OP19

Qualitative evaluation of an AI tool for opportunistic detection of vertebral fractures

Minjie Gao[1]*, Catriona Inverarity[2]*, Jiyoun Chang[3], Manjot Brar[4], Ruphinder Kaur[5], Lauren Gatting[2], Juan I Baeza[1], Anna Barnes[2,5].

1. Department of Public Services Management & Organisation, King's Business School, King's College London. 2. King's Technology Evaluation Centre (KiTEC), London Institute for Healthcare Engineering, King's College London. 3. School of Management, Faculty of Humanities and Social Sciences, University of Liverpool. 4. School of Mental Health & Physiological Sciences, Institute of Psychiatry, Psychology & Neuroscience, King's College London. 5. Medical Physics & Clinical Engineering, Guy's and St Thomas's NHS Foundation Trust, London.

Introduction

Clinical context:
osteoporosis affects >3m people in the UK[1,2]. Unmanaged cases can result in painful fractures which are expensive to treat and affect quality of life.

Unmet need:
early intervention and access to treatment can reduce or prevent future fractures. Vertebral fragility fractures are critical indicators of osteoporosis, and strong predictors of future fracture risk, but may be easy to miss or misdiagnose

99,220
patients estimated to have unidentified fragility fractures (2022)
leading to 2,100
avoidable fractures over the next 2 yrs[3]

~£4.4bn
Estimated annual cost of fragility fractures to the NHS and social care[4,5]

579,722
DALYs lost in the UK due to fragility fractures[6]

Proposed intervention:
Vertebral fragility fractures may be visible on CT scans which include the spine – but may not be detected or reported if this is not the primary indication for the scan. Using AI to review these scans for opportunistic detection could improve early diagnosis and prevent future fractures through timely intervention.

The technology

- **Image processing software** that uses **AI for opportunistic detection** of moderate-to-severe vertebral fractures
- **Addition to standard care** (additional staff time is required to review and report findings)
- Software price varies by number of scans analysed (range from **£38,000 to £90,000 per year**[7]).

Abdominal or chest CT scan → CT image sent via PACS to imaging analytics engine → Scan analysed for vertebral compression fracture → Results available in user interface in PACS viewer → Results reviewed and reported by radiologists

Two deployment modes available:
- **Direct to radiologist** – *AI-flagged cases reviewed and reported case-by-case by radiologists*
- **Direct to FLS** – *a list of AI-flagged cases sent directly to FLS team for review*

and different sensitivity/specificity settings:

Setting	Description
Balanced	**Intended to detect as many VCFs as possible** Increased risk of false positive results. All AI-identified fractures manually verified; resource-intensive.
High	*Described in other studies*
Highest	**Intended to reduce false positive rate / staff review time** Risks missing some vertebral fractures.

Study background

This study (IRAS 317101) used a qualitative approach to investigate how a commercial AI fracture detection tool influences **workflow**, **clinical decision making** and **staff and patient experiences.**

Aim:
Investigate the implementation, adoption and impact of the AI fracture detection tool on staff, services and patients.

Objectives:
- Assess the impact of the AI tool on staff, clinical workflows and patient experience
- Identify challenges and limitations in adoption of the AI tool, including workforce adaptation.

Methods

- Qualitative design to investigate the **implementation**, **adoption** and **impact** of the AI tool on **staff**, **services** and **patients**.
- Semi-structured interviews with purposive sample of healthcare professionals (n=13) and patients (n=5) via MS Teams
- Thematic analysis of transcribed, coded data (per Braun and Clarke) to identify key themes in AI adoption

5 key themes identified:
- Workforce and workflow impact *(263 references)*
- Practical implications of adopting AI *(143 references)*
- Perceived impact on patient care *(162 references)*
- AI adoption and integration *(148 references)*
- Future potential of AI *(100 references)*

Findings

IMPACT ON WORKFORCE & WORKFLOW

How introduction of AI impacted workforce roles and clinical workflows, creating both efficiencies and additional burdens.

- AI **increased number of flagged cases**, increasing time needed
- **Increased workload** in radiology, DEXA, FLS and admin
- Radiologist **workforce shortages complicate feasibility** and **sustainability** of adoption
- **Workforce adaptation:** shifts in responsibilities, changing workloads, workforce planning including downstream capacity.

PRACTICAL IMPLICATIONS OF ADOPTING AI

Ethical, professional & economics challenges associated with AI in healthcare, including trust accuracy and financial implications of using AI for opportunistic detection.

- **Governance & IT delays:** lengthy approval, implementation process
- **Financial considerations:** AI, staffing and integration costs; savings from increased early identification *and intervention*; different cost/ benefit horizons
- **Multi-team coordination:** communication and alignment across multiple teams and systems
- **Managing impact on workforce, workflow & workload:** staff engagement, staff experience and system capacity to process true ***and*** false positives

PERCEIVED IMPACT ON PATIENT CARE

Perceived impact on pathways and experience, including diagnostic efficiency, bottlenecks, and impact on early detection

- **Clinical benefits & efficiency:** increased detection allows more early intervention, if there is downstream capacity (DEXA, FLS)
- **Patient awareness & understanding:** careful communication of opportunistic detection, and use of AI, with patients
- **Patient communication & engagement:** FLS is paramount in clear communication, support and pathway management for identified patients
- **Changes in patient interaction & care delivery:** vary by staff type

AI ADOPTION AND INTEGRATION

AI adoption in hospitals, barriers to seamless integration, and governance challenges associated with implementation.

