

ASCH

2026

**ANNUAL SCIENTIFIC
MEETINGS & WORKSHOPS**

New Frontiers in Hypnosis:
Human Ingenuity, AI Innovation,
and Ethical Boundaries

 **VIRTUAL**

March 20–22, 2026

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- **Matthew Wong, MD** is a clinical neurologist and Clinical Assistant Professor specializing in neurology and epilepsy care at Wake Forest University School of Medicine. He earned his medical degree from McMaster University in Ontario, Canada, and completed his neurology residency as well as a fellowship in clinical neurophysiology and epilepsy at the University of Virginia.
- In addition to his clinical work, he has a practical interest in the application of large language models in medicine. Before medical school, he worked as a software developer, with his first role focused on expert systems for complex hardware configuration.

Disclosures

ASCH and ASCH-ERF jointly provided this program.

No staff or committee members involved in the development, planning or execution of educational content have any financial relationships or conflicts of interest to disclose.

Matthew Wong has no significant financial relationships or conflicts of interest to disclose.

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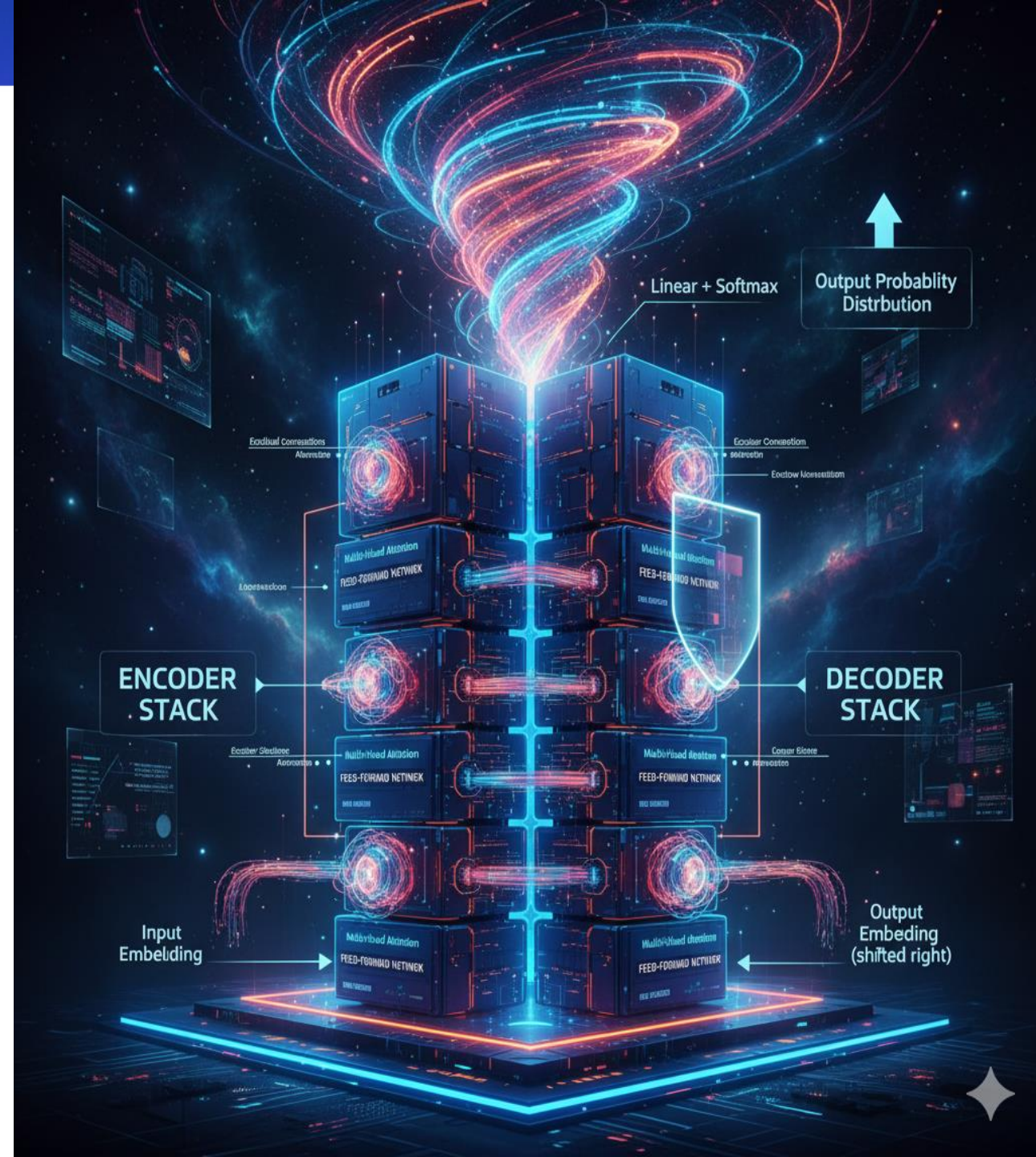
The Growing Utility of AI in Medicine

