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Who Codes Care? Mapping the AI Landscape: Bias Blind spots and Rural and Remote Health

Associate Professor Yangama Jokwiro

Unlocking the Full Potential of Digital Health and AI

From Vision to Value

WHERE ARE WE NOW? THE STATE OF AI IN HEALTHCARE

AI is already embedded in healthcare. The question is no longer 'Should we?' — it's 'How do we use it safely?'

66%

of GPs now report using AI tools in practice

80%

of rural Australian patients lack direct specialist access

47%

of diagnostic errors are preventable with AI-assisted CDS

Documentation & ambient AI

AI scribes and LLMs (GPT-4 class) now generate clinical notes, referral letters, and discharge summaries in real time — reducing documentation burden by up to 70% in pilot studies.

Triage & diagnostic screening

CNNs (Convolutional Neural Networks) identify pathology in chest X-rays, retinal images, and ECGs at radiologist-level accuracy (Rajpurkar et al., 2017; CheXNet).

Clinical decision support

XGBoost and LSTM models power sepsis early-warning (NEWS2-AI), deterioration prediction, and medication safety alerting embedded in EMR systems.

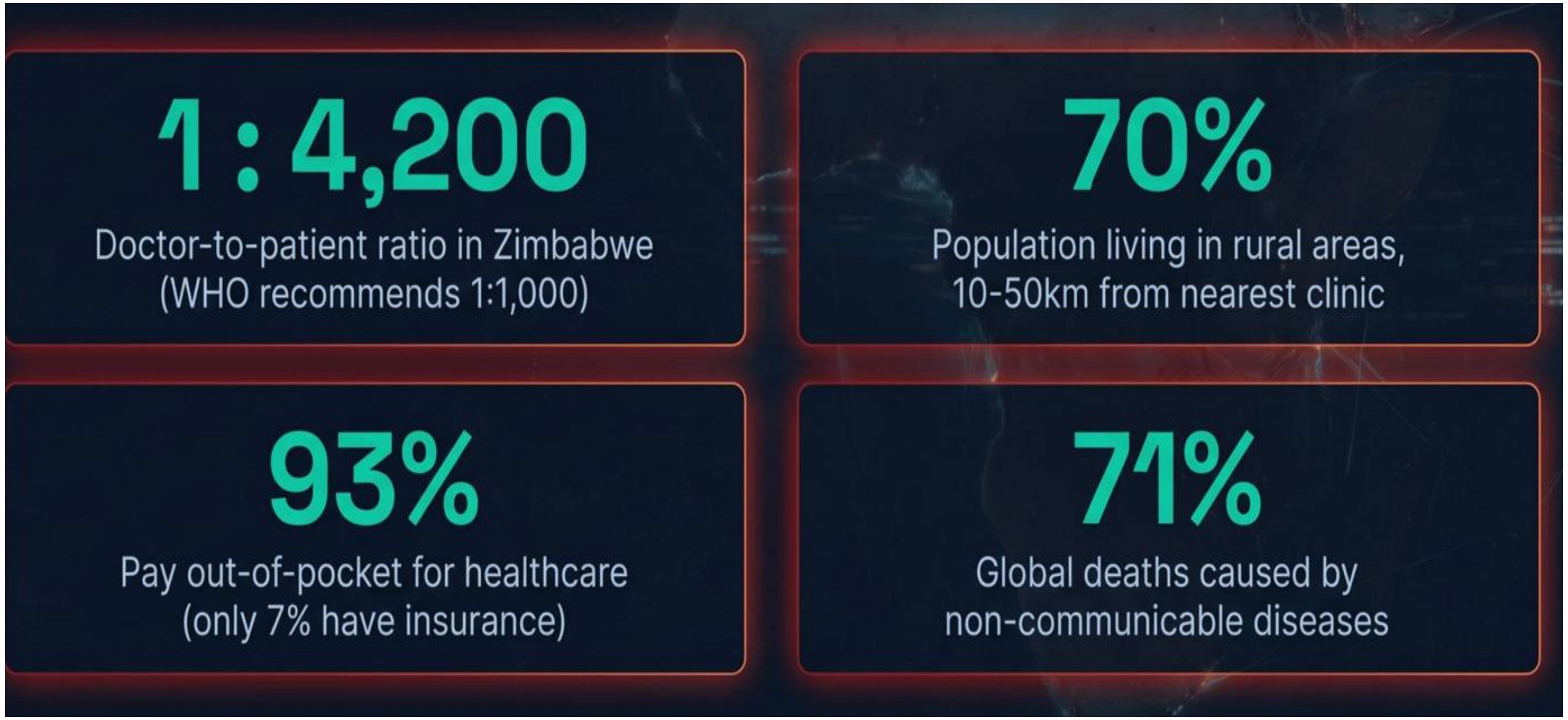
Patient education & access

LLM chatbots and knowledge-graph tools like AskSam® support health literacy, remote consultation and post-discharge patient guidance.

