AI Applications in Healthcare

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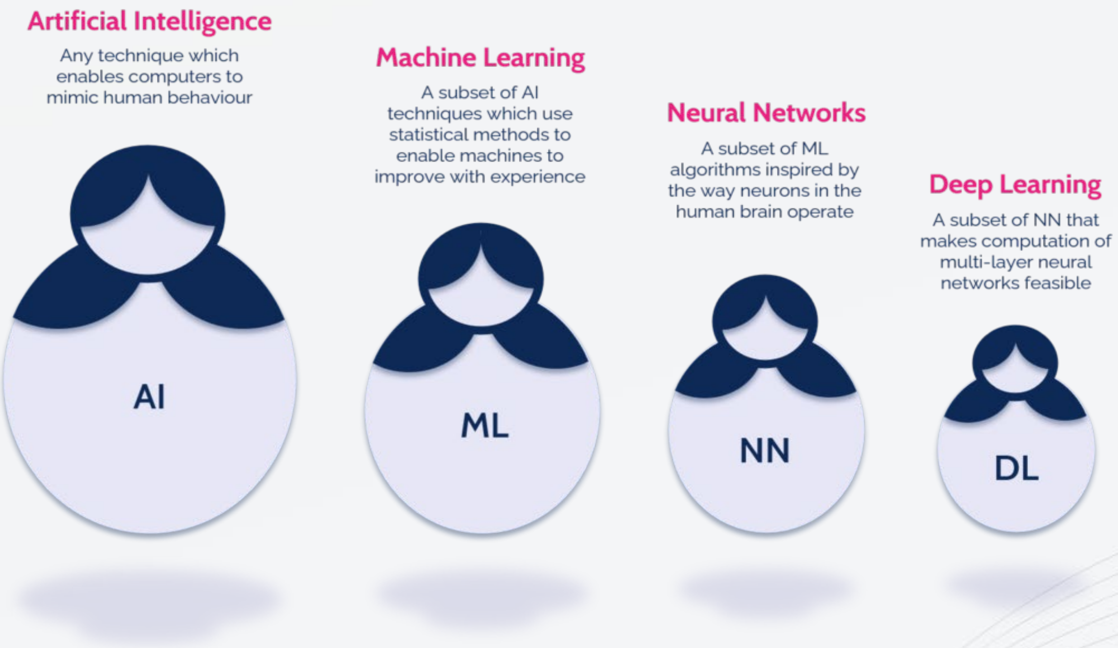
Overview of AI Concepts

Defining AI

Artificial Intelligence is defined as the ability of a digital computer or computer controlled robot to perform tasks commonly associated with intelligent beings.

Natural Language Processing (NLP): A field of AI that focuses on enabling computers to understand, interpret, and generate human language.

Computer Vision: A field of AI that focuses on enabling computers to "see" and interpret images and videos.

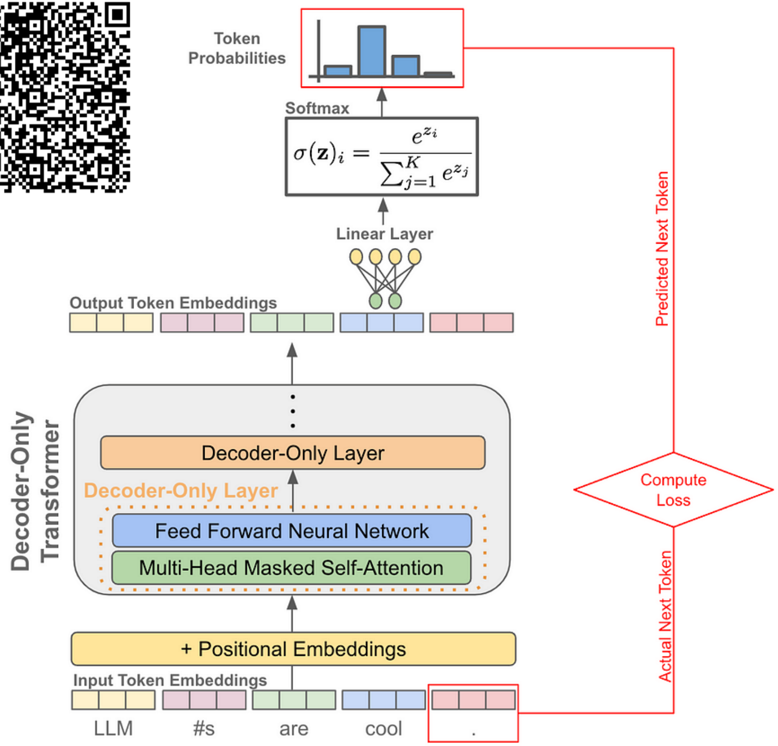


([2023 AMA position statement on AI in Healthcare](#))

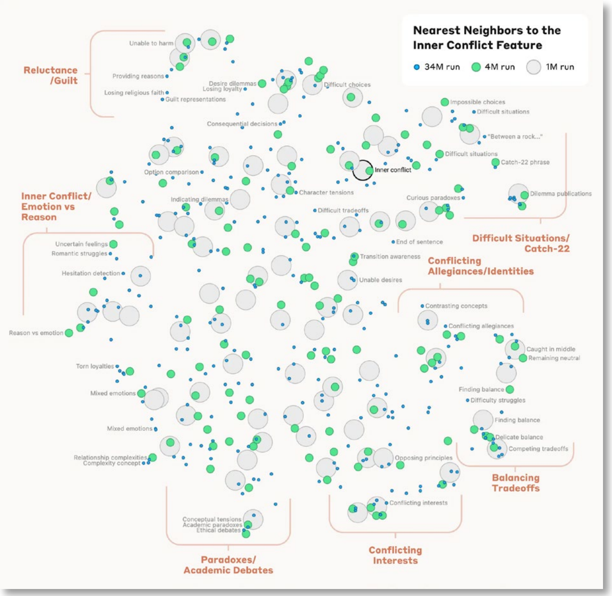
[Machine Learning in healthcare – A brief introduction](#)