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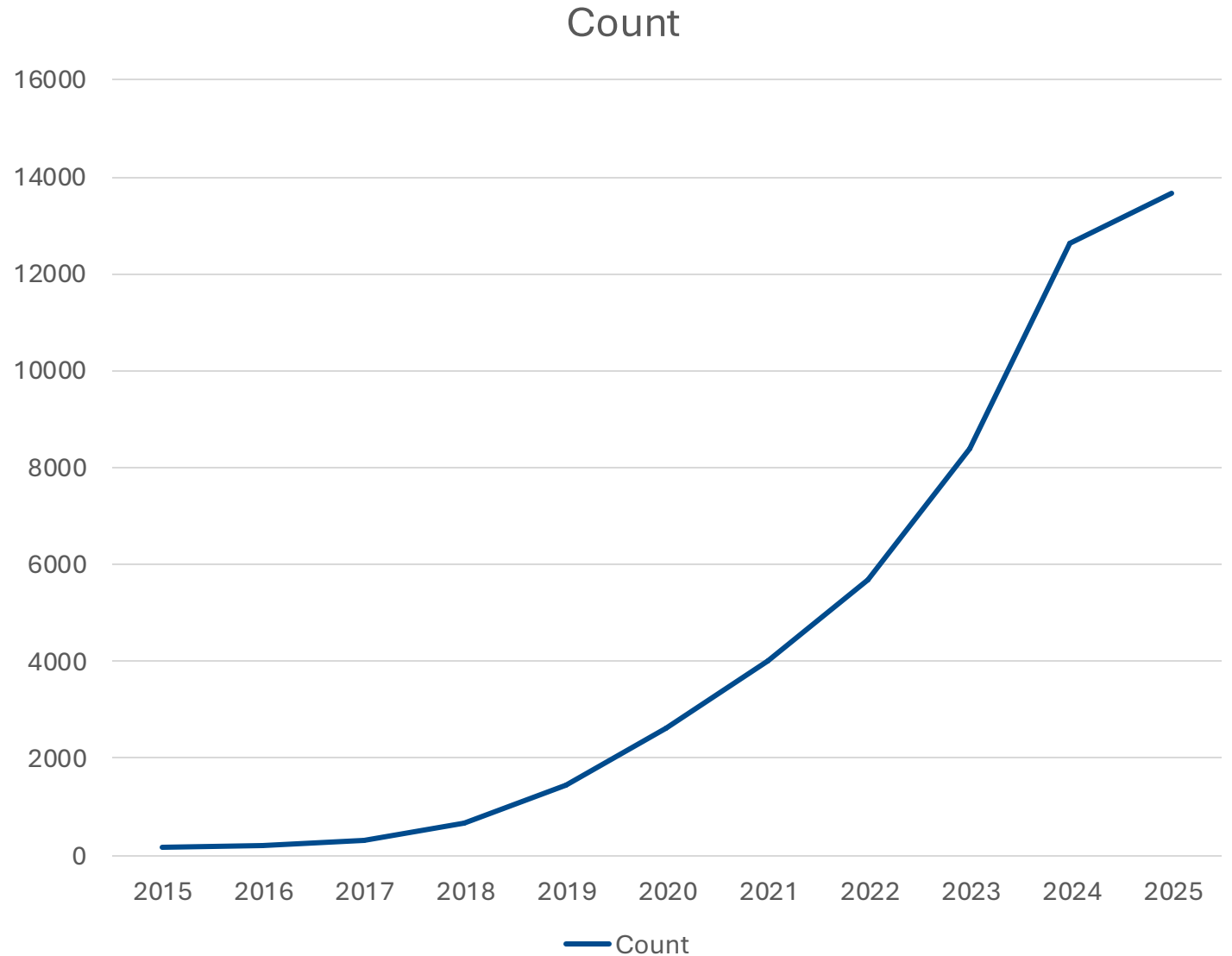


Objectives

- To understand:
 - The definition of artificial intelligence.
 - The history of artificial intelligence in medicine.
 - Difference between AI, Machine Learning and Deep Learning
 - Its limited success and unfortunately its more common failures
 - Domains where it will become useful over time.
 - Look at the AI tools that I use in my day to day practice.



