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Artificial Intelligence for Fracture Risk Prediction: A Bibliometric Analysis of Research Hotspots and Evolutionary Trends

Bo Wang[a,b*], Yin Lian[a,b], Lina Gao[a,b]

[a]*Shenzhen Pingle Orthopedics Hospital (Shenzhen Pingshan Traditional Chinese Medicine Hospital), Shenzhen, Guangdong 518000, China*

[b]*Pingshan Hospital Affiliated to Guangzhou University of Chinese Medicine, Shenzhen, Guangdong 518000, China*

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ABSTRACT

Artificial intelligence (AI) has emerged as a promising approach for improving fracture risk prediction. This study aimed to provide a comprehensive bibliometric overview of research on AI in fracture risk prediction by mapping its temporal evolution, collaborative structure, thematic framework, and disciplinary distribution. Publications were retrieved from the Web of Science Core Collection using a predefined search strategy covering January 2001 to December 2025, including only English-language articles and reviews. After screening and data cleaning, a total of 943 publications were analyzed. Bibliometric analyses were conducted using VOSviewer (v1.6.20) and the Bibliometrix R package (v4.5.1), examining annual publication trends, co-authorship networks at the author, institutional, and country levels, keyword co-occurrence clusters, and subject category distributions. The results showed that research output exhibited three developmental phases, with a marked acceleration after 2020. Collaboration networks demonstrated a clustered and moderately centralized structure, with core institutions and countries—particularly the United States and major European partners—occupying central positions. Keyword co-occurrence analysis identified four principal thematic clusters: AI-based predictive modeling, imaging-derived radiomics and opportunistic screening, FRAX-centered clinical risk assessment, and comorbidity- and pharmacotherapy-related applications. Subject category analysis further revealed progressive interdisciplinary integration, with increasing contributions from radiology and computer science alongside traditional clinical specialties. Overall, AI-based fracture risk prediction research has evolved from clinically grounded risk stratification toward computationally augmented, imaging-integrated, and translationally oriented predictive frameworks. The field demonstrates rapid growth, expanding international collaboration, and increasing interdisciplinary convergence, suggesting continued advancement toward real-world clinical implementation.

1.Introduction

Fractures represent a major global public health burden, contributing substantially to morbidity, mortality, and healthcare expenditure[1]. Hip and vertebral fractures, in particular, are associated with long-term functional impairment and increased risk of subsequent fractures[2]. Early identification of individuals at high risk of fracture is therefore essential for implementing preventive interventions and optimizing resource allocation. Traditional fracture risk assessment tools, such as bone mineral density (BMD) measurement and clinical risk factor - based models, have improved risk stratification; however, their predictive performance remains limited, especially in diverse clinical populations[3].

In recent years, artificial intelligence (AI) has emerged as a transformative approach in medical research and clinical practice. Machine learning and deep learning techniques enable the integration of large-scale clinical data, imaging features, and complex nonlinear relationships to enhance predictive accuracy[4]. In the context of fracture risk prediction, AI-based models have been applied to dual-energy X-ray absorptiometry (DXA), computed tomography (CT), radiomics features, electronic health records, and multimodal datasets[5,6]. These approaches have demonstrated promising improvements in discrimination performance and individualized risk estimation compared with traditional statistical models.

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* Corresponding author.
E-mail address: wangbo_0902@163.com.

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The rapid expansion of AI-driven fracture risk research has led to a growing body of literature spanning multiple disciplines, including endocrinology, orthopedics, radiology, and computer science[7,8]. Collaborative networks among authors, institutions, and countries have also evolved alongside methodological advancements. However, despite this increasing research activity, a comprehensive overview of the knowledge structure, collaboration patterns, thematic evolution, and disciplinary distribution within this field remains limited. Existing reviews have primarily focused on methodological comparisons or clinical performance of predictive models, rather than the broader scientific landscape and developmental trajectory of the domain.

Bibliometric analysis provides a systematic approach to mapping scientific output, identifying research hotspots, and evaluating collaboration networks. By integrating publication trends, co-authorship networks, keyword co-occurrence structures, and subject category distributions, bibliometric methods enable quantitative assessment of both structural and evolutionary characteristics of a research field[9]. Such analyses are particularly valuable in rapidly developing interdisciplinary domains, where thematic shifts and technological transitions may occur over relatively short periods.

Therefore, the present study aims to conduct a comprehensive bibliometric analysis of research on artificial intelligence－based fracture risk prediction using data retrieved from the Web of Science Core Collection. Specifically, we examine annual publication trends, collaboration networks at the author, institutional, and country levels, keyword co-occurrence patterns and thematic clusters, as well as disciplinary distribution and evolution. By providing an integrated overview of research hotspots and development trends, this study seeks to clarify the intellectual structure and global collaboration landscape of AI applications in fracture risk prediction.

