



Generative Al

Use in Non-Billing Purposes

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September 23, 2025



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- Member, Practice Management Committee,
 House of Delegates
- Professor and Chair of Pathology and Laboratory Medicine at University of Louisville
- AP/CP trained with subspecialty fellowships in neuropathology and oncological surgical pathology
- President Elect, Association for Academic
 Pathology (AAPath)



Disclaimer



The information presented today represents the opinions of the panelists and does not represent the opinion or position of the CAP.

This should not be used as a substitute for professional assistance.

The information in this presentation is provided for educational purposes only and is not legal advice.



Disclosure



Dibson Dibe Gondim Patent Application

El-Baz, A., **Gondim, D. D.,** Shalaby, A., Abo El-Ghar, M., Soliman, A., & Abou El-Ghar, M. (2022). *Systems and methods for digital transformation of medical images and fibrosis detection* (U.S. Patent Application No. US20220406049A1). University of Louisville Research Foundation, Inc. https://patents.google.com/patent/US20220406049A1





WILL AI REPLACE PATHOLOGISTS? THE TRUTH FROM LEADING HEMATOLOGY LABS IN

by Similoluwa Oluwalana - August 20, 2025

Devdiscourse on Development

Pathologists face uncertain future in AI era: Will they lead or be left behind?

revolved around the microscope, but the transition to digital platforn

togration. High-resolution whole-slide imaging now allows and computational analysis at scales previous are opening the door for automatic

ARTIFICIAL INTELLIGENCE VS. HUMAN Pathology has has created EXPERTISE IN PATHOLOGY for remote unimagin

Pathologist

Pathologists Versus AI

n it comes to new mology, shouldn't we thinking in terms of laboration rather than mpetition?



across ke

Artificial intelligence, AI, has been one of the most talked-about topics in pathology for years. AI stands on the shoulders of digital pathology, which can already feel threatening to the expert who has maybe spent decades looking at specimens in a microscope. Will all this rapidly developing technology make the New AI tool can diagnose cancer, guide treatment, predict patient survival

News | Articles | April 7, 2025 Paige PanCancer Detect Earns FDA Designation Multi-Tissue Cancer Detection Fact checked by: Jason M. Broderick

Paige PanCancer Detect has gained FDA breakthro

University of Louisville Health Adopts Paige Dec 15, 2021 10:05 AM Eastern Standard Time Al-enabled Cancer Detection Software for

Enhanced Cancer Detection

Memorial Sloan Kettering Cancer Center

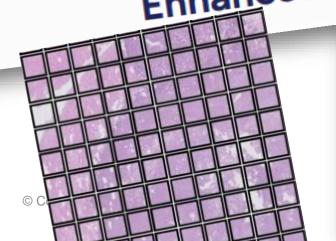
Introducing DeepHeme, A New Al Tool To Improve Blood Cancer

By Julie Grisham, Wednesday, June 11,



Unveiling the future: the impact of artificial intelligence in diagnostic pathology

Kartavya Kumar Verma^{1*}, Ruchira Palmal² and Priyanka Yadav³



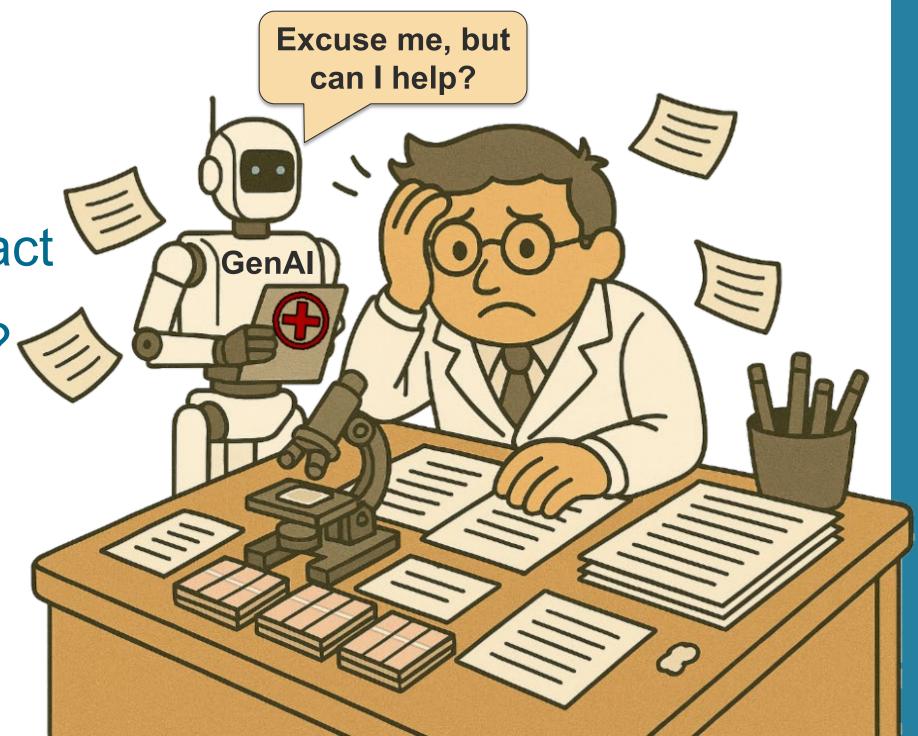


What can GenAl do for me outside of the diagnostic realm?

Can GenAl be my

"desktop assistant" or act

as a medical assistant?





Can GenAl make me more efficient? Alleviate my burnout? Can it...

...prepopulate data, format reports and synoptics, code, order stains, screen final drafts, etc?

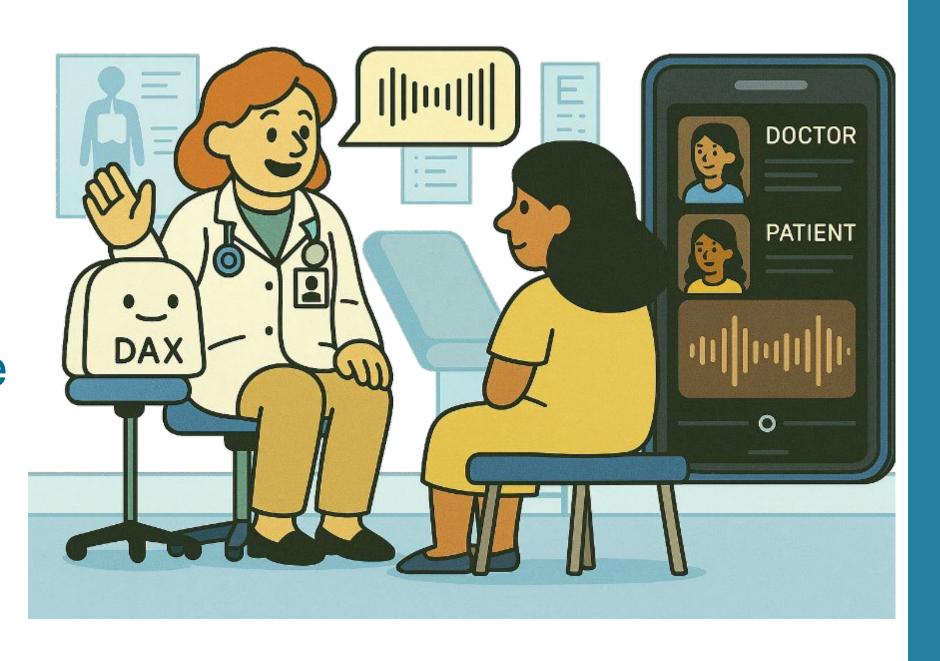
Can GenAl do what

Nuance DAX ambient

listening medical scribe

does for clinical

encounters?



https://www.nuance.com/healthcare/dragon-ai-clinical-solutions/dax-copilot/infographic/move-beyond-scribes-to-automatically-document-care.html?srsltid=AfmBOoqprxHWt2dblYQGshGuEppJ3eEtqR7dDLxRSakL_DZXpf3ZnmO6

Unlocking GenAl's Potential to Streamline Pathology Practice

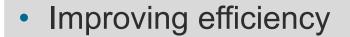
- Rethinking AI in pathology
- Practical benefits, current & future potential
- Enhancing job satisfaction and retention, as well as alleviating burnout

Beyond Diagnostics: How Might GenAl Support Pathologists

Al isn't just about replacing or enhancing diagnostic tasks—it's a powerful tool to enhance and streamline pathology workflows.

Beyond Diagnostics: How Might GenAl Support Pathologists

- Workflow optimization
 - Automated triage
 - Clinical data aggregation
 - Case prioritization & sorting
 - Ordering additional studies
 - Improving turnaround time
- Generating synoptic reports,
 formatting, scrubbing errors, etc



- Reducing errors
- Generating "digital" or virtual stains
- Supporting teaching and training

Reducing admin burden

Improving overall job satisfaction



Today's Objectives

Identify nondiagnostic
applications of AI that can
enhance efficiency in
anatomic pathology
workflows.

Describe how AI tools such as automated documentation systems (eg, DAX) and report formatting solutions can reduce administrative burden and improve accuracy.

Evaluate opportunities to integrate AI into routine pathology tasks, including synoptic reporting, clinical data aggregation, and report prepopulation.