Sources: Laranjo L et al., Lancet Primary Care (2025) | Rajpurkar P et al., CheXNet arXiv:1711.05225 | AIHW Rural Health (2024) | Australian Dept of Health (2026)

Case Study: Health Access & Equity Challenges in LMICs

- Despite differences in scale, the themes outlined are highly relevant to the rural and regional Australian context.
- Population where the perception of risk is poor, but we do not like to be sick or die.



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Harnessing Digital Health and AI to Transform Care Delivery

- Zimbabwe has high mobile penetration (~85% of the population have mobile phone access.
- **Edge Computing** ------------ -AI-powered smartphone tools can turn the devices people already have into personal health monitors.
- Digital interventions often have low marginal costs and can scale rapidly

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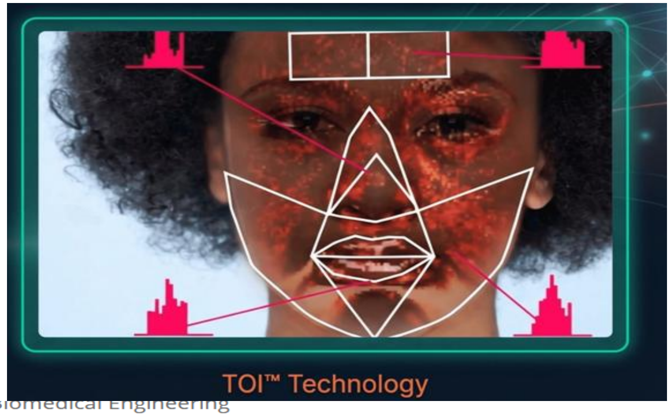
Non-Invasive, Contactless Remote Monitoring Powered by AI



Deep learning and remote photoplethysmography powered advancements in contactless physiological measurement

Wei Chen[1], Zhe Yi[1], Lincoln Jian Rong Lim[2,3], Rebecca Qian Ru Lim[4], Aijie Zhang[1], Zhen Qian[5], Jiaxing Huang[6,7], Jia He[6,7] and Bo Liu[1,8]*

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TABLE 2 Several conventional iPPG signal extraction algorithms for HR measurement.

ROI selection	Feature type	Proposed algorithms	Correlation coefficient (compared to pulse oximeter)	Basic architecture	HR computation methods	Measurement
Center 60% width of the face	RGB	JADE (Poh et al., 2011)	1.00, 0.92 (HR, HRV)	ICA	A custom algorithm to obtain IBI	HR, HRV
Area containing eyes	RGB	SOBI (Zhang et al., 2017)	>0.90	ICA	Time-domain kurtosis	HR
Forehead, cheek	Single channel 560 ± 20 nm	FastICA (Favilla et al., 2019)	≥0.999, ≥0.998 (HR, HRV)	ICA	A multi-scale algorithm for peak estimation	HR, HRV
Face skin area	RGB	Project_ICA (Qi et al., 2019)	0.76, 0.74, 0.69, 0.47 (stationary, interaction with computer, swinging heads, exercise recovery)	ICA	FFT for peak estimation	HR
Cheek	RGB	CHROM, KDICA (Song et al., 2020)	0.981 vs. 0.968, 0.918 (CHROM alone, KDICA alone)	CHROM, ICA	FFT for peak estimation	HR
Face skin area	RGB	CDF optimizing LMA, undercomplete ICA (Gupta et al., 2022)	0.92, 0.94, 0.92 (constrained, motion, illumination variations scenarios)	LMA, ICA	FFT for peak estimation	HR

Biomedical Engineering

Non-invasive prediction of cholesterol levels from photoplethysmogram (PPG)-based features using machine learning techniques: a proof-of-concept study

Erick Javier Argüello-Prada, Angie Vanessa Villota Ojeda & María Yoselin Villota Ojeda

Article: 2467153 | Received 13 Aug 2024, Accepted 23 Dec 2024, Published online: 18 Feb 2025

Cite this article https://doi.org/10.1080/23311916.2025.2467153 Check for updates

