol transarterial chemoembolization for hepatocellular carcinoma: a systematic review of efficacy and safety data. Hepatology (Baltimore, Md) 2016; 64(1):106–116.
8. Corrigendum to "EASL clinical practice guidelines: management of hepatocellular carcinoma" (J Hepatol 69 [2018] 182-236). J Hepatol 2019; 70(4):817.
9. Chang Y, Jeong SW, Young Jang J, et al. Recent updates of transarterial chemoembolilzation in hepatocellular carcinoma. Int J Mol Sci 2020; 21(21):8165.
10. Piscaglia F, Ogasawara S. Patient selection for transarterial chemoembolization in hepatocellular carcinoma: importance of benefit/risk assessment. Liver Cancer 2018; 7(1):104–119.
11. Kim YJ, Lee MH, Choi SY, et al. Magnetic resonance imaging features predictive of an incomplete response to transarterial chemoembolization in patients with hepatocellular carcinoma: a STROBE-compliant study. Medicine 2019; 98(19):e15592.
12. Park HJ, Kim JH, Choi SY, et al. Prediction of Therapeutic response of hepatocellular carcinoma to transcatheter arterial chemoembolization based on pretherapeutic dynamic CT and textural findings. AJR Am J Roentgenol 2017; 209(4):W211–w220.
13. Lambin P, Rios-Velazquez E, Leijenaar R, et al. Radiomics: extracting more information from medical images using advanced feature analysis. Eur J Cancer (Oxford, England: 1990) 2012; 48(4):441–446.
14. Gillies RJ, Kinahan PE, Hricak H. Radiomics: images are more than pictures, they are data. Radiology 2016; 278(2):563–577.
15. Masokano IB, Liu W, Xie S, et al. The application of texture quantification in hepatocellular carcinoma using CT and MRI: a review of perspectives and challenges. Cancer Imaging 2020; 20(1):67.
16. Lambin P, Leijenaar RTH, Deist TM, et al. Radiomics: the bridge between medical imaging and personalized medicine. Nat Rev Clin Oncol 2017; 14(12):749–762.
17. An H, Cao F, Huang Z, et al. CT texture analysis in predicting treatment response and survival in patients with hepatocellular carcinoma treated with transarterial chemoembolization using random forest models. BMC Cancer 2023; 23(1):201.
18. Bai H, Meng S, Xiong C, et al. Preoperative CECT-based Radiomic Signature for Predicting the Response of Transarterial Chemoembolization (TACE) therapy in hepatocellular carcinoma. Cardiovasc Intervent Radiol 2022; 45(10):1524–1533.
19. Bernatz S, Herrmann Y, Kinzler MN, et al. CT-radiomics and clinical risk scores for response and overall survival prognostication in TACE HCC patients. Sci Rep 2023; 13(1):533.
20. Chen M, Shen J, Zhang B, et al. Clinical-radiomic analysis for pretreatment prediction of objective response to first transarterial chemoembolization in hepatocellular carcinoma. Liver Cancer 2021; 10(1):38–51.
21. Chen M, Kong C, Qiao E, et al. Multi-algorithms analysis for pre-treatment prediction of response to transarterial chemoembolization in hepatocellular carcinoma on multiphase MRI. Insights Imaging 2023; 14(1):38.
22. Dai Y, Jiang H, Feng ST, et al. Noninvasive imaging evaluation based on computed tomography of the efficacy of initial transarterial

chemoembolization to predict outcome in patients with hepatocellular carcinoma. J Hepatocell Carcinoma 2022; 9:273–288.
23. Dai Y, Liu D, Xin Y, et al. Efficacy and interpretability analysis of noninvasive imaging based on computed tomography in patients with hepatocellular carcinoma after initial transarterial chemoembolization. Acad Radiol 2023. https://doi.org/10.1016/j.acra.2023.05.027
24. Fan XL, Yan FR, He BS, et al. Computed tomography texture analysis combined with preoperative clinical factors serve as a predictor of early efficacy of transcatheter arterial chemoembolization in hepatocellular carcinoma. Abdom Radiol (New York) 2023; 48(6):2008–2018.
