



Artificial Intelligence in Anterior Cruciate Ligament Tear Diagnosis: A Bibliometric Analysis of the 50 Most Cited Studies

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Abstract

Introduction Since the 2000s, artificial intelligence (AI) publications in medicine have surged, particularly in orthopaedics and radiology. A key area is the diagnosis of anterior cruciate ligament (ACL) tears, where AI enhances detection and treatment strategies. This study aims to perform a bibliometric analysis of AI in ACL tear diagnosis, identifying pivotal studies to guide future research and clinical priorities.

Materials and Methods A bibliometric analysis was conducted using the Web of Science database. The top-50 articles were ranked by citation count and analyzed for basic characteristics and research focus. Trends in diagnostic advancements and AI model utilization were also assessed.

Results The most cited articles, published between 2017 and 2024, peaked in 2021 ($n = 13$). Citation counts ranged from 7 to 401 (median: 8.5 ± 7.0). China ($n = 14$) and the United States ($n = 13$) emerged as the leading contributors. The vast majority (90%) of models were based on convolutional neural networks (CNNs), with 80% undergoing internal validation. Only 5% of the included models utilized a radiomic framework.

Conclusion This bibliometric analysis examines the growing role of AI in ACL tear diagnosis, with a marked increase in research output from 2017 to 2024. Key barriers to the adoption of AI models include algorithmic bias, data privacy, explainability, cost-effectiveness, and interoperability. The underrepresentation of radiomic-based models, despite their diagnostic potential, highlights an avenue for future research. Advancing explainable AI, strengthening validation, and establishing standardized reporting guidelines will be essential to ensure clinical integration to improve patient outcomes.

Keywords

- ACL
- AI
- anterior cruciate ligament
- artificial intelligence

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Introduction

The Use of AI in Healthcare

Since the start of the 2000s, the number of publications relating to artificial intelligence (AI) in medicine has increased by a factor of 36, highlighting the growing focus on leveraging AI to transform healthcare.¹ Orthopaedics and radiology have been at the forefront of this transformation, pioneering the development and integration of clinically relevant AI tools that are reshaping patient care.^{2–4} A notable area of advancement within orthopaedics is the diagnosis of anterior cruciate ligament (ACL) tears, enabling earlier detection and facilitating more timely, effective treatment strategies using AI.^{4,5} As such, conducting an analysis of the most impactful studies utilizing AI for diagnosing ACL tears would provide valuable insights into the longitudinal advancements in AI applications, shedding light on how these technologies have evolved to improve diagnostic accuracy, efficiency, and clinical outcomes over time.

AI in Diagnostic Imaging and Beyond

The role of AI in medical diagnostics extends far beyond ACL tear detection, with significant advancements in various medical fields, particularly in radiology, pathology, and dermatology.^{6–9} AI-powered image analysis has revolutionized the early detection of diseases such as breast cancer, lung nodules, and neurological disorders, enhancing diagnostic accuracy and reducing human error. In musculoskeletal imaging, AI has been leveraged for automated fracture detection and osteoporosis screening, demonstrating its potential in orthopaedic diagnostics.^{10,11} Additionally, machine learning (ML) algorithms are increasingly being utilized for real-time clinical decision support, aiding in the identification of osteoarthritis, and meniscal damage, often concomitant with ACL tears.^{12–14} These developments reinforce the rationale for applying AI in ACL injury diagnosis, as similar deep learning models can be adapted to improve the precision, reproducibility, and efficiency of MRI-based ACL tear detection. Understanding AI's broader diagnostic applications highlights its transformative role in healthcare and provides a solid foundation for its implementation in orthopaedic injury assessment.

The Role of Bibliometrics

Bibliometrics, the quantitative analysis of academic literature, is particularly valuable in understanding the impact and trajectory of AI applications in diagnosing ACL tears.^{15,16} Such analyses identify seminal works, emerging trends, and knowledge gaps, highlighting interdisciplinary collaborations and technological progress.

Aims and Objectives

As such, this study aims to perform a bibliometric analysis in the context of the use of AI in the diagnosis of ACL tears, identifying pivotal studies and guiding researchers and clinicians toward the most impactful developments and future research priorities, and discussing clinical implications within healthcare. This is the first bibliometric analysis on the role of AI in diagnosing ACL injuries by analyzing the 50 most cited publications.

Materials and Methods

Database

The Web of Science database was searched to identify all articles related to the use of AI to diagnose ACL tears.

Selection Criteria

No restrictions were applied regarding publication date or article inclusion, and the search was conducted without exclusions beyond the scope of the topic.

Search Strings

The full search strategy is outlined in ► **Supplementary Table S1** (available in the online version only). No restrictions were imposed on the severity of the ACL tears discussed in each paper.

Screening

After the search, studies that have since been retracted were excluded. The screening process began with titles, followed by abstracts, and concluded with full-text reviews to determine relevance. Only studies mentioning the use of AI for diagnosing ACL injuries were included, either in the title or as a major outcome of the study. Articles were then ranked based on the total number of citations across all databases. Two independent reviewers (S.S.G. and A.P.) conducted separate searches, as per Akmal et al and Lim et al.^{17,18} Each reviewer compiled a list of the 50 most-cited articles, and any discrepancies between the lists were resolved through consensus.