Home > Applied Intelligence > Article

Remote photoplethysmography (rPPG) based learning fatigue detection

Published: 20 September 2023

Volume 53, pages 27951–27965, (2023) Cite this article

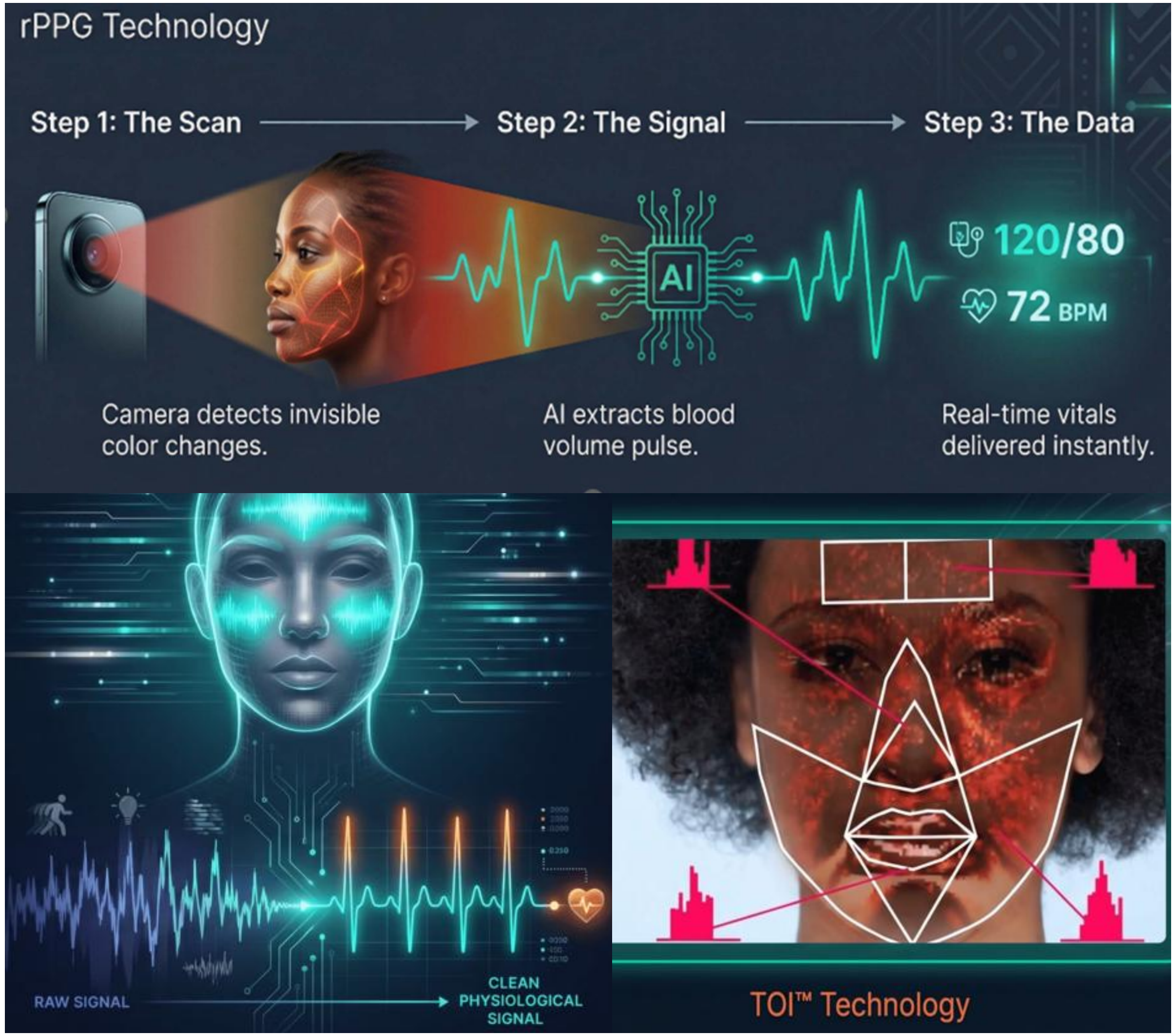
Home > Artificial Intelligence Review > Article

PPG-based glucose sensors: a review

Open access | Published: 23 October 2025

Volume 58, article number 391, (2025) Cite this article

Underpinning Technology – rPPG, TOI, red light (approx. 660 nm) and infrared light (approx. 940 nm)