Large Language Models (LLMs)

LLMs (like ChatGPT - Generative Pre-trained Transformer) are trained with language samples (i.e. the internet) and learn vocabulary and the probabilities of how words are arranged relative to each other – at different scales of distance. They then 'just' predict the next word in a sequence (termed 'next token prediction')



Next word-prediction generates a conceptual map of language; these maps can be altered by changing LLM 'wiring'



Anthropic AI - Transformer Circuits Thread: Mapping the Mind of a Large Language Model; Scaling Monosemanticity – *extracting features from Claude 3 Sonnet*

Large Language Models (LLMs)

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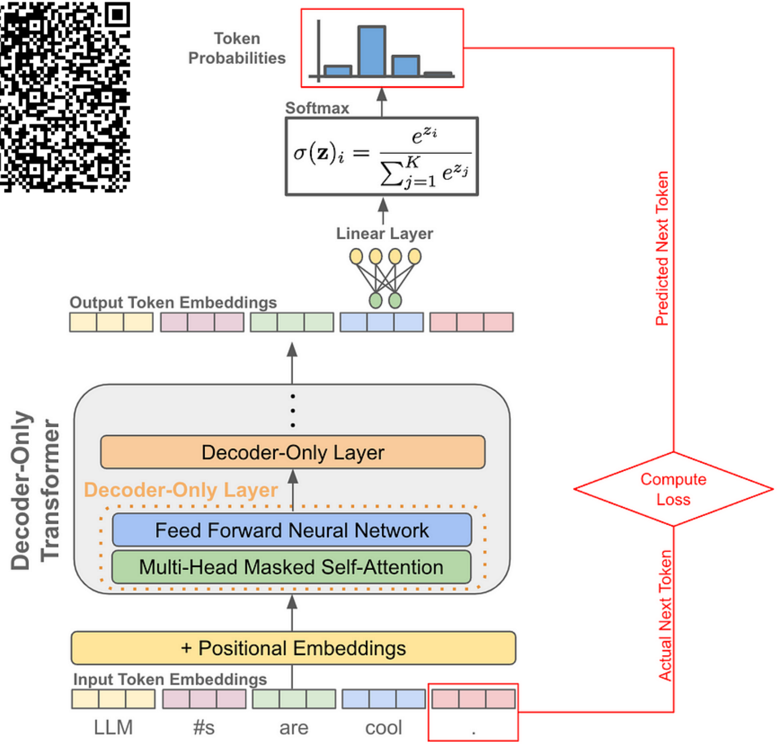
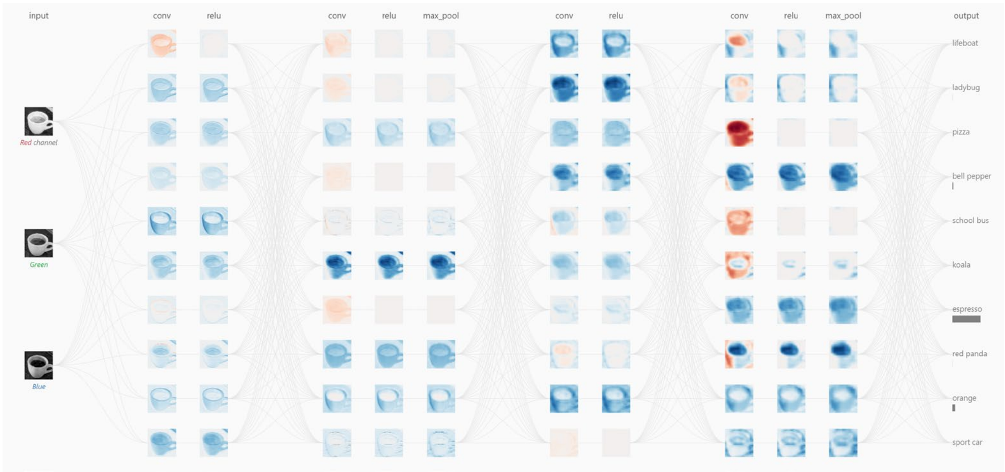


Convolutional Neural Networks (CNNs)

A **CNN** is a neural network: an algorithm used to recognize patterns in image data. CNNs are trained on large image sets, often annotated to define known objects (e.g. cats or cancer). They then learn to detect these objects in new images, classifying them into categories.



CNN Explainer:
Learn Convolutional Neural Network (CNN) in your browser

State of AI in Healthcare

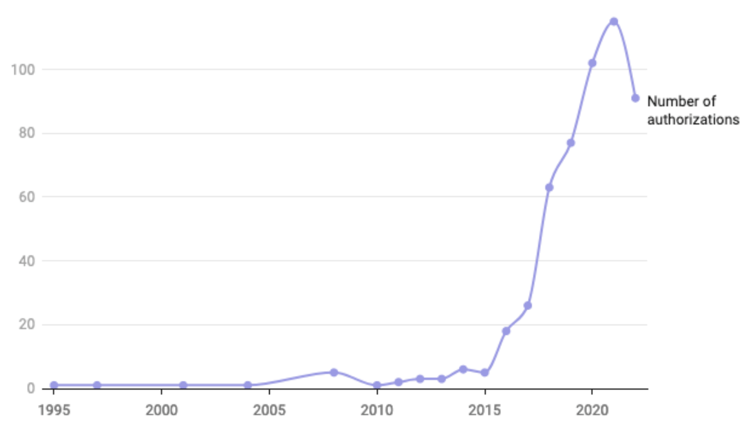
Global Trends

Global investment in healthcare AI has seen dramatic growth:

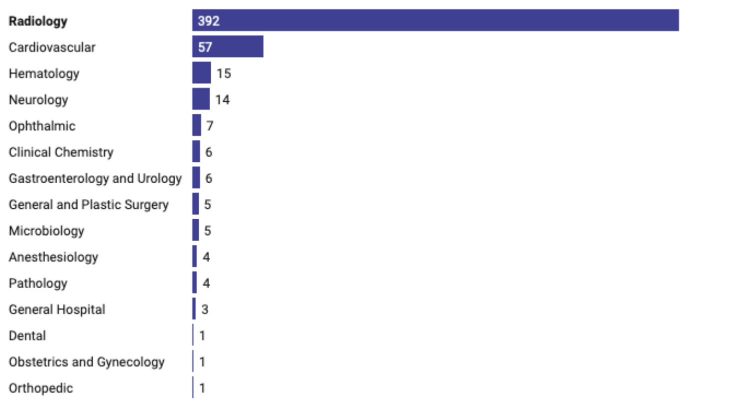
The global healthcare AI market was valued at $15.4 billion in 2022 and is projected to reach $187.95 billion by 2030, growing at a CAGR of 37.5% (Grand View Research, 2023: (https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-healthcare-market)

By January 2023, the FDA had approved over 520 AI and ML algorithms for medical use. Most of these are related to medical imaging and healthcare image and video analysis, and diagnoses, so in the majority of use cases, these are computer vision (CV) models. (https://encord.com/blog/ai-algorithm-fda approval/#:~:text=The%20FDA%20first%20approved%20the,granted%20FDA%20approval%20in%202023)

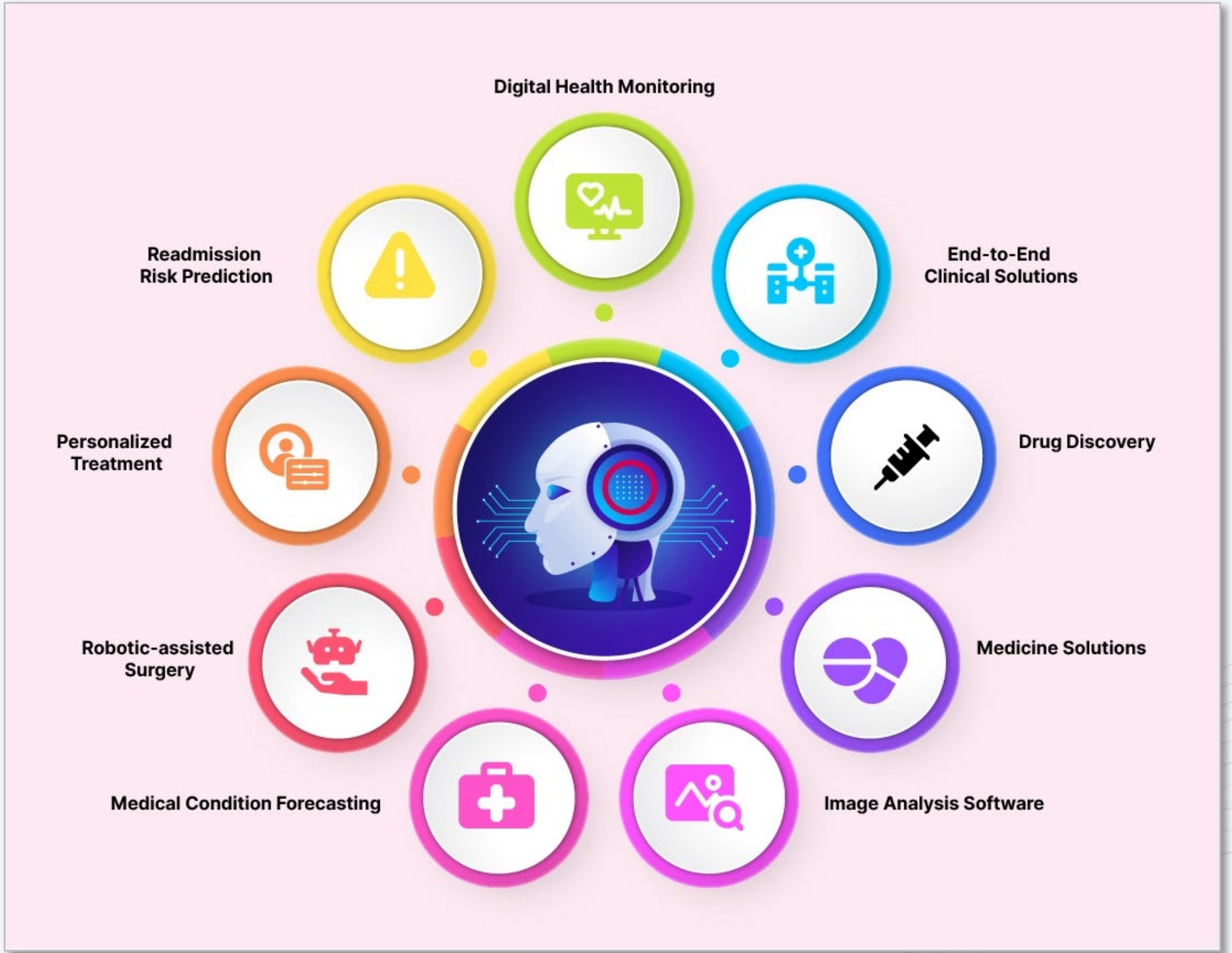
Number of approvals and clearances by the Food and Drug Administration per year.



Number of devices by FDA panel, 1995-2022.



Applications of AI in Healthcare



AI in Electronic Health Record Analysis

NLP in Healthcare

Use of Natural Language Processing with LLMs in clinical notes.

Predictive Analytics

Predictive analytics for assessing patient risks.

Automated Processes

Automated coding, documentation, and clinical decision support systems.