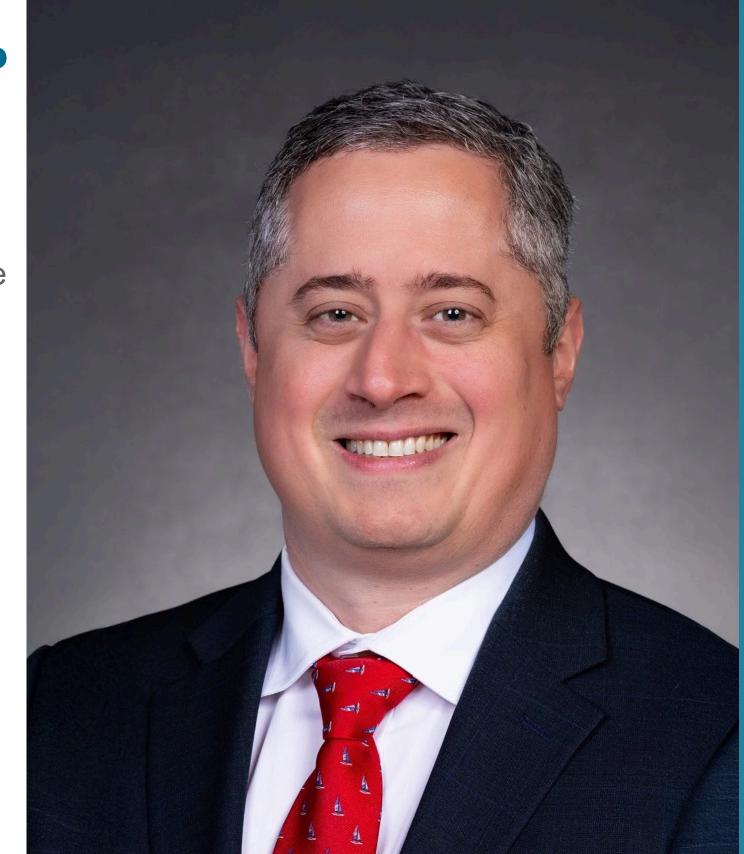
Discuss the potential impact of AI on time management, error reduction, and overall job satisfaction for pathologists.

Describe applications of generative AI for creating digital stains and discuss potential integration into future pathology workflows.

Explore future directions and considerations for implementing AI solutions in pathology practices beyond billing and diagnostics.

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- Member of the Artificial Intelligence Committee, CAP
- Vice Chair of Computational Pathology and Artificial Intelligence at the University of Louisville
- Director of Pathology Informatics and Associate
 Professor of Pathology at the University of Louisville
- Certified by the American Board of Pathology in:
 - Anatomic Pathology
 - Neuropathology
 - Clinical Informatics
- Lead on the large-scale digital pathology and Al Initiative at the University of Louisville



Dr. V.K. Cody Bumgardner, PhD

- Associate Professor of Pathology and Laboratory Medicine
- Assistant Dean for Artificial Intelligence and Data Science at University of Kentucky
- Director of Pathology Informatics at University of Kentucky
- Director of the Center for Applied Artificial Intelligence at University of Kentucky
- Research areas of interest
 - Medical Informatics
 - Distributed Systems
 - Platforms for Learning Health Systems



Generative Al Holds Incredible Potential to Bring Efficiencies to Pathology

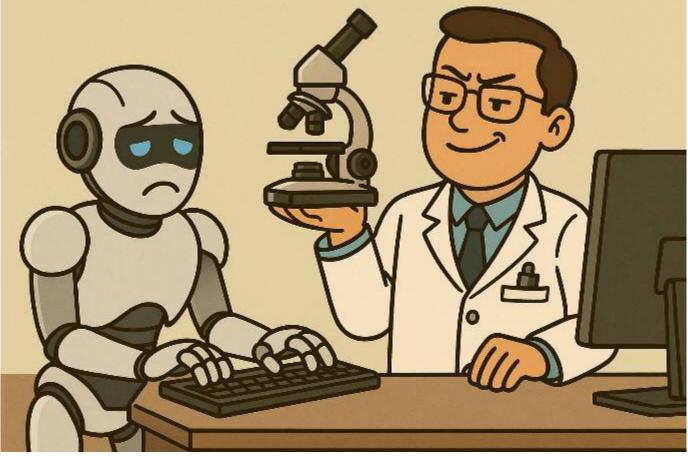


- What is Generative AI (GenAI) and LLMs?
- Pathologist's responsibilities
- How LLMs can support future use cases and practical applications
- We will also discuss how generative AI techniques, such as GANs, can help bring the concept of digital stains to life



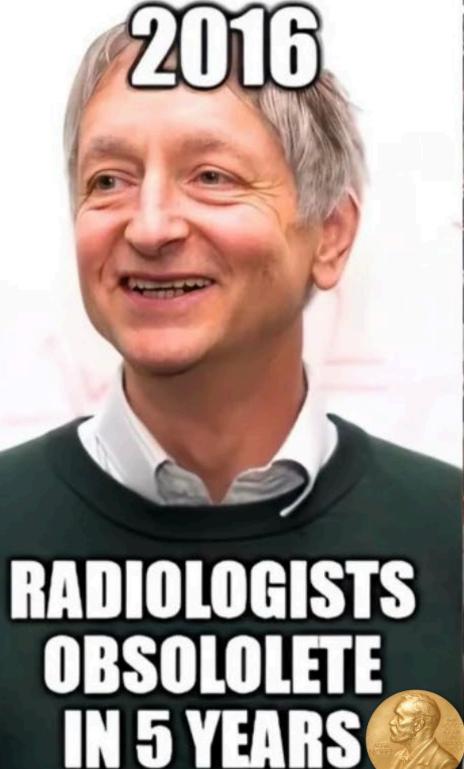
Ask not whether AI can replace you — ask what AI can do for you.





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"It's difficult to make predictions, especially about the future"

Attributed to Niels Bohr



Definitions

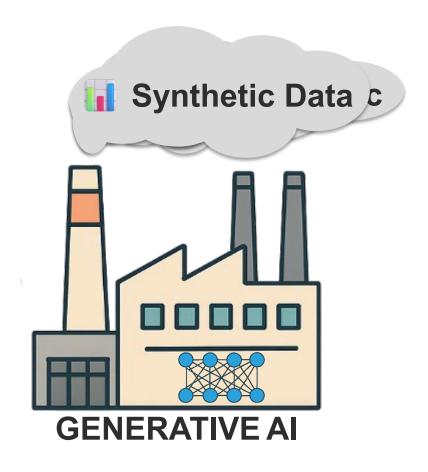


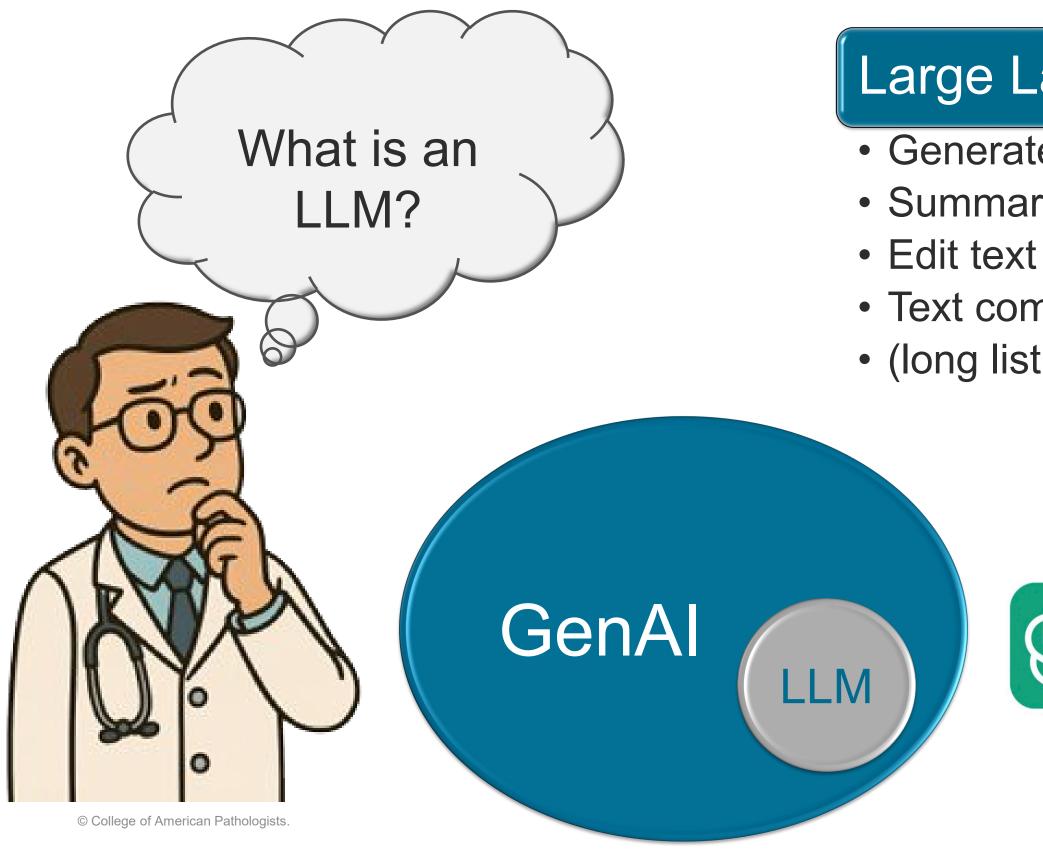
What is Generative AI?

© College of American Pathologists.