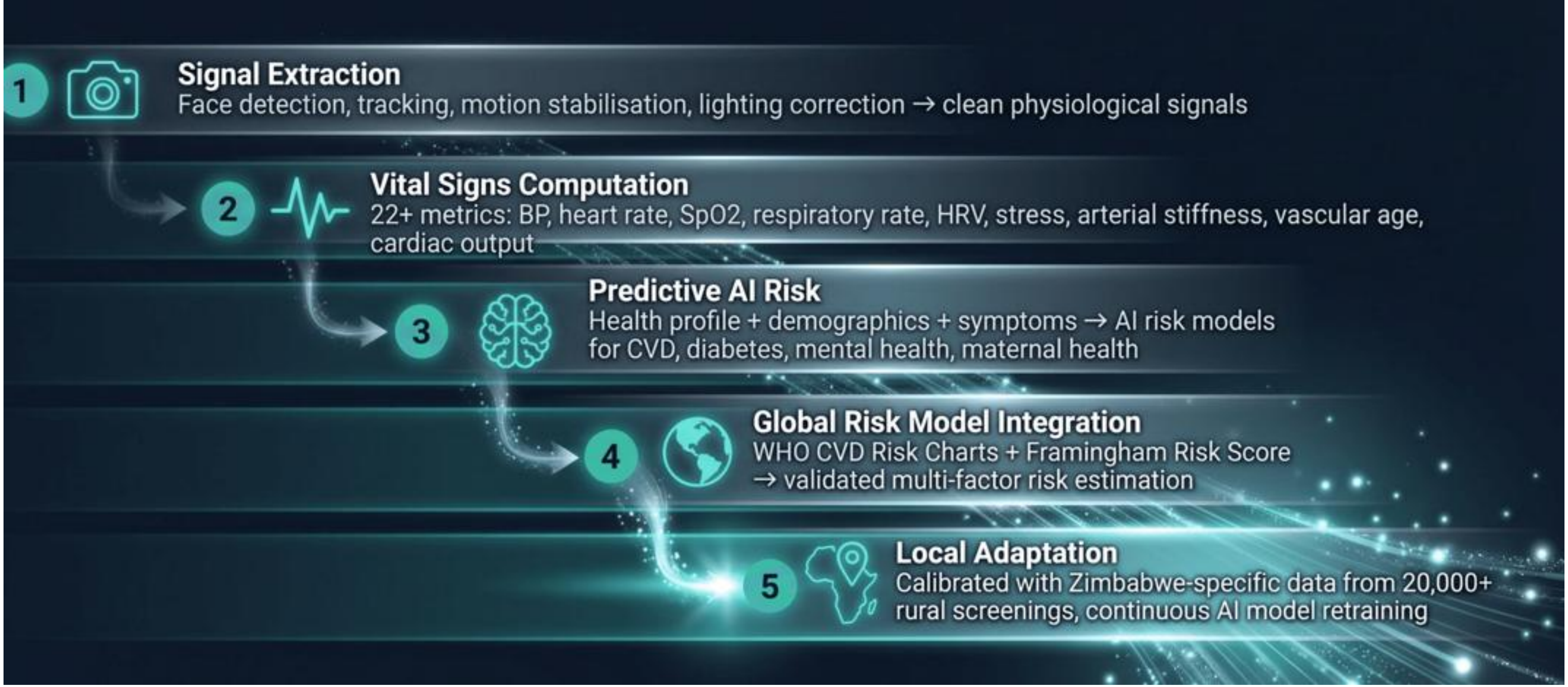


Direct Reading

Heart Rate and HRV
Sp02 and Respiratory Rate
Blood Pressure and Pulse Pressure
Haemoglobin
Glucose
Cardiac Output and Cardiac Workload
Arterial Stiffness
Vascular Age
Cholesterol

Proxy Readings

Hydration
Anaemia,
Stress, Anxiety,
Hypertension and Arrhythmias
Diabetis Mellitus, HbA1 Index.
Preeclampsia, Fatigue



The Five Layer Analysis and Predictive AI Architecture

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The AI 360 Degrees System Decision support System

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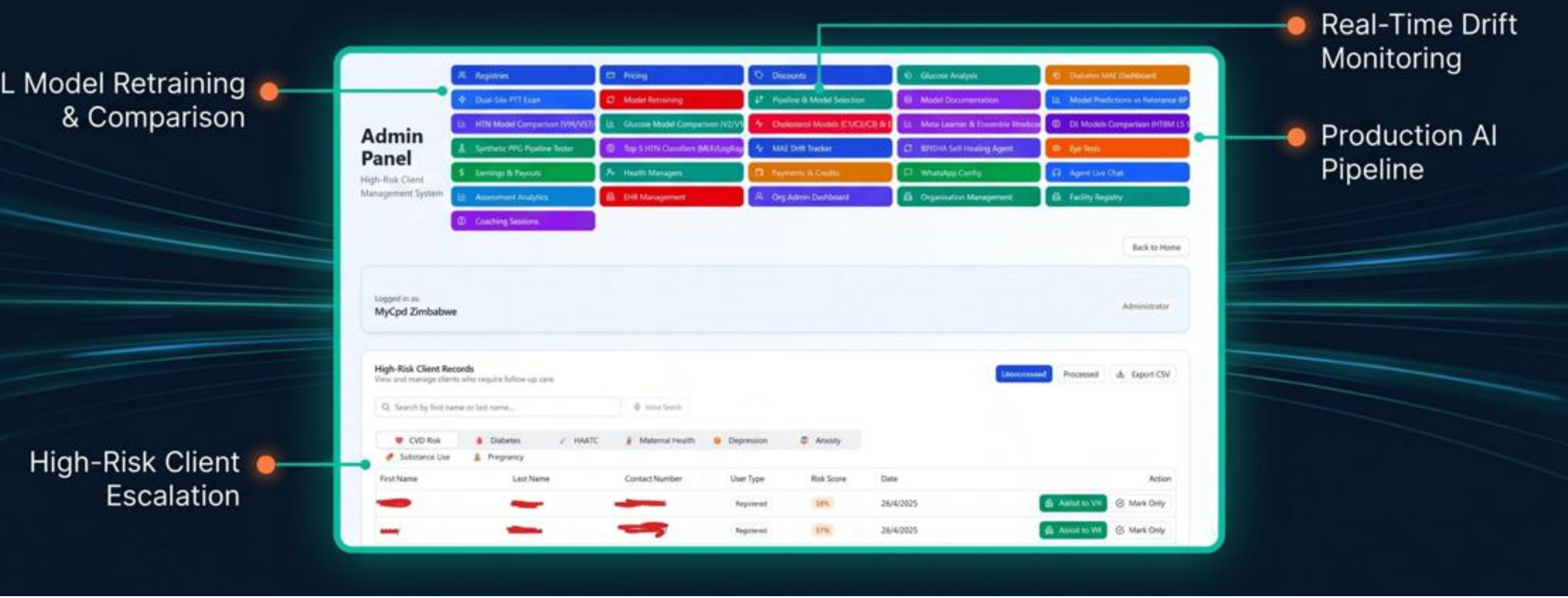