Pubmed Publications with AI or Artificial Intelligence in the Title



“Attention is All You Need”

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Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

*Equal contribution. Listing order is random. Jakob proposed replacing RNNs with self-attention and started the effort to evaluate this idea. Ashish, with Illia, designed and implemented the first Transformer models and has been crucially involved in every aspect of this work. Noam proposed scaled dot-product attention, multi-head attention and the parameter-free position representation and became the other person involved in nearly every detail. Niki designed, implemented, tuned and evaluated countless model variants in our original codebase and tensor2tensor. Llion also experimented with novel model variants, was responsible for our initial codebase, and efficient inference and visualizations. Lukasz and Aidan spent countless long days designing various parts of and implementing tensor2tensor, replacing our earlier codebase, greatly improving results and massively accelerating our research.

[†]Work performed while at Google Brain.

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Long Range Dependency Problem

- The Problem Sentence
- **"The trophy didn't fit in the suitcase because it was too big."**
- What does "it" refer to? The trophy, or the suitcase?
 - Answer: the trophy (it was too big to fit).
- Now translate to French — French adjectives must agree in gender with the noun they describe:
 - trophy → le trophée (masculine)
 - suitcase → la valise (feminine)
- So the translation of "big" depends on which noun "it" refers to:
 - If "it" = trophy "trop grand" (masculine)
 - If "it" = suitcase "trop grande" (feminine)

The Large Language Model

- “A large language model is an AI system trained on very large collections of text, learning statistical patterns of language so that it can answer questions, summarize, translate, or generate new text in a human-like way.”
- OpenAI’s GPT(generative pre-trained transformer) was the first commercially successful of these; The introduction of GPT 3 in May 2020 was the milestone, with the eventual release of ChatGPT built on GPT 3.5 in late 2022.
- What was revolutionary was the evidence of transfer learning; the large language model could do tasks it was never trained on.
 - Translation
 - Arithmetic
 - Question answering
 - Writing software code