Generative AI (GenAI)

- Creates new content
- Patterns learned from vast datasets





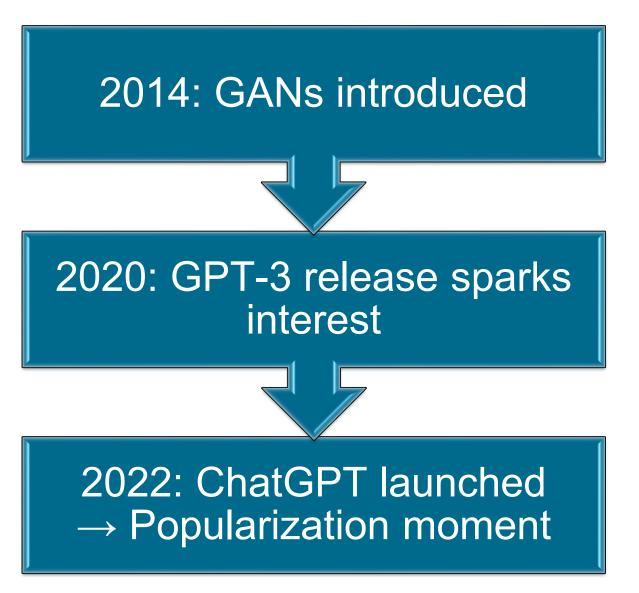
Large Language Model

- Generate text
- Summarize text
- Text comprehension
- (long list of functionalities)

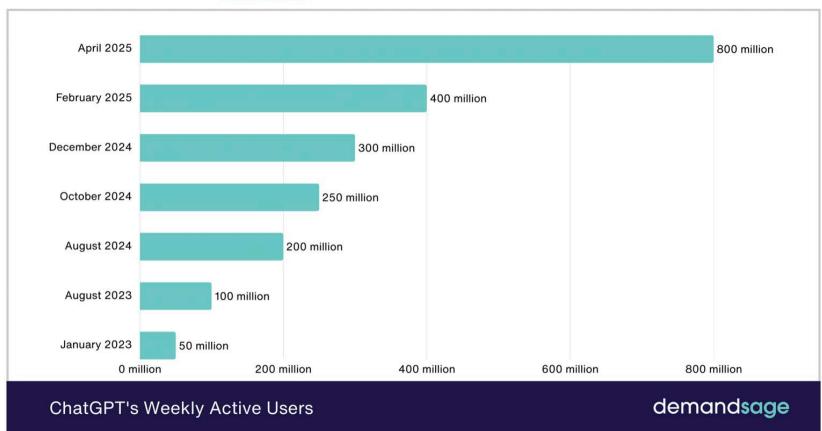
Prominent Example:



Generative AI (GenAI) The Moment it Took the World by Storm







Pathologist's Responsibilities

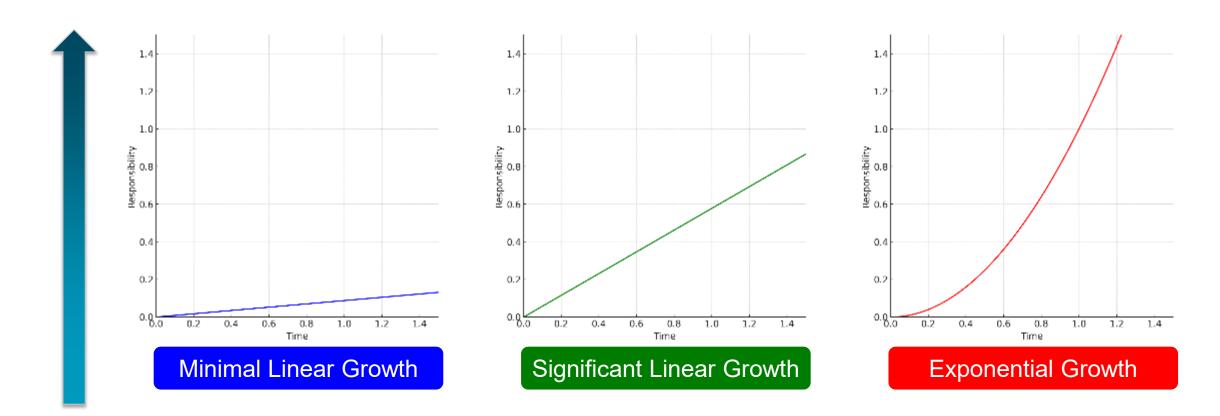


- Pathology is a complex profession
- The number of responsibilities, case complexity, and regulatory aspects is higher than ever and ever-growing



Ever-growing Responsibilities

The challenge isn't if, but how fast responsibilities expand



RESPONSIBILITY GROWTH RATE



Life Beyond Reading Slides...

Pathologists' obligations and responsibilities extend far beyond slide interpretation.

Early industry focus: diagnostic AI applications

Is this truly the area that delivers the most immediate impact for pathologists?

Does it significantly improve productivity?

Were these applications ever on pathologists' wish list?

Diagnostic Activities

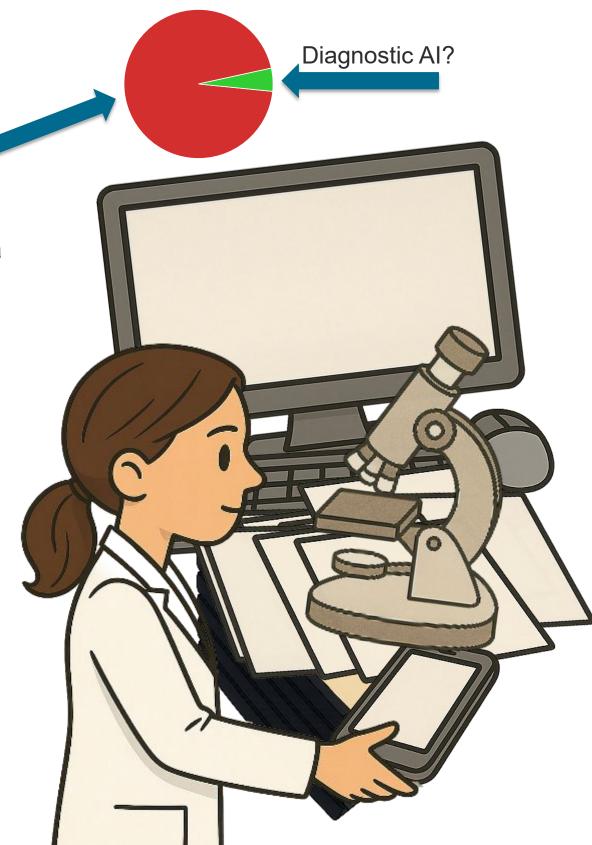
- Case reviews
- Diagnostic slide evaluation
- Ancillary testing (e.g., IHC, molecular requests)
- Correlation with clinical/pathology data
- Communication with clinicians

Clinical & Administrative Duties

- Tumor boards × 3
- Staff evaluation
- Quality assurance (QA)
- Directorships
- Random requests
- Emails
- Meetings

Education & Training

- Resident education
- Resident evaluation
- Professional development
- Continuing medical education (CME)
- Surveys



Inefficiencies

- Delayed slide deliveries
- Suboptimal IT systems
- Managing conflicts

Compliance & Credentialing

- Hospital credentialing
- Board continued accreditation
- Proof of vaccination
- TB annual testing
- Updated CV

Committees & Recruitment

- Recruitment
- Committees
- Interviews

Research & Scholarly Activity

- Publications
- Peer Review
- Lectures

Shortages

- While shortages are less severe in the US, they persist in certain locations
- What solutions could GenAl offer?



97% of NHS departments

Shortage (RCPATH 2018)

- Easy access to clinical history
- ✓ Faster report completion tools
- ✓ Frozen section summaries
- Streamlined stain / ancillary ordering
- Case prioritization

- ✓ Automated detection and grading of prostate cancer
- Automated detection and grading of breast cancer
- Automated detection of lymph node metastasis
- ✓ Automated immunostain quantification
- ✓ Biomarker scoring

PATHOLOGISTS

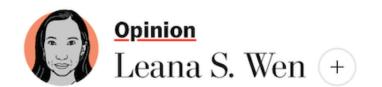
AI INDUSTRY



How Ambient Al Transforms Clinical Documentation Applying Ambient Al to Pathology Workflows



Ambient AI for Clinical Documentation



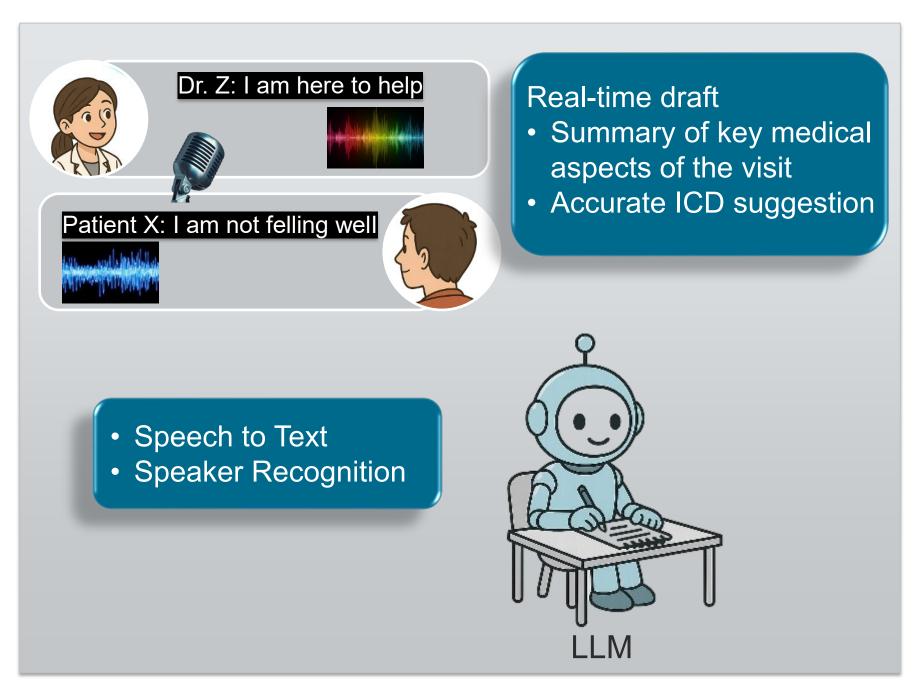
The Washington Post Democracy Dies in Darkness

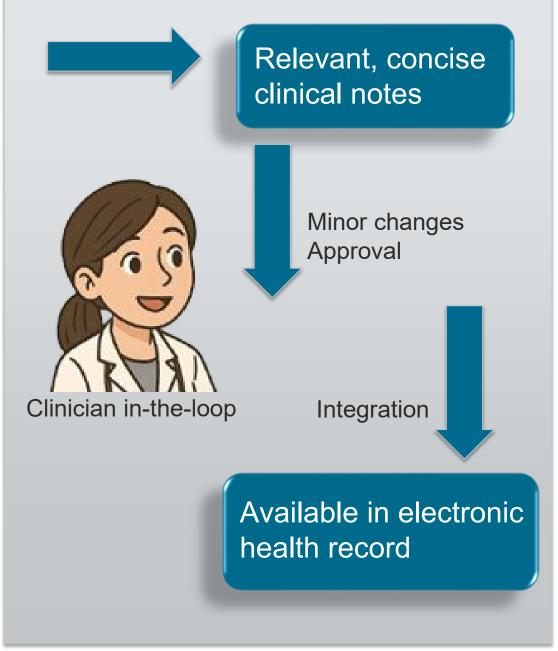
This technology is becoming beloved by doctors and patients alike

How artificial intelligence is helping medical professionals save time and reduce burnout.

