

OsteoAI: A Review of Explainable Artificial Intelligence, Osteoporosis Risk Prediction and Preventive Lifestyle Simulation

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ABSTRACT

Osteoporosis is a long-term skeletal condition in which bone strength decreases and the likelihood of fragility fractures rises. Because the condition can develop without noticeable symptoms, identifying people at elevated risk before a fracture occurs is an important preventive goal. Conventional assessment commonly depends on bone mineral density and established clinical risk tools, although access to screening is not uniform across healthcare settings. Recent studies have examined machine learning (ML), deep learning, medical imaging, and explainable artificial intelligence (XAI) for osteoporosis classification and fracture-risk estimation. This review considers these developments with emphasis on clinical and lifestyle information, interpretable predictions, and decision-support applications. Existing reviews show encouraging results from AI-based methods, but they also point to concerns involving dataset variation, external validation, reporting standards, interpretability, and integration into clinical practice. Building on this evidence, the proposed OsteoAI approach combines routine clinical and lifestyle inputs with explainable ML, risk categories, personalized preventive suggestions, and lifestyle-based “what-if” simulation. The proposed system is presented as a project-level decision-support direction and not as a substitute for professional diagnosis.

KEYWORDS: Osteoporosis, Artificial Intelligence, Machine Learning, Explainable AI, Clinical Decision Support, Risk Prediction, Preventive Healthcare, Lifestyle Simulation

I. INTRODUCTION

Osteoporosis is a chronic skeletal disease in which bone mass falls and the internal structure of bone deteriorates, leaving the skeleton more prone to fracture. Because it often advances silently until a fragility fracture occurs, detecting elevated risk early is central to prevention. OsteoAI treats the problem as one of accessible risk assessment, preventive guidance and clinical decision support, rather than as a stand-alone AI diagnosis. DXA/DEXA remains the reference method for measuring bone mineral density, and established fracture-risk tools combine clinical risk factors with BMD where it is available. In parallel, researchers are testing AI methods on routinely collected clinical data and on medical images.

The volume of this research is large. A 2024 qualitative review of 97 AI studies [1] found that most addressed

osteoporosis classification, fracture detection and risk prediction, with smaller groups on bone-property assessment and segmentation. Broader reviews now span diagnosis, risk prediction and treatment [7], [8]. Yet a high accuracy figure alone does not justify clinical use: models also need proper validation, transparent reporting, outputs that users can interpret, and a defined place in the clinical workflow [1], [2]. This review therefore gathers the literature closest to OsteoAI’s design goals and uses it to identify the opportunities and limits that shape the proposed system.

II. REVIEW SCOPE AND METHODOLOGY

This paper is a focused narrative review written to support the final-year OsteoAI project. It covers four themes: AI and ML for osteoporosis classification and risk prediction; explainable AI and decision support; the use of routinely available clinical information; and obstacles to clinical translation. Sources were identified through searches of PubMed/PMC and related scholarly databases, using queries that paired osteoporosis with AI or machine learning, explainability, fracture prediction and decision support. Systematic reviews, meta-analyses and recent peer-reviewed studies were preferred when they bore directly on the project’s objectives, and the most relevant are cited.

Evidence was grouped thematically and no formal PRISMA process was followed. The paper therefore makes no claim of exhaustive database coverage. It aims instead to give a structured overview of the main research directions, their known limitations, and the gap that motivates OsteoAI.

III. OSTEOPOROSIS AND CONVENTIONAL RISK ASSESSMENT

Conventional osteoporosis assessment generally combines clinical evaluation, bone mineral density measurement, and estimation of fracture risk. The reviewed literature identifies DXA as the reference method for BMD assessment and FRAX as a widely used tool that combines clinical risk factors and, when available, BMD-related information. [1] These established methods form an important baseline for evaluating newer AI approaches. Consequently, an AI-based risk model should have a clearly defined purpose: it may assist with screening or risk stratification, but it should not be presented as an

independent replacement for clinical diagnosis or established diagnostic procedures.

IV. ARTIFICIAL INTELLIGENCE IN OSTEOPOROSIS

A. Machine Learning for Risk Prediction

Machine learning has been used to find relationships among demographic, clinical, biochemical and other patient-level variables. Wu et al. pooled 53 studies, covering 86 prediction models and 41 validation sets, and judged ML to predict fracture risk favourably, while observing that most studies lacked external validation [3]. This breadth suggests that ML can exploit predictor combinations that simple scoring approaches handle poorly, but it also shows that validation quality and model-to-model differences must be weighed instead of relying on a single performance metric.

Khanna et al. trained several ML frameworks on an open dataset of 1,493 patients. Their strongest configuration paired forward feature selection with a stacked multi-level ensemble and reached 89% accuracy; SHAP, LIME, ELI5, Qlattice and feature importance were then used to explain the predictions [4]. The study is relevant to OsteoAI because it shows prediction and explanation sitting in one workflow. One caveat is that the dataset includes bone-density measurements, so it is not directly comparable with OsteoAI's focus on routine clinical and lifestyle inputs.

B. Deep Learning and Radiographic Approaches

Convolutional neural networks have attracted much attention for classifying osteoporosis from radiographs. Liu et al. reviewed 31 such studies and found reported accuracy between 66.1% and 97.9%, sensitivity between 67.4% and 100%, and specificity between 60.0% and 97.5% [5]. The spread illustrates both the promise of imaging-based AI and the inconsistency of the evidence.