25. Guo Z, Zhong N, Xu X, et al. Prediction of hepatocellular carcinoma response to transcatheter arterial chemoembolization: a real-world study based on non-contrast computed tomography radiomics and general image features. J Hepatocell Carcinoma 2021; 8:773–782.
26. Kong C, Zhao Z, Chen W, et al. Prediction of tumor response via a pretreatment MRI radiomics-based nomogram in HCC treated with TACE. Eur Radiol 2021; 31(10):7500–7511.
27. Kuang Y, Li R, Jia P, et al. MRI-based radiomics: nomograms predicting the short-term response after transcatheter arterial chemoembolization (TACE) in hepatocellular carcinoma patients with diameter less than 5 cm. Abdom Radiol (New York) 2021; 46(8):3772–3789.
28. Li L, Kan X, Zhao Y, et al. Radiomics signature: a potential biomarker for the prediction of survival in advanced hepatocellular carcinoma. Int J Med Sci 2021; 18(11):2276–2284.
29. Liu A, Liu B, Duan X, et al. Development of a novel combined nomogram model integrating Rad-score, age and ECOG to predict the survival of patients with hepatocellular carcinoma treated by transcatheter arterial chemoembolization. J Gastrointest Oncol 2022; 13(4):1889–1897.
30. Liu QP, Yang KL, Xu X, et al. Radiomics analysis of pretreatment MRI in predicting tumor response and outcome in hepatocellular carcinoma with transarterial chemoembolization: a two-center collaborative study. Abdom Radiol (New York) 2022; 47(2):651–663.
31. Meng XP, Wang YC, Ju S, et al. Radiomics analysis on multiphase contrast-enhanced CT: a survival prediction tool in patients with hepatocellular carcinoma undergoing transarterial chemoembolization. Front Oncol 2020; 10:1196.
32. Niu XK, He XF. Development of a computed tomography-based radiomics nomogram for prediction of transarterial chemoembolization refractoriness in hepatocellular carcinoma. World J Gastroenterol 2021; 27(2):189–207.
33. Peng J, Huang G, Zhang J, et al. Predicting the initial treatment response to transarterial chemoembolization in intermediate-stage hepatocellular carcinoma by the integration of radiomics and deep learning. Front Oncol 2021; 11:730282.
34. Shi ZX, Li CF, Zhao LF, et al. Computed tomography radiomic features and clinical factors predicting the response to first transarterial chemoembolization in intermediate-stage hepatocellular carcinoma. Hepatobiliary Pancreat Dis Int 2023. https://doi.org/10.1016/j.hbpd.2023.06.011
35. Song W, Yu X, Guo D, et al. MRI-based radiomics: associations with the recurrence-free survival of patients with hepatocellular carcinoma treated with conventional transcatheter arterial chemoembolization. J Magn Reson Imaging 2020; 52(2):461–473.
36. Sun Z, Shi Z, Xin Y, et al. Contrast-enhanced CT imaging features combined with clinical factors to predict the efficacy and prognosis for Transarterial chemoembolization of hepatocellular carcinoma. Acad Radiol 2023. https://doi.org/10.1016/j.acra.2022.12.031
37. Tian Y, Komolafe TE, Chen T, et al. Prediction of TACE treatment response in a preoperative MRI via analysis of integrating deep learning and radiomics features. J Med Biol Eng 2022; 42(2):169–178.
38. Wang DD, Zhang JF, Zhang LH, et al. Clinical-radiomics predictors to identify the suitability of transarterial chemoembolization treatment in intermediate-stage hepatocellular carcinoma: a multicenter study. Hepatobiliary Pancreat Dis Int 2022. https://doi.org/10.1016/j.hbpd.2022.11.005
39. Wang H, Liu Z, Chang Z, et al. Development and validation of a deep learning model for survival prognosis of transcatheter arterial chemoembolization in patients with intermediate-stage hepatocellular carcinoma. Eur J Radiol 2022; 156:110527.
40. Zhao Y, Sheng L, Liu J, et al. Radiomics analysis based on contrast-enhanced MRI for prediction of therapeutic response to transarterial chemoembolization in hepatocellular carcinoma. Front Oncol 2021; 11:582788.
41. Kim J, Choi SJ, Lee SH, et al. Predicting survival using pretreatment CT for patients with hepatocellular carcinoma treated with transarterial chemoembolization: comparison of models using radiomics. AJR Am J Roentgenol 2018; 211(5):1026–1034.