2.Materials and methods

2.1.Data source and search strategy

The data for this study were retrieved from the Web of Science Core Collection (WoSCC). An advanced search strategy was conducted in WoS to identify publications related to artificial intelligence－based fracture risk prediction. The search query was defined as follows:

TS = ((osteoporosis OR "bone fracture*" OR "fragility fracture*" OR "hip fracture*")

AND ("fracture risk" OR prediction OR prognos* OR "risk model*" OR "risk assessment") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR algorithm* OR "neural network*" OR "random forest" OR "support vector machine"))

The search was limited to document types of Article and Review, with language restricted to English. The publication period was defined from January 1, 2001, to December 31, 2025. All retrieved records were exported in plain text format, including full records and cited references. The exported information comprised titles, authors, affiliations, abstracts, keywords, publication years, and reference lists.

A total of 1,514 publications were initially identified. Bibliometric software was used to perform data cleaning and deduplication. Non-research publications, including meeting abstracts, editorials, book reviews, and other non-article document types, were excluded. Two trained researchers independently screened the titles, keywords, and abstracts (and full texts when necessary) to remove publications unrelated to the research topic. Studies that did not focus on fracture risk prediction or assessment, or that primarily addressed unrelated clinical conditions, were excluded. Publications marked as retracted were also removed. After screening, 943 publications were included in the final bibliometric analysis.

2.2.Bibliometric and visualization analysis

Bibliometric analyses and visualization were conducted using VOSviewer (version 1.6.20) and the Bibliometrix R package (version 4.5.1).

The following analyses were performed:

(1) Annual publication trend analysis to evaluate the temporal growth pattern of research output. (2) Co-authorship analysis at the author, institutional, and country levels to examine collaboration networks and structural characteristics. (3) Keyword co-occurrence analysis to identify major research themes and conceptual clusters within the field. (4) Cluster-based content analysis to interpret thematic groupings derived from keyword networks. (5) Subject category analysis based on Web of Science categories to assess disciplinary distribution and evolution.

All network visualizations were generated using VOSviewer, while statistical summaries and heatmaps were produced using the Bibliometrix package in R.

3.Results

This section began with co-authorship analysis to explore the time, authors, countries and other relevant features of the research on AI in fracture risk prediction. Then we clustered the keywords through co-occurrence, and analyzed and extracted the key framework of the research according to the clustering characteristics and literature research.

3.1.Main distribution characteristics of the research

3.1.1.Research time distribution characteristics

The annual distribution of publications reveals a clear evolutionary trajectory in research on artificial intelligence for fracture risk prediction (Fig 1). From 2001 to approximately 2014, the number of publications remained relatively low and increased at a modest pace, reflecting the early exploratory phase of applying computational approaches in osteoporosis and fracture research. Between 2015 and 2019, a gradual upward trend became evident, coinciding with the broader adoption of machine learning methods in medical research.

A pronounced acceleration in publication output was observed after 2020, indicating a rapid expansion of interest in AI-driven predictive modeling. This surge likely corresponds to advancements in deep learning algorithms, the increased availability of large-scale clinical and imaging datasets, and the growing emphasis on precision medicine. The cumulative growth curve demonstrates a steadily increasing research momentum, suggesting that the field has entered a stage of accelerated development. Overall, the temporal distribution indicates a transition from foundational methodological exploration to a period characterized by rapid expansion and technological maturation.

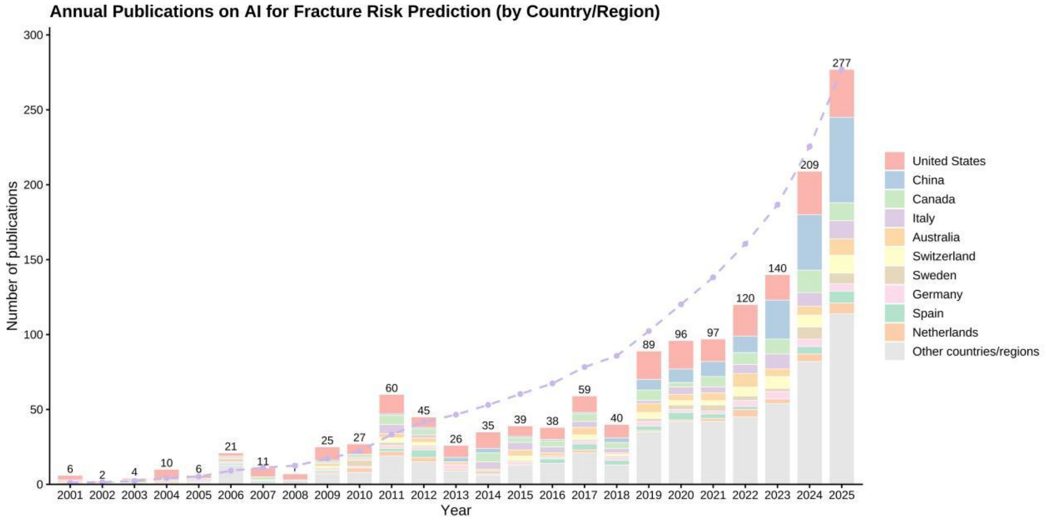

Fig 1. Temporal distribution and cumulative growth of publications(2001–2025)

The stacked bar chart illustrates the annual number of publications on artificial intelligence for fracture risk prediction from 2001 to 2025, categorized by country/region. The top 10 countries/regions in terms of total publication output are displayed individually, while the remaining countries/regions are grouped under "Other countries/regions." The dashed line represents the cumulative percentage of total publications over time. The numerical labels above each bar indicate the total number of publications in the corresponding year.