The final set of 50 peer-reviewed publications underwent detailed analysis by S.S.G., both manually and using Web of Science analysis, with cross-referencing on Scopus and other major databases.¹⁹ For each publication, information was collected on its title, year of publication, total citations, citations per year, authorship, authors' affiliations, journal name, country of origin, article type, validation method, and type of AI model utilized.

Analysis

Tallied tables and graphs were created using Microsoft Excel (version 16.92, Microsoft, Washington, United States). Shapiro–Wilk test confirmed nonparametric distribution; hence, median ($\pm$ median absolute deviation) and 95% Bonnet price confidence intervals were calculated for the overall number of citations. The mean was calculated for the number of citations per year and rounded off to the nearest whole integer. VOS viewer was used to generate the network plots.

Ethical Approval

There was no ethical consideration required for this type of study or analysis.

Results

Overview

Between 2017 and 2024, a total of 1,222 citations were recorded across articles, with an average of 24.4 citations per publication (► **Tables 1–3**).

Table 1 Top-50 cited articles

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Bien et al (2018)	Deep-learning-assisted diagnosis for knee magnetic resonance imaging: development and retrospective validation of MRNet ²⁰	401 (57)	Article	External	CNN	AUC:0.937 Specificity: 0.968 Sensitivity: 0.759 Accuracy: 0.850 ^a
Awan et al (2021)	Efficient detection of knee anterior cruciate ligament from magnetic resonance imaging using deep learning approach ⁴⁹	100 (25)	Article	Internal	CNN	Precision: 0.917 Sensitivity: 0.917 F1: 0.917 Specificity: 0.947 Accuracy: 0.92 AUC: 0.980
Liu et al (2019)	Fully automated diagnosis of anterior cruciate ligament tears on knee MR images by using deep learning ⁵⁰	92 (15)	Article	Internal	CNN	Sensitivity: 0.96 Specificity: 0.96 AUC:0.98
Stajduhar et al (2017)	Semi-automated detection of anterior cruciate ligament injury from MRI ⁵¹	64 (8)	Article	Internal	ML	AUC (complete tear): 0.943 AUC (injury detection): 0.894
Germann et al (2020)	Deep convolutional neural network-based diagnosis of anterior cruciate ligament tears performance comparison of homogenous versus heterogeneous knee MRI cohorts with different pulse sequence protocols and 1.5-T and 3-T magnetic field strengths ⁵²	48 (10)	Article	Internal	DCNN	Sensitivity: 0.961 Specificity: 93.1 AUC: 0.935
Fritz et al (2023)	Radiomics and deep learning for disease detection in musculoskeletal radiology - an overview of novel MRI- and CT-based approaches ⁵³	47 (24)	Review	–	–	–
Kunze et al (2021)	Diagnostic performance of artificial intelligence for detection of anterior cruciate ligament and meniscus tears: a systematic review ⁴	35 (9)	Review	–	–	–
Awan et al (2021)	Improved deep convolutional Neural Network to classify osteoarthritis from anterior cruciate ligament tear using magnetic resonance imaging ⁵⁴	32 (8)	Article	Internal	CNN	Accuracy: 0.986 Precision: 0.98 Sensitivity: 0.98 Specificity: 0.985 F1: 0.98
Fritz et al (2021)	Artificial intelligence for MRI diagnosis of joints: a scoping review of the current state-of-the-art of deep learning-based approaches ⁵⁵	31 (8)	Review	–	–	–
Fayad et al (2021)	A deep learning system for synthetic knee magnetic resonance imaging is artificial intelligence-based fat-suppressed imaging feasible? ⁵⁶	30 (8)	Article	Internal	CNN	–
Siouras et al (2022)	Knee injury detection using deep learning on MRI studies: a systematic review ⁵⁷	29 (10)	Review	–	–	–

(Continued)

Table 1 (Continued)

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Kessler D et al (2020)	The optimisation of deep neural networks for segmenting multiple knee joint tissues from MRIs ⁵⁸	27 (5)	Article	No	GAN	–
Jeon Y et al (2021)	Interpretable and lightweight 3-D deep learning model for automated ACL diagnosis ⁵⁹	26 (7)	Article	External	CNN	Sensitivity (dataset 1): 0.981 Sensitivity (dataset 2): 0.920 Specificity (dataset 1): 0.924 Specificity (dataset 2): 0.975 AUC (dataset 1): 0.983 AUC (dataset 2): 0.983
Tran et al (2022)	Deep learning to detect anterior cruciate ligament tear on knee MRI: multi-continental external validation ⁶⁰	22 (7)	Article	External	CNN	Sensitivity (dataset 1): 0.850 Sensitivity (dataset 2): 0.681 Specificity (dataset 1): 0.894 Specificity (dataset 2): 0.934 AUC (dataset 1): 0.962 AUC (dataset 2): 0.922 Accuracy (dataset 1): 0.875 Accuracy (dataset 2): 0.870
Irmakci et al (2019)	Deep learning for musculoskeletal image analysis ⁶¹	18 (3)	Article	No	CNN	AUC: 0.9388 Sensitivity: 0.6852 Specificity: 0.9545 Accuracy: 0.833

Abbreviations: AUC, area under the receiver operating curve; CNN, convolutional neural networks; GAN, generative adversarial network; DCNN, deep convolutional neural network.

^aPart 1. Not specific to anterior cruciate ligament tears, but includes them in an overall tear detection metric. Citations per annum are rounded to their nearest integer.

