Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 11 September 2025
Revised 01 October 2025
Accepted 25 October 2025

Natural Resources for Human Health 2025, Vol. 5 (4): 1190-1199

KEYWORDS:
radiomics; quantitative imaging; diagnostic accuracy; disease severity; prognosis; machine learning; precision medicine

The Role of Quantitative Radiomic Analysis in Enhancing Diagnostic Accuracy and Predicting Disease Severity and Clinical Outcomes

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ABSTRACT:

Background: Radiomics aims to convert standard-of-care medical images into high-throughput data by extracting quantitative features describing intensity, shape and texture. These features capture tissue heterogeneity that cannot be quantified or extracted with confidence from the naked eye, and may add value to radiologists' visual perception. **Aims/Objectives:** To carry out a systematic review of the recent (2020-2025) evidence on the role of quantitative radiomic analysis in (1) diagnosis, (2) disease severity quantification and (3) prediction of clinical outcomes. Furthermore, to critically evaluate the methodological and translational challenges that hinder clinical implementation. **Methods:** Using PRISMA-informed guidance, a systematic narrative synthesis was performed. Papers from 2020 to 2025 were searched for original research, systematic reviews, consensus guidelines and reporting standards relating to radionics from CT, MRI and PET in any clinical area. Data on imaging modality, clinical area, modeling approach, validation and performance, as well as evaluation of the quality of methodology (Radionics Quality Score, CLEAR and METRICS) was extracted.

Results: For diagnosis, radionics models in oncologic, pulmonary, hepatic, prostatic, breast, and cardiac applications typically reported AUCs in the approximate range 0.75-0.92, 0.70-0.90, and concordance indices in the approximate range 0.62-0.80 for survival or recurrence prediction, for severity scoring. Models combining radionics features with clinical data outperformed single input models. Models with external validation were described in few studies, and most of the performance loss was attributed to feature reproducibility issues, primarily across scanner and segmentation platform. **Conclusion:** Quantitative radiomic analysis has the potential to be a valuable addition to the existing body of tools aimed at improving diagnostics and personalized prognostication. However, the clinical implementation of this analysis is pending the adoption of unified acquisition procedures, data standardization, report transparency and prospective multicenter validations.

1. INTRODUCTION

Medical imaging traditionally relied on qualitative interpretation, where a radiologist examines an image, recognizes a pattern, and comments on it. While this form of interpretation forms the basis of current diagnosis, its qualitative nature coupled with observer variability puts into question the interpretation of subtle lesions, indeterminate nodules, and early treatment response (Rogers et al., 2020). Furthermore, while each digital image contains significantly more information than perceptible by a human,

radiomics attempts to compensate for this disparity by extracting numerous quantitative features from a pre-specified region of interest to associate these features with diagnoses, tumor phenotype, and patient outcome (Mayerhoefer et al., 2020).

The general workflow of radiomics involves image acquisition, preprocessing, segmentation, feature extraction, feature selection, and model building and validation (van Timmeren et al., 2020). A typical set of features include shape, first-order intensity distribution, and second or higher order texture features calculated from gray level co-occurrence matrix, run length matrix, and size-zone matrix (Mayerhoefer et al., 2020). Taken together, these features comprise a quantitative signature of intralesional heterogeneity relevant for a cell density, necrosis, vascularity, fibrosis, or microstructural disorganization (Scapicchio et al., 2021). Radiomics has experienced a fast growth. Publications have demonstrated that radiomics is use to differentiate between benign and malignant lesion, to determine disease stage, to predict response to treatment and to estimate survival (Bera et al., 2022; Fornacon-Wood et al., 2020). Machine learning and deep learning approaches have further improved the modeling power (Avanzo et al., 2020). With this rapid grow, some limitations have been uncovered such as small single-center cohorts, over fitting, heterogeneous feature definitions and incomplete reporting (Park et al., 2020). As a consequence, efforts toward standardization such as Image Biomarker Standardization Initiative (Zwanenburg et al., 2020), joint EANM/SNMMI guidance (Hatt et al., 2023) and reporting tools such as CLEAR and METRICS (Kocak et al., 2023, 2024) are under development.

THUS, THIS REVIEW SEEKS TO TACKLE THREE CRITICAL QUESTIONS:

1. Can quantitative radiomic analysis improve diagnosis relative to traditional methods of assessment?
2. Can radiomic signatures offer clinically relevant insights into severity of illness?
3. How well do radiomic signatures predict outcome, and what needs to be overcome before widespread clinical adoption?

