

# Artificial Intelligence-Brave New World? Artificial Intelligence for Antimicrobial Stewardship

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# Disclosures

No relevant conflicts.

 I have received research funding (funds to organization) from the Canadian Institute for Health Research, World Health Organization, and University of Toronto





# **A Pivotal Moment for Artificial Intelligence**



March 2023 (Stable Diffusion)



February 2024 (Open AI, Sora)









# What is Artificial Intelligence?

"the discipline that creates computer systems capable of activities normally associated with cognitive effort"



Solomonides AE, Koski E, Atabaki SM, Weinberg S, McGreevey III JD, Kannry JL, Petersen C, Lehmann CU. Defining AMIA's artificial intelligence principles. Journal of the American Medical Informatics Association. 2022 Apr 1;29(4):585-91.



# What is Artificial Intelligence?

## **Artificial Intelligence**

Computer systems capable of activities normally associated with cognitive effort

## **Machine Learning**

Training machines to recognize patterns. Using labelled (supervised) or unlabeled (unsupervised) data

## **Deep Learning**

Subfield of machine learning using layered neural networks to learn from vast amounts of data

## Generative AI

Subfield of deep learning that relates to the generation of new data (text, audio, video, images)





# **Artificial Intelligence Publications by Specialty**









# **Applications of AI in Healthcare**





US Government Accountability Office & National Academy of Medicine. Technology Assessment: Artificial Intelligence in Healthcare. 2020. https://www.gao.gov/assets/gao-21-7sp.pdf

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# **Risks of Artificial Intelligence in Healthcare**

Risk	Mitigation Strategy
Model Bias Underlying bias (e.g., race, gender) in dataset can be amplified via Al models.	Ensure high quality data input. Review and Incorporate equity lens to AI implementation
Data Requirements AI/ML model is limited by the quality and completeness.	Ensure sufficient volume and quality of data Structured, and labelled data are ideal. Vo settings should be performed.
Model Drift Relationship between variables can change over time, leading to model instability.	Continuously evaluate model performance if needed.
Automation (Human) Bias Overreliance and excess trust in model output.	Training and education regarding AI literac be encouraged.
<b>Privacy Breaches</b> Risk of patient identification if data are shared beyond facility	Data protection regulations. Cryptographic federated learning decentralizes AI models collaboration.
<b>Explainability</b> Sophisticated AI models are often 'black boxes' thereby reducing trust in their output.	"Explainable AI" approaches like SHAP (SHo exPlanations) can be used to measure the variable.

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Doyen S, Dadario NB. 12 plagues of AI in healthcare: a practical guide to current issues with using machine learning in a medical context. Frontiers in digital health. 2022 May 3;4:765406.

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# **Successful Implementation of AI in Healthcare**



## Acceptance

- Perceived usefulness
- Perceived ease of use
- Organizational support



## **Technical Integration**

- Interface development (e.g., with EHR)
- Partnership with vendors
- Interdisciplinary teams



## **Data and Resources**

- Identified use cases
- Data cleaning and labeling
- Computational resources
- Expertise



### Governance

- Transparency and interpretability
- Mitigating inaccurate output
- Addressing ethical issues (e.g., privacy)
- Validation



Reddy S. Generative AI in healthcare: an implementation science informed translational path on application, integration and governance. Implementation Science. 2024 Mar 15;19(1):27.



