

USE OF ARTIFICIAL INTELLIGENCE IN VASCULAR SURGERY

Charles de Mestral

PRESENTER DISCLOSURE

Presenter: Charles de Mestral

- I have no current relationships with commercial entities

WHAT IS AI?



Artificial Intelligence

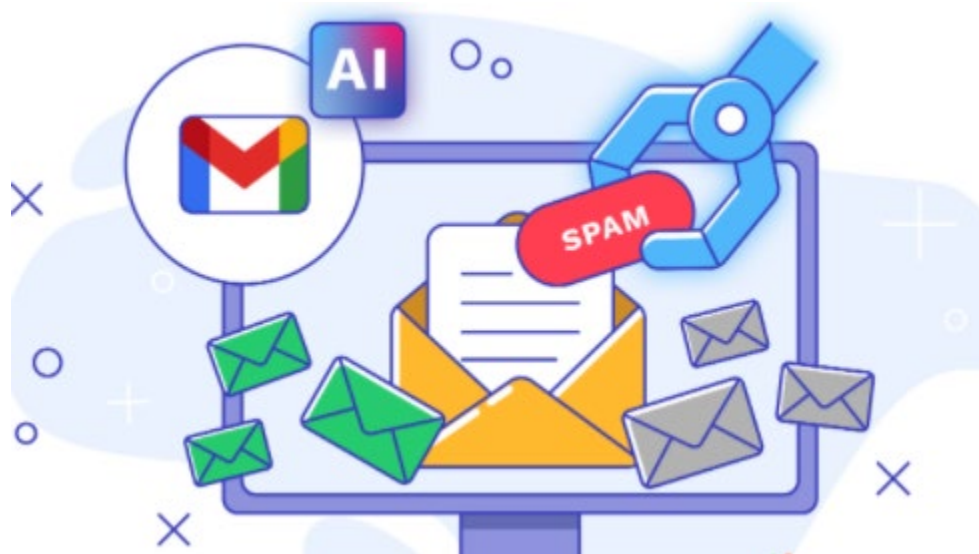
Generative AI

Machine Learning

Large Language Models

Computer Vision

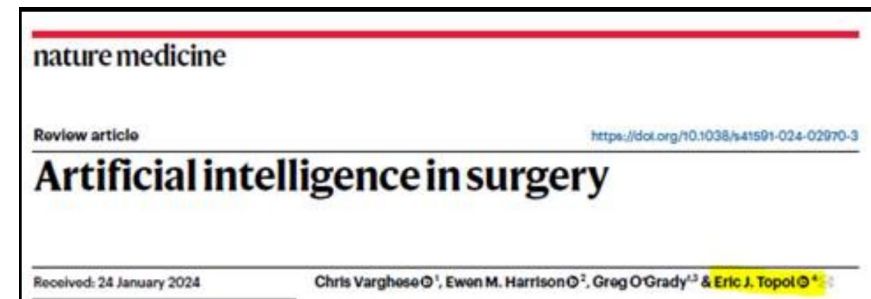
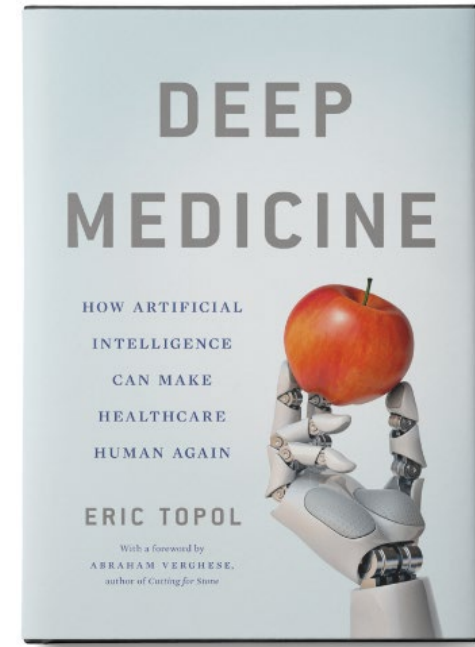
WE USE AI TOOLS EVERY DAY



“AN OBVIOUS AREA WHERE THERE'S HUGE BENEFITS IS HEALTHCARE”