Table 2 Top-50 cited articles

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Li et al (2021)	Deep learning-based magnetic resonance imaging image features for diagnosis of anterior cruciate ligament injury ⁶²	17 (4)	Article	Internal	CNN	Sensitivity: 0.9678 Specificity: 0.9062 Accuracy: 0.9217
Tsai et al (2020)	Knee injury detection using MRI with efficiently-layered network (ELNet) ⁶³	17 (3)	Article	External	CNN	Accuracy: 0.904 Sensitivity: 0.923 Specificity: 0.891 AUC: 0.960 MCC: 0.815
Key et al (2022)	Meniscal tear and ACL injury detection model based on AlexNet and Iterative ReliefF ⁶⁴	16 (5)	Article	Internal	CNN	Accuracy (sagittal): 0.9842 Accuracy (axial): 1 Accuracy (coronal): 1 Sensitivity (sagittal): 0.9583 Sensitivity (axial): 1 Sensitivity (coronal): 1 Specificity (sagittal): 0.9873 Specificity (axial): 1 Specificity (coronal): 1 Precision (sagittal): 0.9020 Precision (axial): 1 Precision (coronal): 1 F-measure (sagittal): 0.9293 F-measure (axial): 1 F-measure (coronal): 1

Table 2 (Continued)

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
						Geometric mean (sagittal): 0.9.27 Geometric mean (axial): 1 Geometric mean (coronal): 1
Garwood et al (2020)	The use of artificial intelligence in the evaluation of knee pathology ⁶⁵	16 (3)	Review	–	–	–
Minamoto et al (2022)	Automated detection of anterior cruciate ligament tears using a deep convolutional neural network ⁶⁶	14 (5)	Article	Internal	CNN	Sensitivity: 0.91 Specificity: 0.86 Accuracy: 0.885 PPV: 0.87 NPV: 0.91
Kara et al (2021)	Detection and classification of knee injuries from MR images using the MRNet dataset with progressively operating deep learning methods ⁶⁷	12 (3)	Article	Internal	CNN	AUC: 0.859
Sridhar et al (2022)	A torn ACL mapping in knee MRI images using Deep Convolution Neural Network with Inception-v3 ⁶⁸	11 (4)	Article	Internal	CNN	Accuracy: 0.9502 Precision: 0.9502 Recall: 0.9513 Specificity: 0.9634 F-measure: 0.9483
Sun et al (2023)	Anterior cruciate ligament tear detection based on deep belief networks and improved honey badger algorithm ⁶⁹	10 (5)	Article	Internal	CNN	Accuracy: 0.96 Sensitivity: 0.98 Specificity: 0.80
Richardson et al (2021)	MR protocol optimization with deep learning: a proof of concept ⁷⁰	10 (3)	Article	Internal	CNN	AUC (NFS): 0.9983 AUC (FS): 0.9988 Specificity (NFS): 0.993 Specificity (FS): 0.993 Sensitivity (NFS): 0.88 Sensitivity (FS): 0.98
Dunnhofer et al (2021)	Improving MRI-based knee disorder diagnosis with pyramidal feature details ⁷¹	9 (2)	Article	Internal	CNN	AUC: 0.972
Lao et al (2019)	Diagnostic accuracy of machine-learning-assisted detection for anterior cruciate ligament injury based on magnetic resonance imaging Protocol for a systematic review and meta-analysis ⁷²	8 (1)	Review	–	–	–
Wang et al (2024)	A deep learning model enhances clinicians' diagnostic accuracy to more than 96% for anterior cruciate ligament ruptures on magnetic resonance imaging ⁷³	7 (7)	Article	External	CNN	Accuracy: 0.897 Sensitivity: 0.853 Specificity: 0.928

(Continued)

Table 2 (Continued)

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Qu et al (2022)	A deep learning approach for anterior cruciate ligament rupture localization on knee MR images ⁷⁴	7 (2)	Article	Internal	CNN	Sensitivity (3D—femoral side): 0.86 Sensitivity (3D—middle): 0.71 Sensitivity (3D—tibial Side): 0.71 Specificity (3D—femoral side): 0.79 Specificity (3D—middle): 0.84 Specificity (3D—tibial side): 0.99 Precision (3D—femoral side): 0.80 Precision (3D—middle): 0.76 Precision (3D—tibial side): 0.83 F1-score (3D—femoral side): 0.83 F1-score (3D—middle): 0.74 F1-score (3D—tibial side): 0.77 Overall accuracy (3D—femoral side): 0.79 Sensitivity (2D—femoral side): 0.65 Sensitivity (2D—middle): 0.66 Sensitivity (2D—tibial side): 0.14 Specificity (2D—femoral side): 0.74 Specificity (2D—middle): 0.64 Specificity (2D—tibial side): 0.95 Precision (2D—femoral side): 0.72 Precision (2D—middle): 0.56 Precision (2D—tibial side): 0.20 F1-score (2D—femoral side): 0.68 F1-score (2D—middle): 0.61 F1-score (2D—tibial side): 0.17 Overall accuracy (2D—femoral side): 0.61
Atito et al (2022)	SB-SSL: slice-based self-supervised transformers for knee abnormality classification from MRI ⁷⁵	6 (2)	Article	Internal	CNN	Accuracy: 0.8917 AUC: 0.954
Zeng et al (2020)	Detecting the presence of anterior cruciate ligament deficiency based on a double pendulum model, intrinsic time-scale decomposition (ITD) and neural networks ⁷⁶	6 (1)	Article	Internal	CNN	Sensitivity: 0.9507 Sensitivity: 0.9408 Accuracy: 0.9483 PPV: 0.9461 NPV: 0.9505 MCC: 0.897

Abbreviations: AUC, area under the receiver operating curve; CNN, convolutional neural networks; FS, feature selection; MCC, Matthews correlation coefficient; NFS, negative matrix factorization; NPV, negative predictive value; PPV, positive predictive value.