The AI Laboratory – Model Training and Contextualisation

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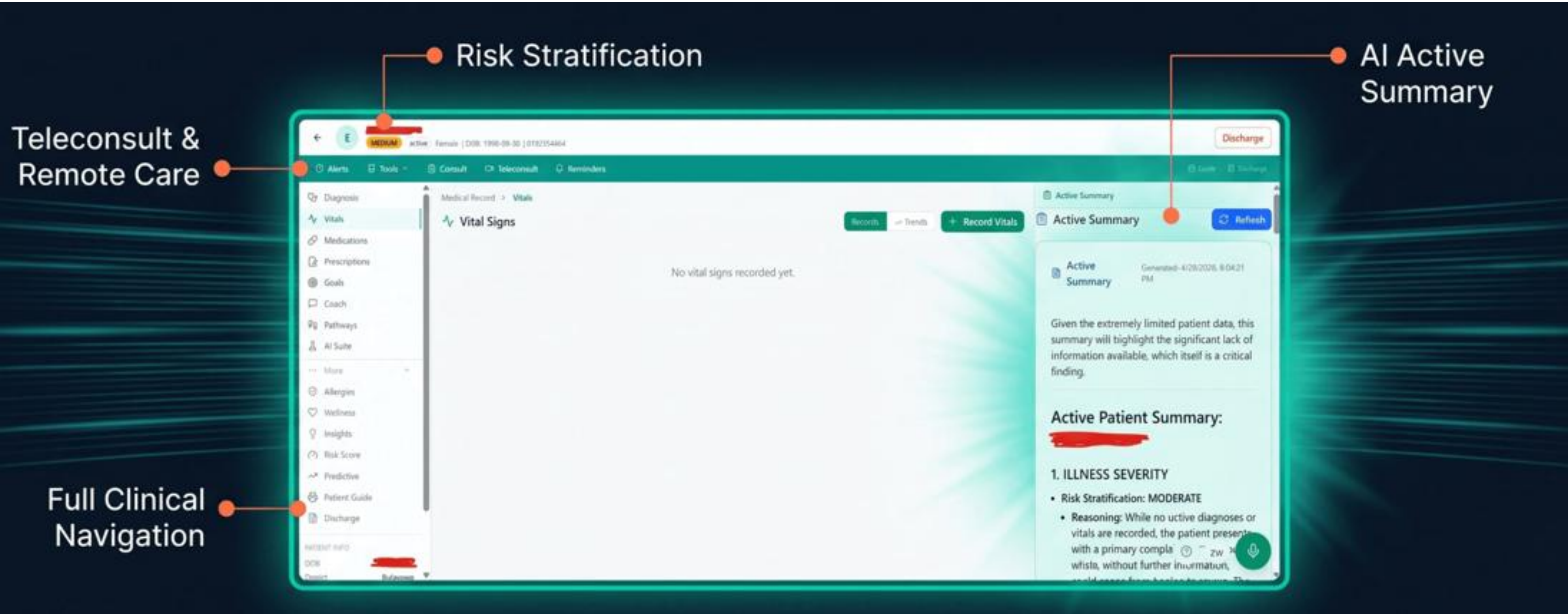
- Each predictor combines rPPG-derived vital signs with validated clinical screening instruments and
- Designed for community health workers and nurses — no specialist training required
- Accessible from any smartphone in any village

The Health Care Worker Landing Page



The EMR Integrated with AI – AI Continuous Monitoring

AI Never Sleeps

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Digital Twin and Digital Coach