“AI CAN ENHANCE HEALTHCARE”



MORE ACCURATE DIAGNOSIS

Towards Accurate Differential Diagnosis with Large Language Models

Daniel McDuff^{*, ‡, 1}, Mike Schaekermann^{*, ‡, 1}, Tao Tu^{*, 1}, Anil Palepu^{*, 1},
Amy Wang¹, Jake Garrison¹, Karan Singhal¹, Yash Sharma¹, Shekoofeh Azizi²,
Kavita Kulkarni¹, Le Hou¹, Yong Cheng², Yun Liu¹,
S Sara Mahdavi¹, Sushant Prakash¹, Anupam Pathak¹, Christopher Semturs¹,
Shwetak Patel¹, Dale R Webster¹, Ewa Dominowska¹,
Juraj Gottweis¹, Joelle Barral², Katherine Chou¹, Greg S Corrado¹, Yossi Matias¹,
Jake Sunshine^{‡, †, 1}, Alan Karthikesalingam^{‡, †, 1} and Vivek Natarajan^{‡, †, 1}

¹Google Research, ²Google DeepMind

Case: [Case Text]

What are the top 10 most likely diagnoses? Be precise, listing one diagnosis per line, and try to cover many unique possibilities (at least 10). The top 10 diagnoses are:

Example Output:

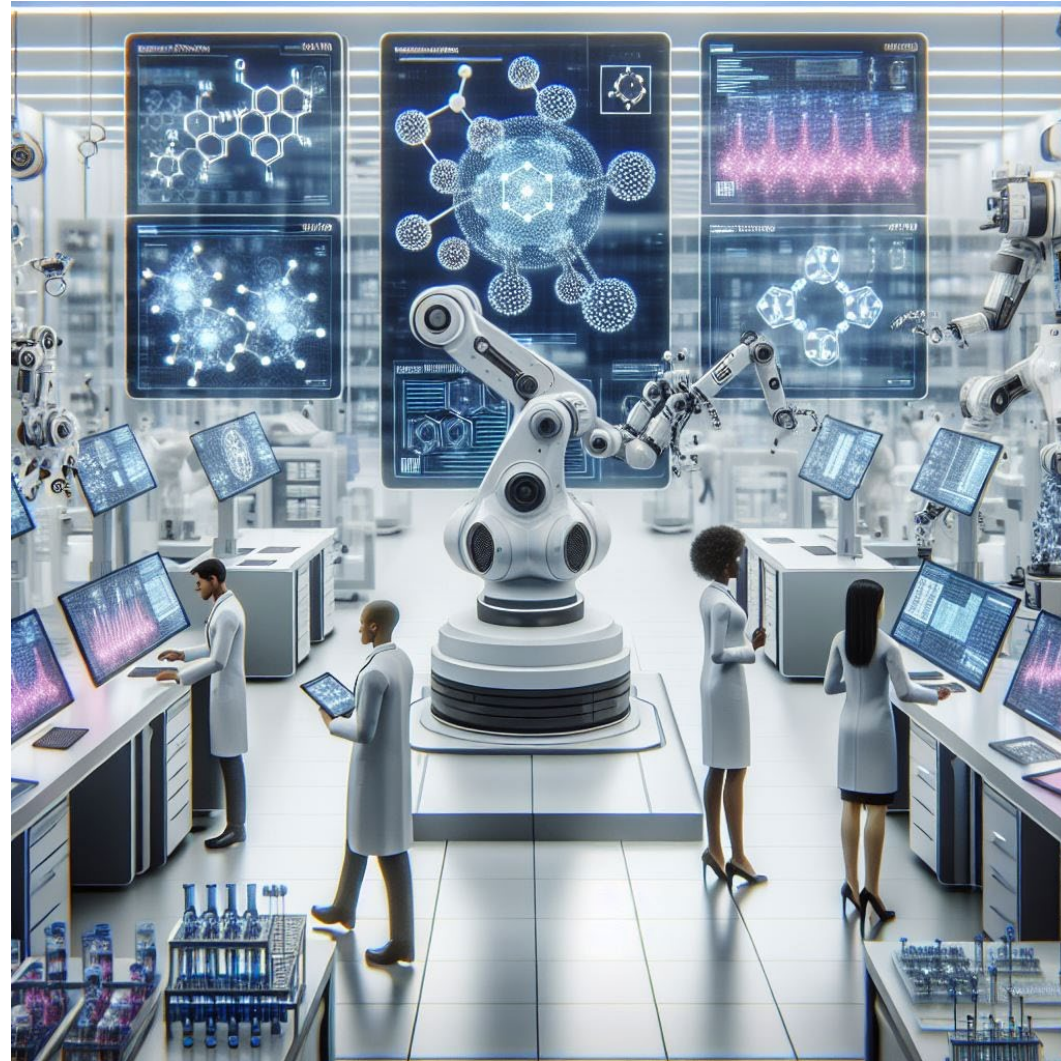
1. Sézary syndrome
2. Adult T-cell leukemia/lymphoma
3. Mycosis fungoides
4. Atopic dermatitis
5. Psoriasis
6. Drug reaction with eosinophilia and systemic symptoms (DRESS)
7. Graft-versus-host disease (GVHD)
8. Cutaneous T-cell lymphoma, not otherwise specified
9. Hypereosinophilic syndrome
10. Systemic lupus erythematosus (SLE)