3.1.2.Distribution characteristics of authors

The co-authorship network consists of multiple collaborative clusters, indicating the presence of distinct research communities within the field (Fig 2). The largest connected component encompasses the majority of active contributors, while several smaller clusters and isolated nodes are also observed. Node size variation reflects heterogeneous publication productivity among authors, with a limited number of high-output authors forming the structural core of the network.

Centrality patterns show that certain authors occupy key bridging positions within clusters, characterized by higher total link strength and greater connectivity. The network topology demonstrates a modular structure, with dense intra-cluster links and comparatively fewer inter-cluster connections. This distribution suggests that collaborations are concentrated within established research teams.

The overlay visualization further indicates temporal heterogeneity across clusters. Earlier contributors are predominantly located within foundational clusters, whereas more recent authors appear in emerging sub-networks, reflecting gradual expansion of collaborative participation over time.

Overall, the co-authorship network reveals a clustered and moderately centralized structure, characterized by uneven productivity distribution and community-based collaboration patterns.

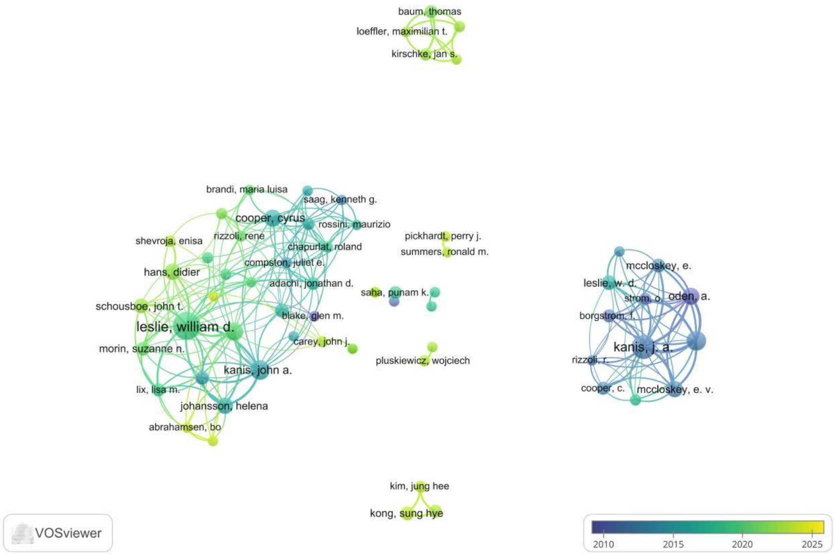

Fig 2. Co-authorship network of authors

Nodes represent authors, and node size corresponds to the number of publications. Links indicate co-authorship relationships, with thicker lines representing stronger collaboration intensity. Different clusters are distinguished by color, reflecting collaborative communities within the field. The color gradient of nodes represents the average publication year, with yellow indicating more recent activity and blue indicating earlier contributions.

3.1.3.Distribution characteristics of organizations

The co-organization collaboration network shows a predominantly connected structure with a clearly identifiable core component and several peripheral sub-networks (Fig 3). Node size indicates substantial heterogeneity in institutional productivity, with a small set of high-output organizations occupying central positions. Multiple hub institutions exhibit high connectivity and total link strength, forming dense collaboration ties with surrounding partners.

The network presents a core–periphery configuration: the core contains institutions with frequent inter-institutional collaborations and short path distances, whereas peripheral institutions are connected through fewer links or appear as small clusters and dyadic partnerships. Link density is higher within the main component than across peripheral groups, and the distribution of links suggests collaboration concentration around a limited number of core organizations.

The overlay visualization indicates temporal variation in institutional participation. Earlier-active organizations are mainly located within the core structure, while more recent contributions are distributed across both the core and newly emerging peripheral clusters. Overall, the organizational collaboration network is characterized by clustered communities, uneven institutional productivity, and hub-dominated connectivity patterns.