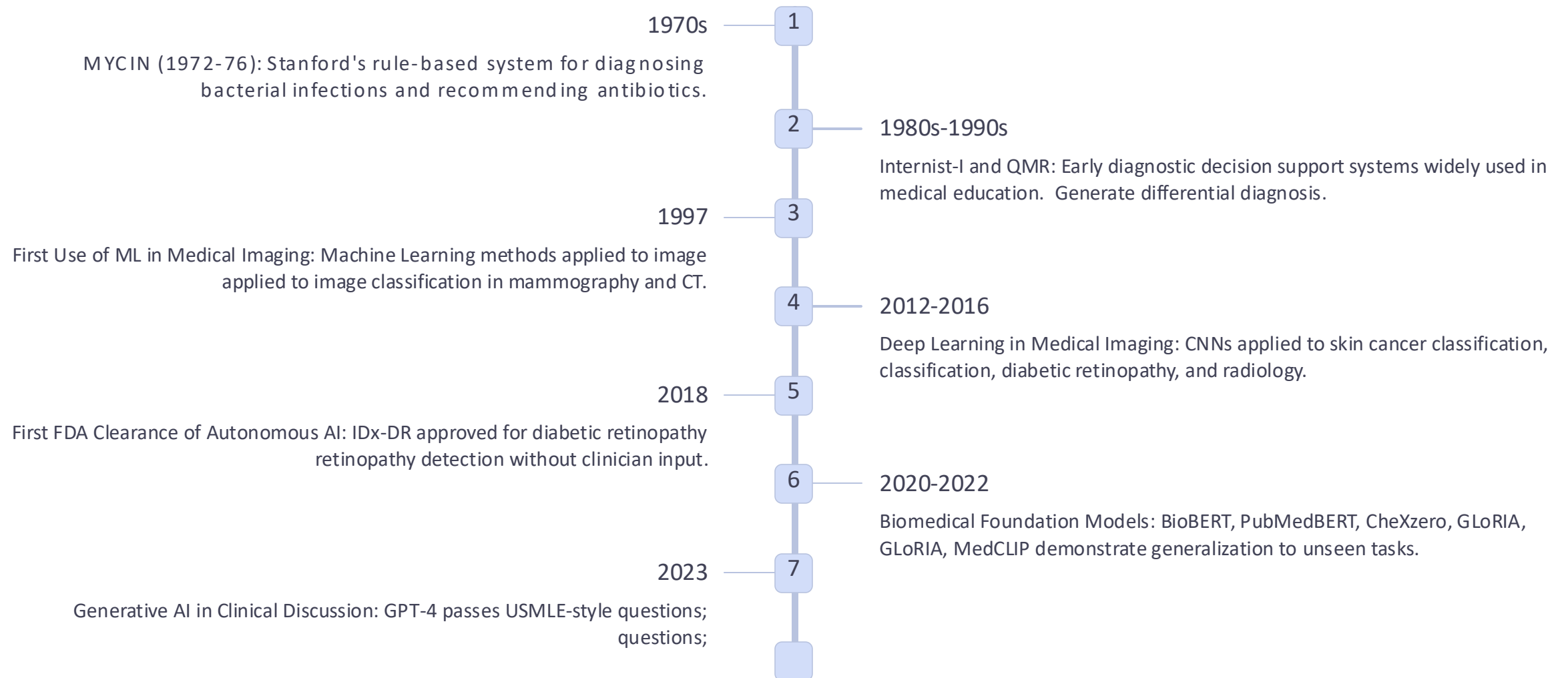
The Large Language Model in Medicine

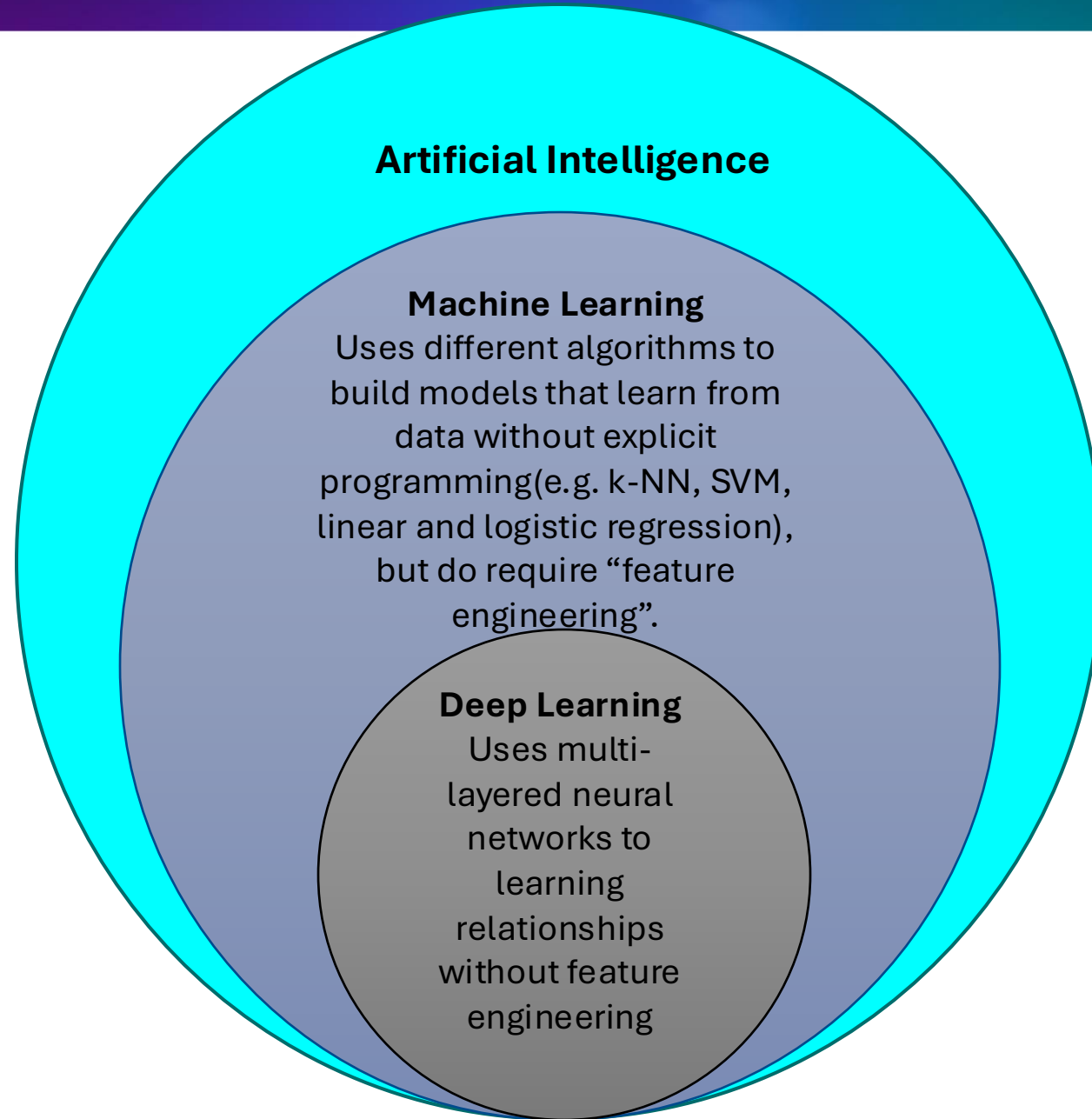
- Subsequent evolution of these models have added capabilities such as “thinking”, and have resulted in current models such as ChatGPT 5, Gemini 3, Claude Opus 4.6
- Given medicine’s large reliance on textual data, excitement occurred about applying LLMs to tasks like note creation, summarization, patient question answering.
- Also, the transformer architecture can handle multimodal data(images, video, sound) which is common in medicine.
- However, large language models are only a one part of artificial intelligence.