[2312.00164 \(arxiv.org\)](https://arxiv.org/abs/2312.00164)

MEDICAL IMAGING ANALYSIS



DRUG DEVELOPMENT



AI & VASCULAR SURGERY



1. Imaging
2. Workflow facilitation
3. Risk Stratification
4. Outcome Prediction
5. Monitoring devices
6. Education – Patients & Clinicians

1- DIAGNOSTIC IMAGING (COMPUTER VISION)

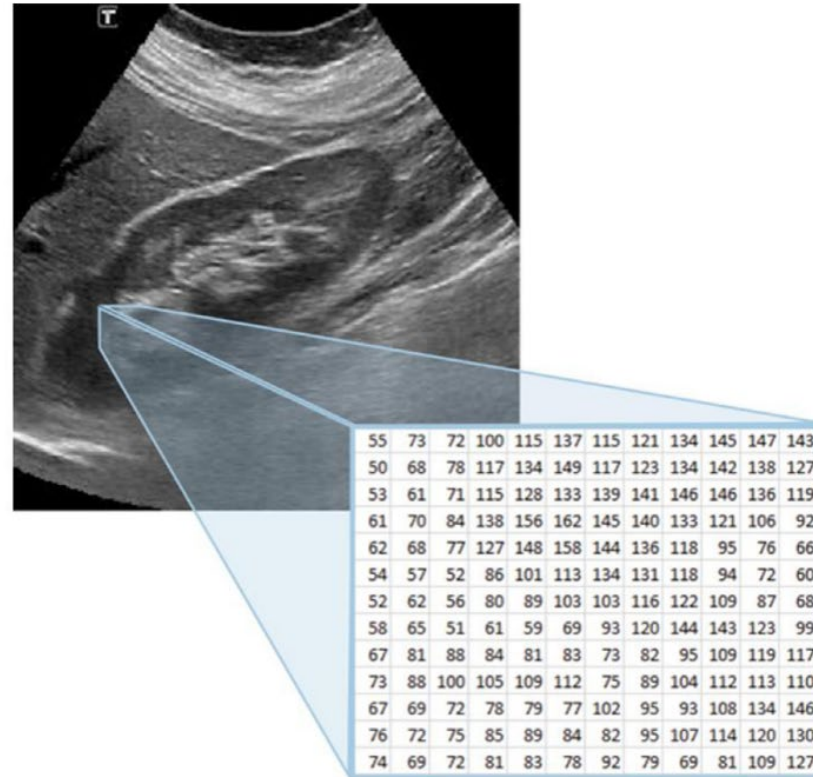
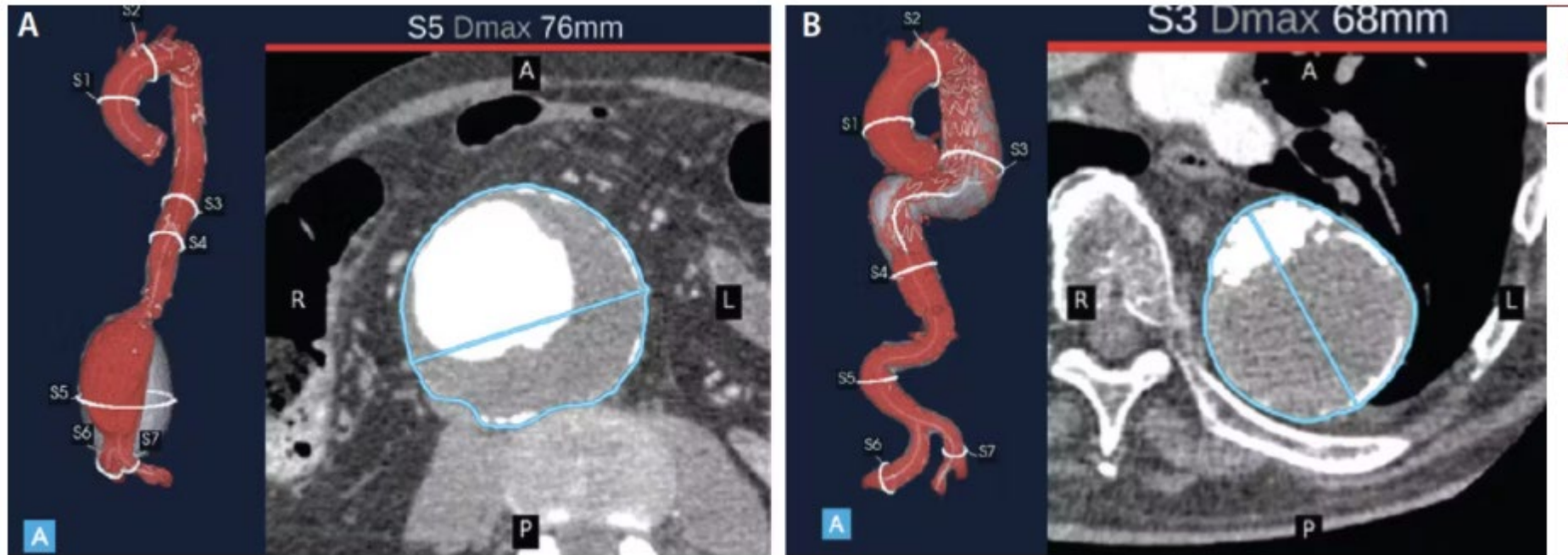


Fig. 1 – Human versus computer vision. A human expert easily classifies this image as an image of the right kidney. For the computer, however, instead of shades of gray, it “sees” a matrix of numbers representing pixel brightness. Computer vision typically involves computing the presence of numerical patterns (features) in this matrix and then applying machine learning algorithms to distinguish images on the basis of these features. From Chartrand et al [6], reprinted with permission.

1- DIAGNOSTIC IMAGING (COMPUTER VISION)



Fabre D et al. Endovascular Today 2023 <https://evtoday.com/articles/2023-mar/ai-automation-and-aortic-aneurysm-care>

1- DIAGNOSTIC IMAGING (COMPUTER VISION)



2- WORKFLOW FACILITATION



70%+ reduction in documentation time; physicians reported almost 4 hours per week saved doing administrative tasks.