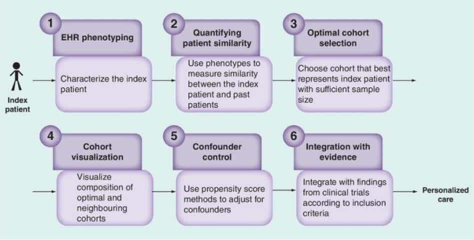
3. Causal AI: Guiding clinical decision-making by estimating heterogeneity of treatment effects from large routinely collected health data

Key points

- We have developed an analytics framework and methodology for measuring and reporting on the use and effectiveness of interventions in heterogenous populations as used in routine care.
- These methods have been used to analyse the effect of: (1) electroconvulsive therapy in patients with severe psychotic disorders; (2) percutaneous catheter ablation in patients with atrial fibrillation; and (3) vitamin D in patients with osteoarthritis.
- The tools generated by this project are being compiled into a CausalAI software package, which can be used by researchers and regulators to address comparative effectiveness questions.

Key links

- Bringing cohort studies to the bedside: framework for a 'green button' to support clinical decision-making. *Journal of Comparative Effectiveness Research* (2015) https://doi.org/10.2217/cer.15.12
- Comparing methods for estimation of heterogeneous treatment effects using observational data from health care databases. *Statistics in Medicine* (2018) https://doi.org/10.1002/sim.7820
- Estimating incidence rates of periprosthetic joint infection after hip and knee arthroplasty for osteoarthritis using linked registry and administrative health data. *The Bone and Joint Journal* (2022) https://doi.org/10.1302/0301-620X.104B9.BJJ-2022-0116.R1
- Targeted estimation of heterogeneous treatment effect in observational survival analysis. *Journal of Biomedical Informatics* (2020) https://doi.org/10.1016/j.jbi.2020.103474



Gallego, Blanca, et al. "Bringing cohort studies to the bedside: framework for a 'green button' to support clinical decision-making." Journal of comparative effectiveness research 4.3 (2015): 191-197.

Figure 1. Proposed process for generating real-time cohort studies at the point of care.

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AI in Medical Imaging & Radiomics

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AI in Imaging

Radiology leads AI adoption, with 30% of practices using some form of AI for image analysis (American College of Radiology Data Science Institute, 2022: (https://www.acrdsi.org/DSI-Services/Define-AI)

AI-powered image interpretation with Convolutional Neural Networks (CNNs).

Detection and Radiomics

- Automated lesion detection & measurement
- Radiomics feature extraction

Research Imaging NSW

Medical imaging and image analysis:
- In humans or animals
- For clinical questions and modality use / optimisation
- With Medical Imaging Analytics (e.g. Radiomic analysis, Deep Learning)

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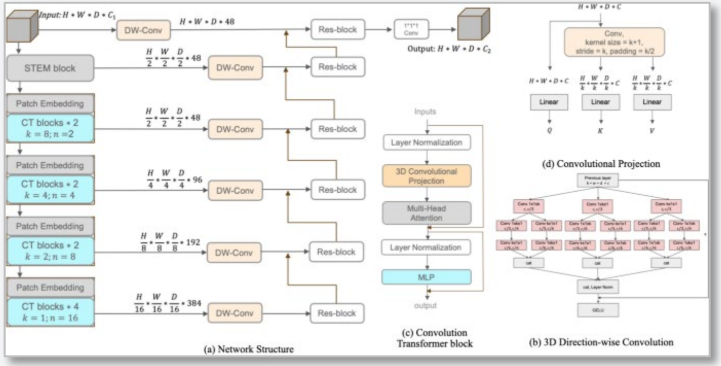
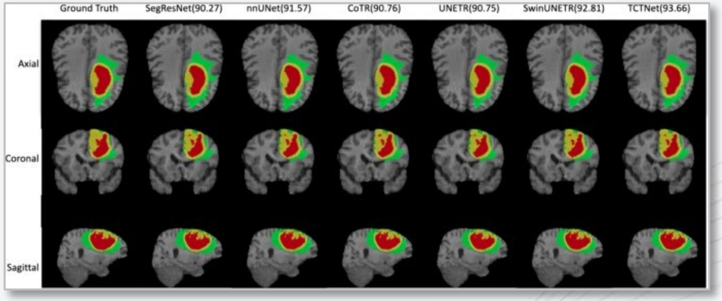




Chu, Z., Singh, S., and Sowmya, A. (2024). Robust Automated Tumour Segmentation Network Using 3D Direction-Wise Convolution and Transformer. J. Imaging Inform. Med. *37*, 2444–2453. https://doi.org/10.1007/s10278-024-01131-9

AI in Digital Pathology

1 **Automated Analysis**

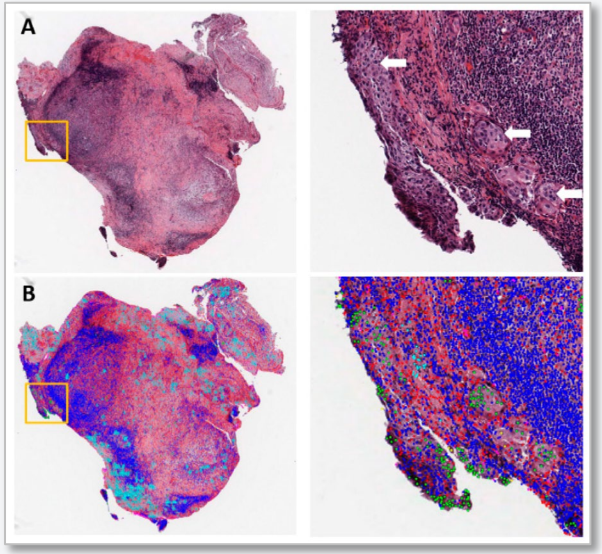
Automated slide analysis for cancer detection and grading.