Personalised Care Through AI-Driven Modelling and Intelligent Guidance

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The work in pictures

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The work in Pictures

The Physical Touch Point – Eye Ball Test

AI Powered Virtual Hospital System

The Hub-and-Spoke Model of Health Care Delivery

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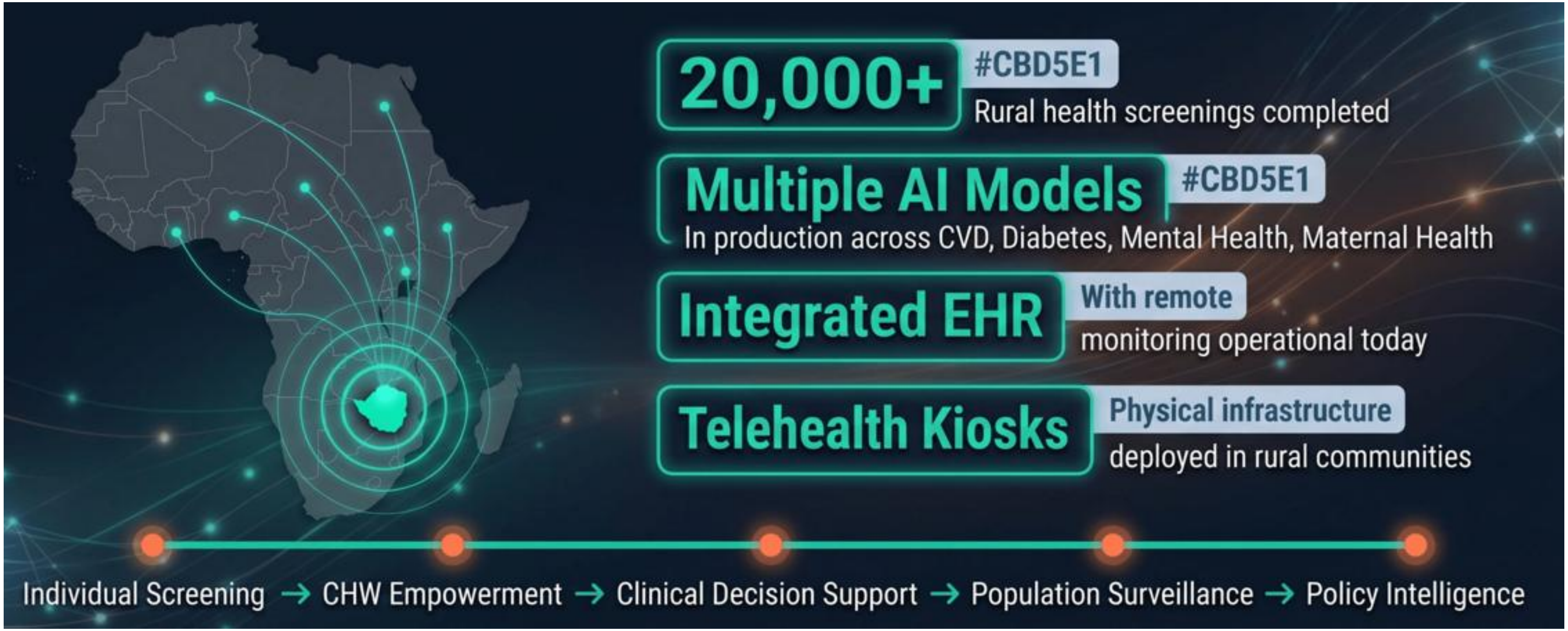
The future of AI Driven Health Care in LMICs



AI can be a Catalyst for Meaningful Change

- Sepsis (early detection)
- Septic shock
- Post-operative care
- Burnout and fatigue syndromes
- Parkinson’s disease (progression & medication response)
- Stroke recovery and early deterioration
- Epilepsy (seizure risk patterns)
- Delirium (especially in older adults)
- Dementia (functional and behavioural change)
- Pre-eclampsia
- Gestational hypertension
- Fetal distress (maternal–fetal correlation)
- Medication Errors
- Anxiety disorders
- Depression

- Efficiencies (40% production efficinency)
  - Ambient Listening (consultation, MDT – meetings)
  - Decision Support

THE ALGORITHMS POWERING CLINICAL

Large Language Models (LLMs)

GPT-4, Med-PaLM 2, BioGPT

Transformer architecture (Vaswani et al., 2017). Self-attention enables clinical note synthesis, differential generation, and patient education drafting.

USE: Ambient documentation, Q&A, care plan drafting

Random Forest & XGBoost

NEWS2-AI, SEWS, sepsis alerts

Ensemble decision-tree methods (Breiman 2001; Chen & Guestrin 2016). Aggregate hundreds of weak learners on tabular vital-sign data for robust risk prediction.

USE: Sepsis early-warning, deterioration prediction

Convolutional Neural Networks (CNN)

CheXNet, RetinalAI, DermAI

Deep learning for spatial feature extraction (LeCun et al. 1998; He et al. ResNet 2016). Detects visual pathology patterns in radiology, fundus and skin images.

USE: X-ray, retinal, dermatology analysis

LSTM / Recurrent Neural Networks

MIMIC-III models, RPM analytics

Sequential time-series processing (Hochreiter & Schmidhuber 1997). Captures temporal dependencies in longitudinal EHR data to model disease trajectories.

USE: ICU deterioration, chronic disease modelling

NLP — BERT / BioBERT / ClinicalBERT

Devlin 2019; Alsentzer 2019

Bidirectional encoders fine-tuned on clinical corpora. Extract medical entities, risk signals, and structured data from unstructured nursing notes and letters.

USE: Note summarisation, symptom flagging, NER

Federated Learning

McMahan et al. 2017

Distributed model training without sharing raw patient data. Local model updates (gradients only) are shared — enabling multi-site AI with full privacy compliance.

USE: Multi-site learning, data governance compliance

Vaswani 2017 | Breiman 2001 | He 2016 | Hochreiter 1997 | Devlin 2019 | McMahan 2017 — all foundational AI references

RISK 1 : CLINICAL ERRORS, HALLUCINATIONS & AI OVERCONFIDENCE

"Generative models like ChatGPT can sound convincing but be factually wrong. They often agree with users even when they're mistaken."