3- RISK STRATIFICATION

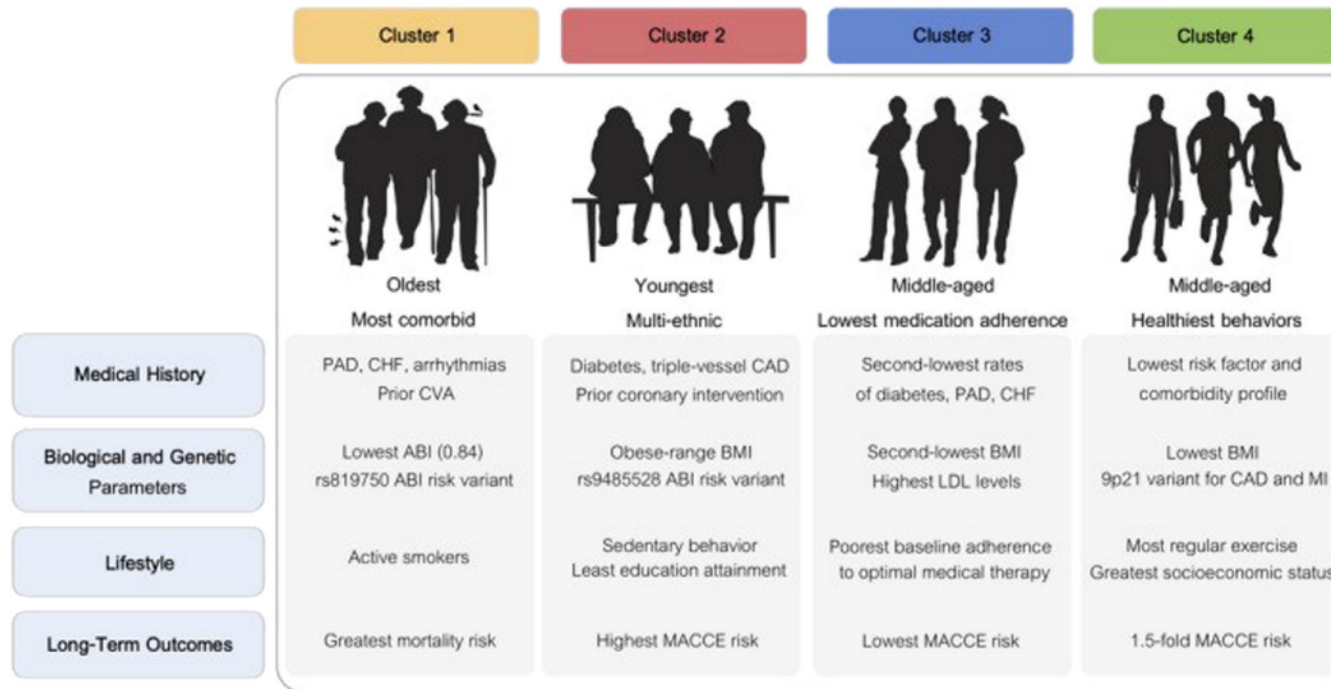


Fig. 2 – Schematic of four artificial intelligence–derived clusters of patients with coronary artery disease (CAD) and significant features. From Flores AM, Schuler A, Eberhard AV, et al. Unsupervised learning for automated detection of coronary artery disease subgroups. *J Am Heart Assoc* 2021;10(23):e021976 [23], reproduced with permission. ABI, ankle-brachial index; BMI, body mass index; CHF, congestive heart failure; CVA, cerebrovascular accident; LDL, low-density lipoprotein; MACCE, major adverse cardiovascular and cerebrovascular event; MI, myocardial infarction; PAD, peripheral artery disease.

3- RISK STRATIFICATION



3- RISK STRATIFICATION

Single Prediction

Batch Prediction

Enter Patient Information

Age

65

Sex - Female?

☐

Elective Admission?

☐

Stroke?

☐

Albumin Level:

0

Albumin Missing?:

☒

Homelessness?:

☐

Congestive Heart Failure?:

☒

Creatinine Level:

100

Creatinine Missing?:

☐

Peripheral Arterial Disease?:

☐

Hypertension?:

☐

Hb A1C Level:

0

Hb A1C Missing?:

☒

Coronary Artery Disease?:

☐

COPD?:

☐

Prediction Time Horizon (Days):

365

Mental Illness?:

☐

Malignancy?:

☐

CKD?:

☐

Submit

Reset

Cumulative Incidence Function

Foot Complication Risk(%)

Time (days)

Foot Complication Risk

Risk at: 365 days	
Event	Risk(%)
Foot complication	2.3000

4- OUTCOME PREDICTION

**ANNALS
OF
SURGERY**

Articles & Issues ▾ Infographics For Authors ▾ Journal Info ▾

ORIGINAL ARTICLES

Using Machine Learning (XGBoost) to Predict Outcomes After Infrainguinal Bypass for Peripheral Artery Disease