42. Morshid A, Elsayes KM, Khalaf AM, et al. A machine learning model to predict hepatocellular carcinoma response to transcatheter arterial chemoembolization. Radiol Artifi Intell 2019; 1(5):e180021.
43. Jin Z, Chen L, Zhong B, et al. Machine-learning analysis of contrast-enhanced computed tomography radiomics predicts patients with hepatocellular carcinoma who are unsuitable for initial transarterial chemoembolization monotherapy: a multicenter study. Trans Oncol 2021; 14(4):101034.
44. Zhang L, Xia W, Yan ZP, et al. Deep learning predicts overall survival of patients with unresectable hepatocellular carcinoma treated by transarterial chemoembolization plus sorafenib. Front Oncol 2020; 10:593292.
45. Zhong J, Hu Y, Si L, et al. A systematic review of radiomics in osteosarcoma: utilizing radiomics quality score as a tool promoting clinical translation. Eur Radiol 2021; 31(3):1526–1535.
46. Zhang J, Li L, Zhe X, et al. The diagnostic performance of machine learning-based radiomics of DCE-MRI in predicting axillary lymph node metastasis in breast cancer: a meta-analysis. Front Oncol 2022; 12:799209.
47. Wesdorp NJ, Hellingman T, Jansma EP, et al. Advanced analytics and artificial intelligence in gastrointestinal cancer: a systematic review of radiomics predicting response to treatment. Eur J Nucl Med Mol Imaging 2021; 48(6):1785–1794.
48. Mühlbauer J, Baessler B, Kriegmair MC, et al. Radiomics in renal cell carcinoma: a systematic review and meta-analysis. Cancers 2021; 13(6):1348.
49. Chen Q, Zhang L, Mo X, et al. Current status and quality of radiomic studies for predicting immunotherapy response and outcome in patients with non-small cell lung cancer: a systematic review and meta-analysis. Eur J Nucl Med Mol Imaging 2021; 49(1):345–360.
50. Neumann PJ, Sanders GD. Cost-effectiveness analysis 2.0. N Eng J Med 2017; 376(3):203–205.
51. Sanduleanu S, Woodruff HC, de Jong EEC, et al. Tracking tumor biology with radiomics: a systematic review utilizing a radiomics quality score. Radiother Oncol 2018; 127(3):349–360.
52. Park JE, Kim D, Kim HS, et al. Quality of science and reporting of radiomics in oncologic studies: room for improvement according to radiomics quality score and TRIPOD statement. Eur Radiol 2020; 30(1):523–536.
53. Sagir Kahraman A. Radiomics in hepatocellular carcinoma. J Gastrointest Cancer 2020; 51(4):1165–1168.
54. Fan Y, Yu Y, Wang X, et al. Texture analysis based on Gd-EOB-DTPA-enhanced MRI for identifying Vessels Encapsulating Tumor Clusters (VETC)-positive hepatocellular carcinoma. J Hepatocell Carcinoma 2021; 8:349–359.
55. Li L, Wu C, Huang Y, et al. Radiomics for the preoperative evaluation of microvascular invasion in hepatocellular carcinoma: a meta-analysis. Front Oncol 2022; 12:831996.
56. Yang L, Gu D, Wei J, et al. A radiomics nomogram for preoperative prediction of microvascular invasion in hepatocellular carcinoma. Liver Cancer 2019; 8(5):373–386.
57. Wen L, Weng S, Yan C, et al. A radiomics nomogram for preoperative prediction of early recurrence of small hepatocellular carcinoma after surgical resection or radiofrequency ablation. Front Oncol 2021; 11:657039.
58. Zhang L, Hu J, Hou J, et al. Radiomics-based model using gadoxetic acid disodium-enhanced MR images: associations with recurrence-free survival of patients with hepatocellular carcinoma treated by surgical resection. Abdom Radiol (New York) 2021; 46(8):3845–3854.
59. Li J, Zhang Y, Ye H, et al. Machine learning-based development of nomogram for hepatocellular carcinoma to predict acute liver function deterioration after drug-eluting beads transarterial chemoembolization. Acad Radiol 2023. https://doi.org/10.1016/j.acra.2023.05.014