Note: Part 2. Citations per annum are rounded to their nearest integer.

Table 3 Top-50 cited articles

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Zhang et al (2024)	A new optimization method for accurate anterior cruciate ligament tear diagnosis using convolutional neural network and modified golden search algorithm ⁷⁷	5 (2)	Article	Internal	CNN	Accuracy: 0.9960 Precision: 0.9873 Specificity: 0.9920 F1: 0.9435 Sensitivity: 0.9503 MCC: 0.9743

Table 3 (Continued)

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Dung et al (2023)	End-to-end deep learning model for segmentation and severity staging of anterior cruciate ligament injuries from MRI ⁴¹	5 (2)	Article	Internal	CNN	Accuracy (intact ACL): 0.90 Sensitivity (intact ACL): 0.91 Specificity (intact ACL): 0.89 Accuracy (partially torn ACL): 0.82 Sensitivity (partially torn ACL): 0.75 Specificity (partially torn ACL): 0.85 Accuracy (fully ruptured ACL): 0.92 Sensitivity (fully ruptured ACL): 0.80 Specificity (fully ruptured ACL): 0.95
Chen et al (2021)	A novel application of unsupervised machine learning and supervised machine learning-derived radiomics in anterior cruciate ligament rupture ⁷⁸	5 (1)	Article	Internal	ML	Sensitivity: 0.8 Specificity: 0.9 AUC: 0.92
Santomartino et al (2024)	Systematic review of artificial intelligence development and evaluation for MRI diagnosis of knee ligament or meniscus tears ⁷⁹	4 (2)	Review	–	–	–
Awan et al (2023)	MGACA-Net: a novel deep learning based multi-scale guided attention and context aggregation for localization of knee anterior cruciate ligament tears region in MRI images ⁸⁰	4 (2)	Article	Internal	CNN	Accuracy: 0.9895 IOU: 0.9955 Dice: 0.9977 Precision: 0.9993 Recall: 0.9999 F1: 0.9988
Dunnhofer et al (2022)	Deep convolutional feature details for better knee disorder diagnoses in magnetic resonance images ⁸¹	4 (1)	Article	Internal	CNN	AUC: 0.972 Sensitivity: 0.815 Specificity: 0.939
Razali et al (2019)	Anterior cruciate ligament (ACL) coronal view injury diagnosis system using Convolutional Neural Network ⁸²	4 (1)	Article	No	CNN	Precision: 0.958 Recall: 0.958
Liang et al (2023)	Effective automatic detection of anterior cruciate ligament injury using convolutional neural network with two attention mechanism modules ⁸³	3 (2)	Article	Internal	CNN	Accuracy: 0.8063 Precision: 0.7741 Sensitivity: 0.9268 Specificity: 0.6509 AUC: 0.8886 F1: 0.8436
He et al (2023)	Combination of the CNN with an amended version of a cooking training-	3 (2)	Article	Internal	CNN	Accuracy: 0.9802 Precision: 0.9715 Specificity: 0.9762

(Continued)

Table 3 (Continued)

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
	based optimizer for diagnosing anterior cruciate ligament tear ⁸⁴					F1: 0.9277 Sensitivity: 0.9345
Chen et al (2023)	A transfer learning approach for staging diagnosis of anterior cruciate ligament injury on a new modified MR dual precision positioning of thin-slice oblique sagittal FS-PDWI sequence ⁸⁵	3 (2)	Article	Internal	CNN	Precision (whole image—normal): 0.952 Recall (whole image—normal): 0.988 F1-score (whole image—normal): 0.969 Precision (whole image—Grade 1): 1.000 Recall (whole image—Grade 1): 1.000 F1-score (whole image—Grade 1): 1.000 Precision (whole image—Grade 2): 0.927 Recall (whole image—Grade 2): 0.950 F1-score (whole image—Grade 2): 0.938 Precision (whole image—Grade 3): 0.960 Recall (whole image—Grade 3): 0.900 F1-score (whole image—Grade 3): 0.929 Precision (ROI—normal): 0.940 Recall (ROI—normal): 0.988 F1-score (ROI—normal): 0.963 Precision (ROI—Grade 1): 0.988 Recall (ROI—Grade 1): 0.988 F1-score (ROI—Grade 1): 0.988 Precision (ROI—Grade 2): 0.925 Recall (ROI—Grade 2): 0.925 F1-score (ROI—Grade 2): 0.925 Precision (ROI—Grade 3): 0.961 Recall (ROI—Grade 3): 0.913 F1-score (ROI—Grade 3): 0.936
Wahid et al (2020)	Multi-layered basis pursuit algorithms for classification of MR images of knee ACL tear ⁸⁶	3 (1)	Article	Internal	Optimal Multilayered Convolutional Sparse Coding (ML-CSC)	Precision: 0.9242 Recall: 0.9268 Accuracy: 0.9220 F1: 0.9242
Voinea et al (2024)	Refined detection and classification of knee ligament injury based on ResNet Convolutional Neural Networks ⁸⁷	2 (2)	Article	Internal	CNN	Accuracy: 0.97147 F1: 0.97238 AUC: 0.99101
Li et al (2023)	Automated diagnosis of anterior cruciate ligament via a weighted multi-view network ⁸⁸	2 (1)	Article	Internal	CNN	AUC (MRI-ACL): 0.97 AUC (MRNet): 0.9268