- Integration described as **protracted and complex process**, requiring substantial **administrative support**, **infrastructural modifications** and **cross-departmental coordination**
- Governance procedures were **slow**, but **important for safety and compliance**
- **Increased knowledge** of local research governance, IT and IG would be beneficial
- Further developments wanted include **additional algorithm training** for improved AI performance, ongoing **data collection**, and **local pilot studies.**

PATIENT PERSPECTIVES OF OPPORTUNISTIC DETECTION

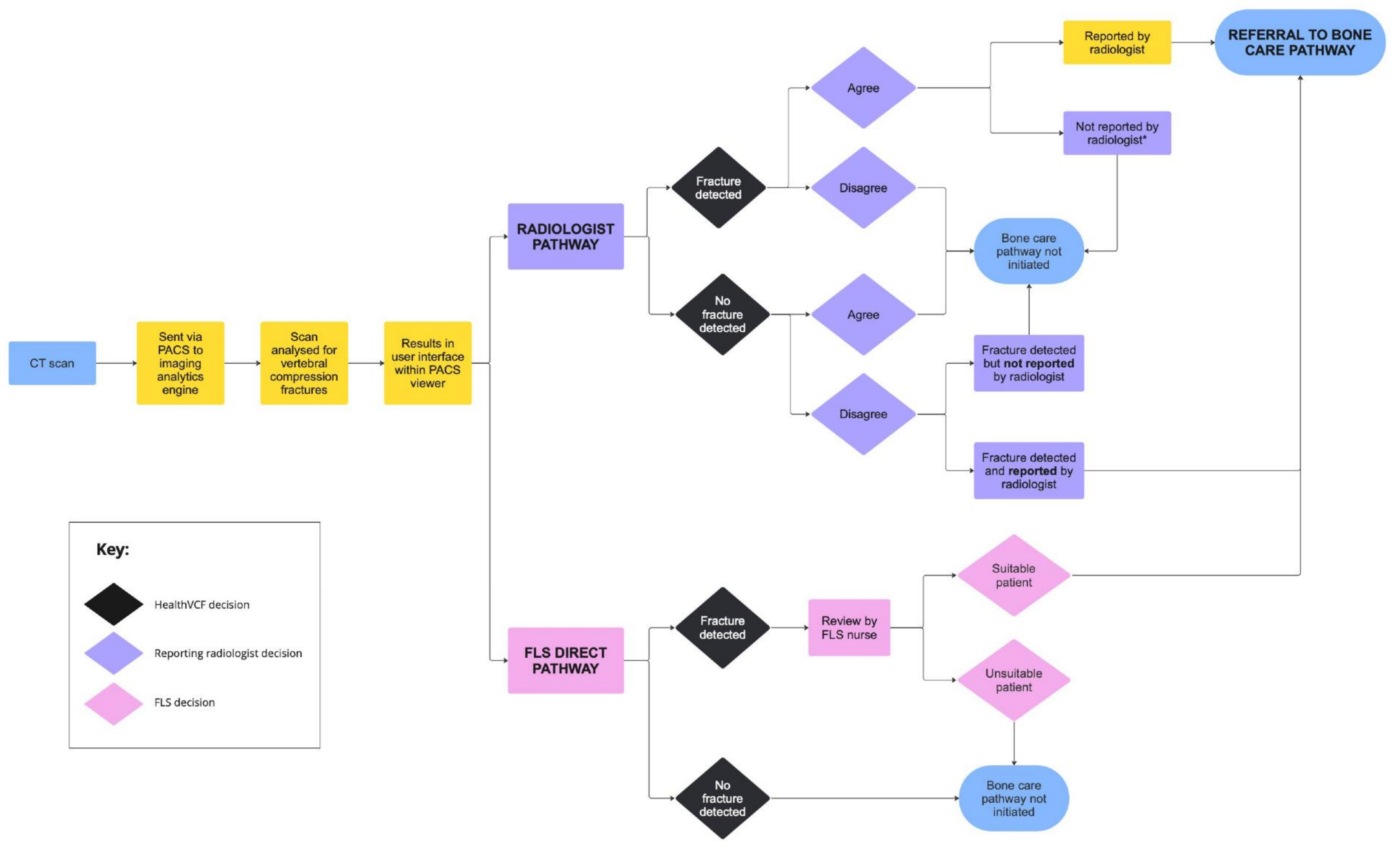
Overall, patients were open to adoption of the AI in fracture pathways, but had concerns about trust & loss of human oversight

- Patients viewed AI as an **effective** tool for early detection, but had concerns about **over-reliance** and loss of clinician competency
- **Transparent communication essential** for maintaining trust, particularly regarding AI's role in incidental findings & potential subsequent diagnosis

FUTURE POTENTIAL OF AI

Perspectives on future of AI, including impact of expanded use, wider applications, increased uptake, and improved performance

- AI could increase yield, but variability in performance was a concern
- **Optimised performance** and better **workflow compatibility and integration** is required for AI to be sustainable
- **Further evidence needed** (validation, evaluation, relevant RWE)
- **Scaled use** of AI requires careful review of systems, pathways & processes



Conclusions

AI **improved opportunistic fracture detection** and identification of osteoporosis patients, but **introduced new complexities** (i.e. increased service pressure, administrative burden)
- AI shifted and expanded responsibilities for radiologists, nurses and managers
- False positive rate necessitates radiologist review, and adds to workload without translating to patient or service benefit

Our findings suggest future studies on AI in radiology should:
- Assess impact across relevant clinical pathways (bottlenecks, resourcing, capacity)
- Explore resource requirements for sustainable use over time
- Assess consequences for patients, staff, healthcare providers and budget holders of formalizing and scaling opportunistic detections
- Explore how patient perspectives, engagement and trust change over time

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