— Assoc. Prof. Liliana Laranjo, Lancet Primary Care 2025

AI Hallucination

LLMs fabricate plausible-sounding but factually incorrect clinical information — medication doses, drug interactions, guideline recommendations. Confidently wrong is dangerous.

Automation Bias

Clinicians over-trust AI outputs and reduce their own clinical vigilance. Documented patient safety risk — especially for NPs working in high-pressure rural environments (Goddard et al., 2012).

Imaging Misidentification

AI surgical navigation errors and fetal anatomy misidentification reported in peer-reviewed litigation cases. CNN models fail on out-of-distribution images not represented in training data.

Medication & Guideline Risk

Open AI tools (ChatGPT, Gemini) may generate incorrect medication doses, outdated guideline recommendations, or missed contraindications — with no indication of uncertainty.

Laranjo L et al., Lancet Primary Care 2025 | Goddard K et al., J Pathol Inform 2012 | Reuters: AI surgical incidents 2026 | AI Healthcare 360: hallucination risks

RISK 2 : AUTOMATION BIAS, INEQUITY & TRAINING DATA GAPS

Automation Bias

When clinicians defer to AI outputs — even when wrong — patient safety is compromised.

- Confidence ≠ accuracy — AI presents wrong answers with identical certainty to correct ones
- Rural NPs face higher risk — time pressure and limited peer consultation increases AI dependence
- Once seen, AI output anchors clinical thinking — even if subsequently doubted (anchoring bias)
- Mitigation: always formulate your assessment BEFORE consulting AI tools (pre-commitment principle)

Algorithmic Bias & Inequity

AI reflects its training data — and training data reflects historical inequity.

- Obermeyer et al. (2019, Science): a widely used US health algorithm systematically disadvantaged Black patients due to biased proxy variables in training data
- Australian training datasets underrepresent Indigenous, rural, CALD and elderly populations — AI outputs may not apply to the patients NPs see most
- Skin condition CNNs trained on light-skinned images fail on darker skin tones — diagnostic accuracy varies by race
- NP responsibility: critically appraise every AI output for population relevance and cultural safety

Obermeyer Z et al., Science 2019 | Goddard K et al., J Pathol Inform 2012 | AIHW Indigenous Health Data 2024 | WHO AI Ethics 2025

RISK 3 : PRIVACY, DATA SOVEREIGNTY & THE OPEN AI DANGER

❌ Open / Public AI Tools

(ChatGPT, Gemini, Copilot — unapproved)

✗ No guarantee of data protection or encryption

✗ No Business Associate Agreement — not HIPAA compliant

✗ Data may be stored, used to retrain models, or accessed by third parties

✗ Patient data entered = potential breach of Australian Privacy Principles

✗ No audit trail — undetectable misuse

✗ Cannot verify accuracy of clinical outputs

✅ Closed / Enterprise AI Systems

(AskSam® — clinically governed)

✓ Controlled clinical environment — no open-internet queries

✓ AES-256 encryption end-to-end — patient data stays with you

✓ ISO 27001 certified, HIPAA compliant, Australian Privacy Act aligned

✓ Full audit trails for every interaction — legal protection

✓ CKG-grounded answers only — no hallucinated content from internet

✓ Patented architecture: hallucination minimisation by design

🔑 **RULE: Never enter patient data into public AI tools unless explicitly approved by your health service. Use only closed, compliant systems.**

RISK 4 : LEGAL LIABILITY, REGULATORY GAPS & CYBERSECURITY

Legal Liability — Who Is Responsible?

When AI contributes to patient harm, liability is currently unclear. Australian courts, regulators and legal scholars agree: existing frameworks were not designed for real-time AI decision-making.

• The Guardian (Oct 2025): "AI could make it harder to establish blame for medical failings"
• Reuters (2026): AI surgical navigation errors linked to patient injuries and lawsuits
• Barry Nilsson (2026): medicolegal liability issues unsettled in Australian law

→ Practical position: You, as the NP, remain clinically and legally accountable — AI does not share liability.

Cybersecurity — The Expanding Attack Surface

AI systems in healthcare create new vulnerability vectors:

• Data tampering / data poisoning: altered training data → incorrect recommendations
• Prompt injection attacks: malicious input manipulates AI behaviour
• Connected device vulnerabilities: smart monitors, infusion pumps, EHR integrations
• Even small successful attacks on AI systems have high clinical impact and delayed detection

→ Example: Altered EHR data → AI generates incorrect sepsis alert → delayed treatment.

Regulatory Gaps

Australian Privacy Principles (APPs) and HIPAA equivalents were designed before real-time AI clinical tools existed.

• TGA AI/ML Guidance (2024) is evolving — not yet fully settled
• Unclear consent requirements for AI-assisted clinical decisions
• Data use agreements with AI vendors may be inadequate
• 'Who owns data entered into an AI system?' remains legally contested

→ NP obligation: Use only compliant, legally vetted systems (e.g. AskSam®). Document AI use in clinical records.