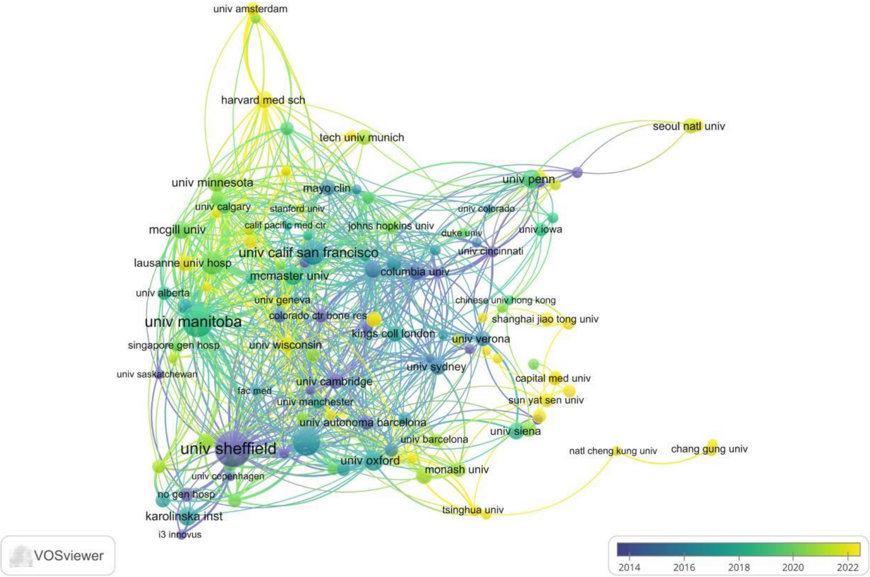

Fig 3. Co-organization collaboration network

Nodes represent institutions, and node size corresponds to publication output. Links indicate inter-institutional collaboration, with thicker lines reflecting stronger collaboration intensity. The network structure illustrates the collaborative patterns and organizational connectivity within the field.

3.1.4.Study the distribution characteristics of countries and regions

The international co-authorship network demonstrates a highly interconnected global collaboration structure (Fig 4). A dominant core component is observed, comprising major research-producing countries with extensive cross-national linkages. The United States, England, China, Canada, and Switzerland occupy central positions within the network, as indicated by larger node sizes and higher total link strength values.

The collaboration pattern exhibits a centralized topology, with the United States functioning as a primary hub connected to multiple countries across Europe, Asia, and Oceania. European countries form a densely connected sub-network characterized by strong intra-regional collaboration. Asian countries, including China and South Korea, show increasing integration into the global collaboration network, with multiple linkages to North American and European partners.

Peripheral nodes represent countries with lower publication output or limited collaboration intensity, often forming smaller bilateral partnerships. The overlay visualization indicates temporal heterogeneity, with earlier contributions concentrated among traditional research-leading countries, while more recent activity is evident in emerging research regions.

Overall, the country-level collaboration network is characterized by a central core of high-output countries, dense intercontinental linkages, and expanding participation from emerging regions.

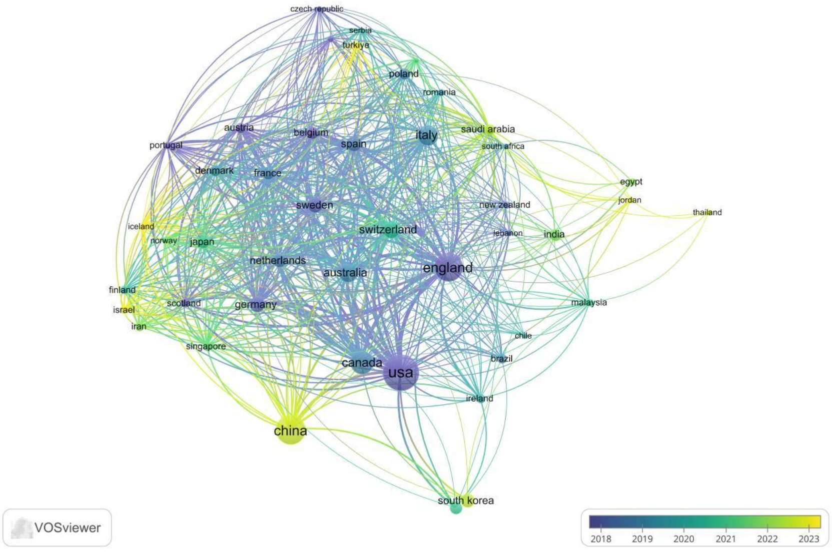

Fig 4. International collaboration network of countries/regions

Nodes represent countries/regions, and node size corresponds to publication output. Links indicate international co-authorship collaborations, with thicker lines representing stronger collaboration intensity. The network structure visualizes global collaboration patterns and connectivity among countries/regions in the field.

3.2.Keyword co-occurrence analysis and cluster-based content analysis

3.2.1.Keyword co-occurrence analysis

The present study analyzed a total of 1,792 author keywords extracted from the included publications. To enhance clustering clarity and highlight the dominant thematic structures within the field, only keywords with a frequency of occurrence not less than five times were retained for network construction. This threshold resulted in the inclusion of 80 keywords, which formed a co-occurrence network comprising 4 clusters, 750 links, and a total link strength of 3,005 (Fig 5).