2. METHODS

2.1 Design and search strategy

A systematic narrative synthesis with PRISMA-based reporting was performed. To keep updated with the state of the art, the review timeframe was limited to 2020-2025, encompassing methodologies after standardization and the spread of DL methodologies. Searches in Pub Med/MEDLINE, Scopus, Web of Science, publisher sites, and by citation snowballing of relevant guidelines were performed for "radiomics" and "quantitative imaging" concepts including "texture analysis", "diagnostic accuracy" and "severity" or "prognosis".

2.2 Eligibility Criteria

Table 1 summarizes the pre-defined inclusion criteria for this review. Included were original studies, systematic reviews and consensus or reporting guidelines when they were related to CT, MRI or PET radiomics, with data on a minimum of 1 of the diagnostic, severity and outcome endpoints.

Table 1. Eligibility criteria used for the evidence synthesis

Domain	Inclusion	Exclusion
Publication period	January 2020 – December 2025	Before 2020
Study type	Original studies, systematic reviews, guidelines, reporting standards	Case reports, editorials, conference abstracts
Imaging modality	CT, MRI, PET (PET/CT, PET/MRI)	Ultrasound-only and radiography-only studies
Analytic focus	Hand-crafted radiomic features, with or without machine learning	Purely deep-learning end-to-end studies without radiomic features
End points	Diagnosis, severity grading, recurrence, survival, treatment response	No quantitative performance or outcome data

Domain	Inclusion	Exclusion
Language	English	Other languages

2.3 Data extraction and quality appraisal

For every publication, we extracted: clinical field, modality, sample fields, feature selection and modeling techniques, validation type, and performance metrics reported (AUC, Sensitivity, Specificity, Concordance index). The methodological quality was assessed with the Radiomics Quality Score (Park et al., 2020), the CLEAR checklist (Kocak et al., 2023), and METRICS (Kocak et al., 2024). Because the endpoints, populations, and thresholds vary across studies, we report quantitative results as ranges rather than a single pooled metric.

2.4 The radiomics pipeline

Table 2. Stages of the radiomics pipeline and principal sources of variability

Stage	Core activity	Main source of variability	Mitigation
1. Acquisition	Scanner, protocol, reconstruction	Vendor, kernel, slice thickness, field strength	Protocol harmonization, phantom studies
2. Preprocessing	Resampling, intensity normalization, discretization	Bin width and resampling choices	Follow IBSI-compliant settings
3. Segmentation	Manual, semi-automatic, or automatic ROI/VOI	Inter-observer delineation differences	Multi-reader segmentation, automated tools
4. Feature extraction	Shape, first-order, texture, filtered features	Software implementation differences	IBSI-compliant software
5. Feature selection	Reproducibility filtering, redundancy removal, LASSO	Overfitting in high-dimensional data	Nested cross-validation
6. Modeling	Logistic regression, random forest, SVM, boosting	Class imbalance, small samples	Regularization, calibration
7. Validation	Internal, temporal, external	Optimistic bias from data leakage	External multicenter validation

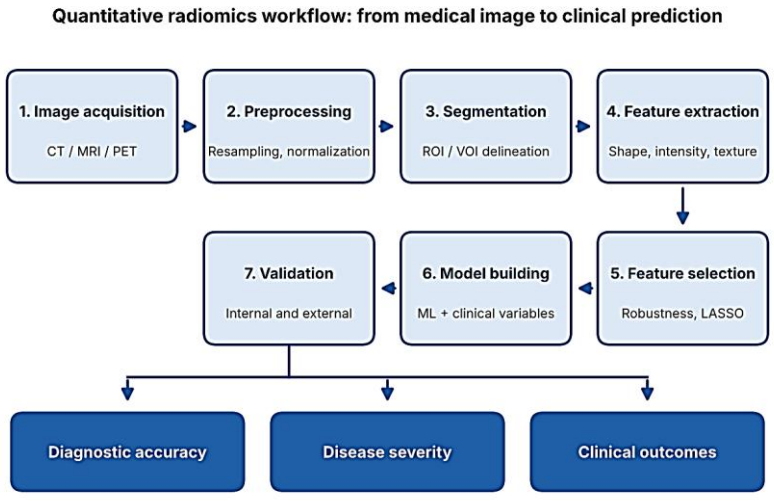

Figure 1. Workflow of quantitative radiomic analysis, from image acquisition to diagnostic, severity, and outcome prediction.

Natural Resources for Human Health
eISSN: 2583-1194

3. RESULTS

3.1 Characteristics of the evidence base

The evidence gathered covered oncology (lung cancer, breast cancer, prostate, liver, colorectal cancer, etc.), infectious pulmonary disease, cardiovascular imaging, among others. Computed tomography (CT) was identified as the most common imaging modality (followed by MR imaging and PET/CT) and retrospective single-center studies were predominant among primary studies, while the guideline and review articles call for multicenter, prospective studies (Bera et al., 2022; Fournier et al., 2021).