March 25, 2025

How Ambient Al Works





Visit

After visit

Study Overview: 100 clinicians (53% male, average age 49) participated in this study examining the effects of ambient AI technology on clinical work.



Mental Workload Improvements

All measures showed significant improvements (p < 0.001):

Mental demand for note writing: Dropped from 12.2 to 6.3

Feeling hurried/rushed: Decreased from 13.2 to 6.4

Effort required for notes: Reduced from 12.5 to 7.4



Job Satisfaction by Specialty

Percentage reporting improved work satisfaction:

- Primary Care: 85.8% (33 of 38 clinicians)
- Medical Subspecialties: 36.4% (4 of 11 clinicians)
- Surgical Subspecialties: 50.0% (4 of 8 clinicians)



Time Savings

Time spent on notes per appointment decreased from 6.2 to 5.3 minutes (p < 0.001)

Gender Differences in Time Savings:

- Female clinicians: 8.1 → 6.7 minutes (bigger reduction)
- Male clinicians: 4.7 → 4.2 minutes (smaller reduction)



Burnout Results

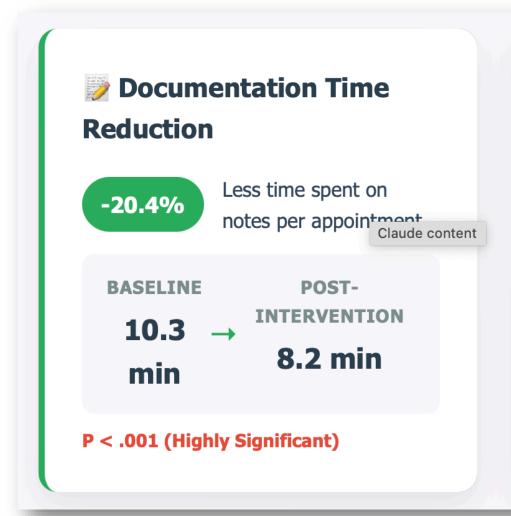
Burnout decreased from 42.1% to 35.1% of clinicians, though this change was not statistically significant (p = 0.12).

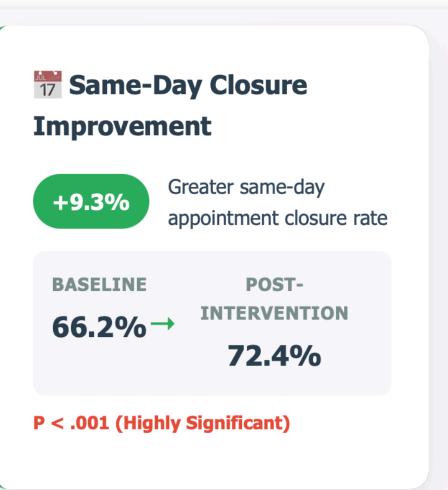
Stults, Cheryl D., et al. "Evaluation of an ambient artificial intelligence documentation platform for clinicians." JAMA Network Open 8.5 (2025): e258614-e258614.

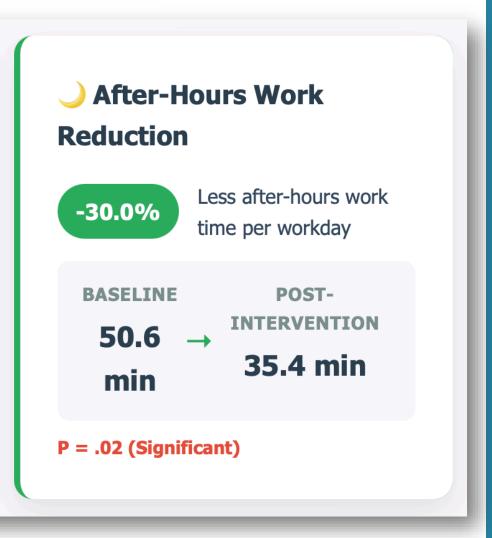
46
CLINICIANS

17
MEDICAL SPECIALTIES

MEAN YEARS EXPERIENCE





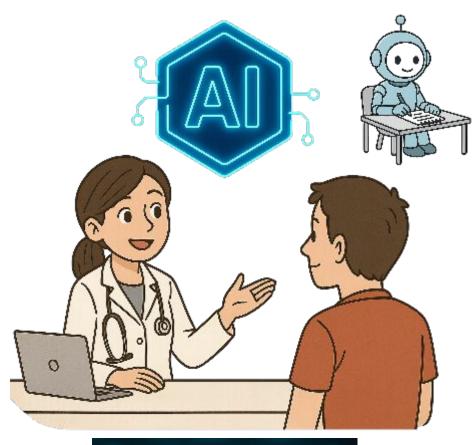


Less pajama time!





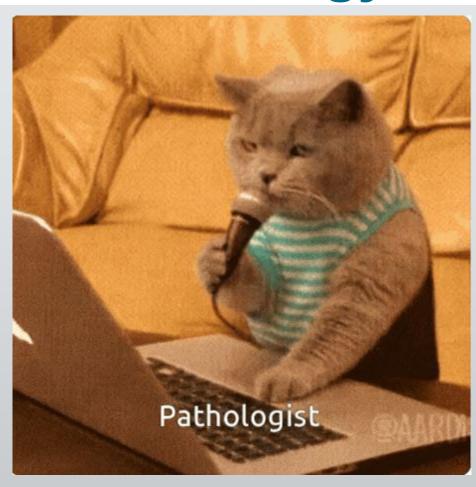




GenAl powered

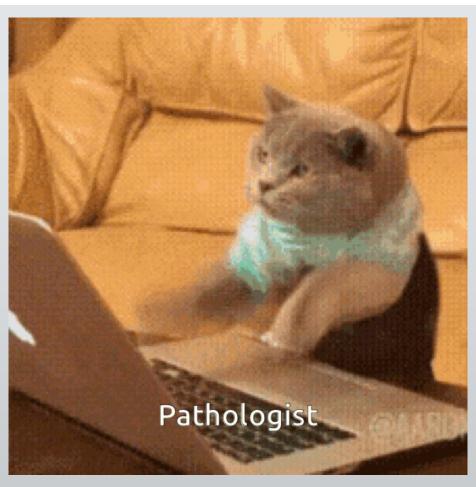
State of Pathology Reporting 2025

Support



Transcriptionist or dictation software available (but still requires numerous mouse clicks and keyboard commands)

