Artificial Intelligence in Healthcare and Clinical Medicine

What will this mean for life and health insurance in Asia-Pacific?

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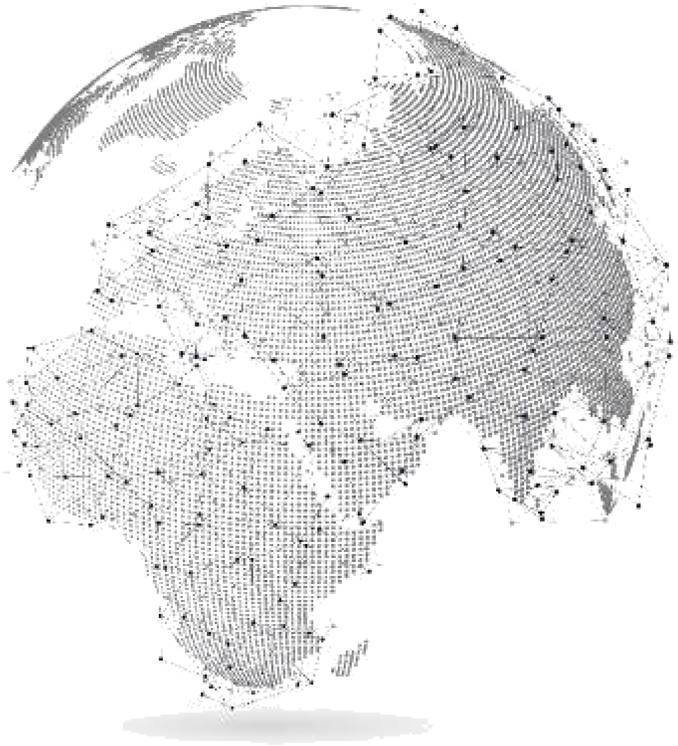

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A.I. applications in healthcare

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01

Medical research – clinical trials

02

Health assistance

03

Disease detection and diagnosis

04

Precision medicine

05

Prognosis/ Triaging – Mining EHR

A.I. applications in healthcare

Examples: outpatient and inpatient

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Clinical trial (CT) support

All phases of CT can be supported:

Preclinical, design, recruitment, conduct and analysis

Health assistance

Examples

- Medication adherence tools
- Virtual nurses, remote measurement of vital parameters

Disease detection and diagnosis

Examples

- Imaging analysis in radiology, endoscopy, ultrasound, ophthalmology
- Mental Health screening via voice and video analysis

Precision medicine

Example

Target identification, detection of new compounds, toxicity prediction

Prognosis and triaging tools

Example

Mining EHRs to predict clinical outcome inpatient and outpatient

A.I. in clinical trials

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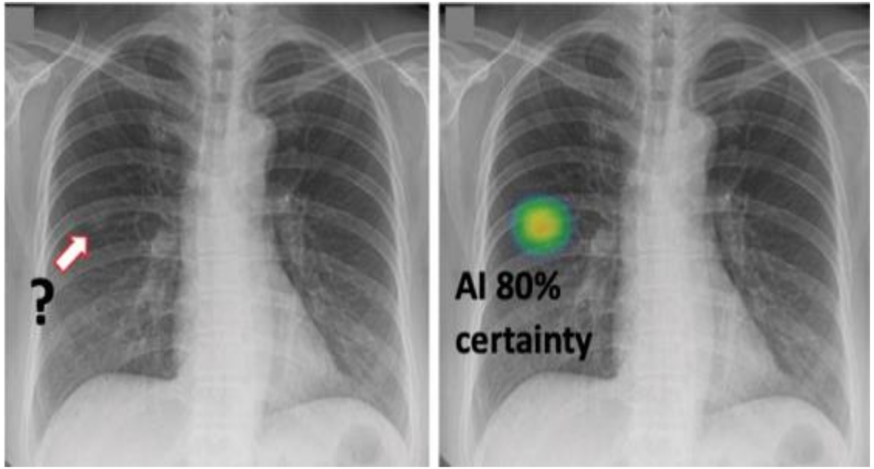
	Pre-clinical	Design	Recruitment	Conduct	Analysis
Therapeutic areas	Endocrine Oncology	Cardiovascular Infectious disease Oncology	Cardiovascular Endocrine Infectious disease Mental health Neurology Oncology Respiratory	Cardiovascular Infectious disease Mental health Neurology	Cardiovascular Infectious disease Neurology Oncology Respiratory
Opportunities	▪ Enhance and accelerate identification of new targets ▪ Predict toxicity, including serious side effects ▪ Identify higher risk compounds	▪ Identify fast progressors, to reduce trial length ▪ Predict and prevent patient dropouts ▪ Reduce trial sample size ▪ Improve hypothesis generation ▪ Predict tumor response and survival rates ▪ Optimize trial and protocol design ▪ Predict probability of trial and/or regulatory success ▪ Reduce the number of trial arms by using synthetic data	▪ Match potential trial participants with CTs ▪ Automated trial recommendations ▪ Accelerate site initiation and recruitment based on investigators ranking	▪ Improve safety oversight and CT measurements via near real time visualizations using AI-based sensors/wearables ▪ Improve medication adherence ▪ Automated annotation of medical images ▪ Improve workflow for medical imaging classification	▪ Identify key risk factors and fast responders ▪ Enable more comprehensive and insightful analysis ▪ Better handling of missing data ▪ Robust mechanism for imputing patient's condition for missed visits ▪ Automated data extraction, with reduced human error
Challenges	▪ Lack of open-source PK and PD data sets to build models ▪ Model interpretation and explainability based on biomolecular mechanism	▪ Lack of good quality, curated and complete datasets ▪ Validation of synthetic control arms ▪ Collaborative building of protocols for collection, archive and organization of large datasets	▪ Complex protocol design and inclusion/exclusion criteria ▪ Lack of standard language for eligibility criteria	▪ Building up a repository of good, standardized images required for algorithm training ▪ Knowledge and usability of sensors and wearables by participants	Validation of Algorithms and acceptance of results for regulatory approval

Source: Askin S. et al: "Artificial Intelligence Applied to clinical trials: opportunities and Challenges", Health and Technology (2023) 13:203–213, graphic modified

A.I. in radiology

Can AI assist in assessment of imaging?