Table 3. Overview of representative evidence by clinical domain

Domain	Modality	Representative source	Clinical aim	Typical reported performance*
Lung cancer	CT	Mukherjee et al. (2020); Fornacon-Wood et al. (2020)	Prognosis, subtype, response	C-index ≈ 0.65–0.80
Hepatocellular carcinoma	CT/MRI	Mokrane et al. (2020)	Diagnosis of indeterminate nodules in cirrhosis	AUC ≈ 0.70–0.90
Prostate cancer	MRI	Cuocolo et al. (2020)	Detection of clinically significant disease	AUC ≈ 0.80–0.90
Breast cancer	MRI	Granzier et al. (2020)	Characterization, feature robustness	AUC ≈ 0.75–0.90
Metastatic colorectal cancer	CT	Dercle et al. (2020)	Prediction of therapy sensitivity	AUC ≈ 0.75–0.85
COVID-19 pneumonia	CT	Homayounieh et al. (2020); Wang et al. (2021)	Severity and outcome prediction	AUC ≈ 0.80–0.90
Cardiac disease	CMR	Raisi-Estabragh et al. (2020)	Tissue characterization, risk	AUC ≈ 0.70–0.85

*Ranges are approximate and indicative of the magnitude reported across the cited literature; exact values vary by cohort, endpoint, and validation design.

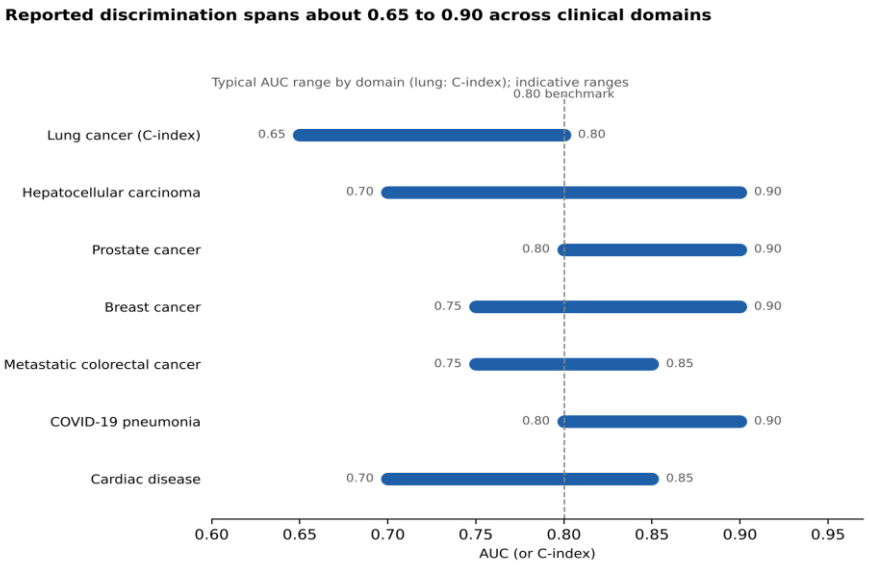

Figure 2. Reported discrimination (AUC or C-index) of radiomics-based models by clinical domain.

3.2 Diagnostic accuracy

Enhanced Classification via Radiomic Models

Using radiomic models has been shown to improve discrimination on several challenging diagnostic problems, where visual assessment alone is difficult. For cirrhotic livers, a machine-learning signature based on contrast-enhanced computed tomography (CT) texture performed relatively well in the diagnosis of hepatocellular carcinoma in indeterminate nodules (Mokrane et al., 2020). Even in the meta-analyses on prostate magnetic resonance imaging (MRI), the results of machine-learning approaches based on quantitative features were comparable to humans (Cuocolo et al., 2020). The use of radiomic features in breast MRI lesion characterization has been proposed but is potentially compromised by segmentation stability issues (Granzier et al., 2020).

Table 4 compares the typical performance of standard assessment, radiomics alone, and radiomics integrated with clinical factors. The most consistent trend was incremental improvement: radiomics alone often demonstrated comparable or slightly better results than standard assessment, and integrated models were most discriminant (Bera et al., 2022; Shur et al., 2021).