The Various Definitions of Artificial Intelligence

- Classical(McCarthy - 1955) - "The science and engineering of making intelligent intelligent machines, especially intelligent computer programs."
- Philosophical - "The simulation or replication of human intelligence in machines, machines, including reasoning and consciousness."

AI in Medicine: Timeline of Key Developments



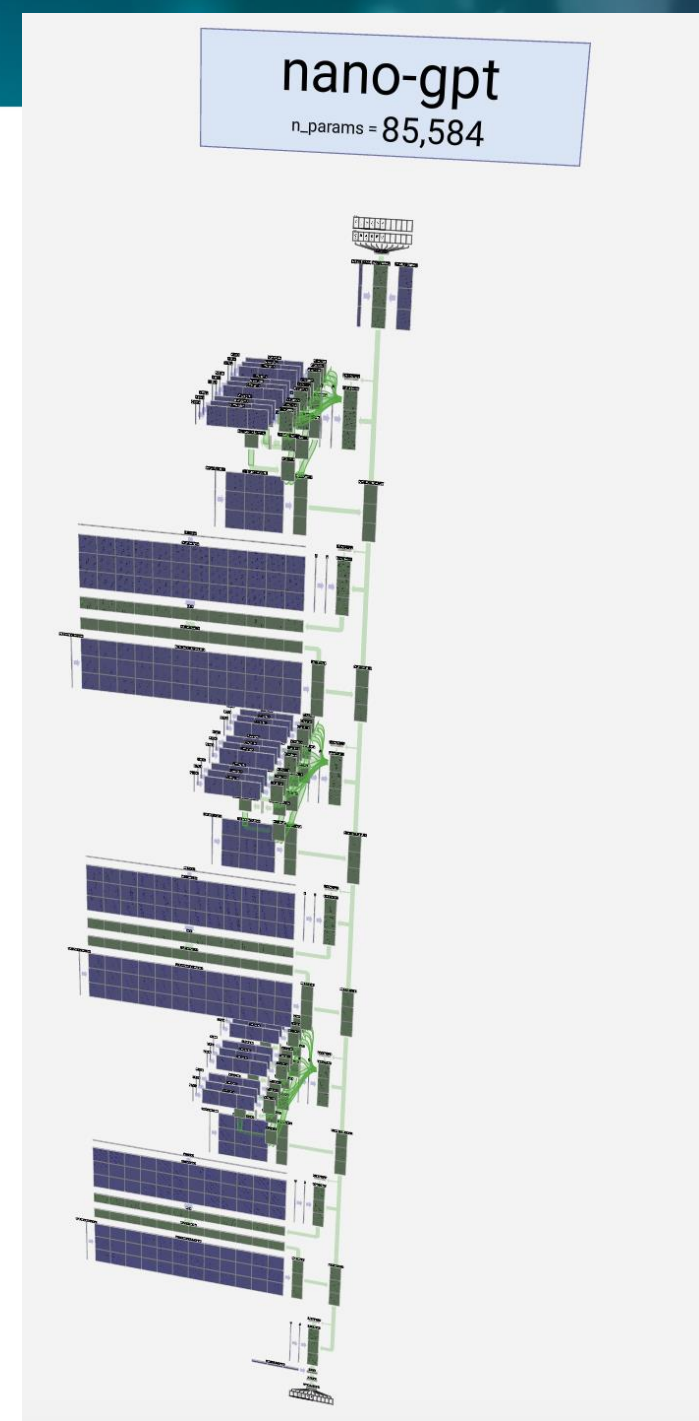


Machine Learning

- Machine learning is teaching a computer to recognize patterns by showing it thousands of examples, rather than writing the rules yourself.
- Popular algorithms –
 - Linear Regression – predicts continuous outcomes
 - Logistic Regression – yes/no outcomes, classification
 - Decision Trees – classification
 - Random Forests – classification
- Became popular with “big data”
- **Needs feature engineering – identifying the important variables to base predictions on.**