Table 3 (Continued)

Author (year)	Title	Total citations (per annum)	Study type	Validation	AI type	Model performance
Shetty et al (2023)	A comprehensive review on the diagnosis of knee injury by deep learning-based magnetic resonance imaging ⁸⁹	2 (1)	Review	–	–	–
Herman et al (2024)	A systematic review on deep learning model in computer-aided diagnosis for anterior cruciate ligament injury ⁹⁰	1 (1)	Review	–	–	–
Chan et al (2024)	Improved anterior cruciate ligament tear diagnosis using gated recurrent unit networks and hybrid Tasmanian devil optimization ⁹¹	1 (1)	Article	Internal	CNN	Accuracy: 0.9789 Precision: 0.9817 Specificity: 0.9830 F1: 0.9867 Sensitivity: 0.9849 MCC: 0.8552
Lin et al (2023)	A channel correction and spatial attention framework for anterior cruciate ligament tear with ordinal loss ⁹²	1 (1)	Article	Internal	CNN	Accuracy: 0.833 Precision: 0.488 Recall: 0.512 Specificity: 0.852 F1: 0.498
Chen et al (2022)	Artificial intelligence-assisted diagnosis of anterior cruciate ligament tears from magnetic resonance images: algorithm development and validation study ⁹³	1 (0)	Article	External	CNN	Accuracy: 0.9959 Sensitivity: 0.9834 Specificity: 0.9969 Precision: 0.9595 F1: 0.9713
Haddadian et al (2022)	Transfer learning and data augmentation in the diagnosis of knee MRI ⁶⁷	1 (0)	Article	Internal	CNN	–
Sezen et al (2022)	Diagnosing knee injuries from MRI with transformer based deep learning ⁹⁴	1 (0)	Review	–	–	–

Abbreviations: ACL, anterior cruciate ligament; CNN, convolutional neural networks; ML, machine learning.

Note: Part 3. Citations per annum are rounded to their nearest integer.

The most cited article during this period, authored by Bien et al, titled “Deep-learning-assisted diagnosis for knee magnetic resonance imaging: development and retrospective validation of MRNet,” accumulated 401 citations, averaging 57 citations per year.²⁰ The greatest number of papers ($n = 13$) was published in 2021, slowly decreasing to four studies by 2024 (►Fig. 1).

AI Models

Of the 50 studies analyzed, 40 focused on proposing or evaluating a model, while the remaining 10 were review

articles. Among the studies involving models, most employed internal validation (31, 77.5%), followed by external validation (6, 15%), with a smaller proportion not specifying their validation method (3, 7.5%). The majority of the proposed models were based on convolutional neural networks (36, 90%), while the remaining used either unspecified ML approaches (3, 7.5%) or a generative adversarial network framework (1, 2.5%). This emphasizes the dominance of CNNs in model development and validation. Only two (5%) of the included models utilized a radiomic-based approach.