# **Three Epochs of AI in Healthcare**

	1950s						
Approximate		2011					
beginning year			2018-2022				
	Al 1.0 Symbolic AI and probabilistic models	AI 2.0 Deep learning	AI 3.0 Foundation models				
Core functionality and key features	Follows directly encoded rules (if-then rules or decision trees)	Predicts and/or classifies information Task-specific (1 task at a time); requires new data and retraining to perform new tasks	Generates new content (text, sound, images) Performs different types of tasks without new data or retraining; prompt creates new model behaviors				
Training method	Rules based on expert knowledge are hand-encoded in traditional programming	Learning patterns based on examples labeled as ground truth	Self-supervised learning from large datasets to predict the next word or sentence in a sequence				
Performance capabilities	Follows decision path encoded in its rules. Eg, ask a series of questions to determine whether a picture is a cat or a dog.	Classifies information based on training: "Is this a cat or a dog?" "How many dogs will be in the park at noon?"	Interprets and responds to complex questions: "Explain the difference between a cat and a dog."				
Examples of performance	IBM's Deep Blue beat the world champion in chess <b>Health care:</b> Rule-based clinical decision support tools	Photo searching without manual tagging, voice recognition, language translation <b>Health care:</b> diabetic retinopathy detection, breast cancer and lung cancer screening, skin condition classification, predictions based on electronic health records	Writing assistants in word processors, software coding assistants, chatbots Health care: Med-PaLM and Med-PaLM-2, medically tuned large language models, PubMedGPT, BioGPT				
Examples of challenges and risks	Human logic errors and bias in encoded rules lead to limited capability with real-world situations	Out-of-distribution problems (real-time data differs from training data) Catastrophic forgetting (not remembering early parts of a long sequence of text) Bias related to underlying training data	Hallucinations (plausible but incorrect responses based solely on predictions) Grounding and attribution Bias related to underlying training data and semantics of language in datasets				

Howell MD, Corrado GS, DeSalvo KB. Three Epochs of Artificial Intelligence in Health Care. JAMA. 2024;331(3):242-4.







## Symbolic AI and Probabilistic Models





# **1.0 Symbolic Al and Probabilistic Models**

## **Clinical decision support rules**

- Allergy and drug-interaction check in electronic health records
- Dosing calculators
- Best practice advisory (BPA) alerts •

<ul> <li>Avoid order for C. difficile test in patients on laxatives</li> <li>Indwelling urinary catheter in place &gt; 48 hours</li> <li>Prompt to indicate symptoms when ordering urine culture in hemodynamically stable patients</li> <li>Screening tool to predict risk of C. difficile based</li> <li>Positive C difficile assay without treatment</li> <li>Flag to re-assess duration of broad spectrum an Re-assess vancomycin after &gt;72 hours if no MRS.</li> <li>Bug-drug mismatch alert</li> <li>Highly bioavailable antibiotic receiving oral mediates</li> </ul>	D	iagnostic Stewardship Alerts	Antimicrobial Stewardship Alerts
Sepsis alert based on lab criteria/vitals	•	Avoid order for C. <i>difficile</i> test in patients on laxatives Indwelling urinary catheter in place > 48 hours Prompt to indicate symptoms when ordering urine culture in hemodynamically stable patients	<ul> <li>Screening tool to predict risk of C. difficile based on</li> <li>Positive C difficile assay without treatment</li> <li>Flag to re-assess duration of broad spectrum antibio</li> <li>Re-assess vancomycin after &gt;72 hours if no MRSA ide</li> <li>Bug-drug mismatch alert</li> <li>Highly bioavailable antibiotic receiving oral meds/di</li> <li>Sepsis alert based on lab criteria/vitals</li> </ul>



- Identify, synthesize, and evaluate antimicrobial stewardship alerts and algorithms
- Prioritize and provide recommendations for ASP implementation of alerts

1. Van Dort BA, et al. JAC. 2022;77(7):1828-37. 2. Heil EL, et al. OFID 2023





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## The Era of Machine and Deep Learning





## Streamlining Antimicrobial Stewardship Workflow

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- Acute teaching hospital in S. Korea, prospective audit and feedback data
- Machine learning was used to identify predictors for a PAF intervention amongst >160 variables

Predictors of PAF Intervention		
Discontinue	Intravenous to Oral	De-Escalation
<ul> <li>Infection recovery</li> <li>Illness severity score, body temp, CRP, absence of SIRS, % mature neutrophils, absence of blood cx in past 3 days</li> </ul>	<ul> <li>Infection recovery</li> <li>Taking oral medications in past 3 days</li> </ul>	<ul> <li>Targeted antibiotic use</li> <li>Susceptibility to narrower age</li> <li>Negative predictors: mechai ventilation, supplemental O2</li> </ul>

Compared to PAF based on length of therapy, models identified a higher number of patients for intervention  $\uparrow 17-41\%$ 

> Tran-The T, Heo E, Lim S, Suh Y, Heo KN, Lee EE, Lee HY, Kim ES, Lee JY, Jung SY. Development of machine learning algorithms for scaling-up antibiotic stewardship. International Journal of Medical Informatics. 2024;181:105300.