Deep Learning

- Deep learning generally doesn't rely on identifying the data that you want the algorithm to base itself on.
- Refers to the many layers of the neural network
 - Refers to the depth of the hidden layers – GPT 3 has 96 layers.
- Many different types
 - Image analysis – convolutional neural networks(CNN)
 - Time series data – recurrent neural networks(RNN)
 - Generative neural networks(GANs)
 - Graph neural networks.
 - Transformers



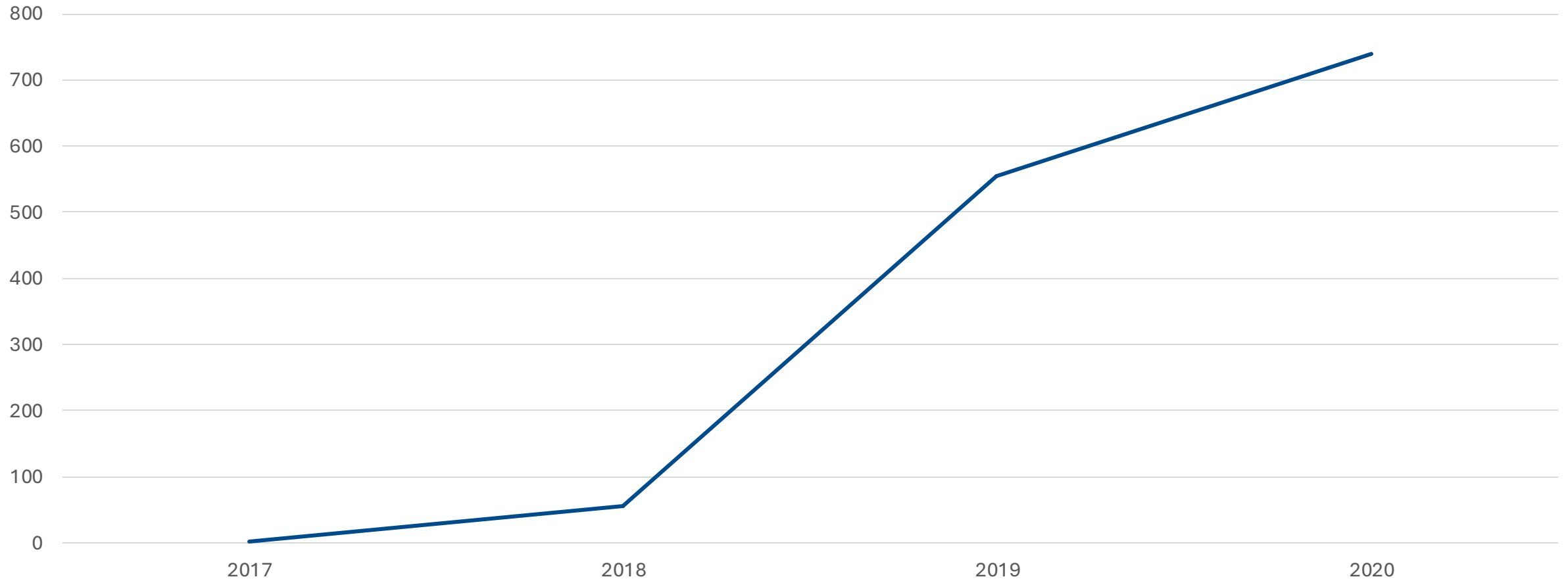
Deep Neural Networks, Pros and Cons

- Advantages
 - Eliminates manual feature engineering
 - Captures complex non-linear patterns
 - Generalizability across domains.
 - Scalability with data
- Problems
 - Data hungry
 - Black-box representations
 - Computational cost

Areas of Potential and Ongoing Use in Medicine

- Diagnosis and Risk Prediction
 - Image Interpretation, Pathology Interpretation
- Treatment Planning and Precision Medicine
 - Therapeutic recommendations, Radiation Planning, Pharmacogenomics
- Monitoring and Management
 - Disease progression, Chatbots and Virtual Health Assistants, Wearable and remote monitoring.
- Operational and Administrative Efficiency
 - Triage and Scheduling, Clinical Documentation, Clinical Summarization
- Drug Discover and Development
 - Molecular Modeling(e.g. AlphaFold2), Clinical Trial Matching,
- Education and Training
 - Simulation of Patients Encounters
 - Adaptive Learning
 - Literature Review.