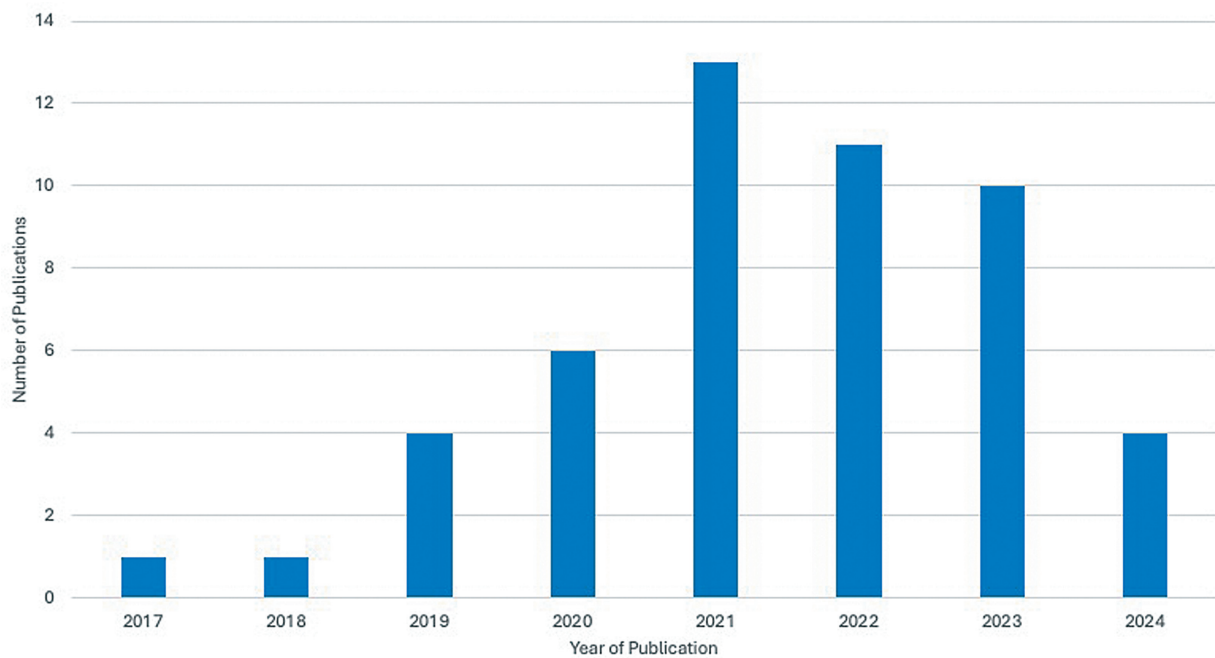


Fig. 1 Number of articles per year. Describes the number of articles in the top-50 published per year.

Journal

Biomedical Signal Processing and Control was the most common journal, with 4 studies in the top-50 cited. It was closely followed by *Investigative Radiology* ($n=3$), while six other journals each had 2 studies in the top 50 (►**Supplementary Table S2** [available in the online version only]).

Authors and Institutions

►**Supplementary Table S3** (available in the online version only) highlights the authors with more than three articles among the top 50 cited, drawn from a pool of 288 authors. Fritz was the most frequent contributor, representing 8% of the total records ($n=4$). Following closely are Awan, Fritz, Rahim, and Salim, each contributing 6% ($n=3$) of the records. ►**Supplementary Table S4** (available in the online version only) focused on the institutional affiliations of these research contributors, listing the seven institutions associated with three or more studies. The Universiti Teknologi Malaysia and the University of Zurich lead the group, each contributing 8% ($n=4$) of the total records. Institutions such as the Islamic University College, Johns Hopkins University, New York University, and the University of Geneva each account for 6% ($n=3$) of the records. Of the publications analyzed, only one was single-authored, while the remaining 49 were produced through multiauthor collaboration.

Country/Language

Of the top-50 cited articles, the majority originated from China with 28 studies, followed by the United States with 26 studies. Malaysia contributed 12 studies, while countries such as England, Switzerland, and Turkey each accounted for 10 studies. A full list of contributing countries can be found in

►**Supplementary Table S5** (available in the online version only). All studies were available in English.

Collaboration Networks

The author collaboration network (►**Fig. 2**) revealed a highly interconnected core of researchers, with individuals such as Li, Chen, and Wang occupying central positions, suggesting their prominence and frequent co-authorship within ACL-related research. This central cluster was surrounded by smaller, less connected groups, indicating localized or specialized research communities. The author keyword co-occurrence map (►**Fig. 3**) identified ACL as the dominant theme, closely linked to terms such as magnetic resonance imaging, ML, and AI, reflecting a strong interdisciplinary focus on combining clinical diagnostics with AI-driven technologies. These connections were further supported by a text-based co-occurrence analysis of titles and abstracts (►**Fig. 4**), which reinforced the centrality of ACL while also highlighting terms related to model evaluation (accuracy, sensitivity, specificity, and CNN), alongside clinical terms like diagnosis and MRI. Together, these findings demonstrate that research on the use of AI in the diagnosis of ACL tears has a growing emphasis on the validation and performance assessment of predictive models.

Discussion

Principal findings: This bibliometric analysis of the top-50 cited studies on AI in diagnosing ACL tears highlights the rapid expansion of research in this field, particularly between 2017 and 2024. The study identifies key contributors, institutions, and publication trends, with a peak in research output occurring in 2021. Notably, China and the United