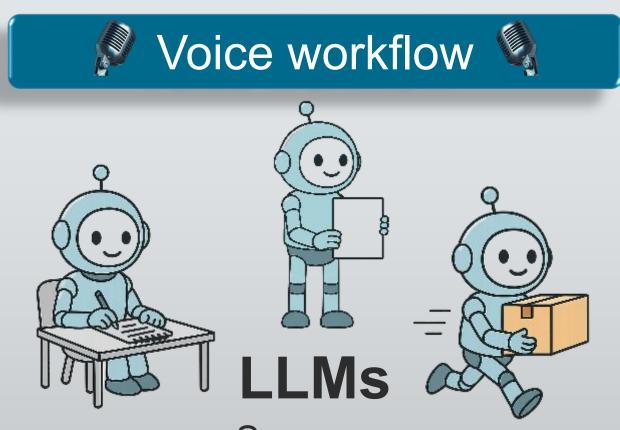
Limited support



No transcriptionist
No dictation software
No templates

Aspirational, But Possible Today – Agentic/LLMs

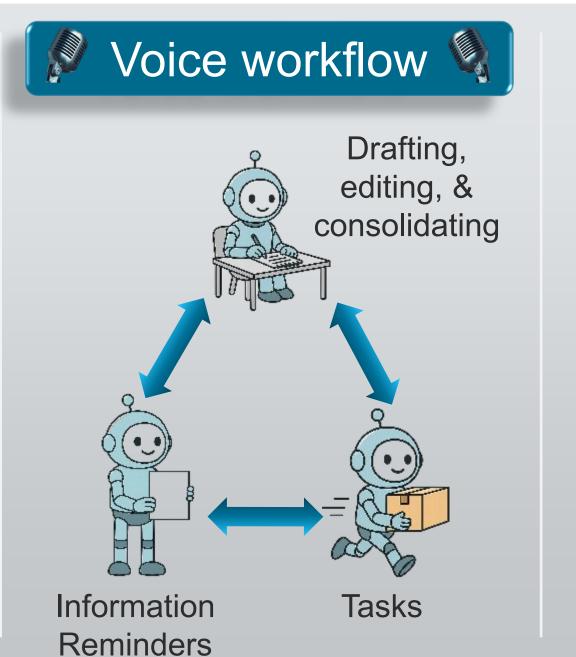


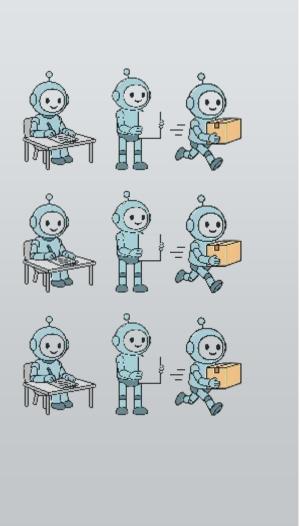


Summary
Report Draft
Report Creation
Ordering stains
Reminders

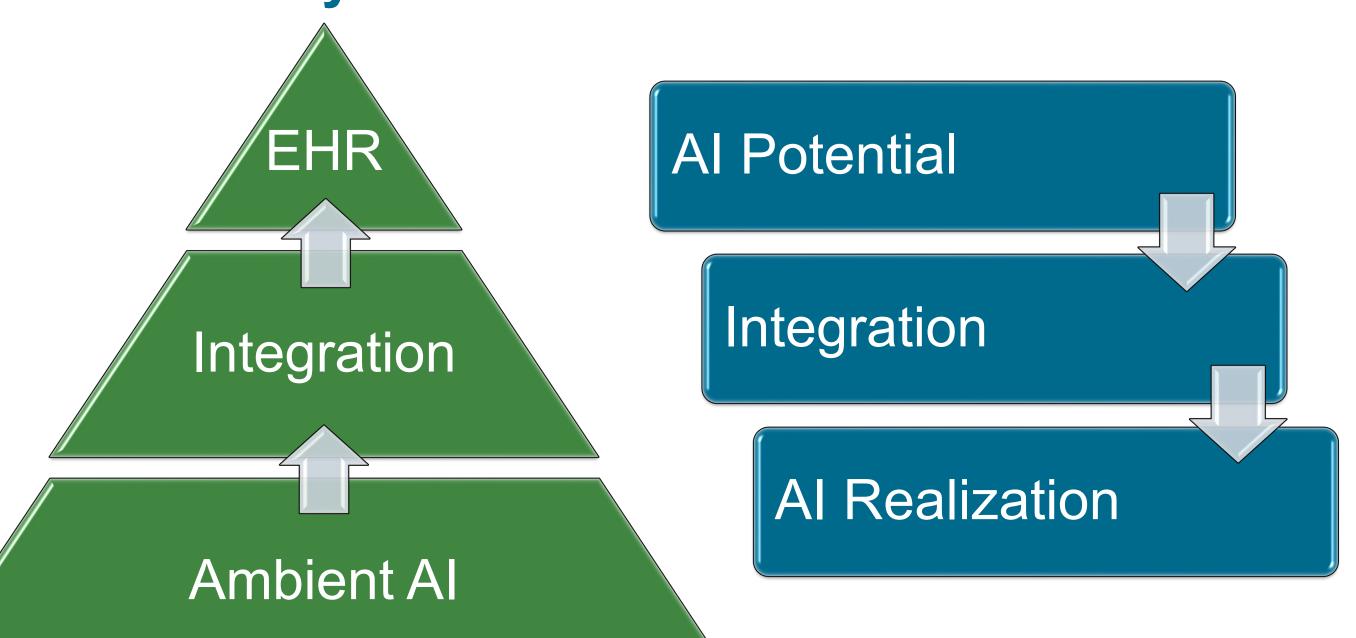
Aspirational, But Possible Today – Agentic/LLMs



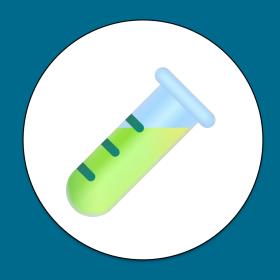




Integration = Key Features That Enable Ambient Al Functionality



How Integration Converts GenAl into Real Impact



Level 0: Experimentation

Copy & Paste

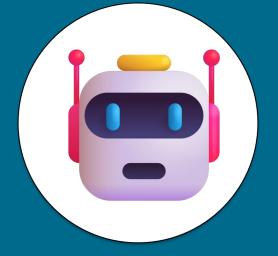
- Fast experimentation
- Low cost
- No streamlined workflow



Level 1: Integration

User-Selected Prompts with API Integration

- Users choose from predetermined prompts
- Requires API integration (higher cost, maintenance)
- Enables streamlined workflow

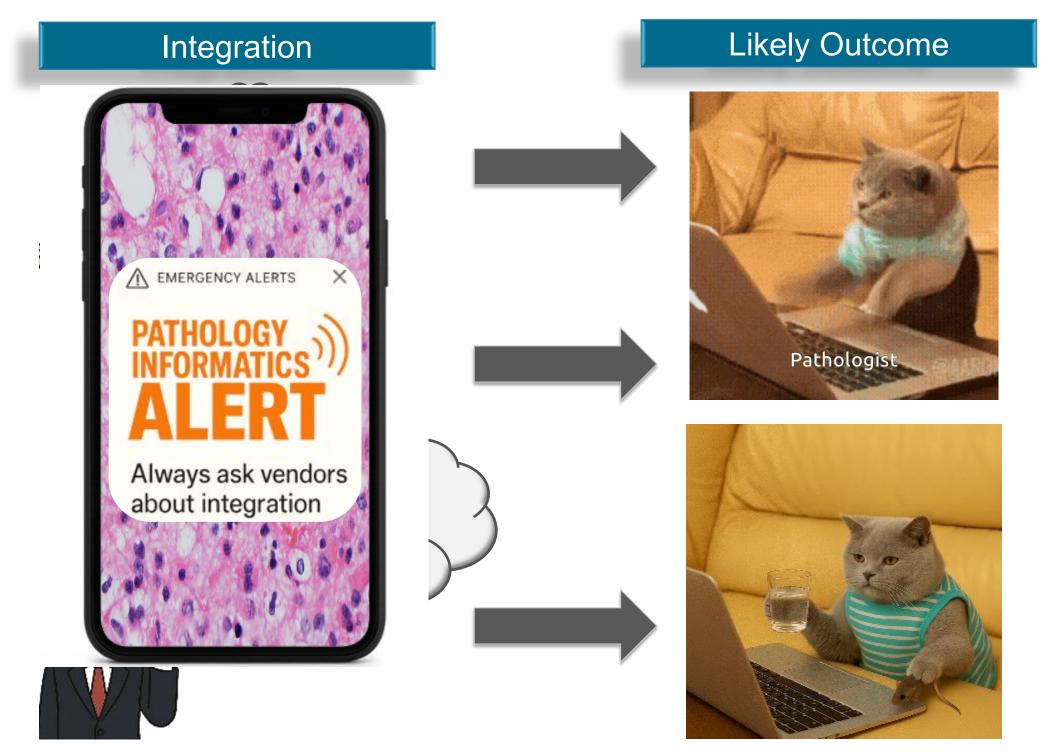


Level 2: Automation

Automated Al Selection

- Al autonomously selects prompts/tasks (no user input)
- Seamless integration
- Optimal streamlined workflow

Asking Vendors About Integration!





GenAl - Automated Summarization





Al can Outperform Humans in Writing Medical Summaries

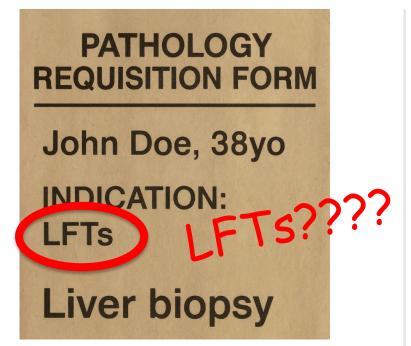
nature medicine

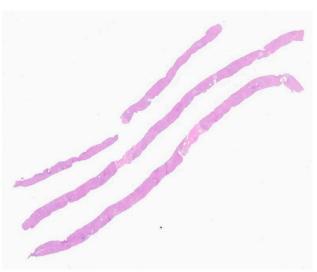
Article

https://doi.org/10.1038/s41591-024-02855-5

Adapted large language models can outperform medical experts in clinical text summarization

Current Approach





- LET's, Viral Serology, Autoimmune
- Medical Imaging
 Ultrasound, CT, MRI Findings
- Genetic Testing
 Wilson's, Hemochromatosis
- Medication History
 Hepatotoxic Drugs, Alcohol
- Previous Biopsies
 Serial Assessment Data

EHR Expedition
(Electronic Health Records)



Information Available

Information Needed

Retrieving Information

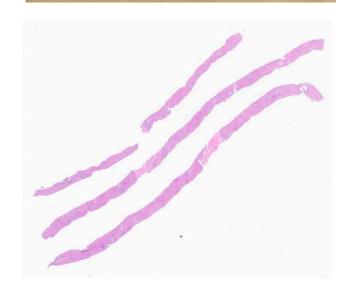
AI Summarization Approach

PATHOLOGY REQUISITION FORM

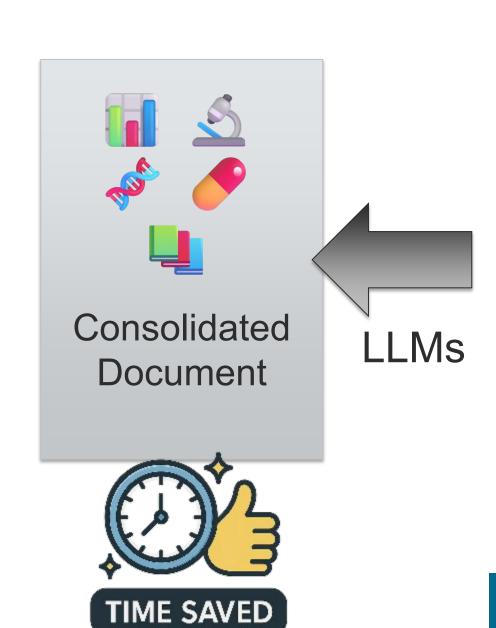
John Doe, 38yo

INDICATION: LFTs

Liver biopsy



Information Available



LETs, Viral Serology, Autoimmune

Medical Imaging
Ultrasound, CT, MRI Findings

Genetic Testing
Wilson's, Hemochromatosis

Medication History
Hepatotoxic Drugs, Alcohol

Previous Biopsies
Serial Assessment Data

Information Needed

LLM Processing Pipeline

LETS, Viral Serology, Autoimmune

Medical Imaging
Ultrasound, CT, MRI Findings

Genetic Testing
Wilson's, Hemochromatosis

Medication History
Hepatotoxic Drugs, Alcohol

Previous Biopsies
Serial Assessment Data

Medical Text Analysis

Clinical terminology

extraction, symptom parsing

** Differential Diagnosis
Disease probability ranking,
etiology assessment

Multi-Modal Fusion Lab-imaging-clinical correlation analysis Comprehensive
Al-assisted
Medical
Summary

EHR Data Sources



LLM

LLMs – Essential to Experiment to Discover Possibilities

LLMs Exploring Use Cases



HIPAA Compliance

Never send **HIPAA-protected data** to external LLMs such as **ChatGPT**, unless your healthcare organization has established **appropriate business associate agreements** and technical safeguards in place.