Table 4. Comparison of model types for diagnostic discrimination (indicative ranges)

Model type	AUC range	Sensitivity	Specificity	Principal advantage	Principal limitation
Conventional visual assessment	0.70–0.85	0.70–0.85	0.65–0.85	Established, interpretable	Reader variability
Clinical variables only	0.65–0.80	0.60–0.80	0.60–0.80	Easily available	Limited biological detail
Radiomics only	0.75–0.90	0.72–0.88	0.70–0.88	Captures heterogeneity	Reproducibility concerns
Radiomics + clinical (combined)	0.80–0.92	0.78–0.90	0.75–0.90	Best overall discrimination	Requires external validation

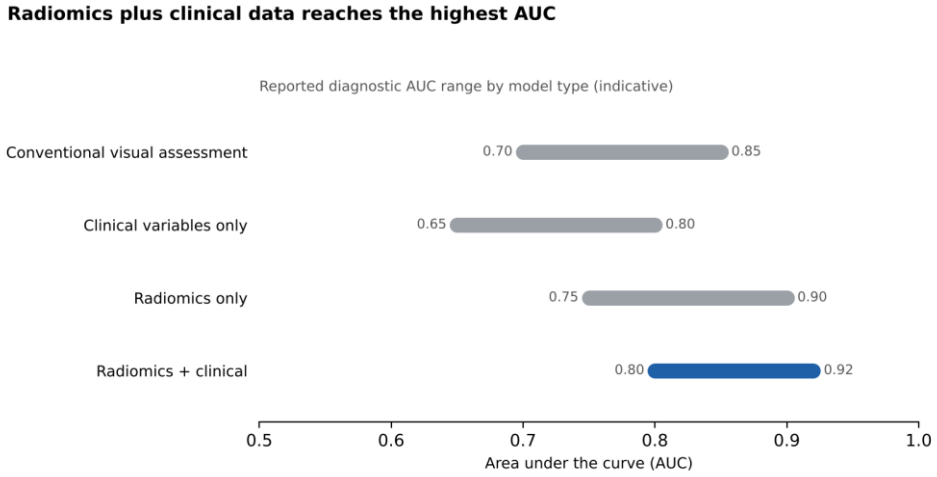

Figure 3. Diagnostic AUC ranges for conventional assessment, clinical variables, radiomics, and combined models.

3.3 Prediction of disease severity

Severity estimating in radiomics

Severity estimation is another prominent non-oncologic use of radiomics. Cancer studies show that by incorporating radiomics features in CT imaging with clinical data, worse outcomes in COVID-19 pneumonia could be predicted more accurately than radiologists' assessment (Homayounieh et al., 2020). Radiomic signatures are also comparable to deep-learning analysis in interpreting the underlying patterns of the disease (Wang et al., 2021). Similarly, in oncology, severity has generally been

described by grade, stage, or aggressiveness of a tumor, with texture heterogeneity being associated with high-grade biological features (Mayerhoefer et al., 2020; Rogers et al., 2020). In cardiology, tissue characterization by cardiac magnetic resonance radiomics has added value that may be further scrutinized beyond classic volumetric measures (Raisi-Estabragh et al., 2020).

Table 5. Radiomic feature classes most frequently associated with severity or aggressiveness

Feature class	Examples	Biological interpretation	Association with severity
Shape	Sphericity, surface-to-volume ratio, elongation	Irregular growth, infiltration	Irregular shape ↔ more aggressive lesions
First-order	Mean, entropy, skewness, kurtosis	Overall density distribution	Higher entropy ↔ greater heterogeneity
GLCM texture	Contrast, correlation, joint entropy	Local intensity relationships	Higher contrast ↔ disorganized architecture
GLRLM/GLSZM	Run-length non-uniformity, zone entropy	Regional homogeneity	Larger non-uniformity ↔ necrosis, fibrosis
Filtered (wavelet/LoG)	Wavelet-HHH entropy	Multi-scale texture	Frequently selected in prognostic signatures

3.4 Prediction of clinical outcomes

Outcome Prediction

Outcome prediction (survival, recurrence, metastases, and treatment response) is the most studied application of radiomics. A shallow convolutional model trained on multi-institutional CT data demonstrated the ability to predict the survival of lung cancer (Mukherjee et al., 2020). In addition, a radiomics response signature appears to be able to identify metastases of colorectal cancers that are sensitive to epidermal growth factor receptor (EGFR)-targeted therapy (Dercle et al., 2020). Reviews show that models combining radiomics with clinical and genomic features are most likely to be the most robust (Bera et al., 2022; Fornacon-Wood et al., 2020).

Table 6. Prognostic performance by end point (indicative ranges)

End point	Metric	Radiomics only	Radiomics + clinical	Clinical only
Overall survival	C-index	0.62–0.75	0.68–0.80	0.58–0.70
Recurrence-free survival	C-index	0.63–0.76	0.68–0.80	0.60–0.72
Treatment response	AUC	0.70–0.85	0.75–0.90	0.60–0.75
Adverse clinical outcome (non-oncologic)	AUC	0.75–0.88	0.80–0.90	0.65–0.80