The frequency distribution further indicates a stratified thematic structure. Among the 1,792 keywords, 80 appeared at least five times, 42 appeared more than ten times, and only 18 appeared more than twenty times. This distribution suggests that, while a substantial number of concepts contribute to the research landscape of artificial intelligence–based fracture risk prediction, only a relatively limited set of core terms exhibits high recurrence and strong interconnectivity. In other words, the field demonstrates both thematic breadth and emerging structural consolidation.

The most frequently occurring keywords were: fracture risk, machine learning, osteoporosis, artificial intelligence, bone mineral density, deep learning, radiomics, FRAX, hip fracture, and prediction model (full frequency list shown in Fig 5). These high-frequency terms occupy central positions within the network, characterized by larger node sizes and higher total link strength values, indicating their foundational role in shaping the intellectual architecture of the domain.

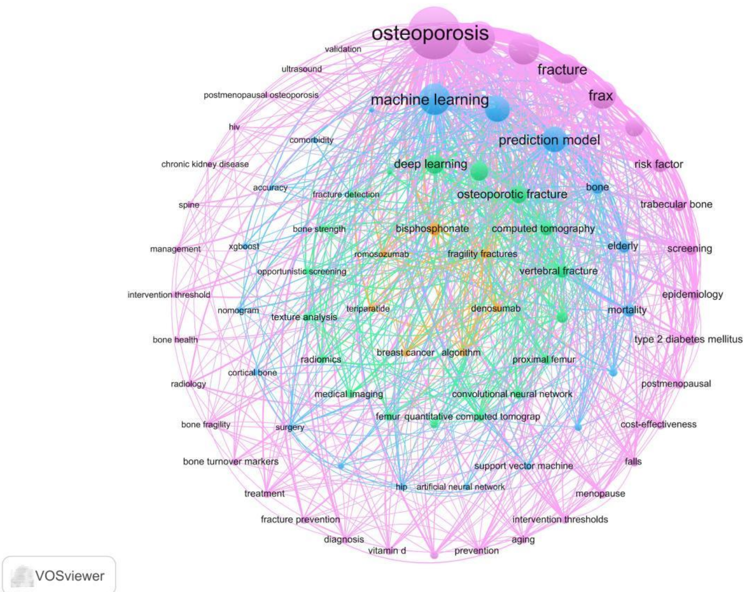

Fig 5. The network visualization of co-occurrence-author keywords

The network was generated using VOSviewer based on author keywords with a minimum occurrence threshold of 5. Each node represents a keyword, and node size is proportional to its frequency. Links indicate co-occurrence relationships, and link thickness reflects the strength of association. Colors represent different clusters identified through the modularity-based clustering algorithm. The relative positions of nodes are determined by association strength, with closer nodes indicating stronger co-occurrence relationships.

3.2.2.Keyword cluster-based content analysis

The network comprised 4 clusters, represent the principal thematic structures within the field(Fig 5 and Table 1).

(1)Cluster 1: AI-Based Predictive Modeling for Fracture Risk

Cluster 1 represents the methodological core of the field, focusing on artificial intelligence–driven fracture risk prediction models. This cluster includes machine learning algorithms such as random forest, support vector machine, deep learning, artificial neural networks, and logistic regression, alongside terms related to prediction models and validation. The co-occurrence pattern indicates that improving predictive performance, optimizing feature selection, and comparing algorithmic efficiency constitute central research themes. The prominence of these keywords suggests that the field is progressively shifting from traditional statistical models toward data-driven, AI-enhanced predictive frameworks.

(2)Cluster 2: Imaging-Derived Radiomics and Opportunistic Screening

Cluster 2 highlights imaging-based approaches that integrate radiomics and opportunistic screening strategies into fracture risk prediction. Keywords such as computed tomography, quantitative imaging, radiomics, and medical imaging reflect the increasing reliance on high-dimensional imaging features extracted from CT or DXA scans. This cluster illustrates how AI techniques are being applied to imaging data to enhance risk stratification beyond conventional bone mineral density measurements. The structure of this cluster suggests a technological pathway in which imaging biomarkers and automated feature extraction serve as critical components of next-generation fracture prediction systems.

(3) Cluster 3: Clinical Risk Assessment and FRAX-Centered Stratification

Cluster 3 encompasses traditional clinical risk assessment frameworks, including FRAX, bone mineral density, clinical risk factors, and intervention thresholds. The presence of trabecular bone score and osteoporosis-related terms indicates that this cluster represents the foundational paradigm of fracture risk stratification. Rather than being purely algorithm-driven, this cluster reflects the established clinical context upon which AI models are increasingly built and validated. The network structure suggests that contemporary AI-based prediction research is frequently grounded in, or compared against, FRAX-based assessment systems to demonstrate incremental predictive value.