Local Deployment Strategy

Explore **local LLM deployment** options where sensitive data remains within your secure infrastructure, significantly improving privacy controls and regulatory compliance.



Synthetic Data Generation

Utilize LLMs to generate **synthetic pathology reports** and anonymized medical documentation for safe experimentation, training, and workflow development without exposing real patient information.



Institutional Review and Guidelines

Always consult your **institutional guidelines** and **Institutional Review Board (IRB)** requirements before implementing LLM solutions, especially for research applications involving patient data or clinical workflows.



www.ollama.com

Recommended Solution: Ollama enables on-premises deployment of various language models, ensuring complete data sovereignty and control.

QA – Text Discrepancies Going Beyond 10% Reports

Specimen:

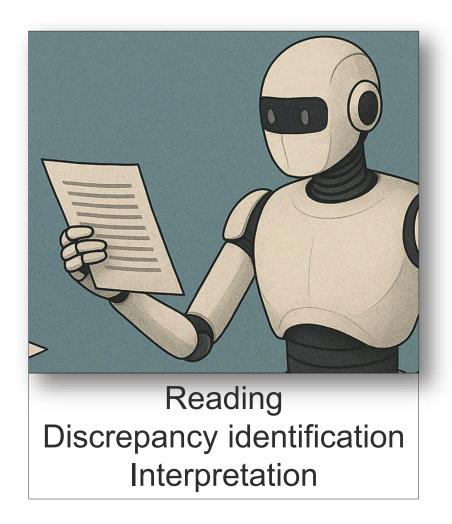
Right breast, biopsy

Clinical History:

Breast mass

Diagnosis:

Breast, left, biopsy: Ductal adenocarcinoma



LLM output:

This kind of discrepancy is significant because laterality (right vs. left breast) directly affects **patient management and treatment decisions** (e.g., surgery, radiation therapy, targeted breast imaging). Mislabeling could result in inappropriate therapy to the wrong breast.

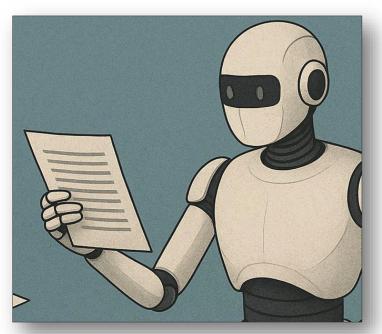
Supporting Resident Education

Diagnosis (resident)

Breast, right, biopsy:

Fibrocystic changes

Resident Report (Draft)



Diagnosis (faculty)

Breast, right, biopsy:

Ductal adenocarcinoma

LLM output: Type of Discrepancy (Classification):

Diagnostic discrepancy (benign vs. malignant).

Clinical Significance:

 Very high — misclassifying a malignant lesion as benign could lead to missed or delayed cancer treatment.

Possible Causes:

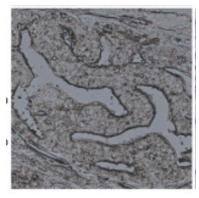
- Under-recognition of cytologic/nuclear atypia by the resident
- Over-reliance on benign background changes
- Limited diagnostic experience (common in early training)



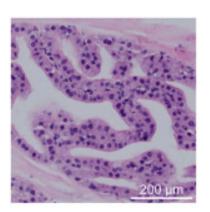
GenAI - Unlocking Digital Stains No More Waiting for Stains

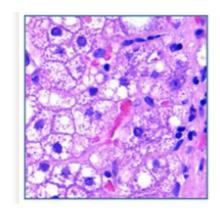


Digital Stains

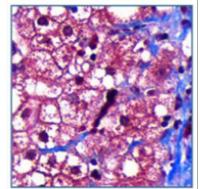














Zero Wait Time

Instant results eliminate traditional staining delays and improve diagnostic turnaround times

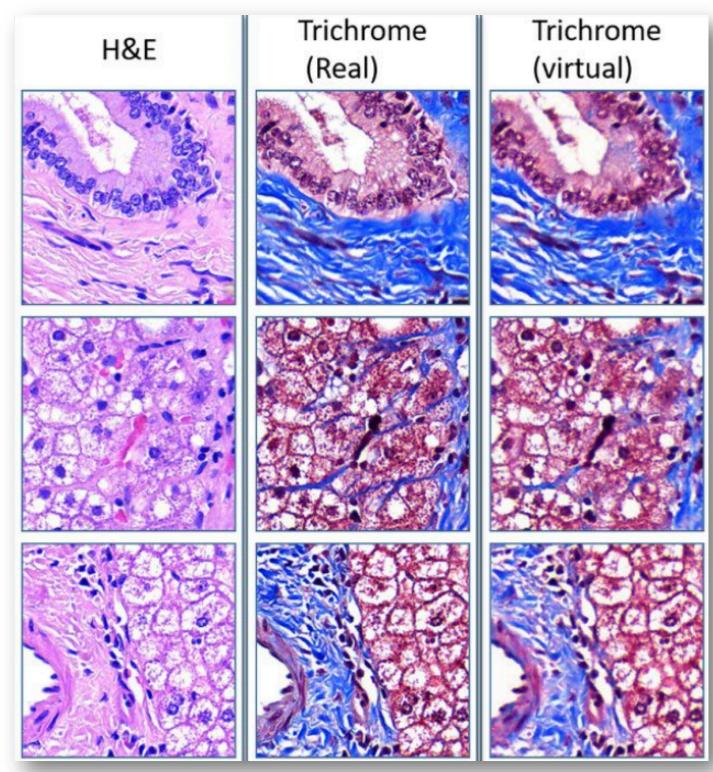
Significant Cost Savings on Histology

Reduces reagent costs, labor expenses, and equipment maintenance while maintaining diagnostic quality



Tissue Conservation

Preserves valuable tissue samples by reducing the need for multiple physical sections





Medical Image Analysis

Volume 81, October 2022, 102537

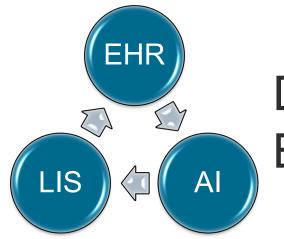


Conditional GANs based system for fibrosis detection and quantification in Hematoxylin and Eosin whole slide images

Ahmed Naglah a, Fahmi Khalifa a, Ayman El-Baz a 💍 🖾 , Dibson Gondim b

Mr. Integration is Running the Show



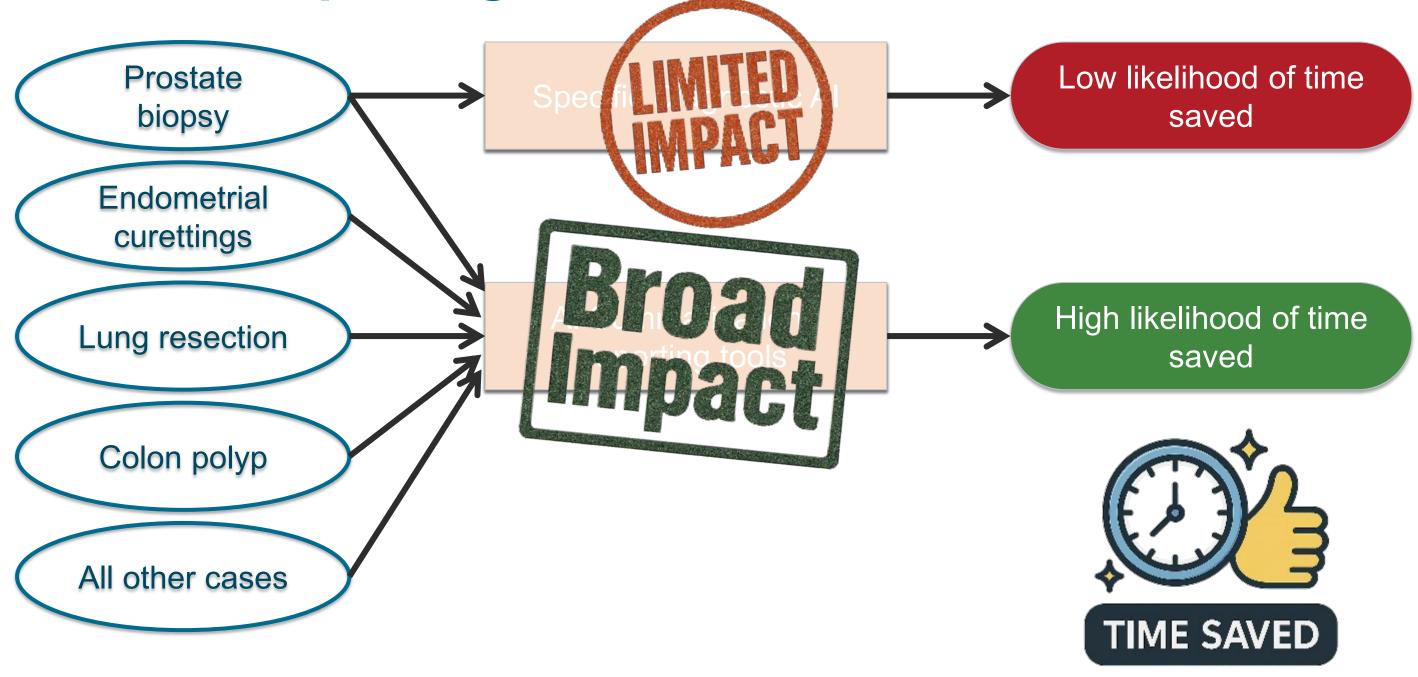


Data Exchange Between Systems



NO Mr. Integration, NO show & NO time saved!