Patient Concerns — WHO Evidence

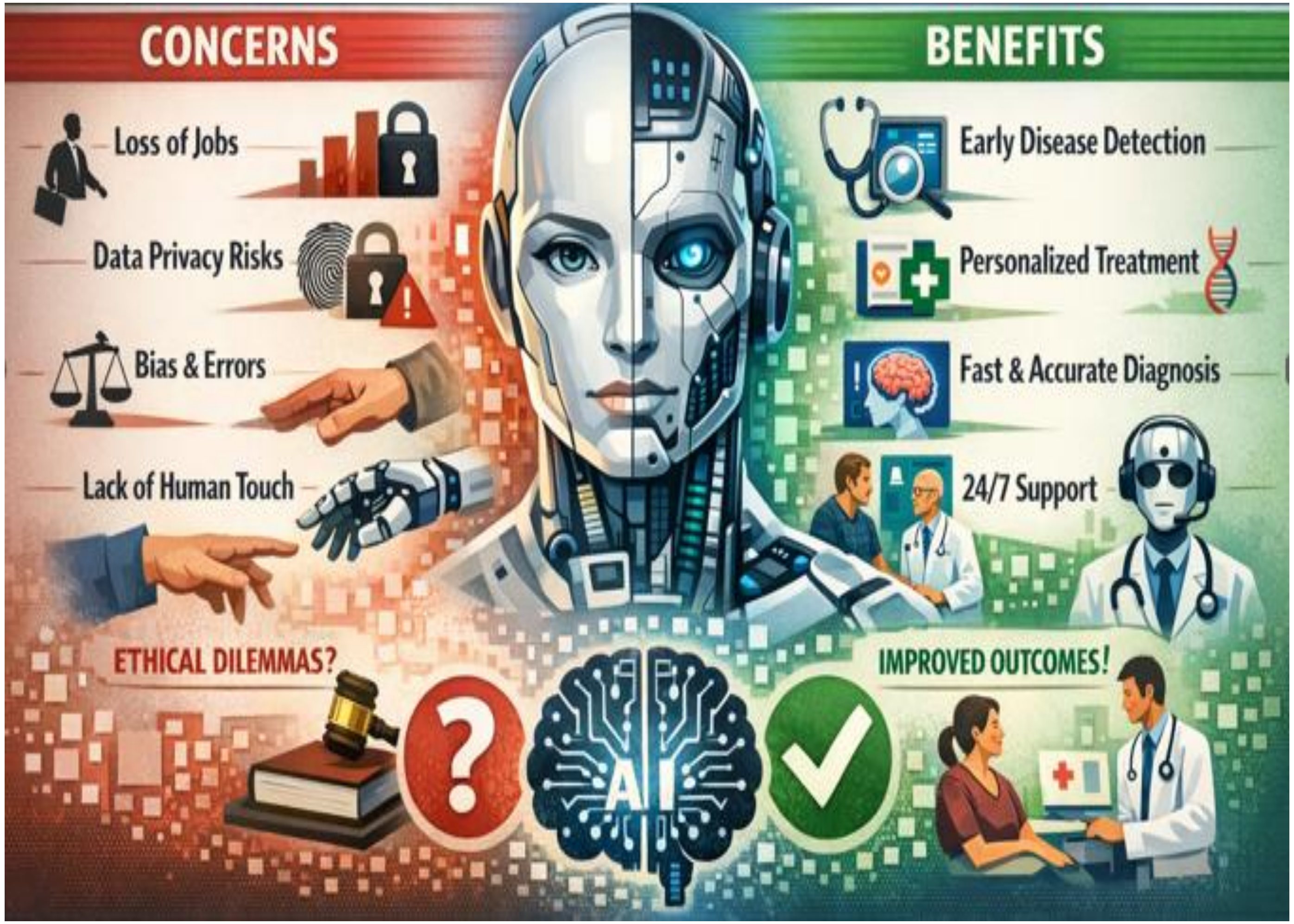
WHO Europe (Nov 2025): Three major patient concerns about AI in healthcare:

1. Patient safety — fear of AI errors causing direct harm
2. Fair access — concern that AI benefits will not reach all populations equitably
3. Digital privacy — uncertainty about data storage, use and third-party sharing

→ NP role: Advocate for AI systems that address all three concerns. Obtain informed consent when AI tools substantively inform clinical decisions.

The Guardian Oct 2025 | Reuters 2026 | Barry Nilsson 2026 | WHO Europe Nov 2025 | ArXiv: cybersecurity data poisoning | TGA AI/ML Guidance 2024

Final Thoughts



1. If you can not explain the AI technology that you are using, then you should not use it
2. Nurses and Midwives should be building the AI models.
3. We can fundamentally shift from compliance task completion to healing using AI.
4. There is a need to think about Privacy and Data Sovereignty.

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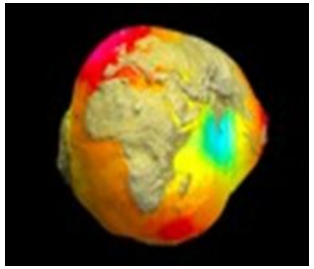

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