2 **Quality Improvement**

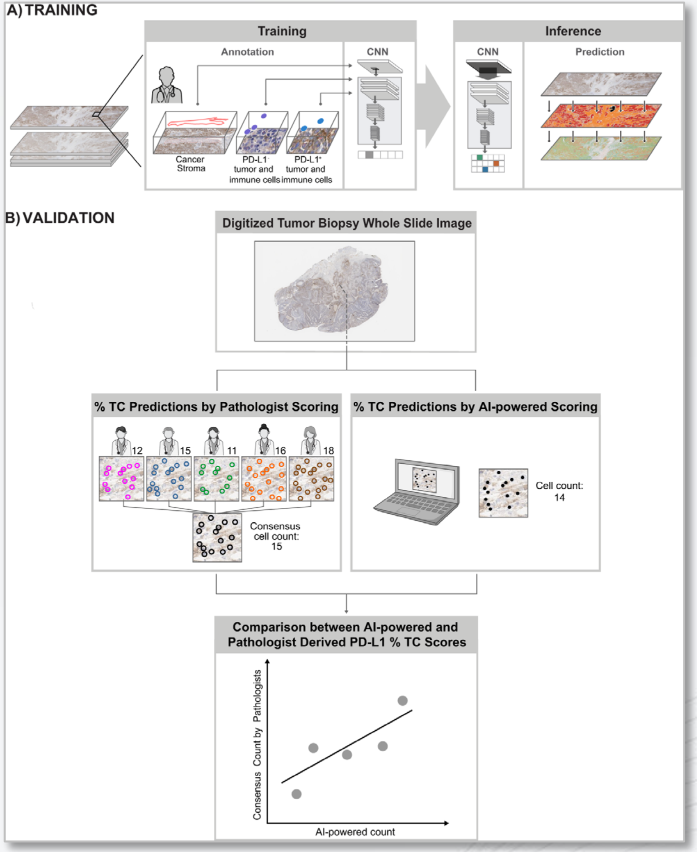
Quality control, standardization, and workflow optimization in diagnostics.

3 **Diagnostic Accuracy**

Impact of digital pathology on diagnostic accuracy.



Wang, S., Yang, D.M., Rong, R., Zhan, X., Fujimoto, J., Liu, H., Minna, J., Wistuba, I.I., Xie, Y., and Xiao, G. (2019). Artificial Intelligence in Lung Cancer Pathology Image Analysis. Cancers *11*, 1673. https://doi.org/10.3390/cancers11111673



Baxi, V., Lee, G., Duan, C., Pandya, D., Cohen, D.N., Edwards, R., Chang, H., Li, J., Elliott, H., Pokkalla, H., et al. (2022). Association of artificial intelligence-powered and manual quantification of programmed death-ligand 1 (PD-L1) expression with outcomes in patients treated with nivolumab ± ipilimumab. Mod. Pathol. *35*, 1529–1539. https://doi.org/10.1038/s41379-022-01119-2

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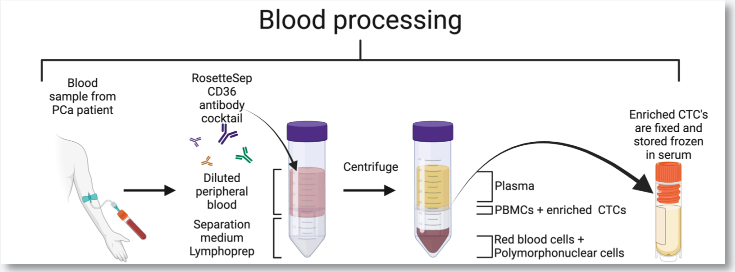
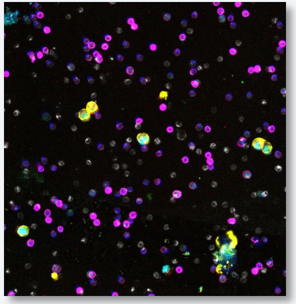
AI in Precision Medicine: *Supporting Clinical Decision-Making*

Precision Medicine, Biomarker Discovery & Patient Stratification

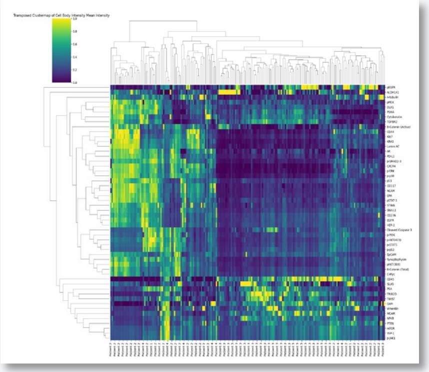
AI extracts patterns from patient molecular sampling (Omics)

- Guides optimal therapy selection and biomarker discovery
- Enables to targeted patient stratification to clinical trials



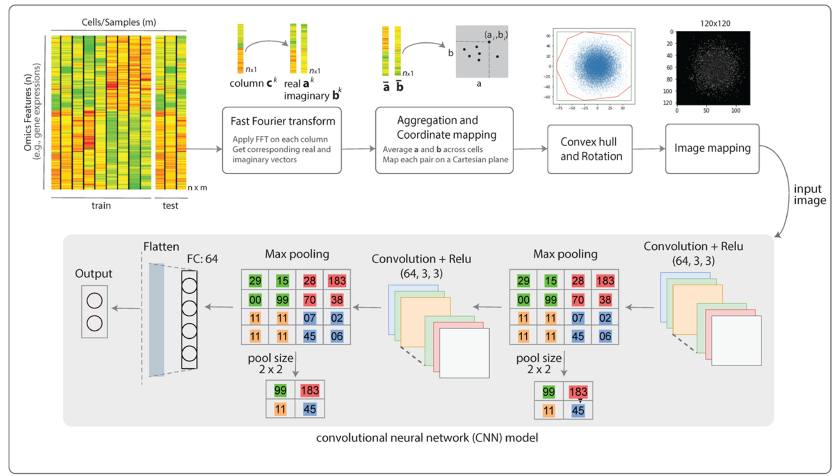


Circulating Tumour Cell Imaging



Multi-modal Data Integration

AI integrates genomic, proteomic, lipidomic, metabolomic data to detect disease states



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AI in Drug Discovery & Development

Computational Biology

Using computational structural biology and ‘Alphafold’