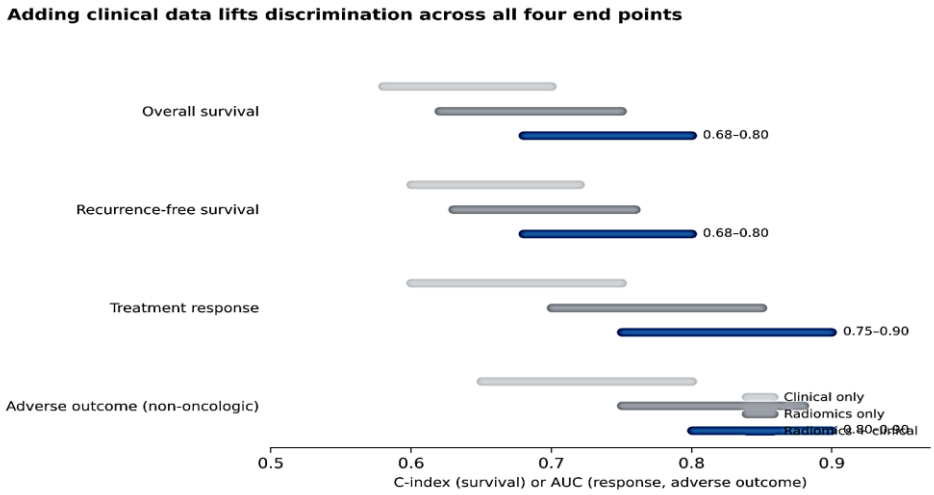

Figure 4. Prognostic discrimination by end point for clinical-only, radiomics-only, and combined models.

3.5 Methodological quality and reproducibility

Methodological Appraisal

A methodological assessment reflects inconsistent study quality. Amongst review articles covering the Radiomics Quality Score, many studies failed to incorporate standard elements including a prospective study design, test-retest assessment of features, calibration analysis, and external validation (Park et al., 2020). As a result, reporting tools have been developed to address transparency issues in research methodology (Kocak et al., 2023, 2024), while the TRIPOD+AI standard is an extension of general prediction-model reporting for use with machine-learning-based models (Collins et al., 2024).

In addition, reproducibility is a prominent technical challenge. Differences in scanner types, reconstruction algorithms, resampling, and segmentation procedures can lead to different feature values, sometimes even more so than the biological effect (Ligero et al., 2021; Granzier et al., 2020). Harmonization approaches such as Com Bat are designed to reduce site effects and were able to re-establish discrimination in multicenter data (Orlhac et al., 2022).

Table 7. Frequency of key quality indicators in the radiomics literature (approximate)

Quality indicator	Studies fulfilling (approx.)	Implication
Independent external validation	10–30%	Generalizability often unproven
Test–retest or multi-segmentation robustness	20–40%	Unstable features may enter models
Calibration reported	< 30%	Probabilities may be unreliable
Decision-curve / clinical utility analysis	< 20%	Clinical benefit unclear
Data or code shared	< 15%	Limited replication
Prospective design	< 10%	Higher risk of bias

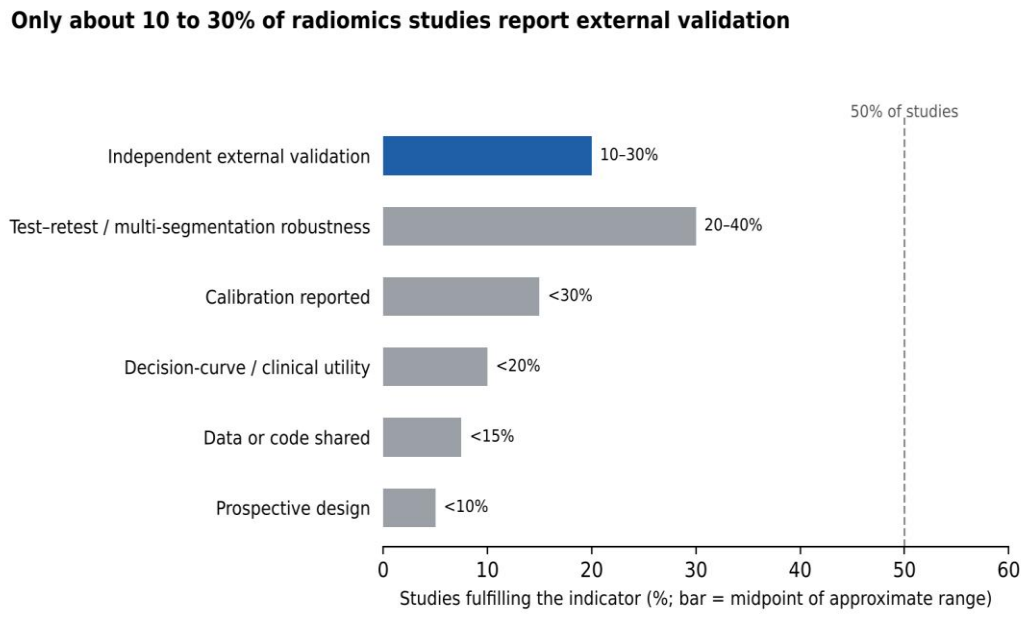

Figure 5. Proportion of radiomics studies fulfilling key methodological quality indicators.