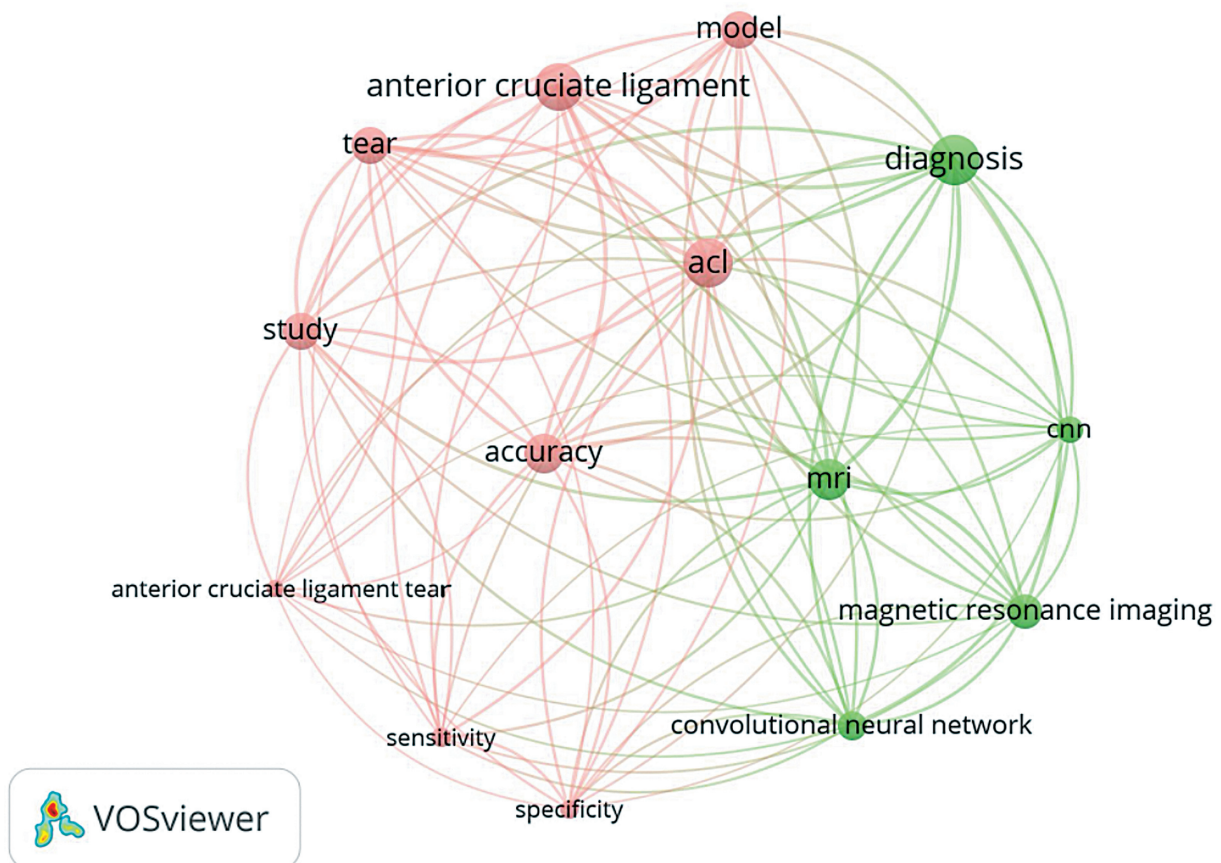


Fig. 4 Text-based co-occurrence network. Text-based co-occurrence network derived from titles and abstracts of publications.

States emerged as leading contributors, with a strong presence of CNNs in model development, reflecting the dominance of deep learning in this domain. Additionally, the analysis reveals that most studies underwent internal validation, reinforcing the need for more external validation efforts to ensure clinical applicability. Our thematic analysis found that ACL themed research using AI-driven diagnostic imaging seem to have a growing emphasis on model validation and performance assessment. These findings provide valuable insights into the evolution of AI in musculoskeletal radiology and orthopaedics, shaping future research directions and clinical implementation strategies.

Geographical and Institutional Contributions to AI Research

The distribution of AI research in ACL tear diagnosis demonstrates a strong geographical concentration, with China ($n=14$) and the United States ($n=13$) emerging as the leading contributors. This dominance reflects the substantial investments in AI-driven medical research by these nations, supported by well-established imaging databases, access to large patient cohorts, and government-backed AI initiatives.^{21–24} China's increasing research output aligns with its broader strategic focus on AI in healthcare, particularly through national funding schemes and state-sponsored AI development programs.^{25,26} Similarly, the United States's leadership in AI-driven radiology stems is bolstered by NIH

funding, industry partnerships, and leading academic institutions actively pioneering deep learning applications in medical imaging.^{27,28}

Interestingly, despite their contributions to AI in musculoskeletal imaging, European countries were less represented in the top-50 cited articles, with England, Switzerland, and Turkey each contributing 10 studies. This discrepancy may be attributed to differing regulatory frameworks, data-sharing restrictions under GDPR, and varying levels of AI adoption within clinical practice.^{29,30} In contrast, the United States benefits from more permissive AI implementation policies, allowing for faster model deployment and clinical integration.²⁸ These regulatory and institutional differences highlight the need for greater cross-border collaboration, with evidence showing this yields the best outcomes, particularly in developing standardized reporting frameworks and ensuring AI model interoperability across healthcare systems.²⁴

Another notable trend was the concentration of research within specific academic institutions, with the Universiti Teknologi Malaysia and the University of Zurich each contributing four studies. This institutional clustering suggests that a few key centers drive much of the AI research in ACL tear diagnosis, leveraging their expertise in deep learning and radiology. However, the limited diversity of contributing institutions raises concerns about research generalizability, as findings may not fully capture global variations in imaging

protocols, patient demographics, and clinical workflows. Encouraging broader institutional participation through open-access datasets, collaborative consortia, and multinational AI research initiatives would help democratize AI advancements and enhance their clinical applicability.

The Challenges of Integrating AI into Healthcare Systems

The integration of AI models into any healthcare systems requires careful consideration of ethical and regulatory factors to ensure safe and effective clinical deployment.³¹ Ethically, AI must align with principles of autonomy, beneficence, non-maleficence, and justice, addressing concerns such as algorithmic bias, data privacy, informed consent, and the explainability of outputs.³² AI models trained on unrepresentative datasets risk exacerbating healthcare disparities, while their “black-box” nature raises accountability challenges, necessitating transparency to maintain clinician and patient trust.^{33–35}

For instance in the United Kingdom, regulatory compliance is governed by frameworks such as the Medicines and Healthcare products Regulatory Agency (MHRA), which classifies AI-driven diagnostics and decision-support tools as medical devices, subjecting them to stringent validation under the United Kingdom Medical Device Regulations (MDR), a process that significantly prolongs adoption timelines and limits clinical uptake.³⁶ Additionally, the National Institute for Health and Care Excellence (NICE) sets evidence standards for assessing clinical effectiveness and economic viability before NHS (National Health Service) implementation in the United Kingdom. However, the paucity of studies on the cost-effectiveness of AI in ACL tear diagnosis further restricts its adoption. Moreover, seamless integration with NHS Electronic Health Records (EHRs) and digital infrastructure is essential but presents further challenges, as AI models are required to be specifically tailored to NHS systems, reducing feasibility and requiring significant development efforts that have not been widely explored, especially since the majority of models identified in this study were developed in China and the United States, each of which has different regulatory frameworks.³⁷