Radiographic methods matter for screening, but they sit beside OsteoAI's main direction, which relies on routine clinical and lifestyle data with explainable risk assessment. Imaging-based deep learning is therefore treated as a related research stream rather than the methodological basis of the proposed system.

C. AI for Fracture-Risk Prediction

Fracture prediction has grown into a research area of its own. A systematic review comparing AI with DXA and FRAX found that the AI models in the included studies outperformed both, but also called for multi-centre studies with larger and more diverse populations and longer follow-up before wide application [6]. Broader narrative reviews likewise count fracture-risk prediction among the main AI applications in osteoporosis [2]. Taken together, these works support risk stratification as a worthwhile direction, yet they also show the need to separate performance in experimental settings from demonstrated clinical usefulness.

V. EXPLAINABLE AI AND CLINICAL DECISION SUPPORT

Explainability is a core design idea in OsteoAI. In decision support, a label such as "high risk" is far more useful when the system also shows which patient factors drove it, in terms a user can follow. Khanna et al. added several XAI methods to their osteoporosis classifier precisely to give a rationale for its outputs [4].

The wider literature also stresses open, well-documented development. In their review of 97 studies, Gatineau et al. noted uneven study quality and inconsistent reporting, and argued that standardized development, validation and reporting are prerequisites for clinical translation [1].

In OsteoAI, SHAP and/or LIME can explain individual predictions. Both are model-agnostic and suit tabular clinical and lifestyle inputs. Their outputs, however, describe how the model uses its features; they are not independent diagnoses and do not show that a feature caused the predicted outcome.

VI. COMPARATIVE ANALYSIS OF LITERATURE

Data / Scope	AI Approach	Primary Task	Key Point
97 AI osteoporosis studies	AI / ML / DL	Multiple osteoporosis applications	Quality assessment showing uneven study quality and reporting [1]
53 studies; 86 models	Machine learning	Fracture-risk prediction	Meta-analysis; most studies lacked external validation [3]
1,493-patient open dataset	Ensemble ML + XAI	Osteoporosis risk prediction	Feature selection, stacked ensemble and several explainers [4]
31 radiographic studies	CNN / DL / ML	Radiographic osteoporosis classification	Wide spread in reported accuracy, sensitivity and specificity [5]
AI fracture-prediction studies	AI / ML / DL	Fragility-fracture prediction	Compared with DXA and FRAX; multi-centre validation advised [6]

VII. RESEARCH GAPS

The literature reviewed for OsteoAI points to several gaps. First, a large part of the existing work concentrates on one modality, particularly medical imaging, whereas a practical preventive system can also make use of readily available clinical and lifestyle information. Second, high predictive performance on a particular dataset does not automatically mean that a model will perform similarly across different populations, institutions, or data-collection environments. Recent reviews repeatedly identify limited external validation, methodological variation, and inconsistent reporting as obstacles to clinical translation. [1], [3], [6]

Third, explainability is not always incorporated into the way end users interact with a prediction. A model that produces only a risk category may provide less practical value than one that also communicates the main factors associated with that result. Fourth, risk prediction and preventive lifestyle simulation are frequently addressed as separate problems. This creates an opportunity to connect

risk estimation with interpretable “what-if” scenarios, while avoiding the unsupported claim that simulated lifestyle changes directly establish causal medical outcomes.

VIII. PROPOSED OSTEOAI RESEARCH DIRECTION

Based on the project specification, OsteoAI is envisioned as an AI-powered clinical decision-support system that works primarily with routine clinical and lifestyle information. The proposed workflow includes patient-data collection, data preparation and feature engineering, comparison of ML algorithms, explanation using SHAP/LIME, risk categorization, personalized preventive recommendations, lifestyle simulation, and deployment through an interactive web application.

The proposed architecture therefore takes the literature one step further at the application level. Rather than ending with a numerical prediction, it aims to connect prediction, explanation, prevention-oriented recommendations, and lifestyle simulation within a single workflow. The project specification identifies these elements as key objectives and methodological components. The system should be described as a preliminary risk-assessment and decision-support tool. Before any real-world clinical use, it would require suitable dataset validation, external validation, prospective evaluation, privacy protection, and appropriate professional oversight.

IX. FUTURE RESEARCH DIRECTIONS

Future studies can strengthen this direction by using larger and more diverse datasets, external and multicenter validation, calibration analysis, clinically meaningful evaluation measures, subgroup-level performance assessment, and prospective evaluation within realistic workflows. Multimodal approaches that combine clinical information with imaging or other validated sources are also identified as an emerging direction in recent reviews. [2]

For OsteoAI, further development could include clearer explanation interfaces, validated recommendation rules, longitudinal risk monitoring, uncertainty estimation, and controlled testing of lifestyle simulation. These additions should be evaluated systematically rather than being assumed to improve clinical outcomes.

X. CONCLUSION

The reviewed literature shows a growing role for artificial intelligence in osteoporosis classification, fracture-risk prediction, bone-property assessment, and clinical decision support. Machine learning and deep learning provide ways to analyze complex clinical and imaging information, while XAI methods can make individual model outputs easier to interpret. However, important challenges remain, particularly in validation, dataset heterogeneity, reporting quality, generalizability, and integration into clinical practice.

OsteoAI builds on these research directions by proposing an explainable osteoporosis risk-assessment framework based on clinical and lifestyle information, supported by personalized preventive guidance and lifestyle simulation. The literature provides a clear rationale for this direction, but it also makes clear that rigorous validation and careful clinical positioning are essential before such a system could be considered for real-world healthcare use.

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