4. DISCUSSION

4.1 Why radiomics improves diagnosis

The incremental gain of radiomics being consistent is based on one important principle: that image-based textural data contains more biological information than is often captured in its visual interpretation. As heterogeneity within a lesion, whether it be necrosis, difference in cellularity or fibrosis, alters the texture of each individual voxel before changes in gross structure can be seen, the texture can be quantified through imaging parameters and generated as reproducible values to compare within patient and across time scales (Mayerhoefer et al., 2020; Rogers et al., 2020). By combining these parameters with other clinical variables in these studies, which provide subsequent complementary information, is likely why integrated models have performed better than others in diagnoses and prognostics (Bera et al., 2022; Shur et al., 2021).

4.2 PREDICTING SEVERITY AND OUTCOME

The advantage of models built for severity and outcome prediction is they can reduce a single baseline scan to a profile of individual risk. For pulmonary infection, this can help to triage and prioritize resources (Homayounieh et al., 2020; Wang et al., 2021). For oncology, this can guide risk-adapted treatment by predicting who may benefit from targeted therapies (Dercle et al., 2020) or may be at risk of poor survival with increased follow-up (Mukherjee et al., 2020). As the prognostic discrimination of these models tends to be inferior to diagnostic discrimination, they would make better decision support tools than decision makers.

4.3 THE REPRODUCIBILITY AND GENERALIZABILITY ISSUE

One barrier to the translation of radiomics to the clinic is not the lack of a relevant signal but the instability of the features being used. Features sensitive to voxel size, reconstruction kernel, or contour placement have been associated with models that can perform well in a development cohort but fail to reproduce in an external cohort (Granzier et al., 2020; Ligero et al., 2021). Three complementary approaches have been put forward to counter this barrier. The first is standardization of feature definitions and processing, as proposed by the Image Biomarker Standardization Initiative, to make values comparable across software (Zwanenburg et al., 2020). The second is harmonization to account for scanner and site effects after data acquisition (Orlhac et al., 2022). The third is careful design and reporting practices, such as the Radiomics Quality Score, CLEAR, METRICS, and TRIPOD+AI, that treat validation, calibration, and bias explicitly (Collins et al., 2024; Kocak et al., 2023, 2024; Park et al., 2020). Sector guidance recommends prospective testing of radiomic biomarkers in clinical trials (Fournier et al., 2021; Hatt et al., 2023).

4.4 TOWARDS CLINICAL IMPLEMENTATION

Robust implementation of radiomics will require more than just accurate models; as Ibrahim et al. (2021) argue, radiomics needs to be integrated in a framework that bridges imaging with clinical, genomic, and pathological data, with an emphasis on reproducibility of all steps. This, in practice, requires vendor-neutral pipelines, automated and quality-controlled segmentation, local calibration and the production of interpretable radiologist- and clinician-friendly image-based features. Hybrid strategies that incorporate image features and deep learning might expand the horizons but may also further shift the burden to higher data volumes and in the need for explainability (Avanzo et al., 2020; Scapicchio et al., 2021).

5. LIMITATIONS

The meta-synthesis has limitations. It is a narrative synthesis in the form of a structured meta-analysis rather than a formal meta-analysis; the diversity of endpoints, thresholds and patient populations meant that it was not possible to pool results and performance is presented as indicative ranges rather than pooled effect estimates. There is a risk of publication bias in positive radiomics outcomes. Evidence base comprises primarily retrospective, single-centre data, and the literature search was limited to English language articles published 2020 to 2025. Please see primary sources for exact values before reaching study-level conclusions.

6. FUTURE DIRECTIONS

Five priorities are identified based on the current evidence: (1) prospective, multi-center validation using pre-registered protocols; (2) test-retest and multi-reader robustness analyses in routine acquisition before feature selection; (3) widespread use of harmonization and IBSI-compliant software; (4) transparency in reporting (eg, calibration, decision-curve analysis, open

code); and (5) radiomics, which incorporates clinical, genomic, and pathology data in clinically meaningful, explainable multimodal models, with an assessment of real-world clinical utility and cost-effectiveness.

7. CONCLUSION

Quantitative radiomics analysis provides quantifiable gains in diagnostic accuracy, facilitate disease severity assessment and enable a more personalised prediction of the clinical course, especially when incorporated with clinical data. The clinical utility of radiomics may not be achieved until the deficiencies associated with reproducibility, validation and reporting are remedied. With standardized pipelines, harmonisation and prospective multicenter evidence radiomics can evolve from an experimental research method into a robust tool for precision imaging.