(4) Cluster 4: Comorbidity, Pharmacotherapy, and Population Context

Cluster 4 relates to comorbid conditions, pharmacological interventions, and demographic characteristics associated with fracture risk. Keywords such as diabetes, chronic kidney disease, rheumatoid arthritis, bisphosphonates, denosumab, and elderly populations indicate that this cluster reflects broader clinical environments in which fracture risk prediction models are applied. The co-occurrence relationships suggest that AI-based tools are increasingly evaluated within complex patient populations characterized by multimorbidity and treatment exposure. This cluster emphasizes the translational dimension of fracture risk prediction, highlighting the integration of predictive modeling into real-world clinical management.

Table 1. Keywords content analysis based on clustering

Cluster	Topics	Keywords
1	AI-Based Predictive Modeling for Fracture Risk	accuracy, artificial neural network, bone, comorbidity, cortical bone, elderly, feature selection, hip, hip fracture, machine learning, magnetic resonance imaging, mortality, nomogram, prediction model, random forest, sarcopenia, support vector machine, surgery, xgboost
2	Imaging-Derived Radiomics and Opportunistic Screening	artificial intelligence, bone strength, classification, computed tomography, convolutional neural network, deep learning, femur, finite element analysis, fracture detection, medical imaging, opportunistic screening, osteoporotic fracture, primary care, proximal femur, quantitative computed tomography, radiomics, texture analysis, vertebral fracture
3	Clinical Risk Assessment and FRAX-Centered Stratification	aging, bone fragility, bone health, bone mineral density, bone turnover markers, chronic kidney disease, cost-effectiveness, diagnosis, dual-energy x-ray absorptiometry, epidemiology, falls, fracture, fracture prevention, fracture risk, frax, hiv, intervention threshold, intervention thresholds, management, menopause, osteoporosis, postmenopausal, postmenopausal osteoporosis, prevention, radiology, rheumatoid arthritis, risk factor, screening, spine, trabecular bone, treatment, type 2 diabetes mellitus, ultrasound, validation, vitamin d, women
4	Comorbidity, Pharmacotherapy, and Population Context	algorithm, bisphosphonate, breast cancer, denosumab, fragility fractures, romosozumab, teriparatide

3.3.Subject category distribution and disciplinary structure

The analysis of Web of Science subject categories identified a multidisciplinary distribution pattern within the field. The top 15 subject categories accounted for the majority of publications and were included in the visualization (Fig 6). The dominant categories include Endocrinology & Metabolism, Orthopedics, Radiology, Nuclear Medicine & Medical Imaging, and Computer Science, Artificial

Intelligence, reflecting the combined clinical and computational characteristics of the research domain.

Temporal distribution demonstrates that early publications were primarily concentrated in clinical specialties, particularly endocrinology and orthopedics. Over time, radiology and imaging-related categories showed increasing representation. In recent years, computer science–related categories exhibited a marked rise in annual output, indicating the growing integration of artificial intelligence methodologies into fracture risk research.

Overall, the subject category distribution highlights the coexistence of clinical medicine, medical imaging, and computational sciences within the field, forming a cross-disciplinary research structure.

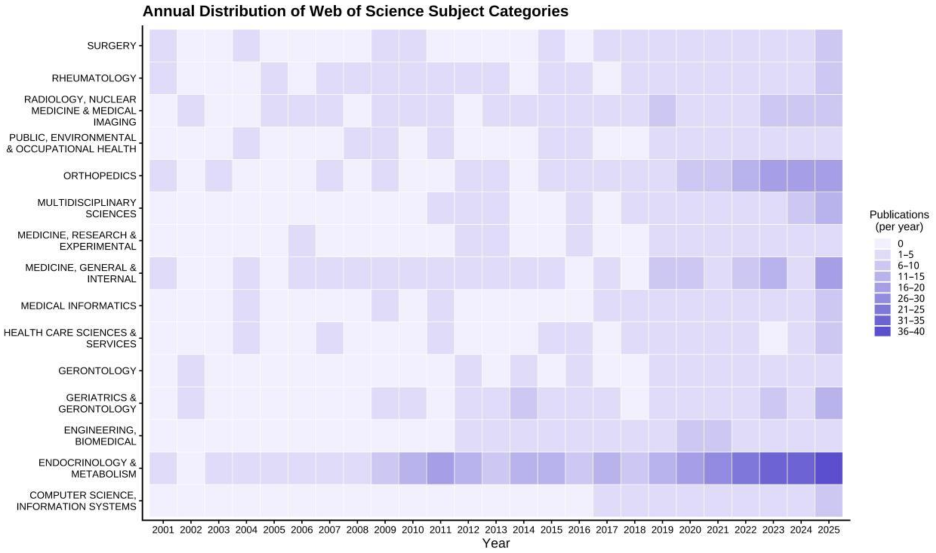

Fig 6. Annual distribution of Web of Science subject categories

Heatmap showing the annual number of publications across the top Web of Science subject categories from 2001 to 2025. Only the 15 subject categories with the highest cumulative publication output are displayed. Color intensity represents the number of publications per year, grouped in intervals of five publications. Subject categories are ordered by total publication output in descending order.