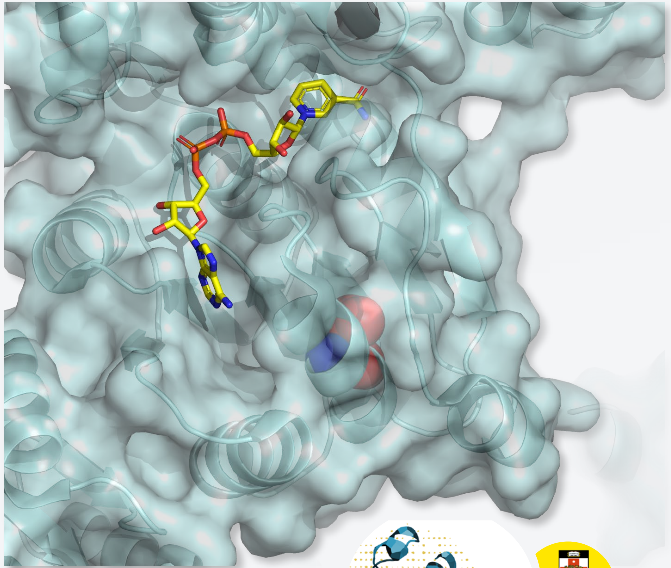
Optimization

Target identification, drug-protein interaction prediction

Efficiency

Reducing cost & time in drug development (protein structure = ~~1 year~~ = 12.5 hours, $70)

- Structure of a single protein with generally high accuracy
- Some structures of complexes
- Diffusion models can help design protein ‘binders’
- ‘Mixed’ chemistry- eg. proteins AND nucleic acid, protein AND drug models



- Alphafold used to predict mutant protein structure given mutations found in Australian children with congenital and early onset muscle disorders.
- Helped identify molecular mechanism of disease & provided a means of diagnosis for several clinical cases.
- Results in one case have already filtered through to directing therapeutic
- **Dr Emily Oates**, UNSW Faculty of Science

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UNSW SYDNEY

Remote Patient Monitoring: AI detects & predicts health events

1

Technology Integration

Integrating wearable technology for real-time health monitoring and early warnings.

2

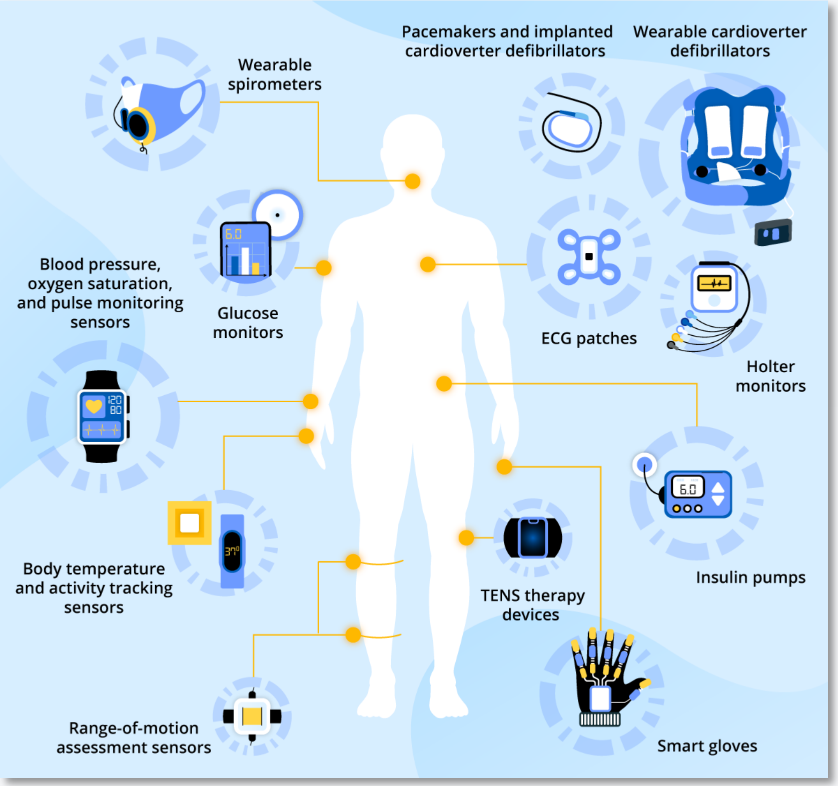
Telehealth

Advancements in telehealth services

3

Patient Compliance

Improving patient engagement and compliance.



- TeleClinicalCare (TCC), UNSW Graduate School of Biomedical Engineering
- Professor Nigel Lovell
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Already working with SESLHD for monitoring of patients at risk of heart failure

AI to Enhance Laboratory Medicine & Patient Experience

Automation & Quality Control in Laboratory Medicine

Specimen processing automation: AI guides robotic systems to improve specimen handling, reducing manual steps and minimizing contamination

Automated result verification: AI validates test results before release, flagging outliers that require manual review while auto-releasing normal results

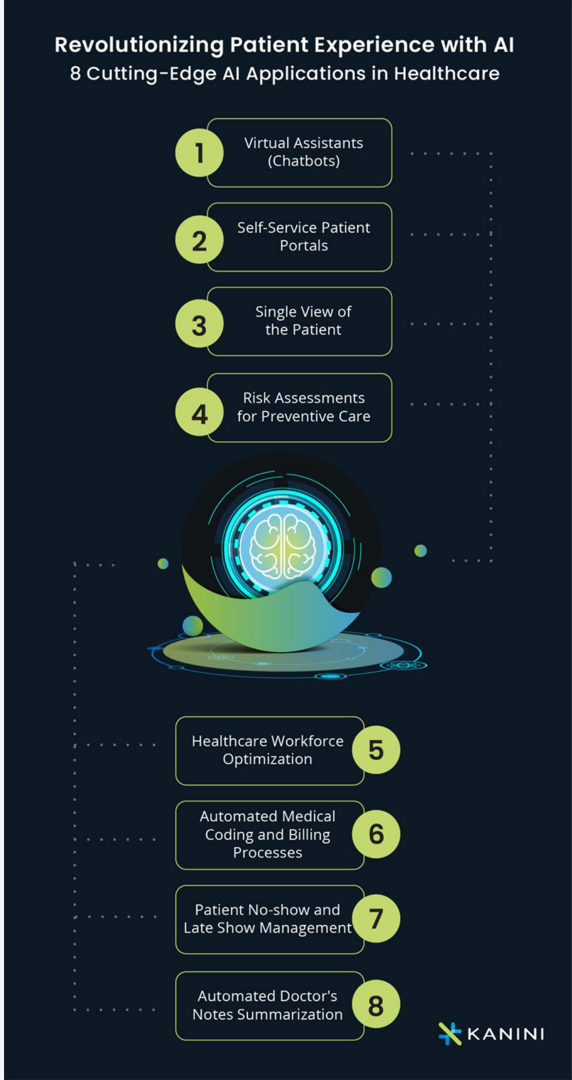
Workflow optimization: AI predicts laboratory workloads and optimizes scheduling of tests, staff, and equipment