Neurology Original Research Articles – Deep Learning



Barriers to Deployment

Category

1. Regulatory

2. Clinical Validation

3. Workflow Integration

4. Trust and Interpretability

5. Reimbursement & Business Case

6. Data Quality & Infrastructure

7. Equity and Bias

Barrier

✗ Lack of FDA or CE approval

✗ Lack of prospective trials

✗ Hard to embed into EHRs, PACS, or clinical flow

✗ “Black box” concerns

✗ Fear of liability

✗ No CPT codes or billing pathways

✗ No financial incentive for adoption

✗ Messy, incomplete, or delayed data

✗ EHR heterogeneity

✗ Underperformance on certain populations

✗ Lack of representative training data

Epic Sepsis Model – An Epic Failure

Original Investigation

FREE

External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients

Andrew Wong, MD¹; Erkin Otles, MEng^{2,3}; John P. Donnelly, PhD⁴; [et al](#)

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Key Points

Question How accurately does the Epic Sepsis Model, a proprietary sepsis prediction model implemented at hundreds of US hospitals, predict the onset of sepsis?

Findings In this cohort study of 27 697 patients undergoing 38 455 hospitalizations, sepsis occurred in 7% of the hospitalizations. The Epic Sepsis Model predicted the onset of sepsis with an area under the curve of 0.63, which is substantially worse than the performance reported by its developer.

Meaning This study suggests that the Epic Sepsis Model poorly predicts sepsis; its widespread adoption despite poor performance raises fundamental concerns about sepsis management on a national level.

Key Findings

- Evaluated Epic Sepsis Model (ESM) at Michigan Medicine (University of Michigan) across over 27,000 patients.
- Found that the model:
 - Missed 67% of sepsis cases not flagged in advance
 - Had low sensitivity (~33%) for early detection
 - Generated many false positives, contributing to alert fatigue
 - Was not transparent or interpretable (proprietary black box)

Poor Engineering

- Training Bias and Overfitting
 - Training data was likely overfitted to Epic's development environment
 - Never validated on diverse data.
 - Likely learned relationships that don't hold out of the original training set
 - E.g. Might have learned patterns based on the hospital's workflow, note templates
 - Admitted to ICU -> high risk of sepsis.
- Data Leakage
 - Data was allowed to be used for training, that shouldn't have been included. For example, it is likely that an anti-biotics order, ordering blood cultures, sepsis diagnostic code was a predictive variable(temporal leakage).
- Model was not FDA approved, although that doesn't necessarily help.

Not all AI health tools with regulatory authorization are clinically validated

Sammy Chouffani El Fassi, Adonis Abdullah, Ying Fang, Sarabesh Natarajan, Awab Bin Masroor, Naya Kayali, Simran Prakash & Gail E. Henderson

 Check for updates

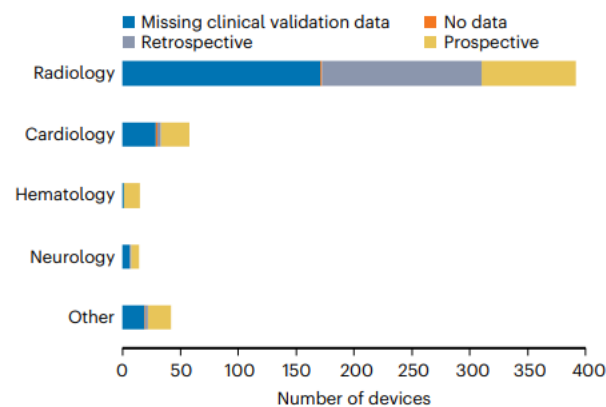


Fig. 1 | Validation methods for FDA-authorized AI devices by specialty. The number of FDA-authorized AI devices by specialty, together with details of clinical validation, based on 521 authorizations from 1995 to 2022. 'Other' includes devices authorized for uses in dentistry, obstetrics and gynecology, orthopedics, general hospital medicine, pathology, anesthesiology, general and plastic surgery, microbiology, clinical chemistry, gastroenterology, urology and ophthalmology.