4.Methodology－the “prediction-interpretation-intervention”

This bibliometric study provides a comprehensive overview of the global research landscape of artificial intelligence (AI) in fracture risk prediction from 2001 to 2025. By integrating temporal trends, collaboration networks, keyword co-occurrence structures, and disciplinary distribution, the findings reveal a rapidly expanding and increasingly interdisciplinary research domain characterized by methodological innovation, international collaboration, and thematic diversification.

4.1.Evolutionary trajectory of the field

The temporal analysis demonstrates a clear three-phase developmental trajectory. During the early stage (2001–2014), research output remained limited and largely exploratory, reflecting initial attempts to apply computational techniques within osteoporosis and fracture research. This phase was primarily grounded in traditional clinical risk assessment paradigms, with limited integration of advanced AI methodologies[10,11].

Between 2015 and 2019, publication output began to increase steadily, corresponding to broader adoption of machine learning in medical research[12,13]. The acceleration observed after 2020 indicates a transition into a phase of rapid expansion. This surge likely reflects the maturation of deep learning algorithms, increased computational capacity, and the widespread availability of large-scale imaging and electronic health record datasets. The cumulative growth curve suggests that the field has moved beyond experimental application and entered a stage of technological consolidation and translational exploration[14,15].

4.2.Collaboration patterns and structural characteristics

The co-authorship, institutional, and country-level networks collectively reveal a structured yet moderately centralized collaboration landscape. At the author level, the network exhibits a modular configuration with several distinct clusters. A limited number of high-productivity researchers form the structural core, while newer contributors are progressively integrated into emerging collaborative communities[16,17]. This pattern suggests that the field is anchored in established research groups while gradually expanding toward broader interdisciplinary participation[18].

Institutional collaboration presents a core–periphery structure, with high-output academic and medical centers functioning as hubs that maintain dense inter-institutional connections. Such centralization indicates that research capacity remains concentrated within leading institutions possessing advanced imaging infrastructure, clinical cohorts, and computational expertise[19,20].

At the country level, international collaboration is highly interconnected, with the United States functioning as a major hub in the global network. European countries form tightly linked regional clusters, while Asian countries—particularly China—demonstrate increasing integration into the global research ecosystem[21]. The expansion of international linkages reflects both technological globalization and the growing recognition of fracture risk as a shared public health challenge[22].

4.3.Thematic structure and knowledge framework

The four thematic clusters identified in this study do not merely represent topical groupings; rather, they collectively reflect the structural evolution of a research domain transitioning from clinically anchored risk stratification to computationally enhanced predictive ecosystems. The clusters reveal how methodological innovation, technological expansion, and translational integration interact to shape the intellectual trajectory of AI-based fracture risk prediction.

Cluster 1, centered on machine learning algorithms and predictive validation, represents the methodological engine of the field. The dominance of terms such as random forest, support vector machine, deep learning, and neural networks signals a clear movement toward performance-driven modeling paradigms[23-25]. However, the persistent presence of logistic regression suggests that the field remains in a comparative rather than replacement phase[26,27]. This coexistence indicates methodological pluralism, where classical statistical frameworks continue to serve as benchmarks against which AI models demonstrate incremental improvement. The rapid growth in publications after 2020 corresponds closely with the increasing prominence of this cluster. This temporal alignment suggests that algorithmic optimization has become the primary driver of research expansion. The emphasis on validation and feature selection further indicates growing awareness of overfitting, generalizability, and external applicability—issues that have historically limited predictive modeling in clinical contexts[6,28]. Thus, Cluster 1 reflects both technological advancement and methodological self-correction.

Cluster 2 illustrates a technological inflection point in fracture risk research. The integration of radiomics and quantitative imaging marks a departure from reliance on bone mineral density as a singular predictive indicator. Instead, AI-enabled feature extraction allows high-dimensional characterization of bone microarchitecture and tissue heterogeneity[29,30]. This development aligns with the observed rise of radiology and medical imaging subject categories over time. The emergence of opportunistic screening further reflects a systems-level shift toward data reuse and embedded risk assessment within routine clinical workflows[31]. Imaging-based AI models are therefore not only technological innovations but also infrastructural transformations, redefining how fracture risk is detected and operationalized in healthcare systems[30]. Importantly, Cluster 2 bridges methodological innovation (Cluster 1) and clinical application (Cluster 3), indicating that imaging serves as a mediating layer through which computational methods gain clinical relevance.

