Assignment 3: Literature Review

KIT714 ICT Research Principles

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Artificial Intelligence in Healthcare: Advancing Diagnostics, Predictive Analytics, and Personalised Treatment

BY

Group - 8

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1. Introduction

Artificial Intelligence (AI) is reshaping healthcare by improving diagnosis and decision making. Using machine learning and deep neural networks, AI analyses complex medical data such as imaging, genomic information and electronic health records to enhance accuracy and efficiency (Topol, 2019; Beam & Kohane, 2018). Despite its potential, data bias and ethical concerns still limit adoption (Amann et al., 2020).

This literature review critically examines current studies on AI in diagnostics, predictive analytics and personalised treatment. It evaluates the methodological quality of existing research, compares key approaches, and identifies an ICT related gap that connects technology capability with human trust in healthcare environments.

2. Literature Review - Critical Analysis and Synthesis

2.1. AI in Medical Diagnostics

Several studies have demonstrated that AI can match or exceed human expertise in medical imaging. Esteva et al. (2017) trained a convolutional neural network that classified skin lesions with accuracy comparable to dermatologists. Lundervold and Lundervold (2019) found that AI based MRI analysis improved consistency and reduced manual workload, while Rajpurkar et al. (2022) reported that chest X-ray algorithms sometimes outperformed radiologists. Collectively, these studies show AI delivers high diagnostic precision.

However, interpretability remains a major limitation. Amann et al. (2020) explained that many deep learning systems operate as “black boxes”, which reduces clinician confidence and limits accountability. Johnson et al. (2022) observed that most diagnostic algorithms rely on restricted datasets, which reduces generalisability to diverse clinical settings. AI’s diagnostic success depends on transparent design, diverse data and clinician collaboration. Taken together, these studies show that while deep learning achieves radiologist level accuracy (Esteva et al., 2019; Liu et al., 2022), adoption depends on explainable and accountable model integration.

2.2. AI for Predictive Analytics and Early Intervention

Predictive analytics allows healthcare providers to act before medical conditions worsen. Ching et al. (2018) showed that AI could predict sepsis and hospital readmissions with strong accuracy, and Miotto et al. (2018) introduced DeepPatient, a model capable of forecasting multiple diseases from health records. Wang et al. (2021) demonstrated that AI can predict COVID-19 transmission trends to support timely public health interventions.

While valuable, these models face challenges of interoperability and data privacy. Beam and Kohane (2018) noted that inconsistent data formats and weak integration between systems reduce scalability. Price and Cohen (2019) highlighted that reliance on sensitive patient data raises privacy and consent concerns.

Comparing studies reveals that Ching et al. (2018) focused on individual level prediction, while Wang et al. (2021) addressed population level forecasting. Both confirmed that success depends on secure ICT infrastructures. Predictive analytics is limited more by governance than by algorithms. Evidence from clinical data modelling (Rajkomar et al., 2018; Miotto et al., 2021) shows mature performance, but scaling depends on interoperable and privacy preserving EHR systems.

2.3. AI in Personalised Treatment

AI is reshaping personalised medicine by using patient specific data to tailor therapy. Chen and Asch (2017) found that machine learning optimises drug recommendations and reduces adverse reactions. Beam and Kohane (2018) argued that combining genetic, clinical and behavioural data enables precise treatment selection. Johnson et al. (2022) showed that AI can improve cancer outcomes through intelligent drug combination prediction.

Despite advances, literature shows imbalance between technical optimisation and clinical usability. Amann et al. (2020) warned that biased training data can reproduce inequities in healthcare delivery. Price and Cohen (2019) added that legal uncertainty surrounding ownership and reuse of data continues to complicate implementation. Few studies assess clinician trust in AI, though it affects adoption. Success of personalised AI systems relies on transparency, trust and user centred ICT design. Collectively, these studies highlight that while algorithmic personalisation supports precision oncology (Johnson et al., 2020), equitable benefits will require transparent data governance and continuous auditing to prevent biased clinical recommendations.

2.4. Cross-Cutting Ethical and Data Governance Issues

Across all themes, fairness, accountability and transparency are repeatedly identified as essential for responsible AI in healthcare. Amann et al. (2020) emphasised that poor explainability and algorithmic bias threaten patient safety. Topol (2019) and Lundervold and Lundervold (2019) pointed out that clinical acceptance depends on systems that complement human expertise rather than replace it. Price and Cohen (2019) discussed how the absence of clear policies for data ownership and consent jeopardises patient autonomy.

Recent studies show a shift from purely technical development toward socio technical alignment, recognising that human trust and ethical governance define sustainable AI adoption. In short, AI in healthcare is as much an ICT management issue as it is a scientific one.

2.5. Overall Synthesis of Literature

Across diagnostics, predictive analytics, and personalised treatment, a consistent pattern emerges: technical performance of AI systems is strong, yet adoption depends on clinician trust, explainability, and regulatory assurance. Strengths include accuracy, efficiency and improved detection speed (Topol, 2019). Weaknesses include dataset bias and fragmented ICT infrastructures that limit validation. Integrating technical and human centred perspectives therefore remains the key frontier for advancing trustworthy AI in healthcare.

Strengths: Demonstrated diagnostic precision, improved clinical efficiency, and capacity for early intervention.

Weaknesses: Limited explainability, poor cross system integration, and insufficient evaluation of clinician AI collaboration.

3. Research Gap and Question

The reviewed studies consistently demonstrate that AI improves accuracy, speed and personalisation in medical care. Yet most research focuses on algorithms rather than how clinicians use AI in practice. The human AI interface, which shapes trust, usability and accountability, is rarely examined in depth.

This oversight exposes a clear ICT related gap: understanding how professional trust and system transparency influence the effective use of AI in real clinical settings. Addressing this gap is essential for developing reliable and ethically responsible healthcare technologies.

This gap is fundamentally an ICT systems design issue that involves creating explainable interfaces, auditable decision pathways and interoperable infrastructures that align algorithmic reasoning with clinician judgment. Addressing these design factors will help ensure AI tools enhance, rather than replace, human decision making.

Research Question:
How do healthcare professionals perceive and trust AI based diagnostic systems within clinical decision making processes?

Investigating this question will support human centred ICT design and close the gap between innovation and clinical adoption.

- A reflective statement describing the use of Generative AI tools in this research process is provided in Appendix A.

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5. Appendix A: Generative AI Use Reflection

Generative AI tools such as ChatGPT and Microsoft Copilot were used to support early drafting, grammar checking and idea organisation. ChatGPT helped structure topic headings and transitions between sections, while Copilot assisted in verifying references and aligning formatting with APA 7th style. Every suggestion from these tools was manually reviewed and verified using peer reviewed academic sources from the UTAS Library and Google Scholar.

This process improved writing efficiency but also highlighted limitations. The tools occasionally produced overly general phrasing or omitted contextual depth, which required human correction. Recognising these limitations encouraged more careful reading and stronger critical judgment. The final content is entirely based on academic literature and independent interpretation, ensuring authenticity and adherence to UTAS integrity policies.

Engaging with these tools also strengthened my critical reading discipline, as each AI generated suggestion was traced back to credible evidence before acceptance. This verification habit deepened my understanding of academic rigour and reinforced responsible technology use. The experience enhanced my ability to evaluate digital tools ethically and will guide my future research toward transparent, evidence

based practice.

This reflective process demonstrated that while generative tools can enhance workflow and clarity, academic reasoning, verification and ethical awareness must always remain under the researcher’s control.