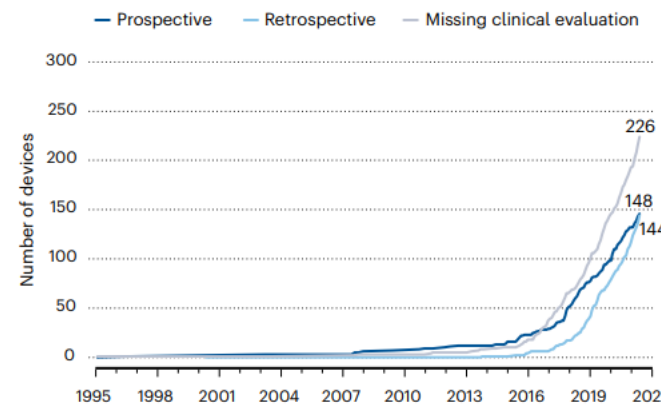


Fig. 2 | Validation methods for FDA-authorized AI devices over time. The number of FDA authorizations for AI devices on the basis of prospective or retrospective clinical validation, together with the number of authorizations without clinical validation data, from 1995 to 2022.

FDA Tools Still Need to be Validated

- IDx-DR (now Digital Diagnostics)
 - Received FDA clearance in 2018 for autonomous detection of diabetic retinopathy.
 - One of the best validated systems.
 - Real-world studies conducted in primary care settings revealed challenges such as poor image quality, workflow inefficiencies, and reduced sensitivity in certain demographics, resulting in fewer completed screenings than anticipated.
- FDA-Cleared AI Models for COVID-19 Chest X-rays
 - Several models received expedited FDA clearance during 2020–2021.
 - Many were later found to be trained on limited and biased datasets, including reliance on hospital metadata labels (e.g., portable chest X-rays being labeled COVID-positive).
 - A 2021 review concluded that most models failed external validation.
 - Reference: Roberts et al., Nature Machine Intelligence, 2021. <https://www.nature.com/articles/s42256-021-00307-0>

Opportunities for Validation Research

| | |
|-------------------------|---|
| Real-world performance | Does the model still perform when used by real clinicians? Does it continue to perform(model drift) |
| Generalizability | Does the model work in rural, pediatric, or safety-net hospitals? |
| Head-to-head comparison | Which AI sepsis tool performs best under the same conditions? |
| Bias & fairness | Does the tool underperform on underrepresented populations? |
| Workflow integration | How do clinicians respond to the model's outputs? |
| Cost-effectiveness | Does the model save money or improve efficiency? |

Back to the Transformer

- Main uses in health care currently
 - Ambient dictation – uses a transformer for speech recognition, and then another transformer(in DAX Copilot case), GPT to write a note from a conversation.
 - Chart summarization – extract the important parts of the chart for a provider.
 - Inbox management – some centers have experimented with replying to patient queries.
 - Chatbots – answer medical questions, can be fine tuned for a particular specialty.

Transformers used in 3rd Party tools

OpenEvidence

ChatGPT,
Claude,
Gemini

NotebookLM
from Google

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 New Question



What evidence exists for the use of LITT in MTS?

▼ Finished thinking

Laser interstitial thermal therapy (LITT) is supported by high-quality evidence as a minimally invasive surgical option for drug-resistant mesial temporal lobe epilepsy (MTLE), including cases with mesial temporal sclerosis (MTS). Multiple prospective multicenter cohort studies and meta-analyses demonstrate that LITT achieves Engel I seizure freedom rates of approximately 55–58% at 1–2 years, with durable outcomes and improved quality of life, and a major complication rate of 2–4%—lower than traditional open resection procedures such as anterior temporal lobectomy (ATL) or selective amygdalohippocampectomy.^[1-4]

Meta-analyses and systematic reviews confirm that seizure outcomes after LITT are somewhat lower than ATL (Engel I rates 55–58% for LITT vs. 66–69% for ATL), but LITT offers a favorable safety profile, shorter hospital stays, and reduced neurocognitive morbidity, especially for dominant hemisphere procedures.^[3-5] Subgroup analyses consistently show that patients with MTS have better seizure outcomes after LITT compared to those without MTS, with Engel I rates up to 64% in MTS cohorts.^[3]^[5-6] The extent and targeting of ablation, particularly of the amygdalohippocampal complex, are associated with improved seizure outcomes.^{[5][7]}

Ask a follow-up question...





ChatGPT 5 ▾



What are you working on?

+ | Ask anything



Conclusions

- Artificial Intelligence in Medicine are showing promise
- However, there is a long ways to go between research and eventual implementation.
- As clinicians and researchers we have to be vigilant about the how these tools are validated.
- The FDA is unlikely to be a suitable organization for the validation of these tools.
- Commercial AI based tools deserve extra scrutiny.
- There still remains potential utility of AI, in particular deep learning and transformers in medicine and neurology.