Cluster 3 represents the epistemological foundation of the field. The continued centrality of FRAX, bone mineral density, and clinical risk factors underscores the enduring authority of established clinical paradigms[32-34]. The fact that AI-related keywords co-occur with FRAX suggests that algorithmic approaches are frequently developed in relation to, rather than independent from, traditional risk assessment tools[35]. This pattern reflects a path-dependent evolution: fracture prediction research retains strong clinical anchoring, and new methodologies must demonstrate compatibility or superiority within existing clinical frameworks. Such structural embedding may partly explain why the field has expanded rapidly without fragmenting conceptually. AI approaches are not redefining fracture risk from first principles but are augmenting established stratification systems[36]. The persistent prominence of this cluster also indicates that translational credibility remains tied to clinically interpretable variables, highlighting the ongoing tension between algorithmic complexity and clinical transparency.

Cluster 4 extends the knowledge structure into the domain of real-world clinical complexity. The appearance of chronic diseases and pharmacological agents within the keyword network reflects increasing recognition that fracture risk does not exist in isolation but is embedded within multimorbid and treatment-exposed populations[37,38].This cluster aligns with the observed expansion of international collaboration and institutional networking, suggesting that large, heterogeneous datasets are increasingly required to capture real-world variability[39,40]. The integration of comorbidity and medication variables indicates that the field is moving beyond model development toward context-sensitive risk prediction. In structural terms, Cluster 4 represents the outer translational layer of the knowledge framework, where predictive algorithms intersect with therapeutic decision-making and population health management.

When examined collectively, the four clusters reveal a layered and integrative knowledge system. Cluster 3 provides the foundational clinical paradigm; Cluster 2 enriches predictive inputs through imaging-derived features; Cluster 1 advances algorithmic optimization; and Cluster 4 situates prediction within complex real-world contexts. The temporal acceleration observed after 2020 suggests that the methodological layer (Cluster 1) has recently gained dominance, yet its sustained connectivity with clinical and imaging clusters indicates that integration rather than disruption defines the field ’ s evolution[41,42]. Unlike some AI-driven domains characterized by conceptual fragmentation, fracture risk prediction research demonstrates structural coherence, anchored by longstanding clinical frameworks. Thus, the thematic architecture reflects a transition from rule-based stratification toward computational augmentation, embedded within interdisciplinary collaboration networks and expanding translational contexts[43,44]. This integrative progression suggests that the future trajectory of the field will likely depend on harmonizing methodological sophistication with clinical interpretability and real-world applicability.

4.4.Interdisciplinary integration

The subject category analysis further confirms the multidisciplinary nature of this field. Early publications were primarily concentrated within endocrinology and orthopedics, reflecting the clinical origins of fracture risk research[45,46]. Over time, radiology and medical imaging disciplines gained prominence, paralleling the development of imaging-based biomarkers[47,48]. More recently, computer science and artificial intelligence categories have shown marked growth, indicating deepening integration of computational methodologies[49,50]. This progression demonstrates a gradual convergence of clinical medicine, imaging science, and computational analytics. The disciplinary shift suggests that AI-driven fracture risk prediction is evolving from a clinically anchored problem toward a computationally enhanced, cross-disciplinary research domain.

5.Research implications and future outlook

5.1.Implications and future directions

The rapid growth of AI-based fracture risk research highlights its considerable potential for clinical translation. However, the bibliometric network analysis in this study reveals a partially centralized collaboration structure and relatively limited connectivity between thematic research clusters. These structural characteristics suggest that the field may benefit from stronger cross-disciplinary collaboration. Future studies should therefore promote closer integration between clinical researchers, imaging scientists, and data scientists to facilitate knowledge exchange across methodological and clinical domains.

Another important direction is enhancing cross-cluster integration within the research landscape. The present analysis shows that algorithm development, imaging-based radiomics, and clinical risk assessment often evolve in parallel rather than in fully integrated frameworks. Future work should aim to bridge these domains by developing models that simultaneously incorporate clinical risk factors, imaging-derived features, and advanced machine learning algorithms.

In addition, expanding multi-institutional and international collaboration may help overcome the current concentration of research activity within a limited number of institutions. Larger and more diverse datasets would improve model robustness, generalizability, and external validation across different populations.

Finally, future research should continue to advance multimodal data integration, including imaging features, clinical variables, genetic information, and potentially wearable sensor data. Prospective cohort validation, external dataset testing, and real-world implementation studies will also be essential to demonstrate the clinical utility and practical applicability of AI-based fracture risk prediction systems.

5.2.Limitations

This study has several limitations. First, data were retrieved exclusively from the Web of Science Core Collection, which may exclude relevant publications indexed in other databases. Second, only English-language publications were included, potentially introducing language bias. Finally, bibliometric analysis reflects publication patterns rather than direct measures of methodological quality or clinical effectiveness.

Despite these limitations, the present study provides a comprehensive and systematic overview of the structural characteristics, thematic evolution, and collaborative landscape of AI-based fracture risk prediction research.

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