- Controlled trial of 10,476 heath check-up participants randomised to either AI or non-A.I. groups for chest x-ray evaluation
- Detection of actionable nodules increased with A.I. (odds-ratio 2.4)
- The detection rate for malignant lung nodules was higher in the A.I. group compared with the non-A.I. group (0.15% vs 0.0%)
- The A.I. and non-A.I. groups showed similar false referral rates (45.9% vs. 56%)

Source: Nam et al: " AI improves Nodule Detection on Chest Radiographs in a Health Screening Population: A randomized controlled trial", https://doi.org/10.1148/radiol.221894

Large language models (LLMs)


Article

Health system-scale language models are all-purpose prediction engines

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Physicians make critical time-constrained decisions every day. Clinical predictive models can help physicians and administrators make decisions by forecasting clinical and operational events. Existing structured data-based clinical predictive models have limited use in everyday practice owing to complexity in data processing, as well as model development and deployment[1–3]. Here we show that unstructured clinical notes from the electronic health record can enable the training of clinical language models, which can be used as all-purpose clinical predictive engines with low-resistance development and deployment. Our approach leverages recent advances in natural language processing[4,5] to train a large language model for medical language (NYUTron) and subsequently fine-tune it across a wide range of clinical and operational predictive tasks. We evaluated our approach within our health system for five such tasks: 30-day all-cause readmission prediction, in-hospital mortality prediction, comorbidity index prediction, length of stay prediction, and insurance denial prediction. We show that NYUTron has an area under the curve (AUC) of 78.7–94.9%, with an improvement of 5.36–14.7% in the AUC compared with traditional models. We additionally demonstrate the benefits of pretraining with clinical text, the potential for increasing generalizability to different sites through fine-tuning and the full deployment of our system in a prospective, single-arm trial. These results show the potential for using clinical language models in medicine to read alongside physicians and provide guidance at the point of care.

Physicians make difficult decisions every day requiring the integration of a tremendous amount of information. The information needed to make these medical decisions is scattered across various records, for example, a patient's medical history and laboratory and imaging reports. When physicians perform their work, however, all of this information is ultimately integrated into the notes written by physicians to document and summarize patient care.

Clinical predictive models are frequently derived from rules that have existed for decades[6–9], as well as from machine learning methods[10–12], with most relying on structured inputs pulled from the electronic health record (EHR) or direct clinician inputs. This reliance on structured inputs introduces complexity in data processing, as well as in model development and deployment, which in part is responsible for the overwhelming majority of medical predictive algorithms being trained, tested and published, yet never deployed to assess their impact on real-world clinical care. This is frequently referred to as the 'last-mile problem' (refs. 1–3).

One of the most exciting recent developments in modern artificial intelligence (AI) research is large language models (LLMs). These massive neural networks (with millions or even billions of parameters) have been shown to obtain impactful results on a wide range of problems that rely on the reading and interpretation of human language. Several styles of LLMs have been developed over the past few years, broadly ranging from encoder models (such as BERT[4]) to decoder models (such as GPT3; ref. 5). We theorized that LLMs could potentially solve the last-mile problem in medical predictive analytics by simply reading the notes written by physicians, thereby immediately accessing a comprehensive description of a patient's medical state to provide decision support at the point of care across a wide range of clinical and operational tasks.

Here we present our results from developing, evaluating, deploying and prospectively assessing NYUTron, an LLM-based system that can integrate in real time with clinical workflows centred around writing notes and placing electronic orders. Our approach relies on the fact that all clinically useful data and medical professionals' decision-making

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- Large language models are A.I. systems designed to process and analyse vast amounts of unstructured natural language data and then use that information to generate responses to user prompts
- In this study, unstructured clinical notes from EHR enabled the training of clinical language models, used as predictive engines for:

30-day all-cause readmission + In-hospital mortality + Comorbidity index + Length of stay + Insurance denial prediction

Source: Jiang LY et al: "Health system-scale language models are all-purpose prediction engines", Nature 619, 357-362 (2023)

A.I. in healthcare

Potential benefits and challenges in the clinical setting

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Benefits

Performing medical studies as well as drug development will become more efficient and faster

Relevant diagnostic interventions can be scaled up and previous undersupply can be reduced

Shortage of medical stuff can be countered by 24h working AI applications

Risk prediction of diseases/impairments will improve

Outcome of diseases/impairments will improve

Challenges

Transparency–reasoning is not a by-product of algorithms

Data protection – privacy issues (example European Union)

Quality of data used for the models

Legal challenges – liability

Trust of patients and medical doctors

A.I. in healthcare

Potential benefits and challenges for life and health insurance

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Benefits

Improvement of outcomes in applicants with risk factors and existing impairments

Remote identification of risk factors or underlying impairments

Examinations at point of UW might be carried out by non-specialists

Availability of long-term control of diseases/adherence to treatment data – improved prediction – continuous UW

Challenges

Prediction models might be anti-selective, depending on access

Validation questions and trust in technology

Regulatory environment

Costs

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