Error detection: AI identifies preanalytical, analytical, and postanalytical errors through pattern recognition in laboratory data

Patient Experience Enhancement

Chatbots: for appointment scheduling, patient education, and follow-up care

Medication reminders: including integration with wearables



Challenges and Implementation

1

Ethical Issues

Addressing data privacy, security, and bias in AI training.

2

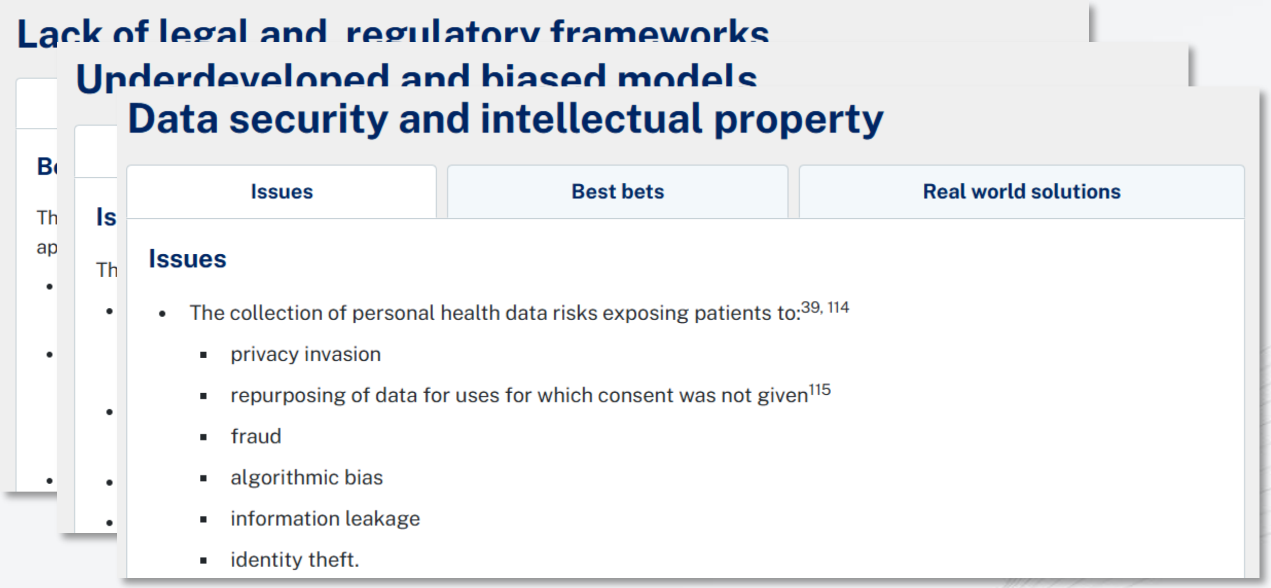
System Integration

Challenges in integrating AI with existing systems and staff training.

3

Regulations

Regulatory compliance, governance & ethics issues.



NSW Agency for Clinical Innovation,
Critical Intelligence Unit:
‘AI system implementation issues and risk mitigation’

International Regulatory Bodies & AI

Key Initiatives

FDA Digital Health Center

The FDA has established the Digital Health Center of Excellence to advance regulatory approaches for digital health technologies (https://www.fda.gov/medical-devices/digital-health-center-excellence)

