Impact of AI-enabled vertebral fracture (VF) identification on Fracture Liaison Service (FLS) Key Performance Indicators (KPIS) and treatment recommendations

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Purpose or Learning Objective:

Vertebral fractures (VFs) are the most prevalent osteoporotic fractures and represent a major predictor of future fragility fractures and mortality. Despite this, VFs are frequently under-diagnosed and under-reported, particularly when identified incidentally on CT imaging performed for non-musculoskeletal indications. Fracture Liaison Services (FLSs) were established to ensure systematic identification, assessment, and management of patients with fragility fractures; however, VF identification remains a persistent challenge for many FLSs, limiting their overall effectiveness.

Recent advances in artificial intelligence (AI) have enabled automated detection of VFs on existing CT scans, creating an opportunity for large-scale, opportunistic case finding without additional imaging or radiation exposure. While several studies have demonstrated the technical accuracy of AI models for vertebral fracture detection, there is limited evidence on how such tools affect real-world FLS performance, clinical workflows, and downstream key performance indicators (KPIs). In particular, it remains unclear whether increased case identification through AI translates into improved assessment, treatment initiation, and follow-up within constrained healthcare systems.

The purpose of this study was to evaluate the system-level impact of AI-enabled VF identification on FLS performance within the National Health Service (NHS) in England and Wales. Specifically, we aimed to compare standardised FLS KPIs before and after implementation of an AI solution for opportunistic VF detection, and to contrast these changes with contemporaneous control sites without AI implementation. By focusing on FLS-wide outcomes rather than algorithm performance alone, this work seeks to inform evidence-based, scalable implementation strategies for AI in osteoporosis care, aligning with the European Congress of Radiology’s emphasis on value-based imaging and clinical impact.

This study is part of the ADOPT trial - **A**I-enabled **D**etection of **O**steo**P**orosis for **T**reatment.

The aims for the overarching project were as follows:

To increase commissioning and adoption of ***AI-enabled vertebral fracture pathways*** by:

1. Generating a **robust, multi-site, clinical evidence** base for AI-VF detection within a real-world clinical pathway
2. Generating an **independent health economic impact assessment** for *AI-enabled VF pathways*, **based on 'hard' clinical endpoints**
3. Optimising the technology and **real-world workflow** to promote successful long-term utilisation, across both radiological and clinical teams with a patient centric approach

Methods or Background:

The Nanox-AI HealthVCF solution, an AI model designed to identify moderate and severe VFs on CT imaging, was implemented across three established FLSs within the NHS. The AI system automatically analysed existing CT scans that included the thoracic and/or lumbar spine, irrespective of the original clinical indication. In recognition of the anticipated increase in case identification, additional funding was provided at each AI site to support FLS administrators and specialist nurses, enabling patient triage, assessment, and follow-up.

To evaluate the impact of AI implementation, FLS KPIs were extracted from the Fracture Liaison Service Database (FLS-DB) of England and Wales. Outcomes from the year prior to AI implementation (2023) were compared with those from the year following implementation (2024). KPIs assessed included fracture identification rates, time to assessment, time to dual-energy X-ray absorptiometry (DXA), falls risk assessment, treatment recommendation, treatment initiation, and follow-up completion.

Control data were obtained from FLS sites that did not implement AI during the same period, allowing differentiation between AI-associated effects and broader temporal trends in FLS performance. Comparative analyses focused on spine fracture patients and non-spine fracture patients to assess whether AI-driven improvements were specific to VF identification. Statistical comparisons were performed using appropriate tests for proportions and continuous measures, with significance defined as $p < 0.05$.

Results or Findings:

Across the three AI-enabled FLS sites, a total of 34,898 CT scans were analysed by the AI system during the post-implementation period. Of these, 10,329 scans were flagged as potentially containing vertebral fractures. Clinical confirmation was available for 9,875 flagged scans, of which 3,347 were confirmed as vertebral fractures.

Following AI implementation, VF identification significantly increased from 36.25% of expected cases pre-AI to 137.3% post-AI, representing a more than three-fold increase. Unexpectantly, identification of non-spine fractures showed a smaller increase over the same period (45.6% pre-AI vs 63.8% post-AI), suggesting that the observed effect was specific to AI-enabled opportunistic VF detection rather than a general improvement in FLS performance when compared with control FLSs with similar baseline VF rates showing only a small increment in VF identification (28.6% vs 31.3%, $p = 0.008$).

For patients identified with spine fractures, several downstream KPIs worsenedfollowing AI implementation. Time to initial FLS assessment and time to DXA scan significantly worsened at some AI-enabled sites, reflecting the increased volume of patients entering the pathway despite the provision of additional FLS staff. However, changes in treatment recommendation differed between AI-FLS site with 2 worsening and 1 not changing.

Conclusion:

This study demonstrates that AI-enabled opportunistic identification of VFs substantially increase the number of patients captured by FLSs, far exceeding expected baseline identification rates. Importantly, this effect not dependent on the level of baseline VF identification, supporting a direct causal relationship between AI implementation and improved VF case finding.

However, the findings also highlight the complex system-level consequences of introducing AI into established clinical pathways. While increased identification represents a clear success from a case-finding perspective, the resulting surge in patient volume placed pressure on downstream FLS processes, particularly at sites with limited capacity for assessment and monitoring. The observed worsening in time to assessment and DXA at some sites illustrates that AI implementation, if not accompanied by sufficiently robust workflow redesign and resource allocation, may inadvertently exacerbate existing bottlenecks.

Conversely, variability in treatment recommendation rates between AI-FLSs suggest that once patients entered the FLS pathway, care quality and clinical decision making can be maintained or enhanced. The variability in treatment recommendation rates between sites further underscores the importance of local implementation context. Differences in clinical thresholds, staffing models, and monitoring practices influenced how increased identification translated into treatment decisions. This indicates that AI can strengthen the front end of the FLS pipeline, but its ultimate clinical value depends on the resilience and scalability of subsequent assessment and management stages.

From a value-based imaging perspective, these findings reinforce that AI should be viewed not as a standalone diagnostic tool, but as a critical enabling technology for pathway-level transformation requiring multidisciplinary alignment.

These results emphasise that the success of AI in osteoporosis care should be judged not solely on detection accuracy, but on its ability to improve meaningful clinical KPIs at the patient level that relate to benefits for patients. Standardised national datasets such as the FLS-DB provide a powerful framework for evaluating such impact and should be integral to future AI adoption strategies.

Using standardised national KPIs for FLS performance, implementation of AI-enabled VFidentification was associated with a substantial increase in the number of patients identified with spine fractures. However, the impact on downstream assessment timelines and treatment recommendation varied between sites, driven largely by differences in local capacity and monitoring pathways. These findings highlight that effective AI deployment within FLSs must be accompanied by efficient assessment, monitoring, and treatment workflows to realise its full clinical value. For FLS-based decision making, AI represents a powerful case-finding tool, but its success depends on thoughtful integration into end-to-end care pathways rather than isolated algorithmic performance.

Personal Information:

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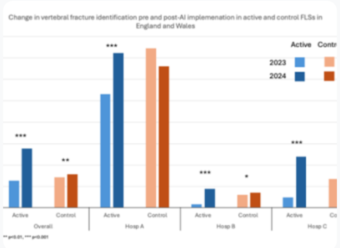

Fig 1: Change in VF identification pre and post-AI implementation in active and control FLSs in England and Wales