REFERENCES

[1] Avanzo, M., Wei, L., Stancanello, J., Vallières, M., Rao, A., Morin, O., Mattonen, S. A., & El Naqa, I. (2020). Machine and deep learning methods for radiomics. Medical Physics, 47(5), e185–e194. https://doi.org/10.1002/mp.13678

[2] Bera, K., Braman, N., Gupta, A., Velcheti, V., & Madabhushi, A. (2022). Predicting cancer outcomes with radiomics and artificial intelligence in radiology. Nature Reviews Clinical Oncology, 19(2), 132–146. https://doi.org/10.1038/s41571-021-00560-7

[3] Collins, G. S., Moons, K. G. M., Dhiman, P., Riley, R. D., Beam, A. L., Van Calster, B., et al. (2024). TRIPOD+AI statement: Updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ, 385, e078378. https://doi.org/10.1136/bmj-2023-078378

[4] Cuocolo, R., Cipullo, M. B., Stanzione, A., Romeo, V., Green, R., Cantoni, V., Ponsiglione, A., Ugga, L., & Imbriaco, M. (2020). Machine learning for the identification of clinically significant prostate cancer on MRI: A meta-analysis. European Radiology, 30(12), 6877–6887. https://doi.org/10.1007/s00330-020-07027-w

[5] Dercle, L., Lu, L., Schwartz, L. H., Qian, M., Tejpar, S., Eggleton, P., Zhao, B., & Piessevaux, H. (2020). Radiomics response signature for identification of metastatic colorectal cancer sensitive to therapies targeting EGFR pathway. Journal of the National Cancer Institute, 112(9), 902–912. https://doi.org/10.1093/jnci/djaa017

[6] Fornacon-Wood, I., Faivre-Finn, C., O'Connor, J. P. B., & Price, G. J. (2020). Radiomics as a personalized medicine tool in lung cancer: Separating the hope from the hype. Lung Cancer, 146, 197–208. https://doi.org/10.1016/j.lungcan.2020.05.028

[7] Fournier, L., Costaridou, L., Bidaut, L., Michoux, N., Lecouvet, F. E., de Geus-Oei, L.-F., et al. (2021). Incorporating radiomics into clinical trials: Expert consensus endorsed by the European Society of Radiology on considerations for data-driven compared to biologically driven quantitative biomarkers. European Radiology, 31(8), 6001–6012. https://doi.org/10.1007/s00330-020-07598-8

[8] Granzier, R. W. Y., Verbakel, N. M. H., Ibrahim, A., van Timmeren, J. E., van Nijnatten, T. J. A., Leijenaar, R. T. H., et al. (2020). MRI-based radiomics in breast cancer: Feature robustness with respect to inter-observer segmentation variability. Scientific Reports, 10, 14163. https://doi.org/10.1038/s41598-020-70940-z

[9] Hatt, M., Krizsan, A. K., Rahmim, A., Bradshaw, T. J., Costa, P. F., Forgacs, A., et al. (2023). Joint EANM/SNMMI guideline on radiomics in nuclear medicine. European Journal of Nuclear Medicine and Molecular Imaging, 50(2), 352–375. https://doi.org/10.1007/s00259-022-06001-6

[10] Homayounieh, F., Ebrahimian, S., Babaei, R., Mobin, H. K., Zhang, E., Bizzo, B. C., et al. (2020). CT radiomics, radiologists, and clinical information in predicting outcome of patients with COVID-19 pneumonia. Radiology: Cardiothoracic Imaging, 2(4), e200322. https://doi.org/10.1148/ryct.2020200322

[11] Ibrahim, A., Primakov, S., Beuque, M., Woodruff, H. C., Halilaj, I., Wu, G., et al. (2021). Radiomics for precision medicine: Current challenges, future prospects, and the proposal of a new framework. Methods, 188, 20–29. https://doi.org/10.1016/j.ymeth.2020.05.022

[12] Kocak, B., Baessler, B., Bakas, S., Cuocolo, R., Fedorov, A., Maier-Hein, L., et al. (2023). CheckList for EvaluAtion of Radiomics research (CLEAR): A step-by-step reporting guideline for authors and reviewers endorsed by ESR and EuSoMII. Insights into Imaging, 14, 75. https://doi.org/10.1186/s13244-023-01415-8

[13] Kocak, B., Akinci D'Antonoli, T., Mercaldo, N., Alberich-Bayarri, A., Baessler, B., Ambrosini, I., et al. (2024). METhodological RadiomICs Score (METRICS): A quality scoring tool for radiomics research endorsed by EuSoMII. Insights into Imaging, 15, 8. https://doi.org/10.1186/s13244-023-01572-w