Benefits of AI and Radiomic Modeling

Given the influx of developments in AI within orthopaedics and radiology, our finding that the number of articles in top-50 cited articles is increasing with time aligns with this narrative, with citations likely limited by the publication dates.³⁸ Radiomic-based models have shown promise, often outperforming traditional approaches, yet their limited presence in highly cited studies raises questions about their broader clinical adoption.³⁹ Radiomics is the extraction of qualitative metrics, often beyond the scope of the human eye, enabling enhanced ACL tear detection by identifying subtle scan variations and defining complex regions of interest for improved tear delineation.⁴⁰ However, models such as the one proposed by Dung et al which integrate radiomic features demonstrated high accuracy in detecting and classifying ACL tears, highlighting their potential in diagnostic

applications.⁴¹ By improving diagnostic precision and enabling more automated ML models, radiomics supports early and reliable diagnoses, reduces misdiagnosis, and facilitates personalized treatment strategies, and can be a useful tool for radiologists to use to screen initial scans, or as a diagnostic adjunct. This would ensure that arthroscopic explorations or ACL reconstruction are not performed unnecessarily, preventing the misuse of resources in an already stretched NHS. Furthermore, its role in refining model development contributes to the creation of more robust and generalizable AI-driven diagnostic tools, ultimately enhancing patient outcomes.

Moreover, the prevalence of internal validation (80%) rather than external validation (15%) highlights a critical gap in ensuring the clinical generalizability of AI models. Internal validation, while useful for optimizing model performance on a specific dataset, does not adequately assess real-world applicability across diverse patient populations and imaging protocols.^{42–44} The limited adoption of external validation suggests a reluctance to test AI models beyond the originating institution, potentially leading to overfitting and reduced clinical reliability. To bridge this gap, future studies should prioritize multi-institutional collaborations, standardize validation frameworks, and ensure rigorous testing across various MRI scanners, anatomical variations, and demographic groups to enhance model robustness.

Future Studies

Future research should prioritize the integration of radiomic models with a strong emphasis on explainable AI to facilitate the seamless incorporation of AI into clinical workflows, in line with European Union AI guidelines.⁴⁵ Comparative analyses of AI models against clinicians, as well as in collaboration with them, are essential, necessitating large-scale external validation to ensure robustness and generalizability. Additionally, efforts should be directed toward the development of more comprehensive and diverse datasets that include scans from heterogeneous populations across different geographical regions, thereby enhancing the representativeness and applicability of AI models. Further investigations should also consider multiple imaging planes, variations in scanner intensity, and the explicit declaration of ground truth definitions in each study to enhance methodological transparency and reproducibility. Moreover, the establishment of overarching and standardized reporting guidelines for AI-based models is crucial to maximizing their clinical and scientific impact while ensuring reproducibility and comparability across studies.⁴⁶

Limitations

The Web of Science was the sole database used due to its accurate and readily available citation data, offering greater utility than alternatives such as Medline or Embase, but likely overlooking several studies.⁴⁷ To mitigate this, references were cross-checked across these databases using the snow-balling technique. The search included all AI models for

ACL tear diagnosis but excluded segmentation tools and non-peer-reviewed studies. Given the limited literature in this field, the findings highlight the need for further research to develop more accurate models with greater clinical impact. To quantitatively assess the impact of articles, we used citation counts. Despite inherent bias due to the Matthew effect, where highly cited articles continue to gain visibility, citation counts do reflect influence on the current landscape of research.⁴⁸ Although the careful selection of keywords and MeSH terms was aided by institutional librarians, some studies may have been overlooked due to variations in terminology or incomplete indexing. Broad search terms were employed to enhance reproducibility and capture the most relevant literature. Lastly, while citation counts serve as a proxy for influence and clinical applicability, they do not inherently reflect research quality, impact, or significance.

Conclusion

This bibliometric analysis underscores the growing role of AI in ACL tear diagnosis, with a significant increase in research output from 2017 to 2024. The dominance of CNNs reflects the reliance on deep learning, while the prevalence of internal validation highlights the need for more external validation to ensure clinical applicability. The leading contributions from China and the United States suggest regional disparities in regulatory frameworks, posing challenges for NHS integration. Key barriers to adoption include algorithmic bias, data privacy concerns, and the lack of explainability in AI outputs, alongside limited cost-effectiveness analyses and interoperability issues with NHS electronic health records. The underrepresentation of radiomic-based models, despite their diagnostic potential, signals an important avenue for future research. Advancing explainable AI, strengthening external validation, enhancing dataset diversity, and establishing standardized reporting guidelines are critical for improving reproducibility. Comparative studies assessing AI against clinicians and within AI-assisted workflows will be essential in evaluating clinical utility. Addressing these challenges is vital to translating AI advancements into meaningful improvements in ACL tear diagnosis and patient outcomes.

Data Availability Statement

All relevant data supporting the findings of this study can be accessed within the Supplementary Digital Content attached to the article.

Conflict of Interest

None declared.

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