Li, Ben MD^{*,†,‡,§}; Eisenberg, Naomi PT MED CCRP^{||}; Beaton, Derek PhD[¶]; Lee, Douglas S. MD, PhD^{#,**,††}; Aljabri, Badr MD^{‡‡}; Verma, Raj MD(c)^{§§}; Wijeyesundera, Duminda N. MD, PhD^{**,††,|||,¶¶}; Rotstein, Ori D. MD, MSc^{*,†,¶¶,##}; de Mestral, Charles MD, PhD^{*,†,**,††,¶¶}; Mamdani, Muhammad PharmD, MA, MPH^{‡,§,¶,**,††,¶¶,***}; Roche-Nagle, Graham MD, MBA^{*,||}; Al-Omran, Mohammed MD, MSc^{*,†,‡,§,¶¶,†††}

Author Information[☑]

Annals of Surgery 279(4):p 705-713, April 2024. | DOI: 10.1097/SLA.00000000000006181

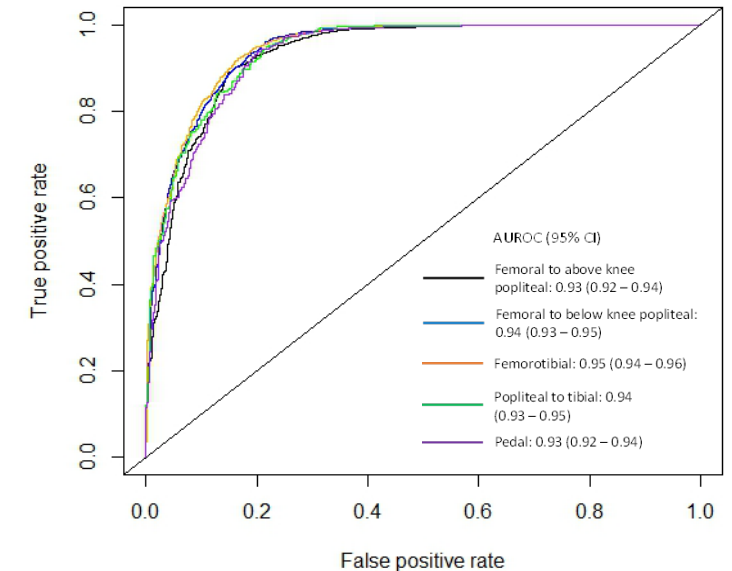
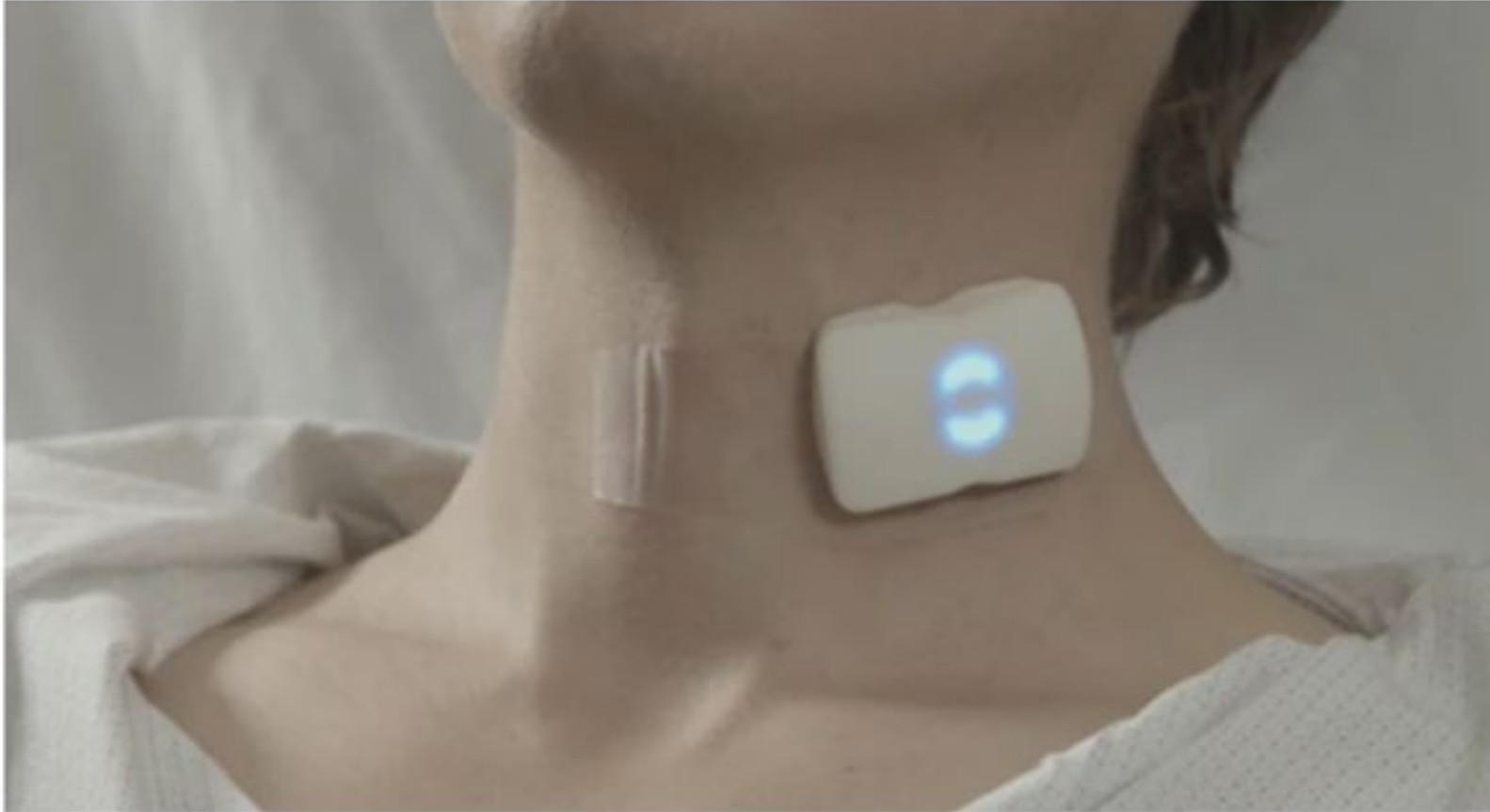