GenAl Reporting/Summarization



Diagnostic

- C, molecular **Potential**
- **√**al pathology data Corleian
- Communication with clinicians

Clinical & Administrative Duties

- Tumor 50
- Staffe
- Potential.
- Emails
- Meetings

Education

- Reside

- of Gential ent gucation (CME)

© College o



Inefficie!

Complian

dentialing

- Hospita
- GenA
- Potential!
- TB an
- Update

Committees

- Recruite/ Gen
- Comn
- **Potential** Interviev

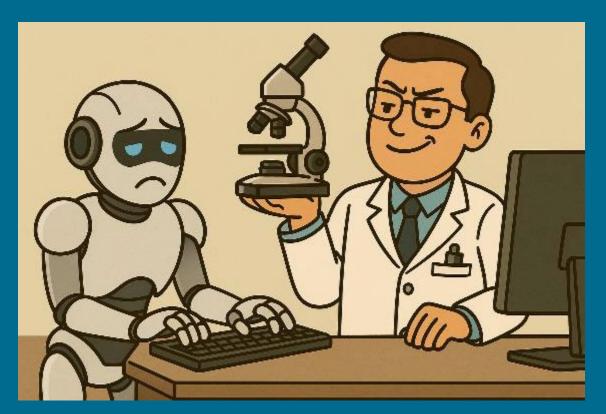
y Activity

- A Potential.

58

GenAl – Take Home Points

- Real impact in drafting clinical notes (peer-reviewed publications)
- More accessible technology (compared with digital pathology)
- Broader impact on pathology workflows
- Diagnostic AI is still limited in its overall impact
- A matter of time for the GenAl industry to support pathology

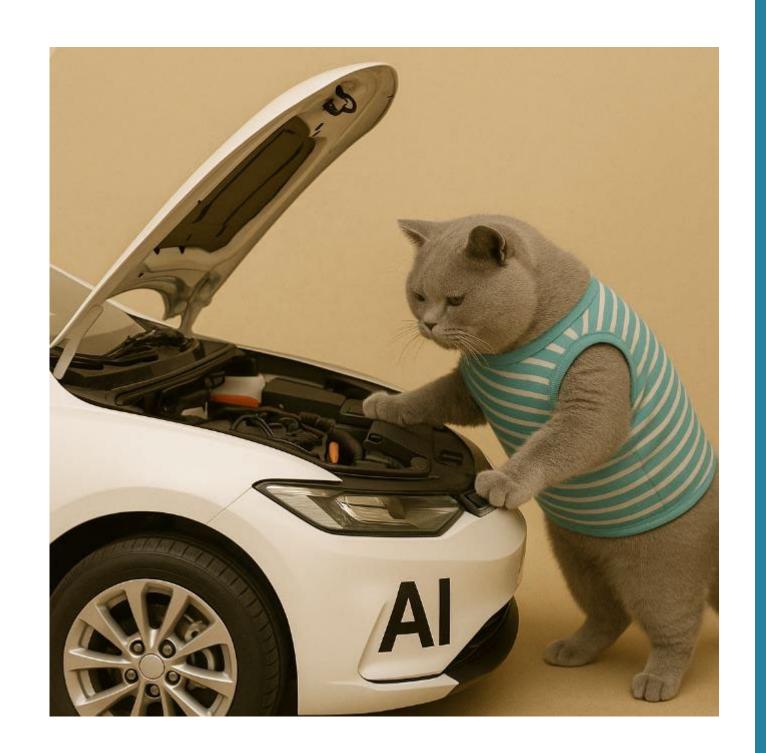




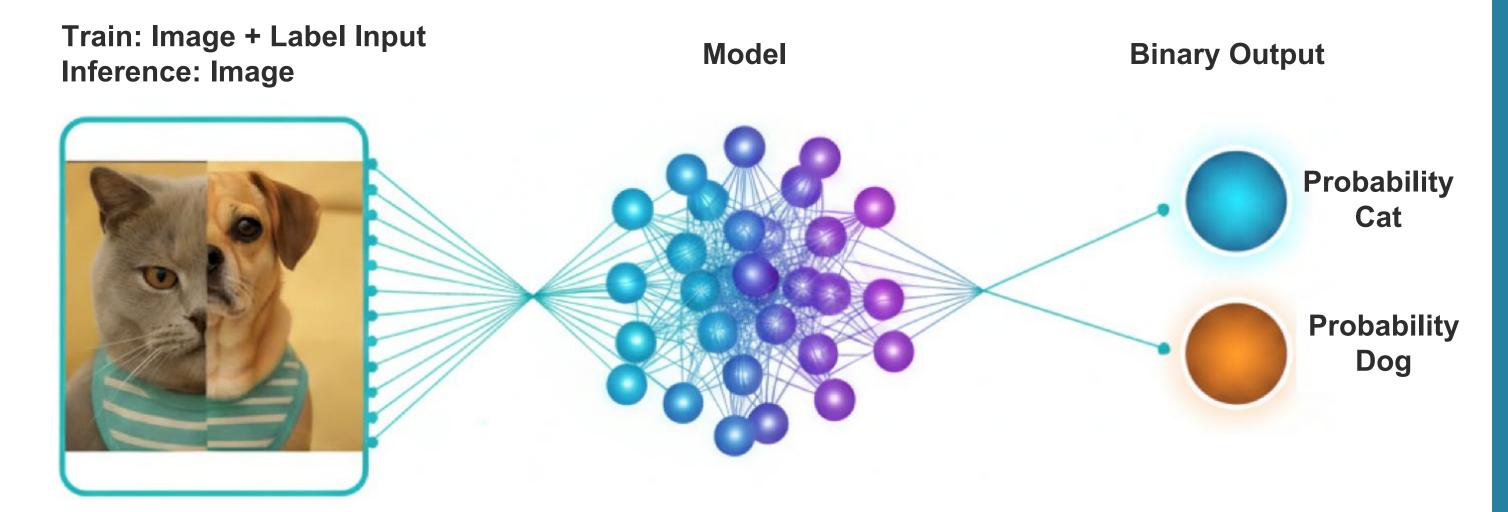
Looking Under the Hood

- How did we get here?
- Important considerations
- What do we think comes next?

- The evolution of Al
 - Narrow models
 - Foundational models
 - Combining data modalities for MLLMs
 - Reasoning models and you
 - Interactive models to Agentic systems



Narrow Models: FDA-cleared Al



- The model learns to differentiate between options, based on classes
- Not all problems can be distilled into classes

Foundational Models

Train: Image Inference: Image







Mask Data

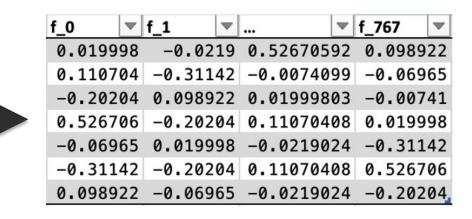






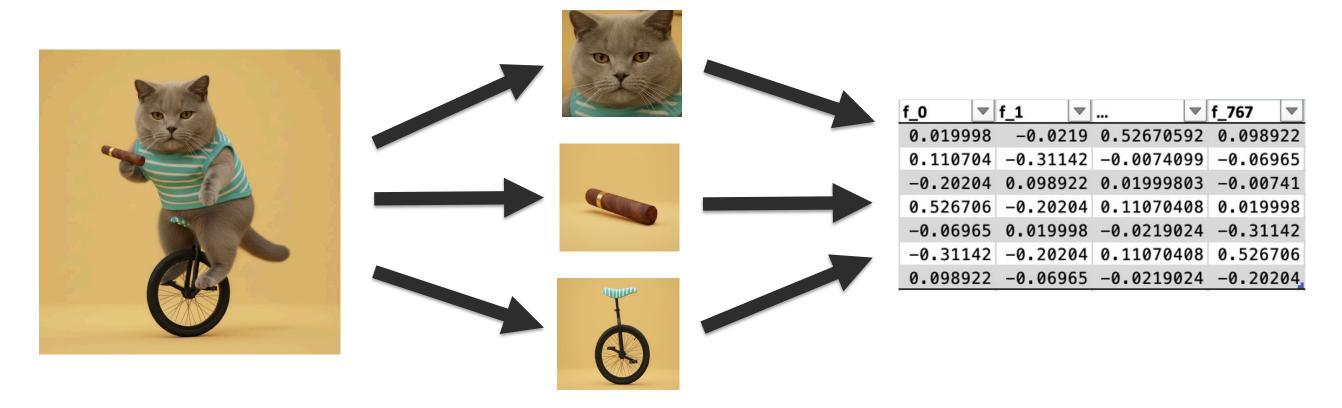


Numeric Output



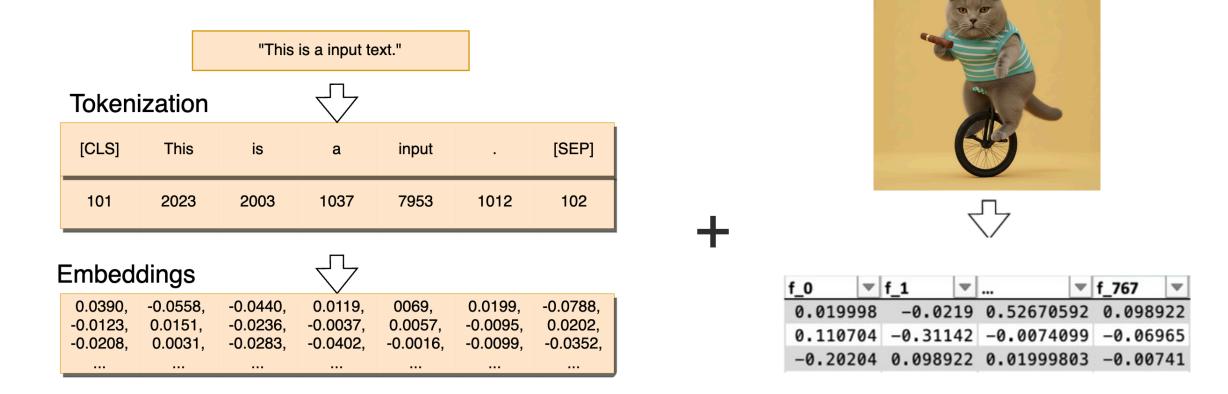
- The model learns to describe data, resulting in numerical features
- Features can be used for binary problems with class labels
- Features can also be used for much more, with or without class labels