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## Streamlining Antimicrobial Stewardship Workflow

- Prospective audit/feedback data from University of Maryland Medical Center
- Machine learning using random forest captured several variables



Compared to standard methods, algorithm reduced reviews by 49%, with 78% sensitivity



Al in Antibiotic Stewardship Opportunities

Consider ML approaches to identify prospective audit and feedback "hotspots"



Goodman KE, Heil EL, Claeys KC, Banoub M, Bork JT. Real-world Antimicrobial Stewardship Experience in a Large Academic Medical Center: Using Statistical and Machine Learning Approaches to Identify Intervention "Hotspots" in an Antibiotic Audit and Feedback Program. OFID 2022



Predicting Antimicrobial Resistance using Laboratory and Health Records Data



FIG 1 Workflow for ML prediction of AMR.



Kim JI, Maguire F, Tsang KK, Gouliouris T, Peacock SJ, McAllister TA, McArthur AG, Beiko RG. Machine learning for antimicrobial resistance prediction: current practice, limitations, and clinical perspective. Clinical microbiology reviews. 2022 Sep 21;35(3):e00179-21.



# 2.0 Machine Learning

## **Predicting Antimicrobial Resistance**





Kherabi Y, Thy M, Bouzid D, Antcliffe DB, Rawson TM, Peiffer-Smadja N. Machine learning to predict antimicrobial resistance: future applications in clinical practice?. Infectious Diseases Now. 2024:104864.

## **Antimicrobial Susceptibility Testing**



# 2.0 Machine Learning

## Precision Infectious Diseases: Improving Antibiotic Appropriateness

	Population	Input	Model	Output
Z	<b>Recurrent UTI</b> Cai T, et al. Antibiotics. 2023.	Current C&S, Prior C&S Prior antibiotics, Treatment success	Artificial Neural Network (ANN)	Clinical efficacy antibiotics
	Intravenous to oral switch Bolton WJ, Nat commun. 2024.	Clinical data (vital signs), IV to PO guidelines	Artificial Neural Network (ANN)	Suggestion for IV
-	Suspected pneumonia Tang S, et al. IDWeek 2023.	Electronic health record clinical, radiographic data	Gradient boosting algorithm	Suggestion for an for lower respirate infection
	<b>Pharyngitis</b> Jin Z, et al. Sci Rep. 2023	Hematological parameters (i.e., CBC)	Various	Likelihood of viral infection



Al in Antibiotic Stewardship Opportunities

• Ensure availability of high quality data; collaborate with experts in AI to build and test models



### of empiric

### to PO switch

### ntibiotic initiation ory tract

### vs. bacterial



**Population-Level Surveillance and Benchmarking** 



## Healthcare Facilities

Patient encounter level variables predict facilitywide antimicrobial usage<sup>1,2</sup>



## Community

Provider and patientlevel variables predict populations high risk for inappropriate antibiotic use for respiratory tract infections<sup>3</sup>





### Al in Antibiotic Stewardship Opportunities

- Implement and evaluate patient-level risk-adjustment to assist in inter-facility benchmarking
- Use AI-assisted methods to identify targets for antimicrobial stewardship intervention



- 1. Chowdhury AS, et al. J Applied Microbiol.
- 2. Moehring RW, et al. JAMA network open. 2021
- 3. King LM, et al. ICHE. 2023.