[14] Ligero, M., Jordi-Ollero, O., Bernatowicz, K., Garcia-Ruiz, A., Delgado-Muñoz, E., Leiva, D., et al. (2021). Minimizing acquisition-related radiomics variability by image resampling and batch effect correction to allow for large-scale data analysis. European Radiology, 31(3), 1460–1470. https://doi.org/10.1007/s00330-020-07174-0

[15] Mayerhoefer, M. E., Materka, A., Langs, G., Häggström, I., Szczypiński, P., Gibbs, P., & Cook, G. (2020). Introduction to radiomics. Journal of Nuclear Medicine, 61(4), 488–495. https://doi.org/10.2967/jnumed.118.222893

[16] Mokrane, F.-Z., Lu, L., Vavasseur, A., Otal, P., Peron, J.-M., Luk, L., et al. (2020). Radiomics machine-learning signature for diagnosis of hepatocellular carcinoma in cirrhotic patients with indeterminate liver nodules. European Radiology, 30(1), 558–570. https://doi.org/10.1007/s00330-019-06347-w

[17] Mukherjee, P., Zhou, M., Lee, E., Schicht, A., Balagurunathan, Y., Napel, S., Gillies, R., Wong, S., Thieme, A., Leung, A., & Gevaert, O. (2020). A shallow convolutional neural network predicts prognosis of lung cancer patients in multi-institutional CT-image data. Nature Machine Intelligence, 2, 274–282. https://doi.org/10.1038/s42256-020-0173-6

[18] Orlhac, F., Eertink, J. J., Cottereau, A.-S., Zijlstra, J. M., Thieblemont, C., Meignan, M., Boellaard, R., & Buvat, I. (2022). A guide to ComBat harmonization of imaging biomarkers in multicenter studies. Journal of Nuclear Medicine, 63(2), 172–179. https://doi.org/10.2967/jnumed.121.262464

[19] Park, J. E., Kim, D., Kim, H. S., Park, S. Y., Kim, J. Y., Cho, S. J., Shin, J. H., & Kim, J. H. (2020). Quality of science and reporting of radiomics in oncologic studies: Room for improvement according to radiomics quality score and TRIPOD statement. European Radiology, 30(1), 523–536. https://doi.org/10.1007/s00330-019-06360-z

[20] Raisi-Estabragh, Z., Izquierdo, C., Campello, V. M., Martin-Isla, C., Jaggi, A., Harvey, N. C., Lekadir, K., & Petersen, S. E. (2020). Cardiac magnetic resonance radiomics: Basic principles and clinical perspectives. European Heart Journal – Cardiovascular Imaging, 21(4), 349–356. https://doi.org/10.1093/ehjci/jeaa028

[21] Rogers, W., Thulasi Seetha, S., Refaee, T. A. G., Lieverse, R. I. Y., Granzier, R. W. Y., Ibrahim, A., et al. (2020). Radiomics: From qualitative to quantitative imaging. British Journal of Radiology, 93(1108), 20190948. https://doi.org/10.1259/bjr.20190948

[22] Scapicchio, C., Gabelloni, M., Barucci, A., Cioni, D., Saba, L., & Neri, E. (2021). A deep look into radiomics. La Radiologia Medica, 126(10), 1296–1311. https://doi.org/10.1007/s11547-021-01389-x

[23] Shur, J. D., Doran, S. J., Kumar, S., ap Dafydd, D., Downey, K., O'Connor, J. P. B., et al. (2021). Radiomics in oncology: A practical guide. RadioGraphics, 41(6), 1717–1732. https://doi.org/10.1148/rg.2021210037

[24] van Timmeren, J. E., Cester, D., Tanadini-Lang, S., Alkadhi, H., & Baessler, B. (2020). Radiomics in medical imaging—"how-to" guide and critical reflection. Insights into Imaging, 11, 91. https://doi.org/10.1186/s13244-020-00887-2

[25] Wang, H., Wang, L., Lee, E. H., Zheng, J., Zhang, W., Halabi, S., et al. (2021). Decoding COVID-19 pneumonia: Comparison of deep learning and radiomics CT image signatures. European Journal of Nuclear Medicine and Molecular Imaging, 48(5), 1478–1486. https://doi.org/10.1007/s00259-020-05075-4

[26] Zwanenburg, A., Vallières, M., Abdalah, M. A., Aerts, H. J. W. L., Andrearczyk, V., Apte, A., et al. (2020). The Image Biomarker Standardization Initiative: Standardized quantitative radiomics for high-throughput image-based phenotyping. Radiology, 295(2), 328–338. https://doi.org/10.1148/radiol.2020191145