Figure 1. Machine learning (XGBoost) model trained on 59,784 patients who underwent infrainguinal bypass in the VQI database to predict 1-year MALE or death using pre-operative demographic and clinical variables

5 - MONITORING



5- MONITORING

Health

AI tool cuts unexpected deaths in hospital by 26%, Canadian study finds

Researchers say early warning system, launched in 2020 at St. Michael's Hospital, is 'saving lives'



[Lauren Pelley](#) · CBC News · Posted: Sep 16, 2024 4:00 AM EDT | Last Updated: September 16



6- EDUCATION OF PATIENTS

JAMA
Network | **Open**[™]



Original Investigation | Surgery

Large Language Model–Based Chatbot vs Surgeon-Generated Informed Consent Documentation for Common Procedures

Hannah Decker, MD; Karen Trang, MD; Joel Ramirez, MD; Alexis Colley, MD, MS; Logan Pierce, MD; Melissa Coleman, MD; Tasce Bongiovanni, MD, MPP, MHS; Genevieve B. Melton, MD, PhD; Elizabeth Wick, MD

Radiology

ORIGINAL RESEARCH • BREAST IMAGING

Appropriateness of Breast Cancer Prevention and Screening Recommendations Provided by ChatGPT

Hana L. Haver, MD • Emily B. Ambinder, MD • Manisha Bahl, MD • Eniola T. Oluyemi, MD • Jean Jeudy, MD • Paul H. Yi, MD

6 - EDUCATION OF CLINICIANS

REVIEW ARTICLE · Volume 2, 100049, 2024 · Open Access

Evaluating the progression of artificial intelligence and large language models in medicine through comparative analysis of ChatGPT-3.5 and ChatGPT-4 in generating vascular surgery recommendations


Arshia P. Javidan, MD, MSc ^a · Tiam Feridooni, MD, PhD ^a · Lauren Gordon, MD, PhD ^a · Sean A. Crawford, MD, PhD ^{a,b}


Affiliations & Notes [▼] Article Info [▼]