Foundational Models



- Features can only be generated for things the model has observed
- They are not like labels and can represent combinations of classes
- Models can describe complex combinations of features that have never been observed

Multimodal LLMs (MLLM)

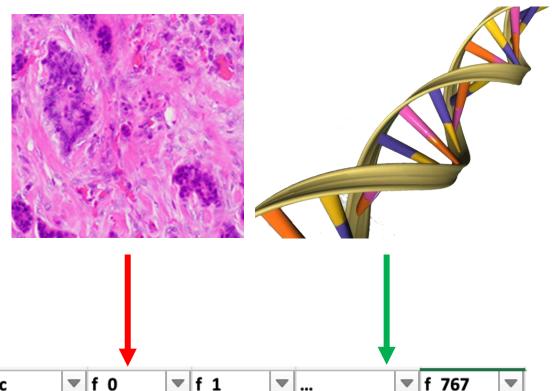


- LLMs at their core work from numerical descriptions of text
- Complex descriptions of images are matched with image features
- Context (features/embeddings) are critical for generative AI performance

Multimodal LLMs (MLLM)

Inputs

- Text, imaging, timeseries (EKG, eICU), genomics, etc.
- Observe large volumes of data and provide numeric characterizations of inputs (cancer, Alzheimer, etc. features)
- Allows us to holistically leverage medical data across disciplines





age	▼ sex	▼ race	■ alb	▼ tlc	▼ f	_0 🔻	f_1 🔻		f_767 🔻
	35	0	1	3.2	0.58	0.019998	-0.0219	0.52670592	0.098922
	66	0	1	2.9	0.72	0.110704	-0.31142	-0.0074099	-0.06965
	43	1	1	1.2	1.7	-0.20204	0.098922	0.01999803	-0.00741
	68	1	1	3.3	0.91	0.526706	-0.20204	0.11070408	0.019998
	40	1	1	1.6	1.12	-0.06965	0.019998	-0.0219024	-0.31142
	27	1	1	3.7	2.02	-0.31142	-0.20204	0.11070408	0.526706
	31	0	1	2.8	0.87	0.098922	-0.06965	-0.0219024	-0.20204

Case Data



PathChat: Al Co-Pilot for Pathology

nature

Article | Published: 19 March 2024

Towards a general-purpose foundation model for computational pathology

Richard J. Chen, Tong Ding, Ming Y. Lu, Drew F. K. Williamson, Guillaume Jaume, Andrew H. Song,
Bowen Chen, Andrew Zhang, Daniel Shao, Muhammad Shaban, Mane Williams, Lukas Oldenburg, Luca
L. Weishaupt, Judy J. Wang, Anurag Vaidya, Long Phi Le, Georg Gerber, Sharifa Sahai, Walt Williams &
Faisal Mahmood

Article | Published: 19 March 2024

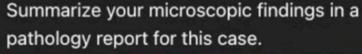
A visual-language foundation model for computational pathology

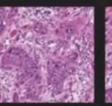
Ming Y. Lu, Bowen Chen, Drew F. K. Williamson, Richard J. Chen, Ivy Liang, Tong Ding, Guillaume

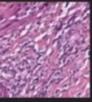
Jaume, Igor Odintsov, Long Phi Le, Georg Gerber, Anil V. Parwani, Andrew Zhang & Faisal Mahmood □

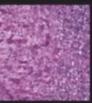
A multimodal generative AI copilot for human pathology

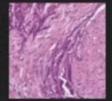
Ming Y. Lu, Bowen Chen, Drew F. K. Williamson, Richard J. Chen, Melissa Zhao, Aaron K. Chow, Kenji Ikemura, Ahrong Kim, Dimitra Pouli, Ankush Patel, Amr Soliman, Chengkuan Chen, Tong Ding, Judy J. Wang, Georg Gerber, Ivy Liang, Long Phi Le, Anil V. Parwani, Luca L. Weishaupt & Faisal Mahmood











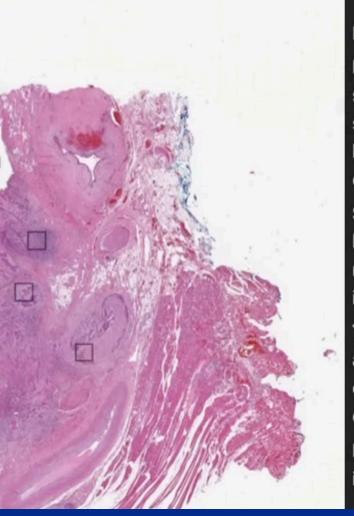
PathChat

First image: The tumor is composed of nests of squamous cells that are infiltrating the surrounding tissue. The squamous cells exhibit keratinization, a hallmark of squamous cell carcinoma.

Second image: There is a prominent lymphocytic infiltrate surrounding the tumor nests. This dense lymphocytic presence is indicative of an immune response to the tumor.

Third image: The tumor nests are surrounded by a desmoplastic stroma, which is a dense, fibrous connective tissue response to the invading tumor cells.

Fourth image: The tumor nests are infiltrating into the nerve sheath, indicating perineural





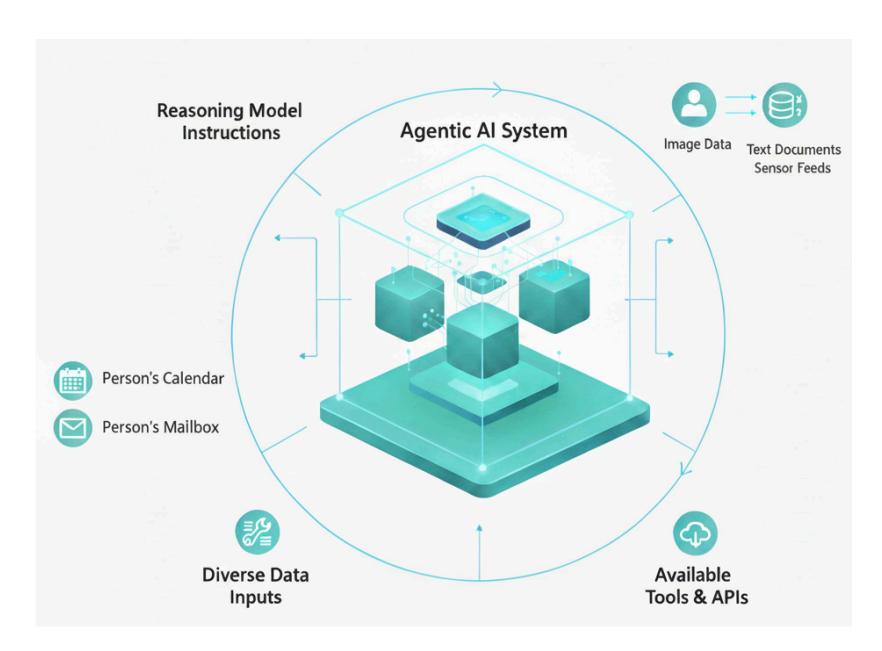
Reasoning Models

- LLMs prompts provide context to the model to generate responses
- Reasoning models allow the user to instruct the model on procedure
- While computational expensive, they open the door to complex processes that would otherwise have to be trained within the model

```
{# Enhanced Template for Generating Clear Explanations and Verifications #}
For a PubMed research article produce a clear, step-by-step explanation of how
If any discrepancies are identified, re-calculate and provide the correct steps
Use the following text for your analysis: [{{text_data}}]
Restate the problem clearly using <think> tags.
Conclude the reasoning with the final answer inside <answer> tags.
Include a <verifier_answer> section containing only the result, formatted in va
<think>
Your analysis will involve providing the following the following outputs:
 -Location: the location(s) where the study took place in the format county, sta
-Participating origination(s): the names of the organizations involved in the \mathbf{s}^{\cdot}
 -Data Collection Site(s): the site(s) where data was collected from participants
 -Patient Recruitment Site: the location in the format of county, state, country
 -Community Engagement: note any community engagement (e.g. county extension age
 -Categories of Treatment: list of categories (e.g. medicine, intervention, ther
-Types of Studies: list of study types (e.g. cross-sectional study, retrospecti
Reasoning:
1. Start with the expression.
2. Explain and solve step by step
3. Conclude with the final result based on the above steps.
Recheck the steps, and answer if there is a discrepancy
</think>
<answer>final answer</answer>
<verifier_answer>clean answer used for verification</verifier_answer>
```

Agentic Al

- Functions as your assistant
- Has access (tool calling) to external systems as you
- Leverages LLM/MLLM for advanced analysis and reasoning models for procedure
- Standards are being developed for A2A



Additional Resources

- Practice Management Webpage
 - https://www.cap.org/member-resources/practice-management
- Previous and Upcoming Roundtables/Webinars
 - https://www.cap.org/calendar/webinars/listing/practice-management-webinar
- Articles Authored by Members of the CAP Practice Management Committee
 - https://www.cap.org/member-resources/articles/category/practice-management
- Practice Management Networking Community
 - o https://www.cap.org/member-resources/practice-management/practice-management-networking-community-application
- Practice Management Frequently Asked Questions
 - o https://www.cap.org/member-resources/practice-management/frequently-asked-questions

Membership

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Visit <u>cap.org</u> to renew your membership or email <u>membership@cap.org</u>.

We value your feedback!



If after attending this discussion and later you applied any of what you learned to your practice, please share your feedback of how it worked for your practice at https://www.cap.org/member-resources/practice-management/practice-management-inquiry-form.



Watch for the session evaluation form. Your feedback is important!