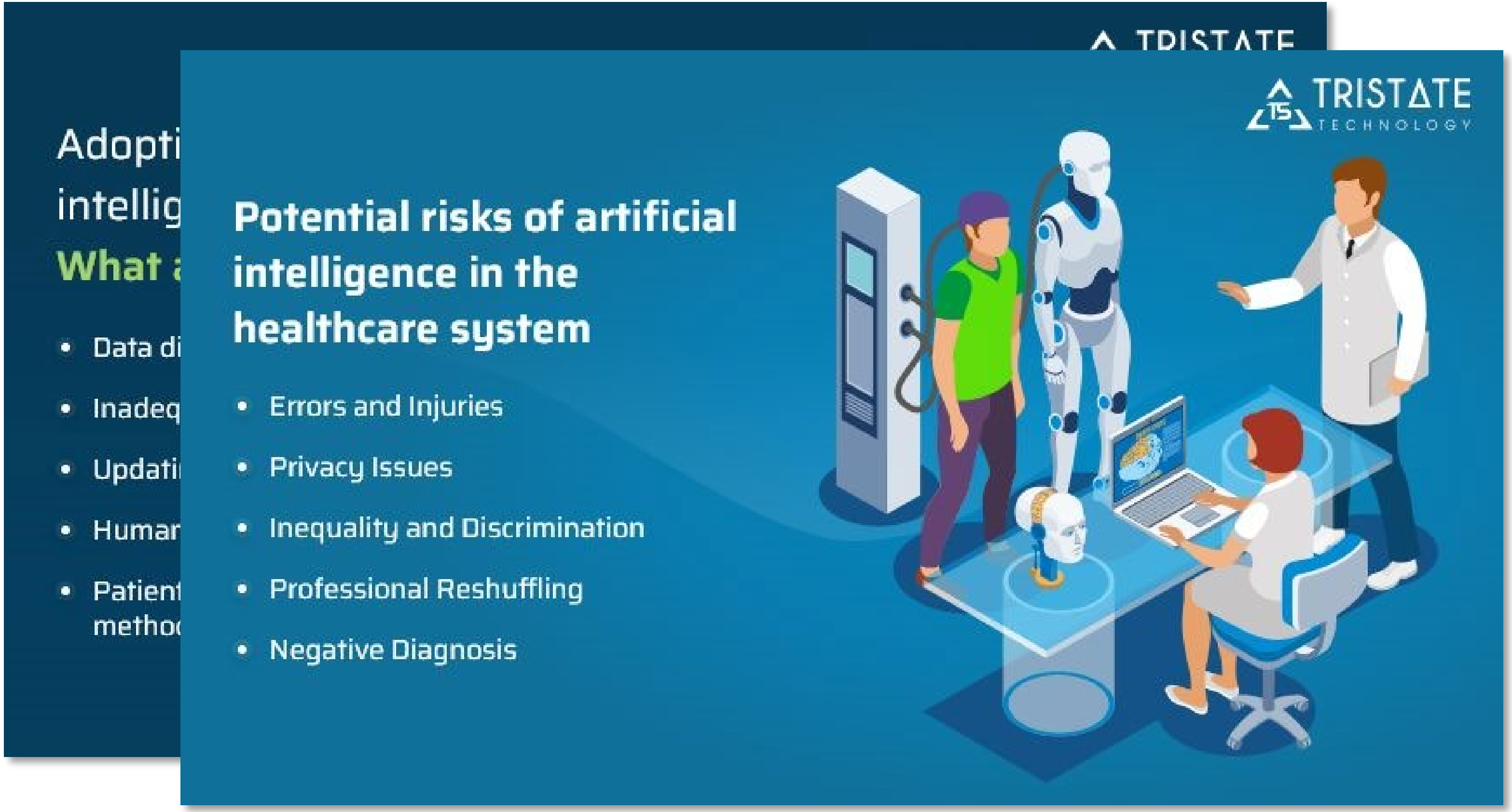
EMA Regulatory Science Strategy

The European Medicines Agency released its Regulatory Science Strategy, emphasizing AI regulation in healthcare (https://www.ema.europa.eu/en/about-us/how-we-work/regulatory-science-strategy)

WHO AI Guidance

In 2023, the WHO published its guidance on ethics and governance of AI for health (https://www.who.int/publications/i/item/9789240029200)

Challenges & Risks of AI in Healthcare



Near-term Trends in Health AI

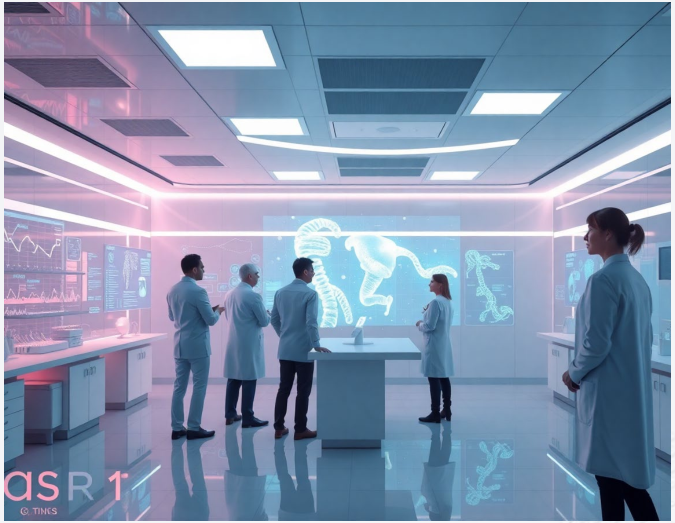
Emerging Trends

Generative AI for clinical documentation: AI assists in generating notes, summarizing encounters, and extracting key information from medical records

Ambient clinical intelligence: AI systems passively listen to patient-provider conversations to document encounters without manual data entry

Federated learning: AI models train across multiple healthcare institutions without sharing sensitive patient data, enabling broader collaboration

Foundation models for healthcare: Large language models fine-tuned with a focus on healthcare data, rather than general domain data / knowledge



Agentic AI

Agentic AI systems act autonomously to accomplish set goals. These systems go beyond responding to direct queries and can:

- Take initiative to plan and execute multi-step actions without constant human direction
- Persist toward goals across multiple interactions or sessions
- Make decisions based on contextual understanding and learned preferences
- Use tools and external systems such as web browsers, APIs, or applications to complete tasks

Multi-agent AI: A game changer for healthcare innovation
- Pariveda Strategy

Multi-Agent AI

Multi-Agent AI systems include multiple AI agents collaborating to achieve shared objectives. Each agent acts independently while exchanging information and coordinating with other agents. This enables complex task completion.

Key principles include:

Autonomy: Each AI agent can act independently, making decisions based on available information & protocols.

Collaboration: Agents also act together, sharing insights and resources to accomplish complex tasks.

Communication: Robust communication frameworks allow agents to exchange information in real-time.

Coordination: Synchronizing the activities of multiple agents ensures they function harmoniously toward common objectives.

AI in Healthcare: Multi-Agent Systems for Better Outcomes
- Integrail


3


https://youtube.com/clip/UgkxHs1b6YtYHmb0DnvZIvQuYnAFwAELctVN?si=DFJ_wOmyftjkMH98

Key Messages

- For the foressable future, AI remains a tool to augment the capabilities of healthcare professionals
- AI requires human oversight, clinical judgment, as well as legal, ethical and integrative frameworks
- Huge potential benefits for both clinicians and patients in terms of outcomes, efficiencies – **but risks are real**, and at many levels
- Focused applications may optimise trade-offs (reward vs risk)

Is has been said that:

"AI won't replace people in the workforce…

People who use AI effectively will replace people who don't…"

Time will tell on both possibilities

AI Applications in Healthcare

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