- **95%** accuracy in generating clinical vascular surgery recommendations in line with guidelines
- **Limitations:** static information, neural hallucinations, lack of authoritative sources

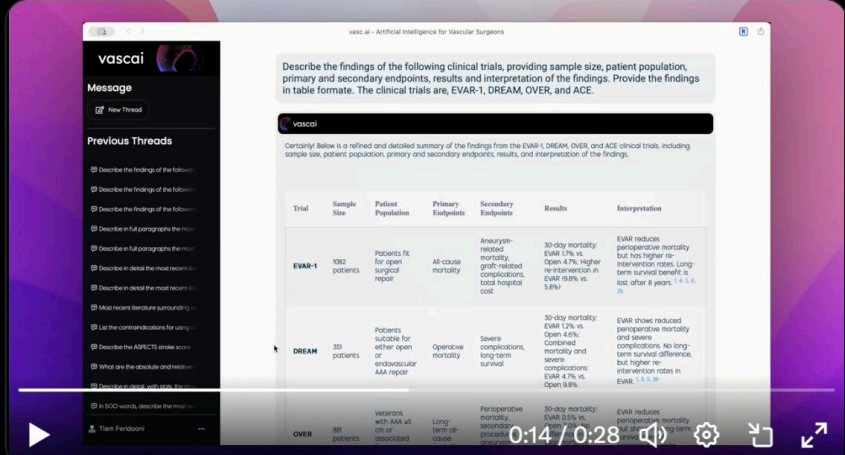
Imagine having an AI assistant tailored specifically for complex aortic research.

Below is an example of [vasc.ai](#) diving deep into clinical trials like EVAR-1, DREAM, OVER, and ACE – comparing findings seamlessly and pulling insights in seconds.

Gone are the days of juggling endless PDFs and trying to extract key details manually. [vasc.ai](#) automates that process, delivering results that elevate your research and boost your clinical impact. 

What could this mean for you? Less time on the grunt work, more time pushing the boundaries of vascular innovation. 

[#VascularAI](#) [#AorticResearch](#) [#MedicalAI](#) [#Vascai](#) [#LLM](#) [#ClinicalTrials](#) [#AortaEd](#)



vasc.ai Artificial Intelligence for Vascular Surgeons

Describe the findings of the following clinical trials, providing sample size, patient population, primary and secondary endpoints, results and interpretation of the findings. Provide the findings in table format. The clinical trials are, EVAR-1, DREAM, OVER, and ACE.

vasc.ai

Certainly! Below is a refined and detailed summary of the findings from the EVAR-1, DREAM, OVER, and ACE clinical trials, including sample size, patient population, primary and secondary endpoints, results, and interpretation of the findings.

Trial	Sample Size	Patient Population	Primary Endpoints	Secondary Endpoints	Results	Interpretation
EVAR-1	1001 patients	Patients fit for open surgical repair	All-cause mortality	Aneurysm-related mortality, graft-related complications, total hospital cost	30-day mortality: EVAR 1.1% vs. Open 4.7%, higher re-intervention rates in EVAR (9.8% vs. 1.8%)	EVAR reduces perioperative mortality but has higher re-intervention rates. Long-term survival benefit is not clear at 8 years, 14.1% vs. 21.1%
DREAM	351 patients	Patients suitable for either open or endovascular AAA repair	Operative mortality	Severe complications, long-term survival	30-day mortality: EVAR 1.2% vs. Open 4.6%. Combined mortality and severe complications: EVAR 4.7% vs. Open 9.8%	EVAR shows reduced perioperative mortality and severe complications, no long-term survival difference, but higher re-intervention rates in EVAR, 13.1% vs. 21.1%
OVER	88 patients	Veterans with AAA at high or dissection	Long-term survival	Perioperative mortality, secondary procedures, postoperative complications	30-day mortality: EVAR 0.5% vs. Open 14.8%	EVAR reduces perioperative mortality but does not improve long-term survival

0:14 / 0:28

RISKS WITH AI-BASED INNOVATION



CHALLENGES WITH AI-BASED INNOVATION



1. Data
2. Bias
3. Lack of clinical validation
4. Implementation
5. Relevance

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