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## Foundation Models and Generative AI





# 3.0 Generative AI

Foundational Model Examples (Large Language Models)

Corporation	Model	Formal Medical Applic
ြ OpenAI	<b>GPT-4</b> Generative Pre-trained Transformer	Integration into EHRs (e notes, report generation listening)
Meta	<b>LLaMA-2</b> Large Language Model Meta Al	<b>Me LLaMA</b> open sourc large language mode
Google	Gemini	<b>Med-PaLM</b> multi-mode large language mode
ANTHROP\C	Claude-3	None at this time



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# GENERATIVE AI AND ANTIMIC ROBIAL STEWARDSHIP Practical Use Cases



## **DEVELOP GUIDANCE**

Screate custom antibiotic stewardship GPTs Develop new guidance documents using prior examples



## EDUCATE

Senerate quizzes from existing content 🐇 Create analogies to explain concepts > Develop infographics and presentations



## SUMMARIZE

Shorten long documents and articles Identify key messages from podcasts and videos Act as a personal meeting note-taker



## RESEARCH

> Perform a lliterature search 😵 Critique your scientific writing ☆ Write statistical analysis code



## **TRANSLATE & SIMPLIFY**

☆ Translate to/ from English Simplify language to a specific reading level or audience



## **MANIPULATE DATA**

Visualize quantitative data Summarize and categorize qualitative data



Caution



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For example prompts



# Education

PROMPT: Please write 5 multiple choice questions to assist trainees to learn about evidence based strategies for antimicrobial stewardship implementation. Base the questions on the attached guideline.



Clinical Infectious Diseases IDSA GUIDELINE



Implementing an Antibiotic Stewardship Program: Guidelines by the Infectious Diseases Society of America and the Society for Healthcare Epidemiology of America

Tamar F. Barlam,<sup>1,a</sup> Sara E. Cosgrove,<sup>2,a</sup> Lilian M. Abbo,<sup>3</sup> Conan MacDougall,<sup>4</sup> Audrey N. Schuetz,<sup>5</sup> Edward J. Septimus,<sup>6</sup> Arjun Srinivasan,<sup>7</sup> Timothy H. Dellit,<sup>8</sup> Yngve T. Falck-Ytter,<sup>9</sup> Neil O. Fishman,<sup>10</sup> Cindy W. Hamilton,<sup>11</sup> Timothy C. Jenkins,<sup>12</sup> Pamela A. Lipsett,<sup>13</sup> Preeti N. Malani,<sup>14</sup> Larissa S. May,<sup>15</sup> Gregory J. Moran,<sup>16</sup> Melinda M. Neuhauser,<sup>17</sup> Jason G. Newland,<sup>18</sup> Christopher A. Ohl,<sup>19</sup> Matthew H. Samore,<sup>20</sup> Susan K. Seo,<sup>21</sup> and Kavita K. Trivedi<sup>22</sup>

**Example Response:** What is the recommended strategy to improve antibiotic utilization and patient outcomes?

- A) Preauthorization only
- B) Prospective audit and feedback only
- C) Both preauthorization and/or prospective audit and feedback
- D) Neither preauthorization nor prospective audit and feedback

Answer: C) Both preauthorization and/or prospective audit and feedback







### Source: ChatGPT 4 Plus. 2024



# Education

**PROMPT:** Based on the attached article create a common clinical case scenario in which antibiotics are overused. Include age, sex, past medical history, history of presenting illness, any relevant laboratory information and interdisciplinary communication.



Antimicrobial Stewardship & Healthcare Epidemiology (2023), 3, e4, 1-4 doi:10.1017/ash.2022.343

### Commentary

### Bacteriuria in older adults triggers confusion in healthcare providers: A mindful pause to treat the worry

Eva M. Amenta MD<sup>1,2</sup> , Robin L.P. Jump MD, PhD<sup>3,4</sup> and Barbara W. Trautner MD, PhD<sup>1,5</sup> <sup>1</sup>Center for Innovations in Quality, Effectiveness, and Safety (IQuESt), Michael E. DeBakey Veterans' Affairs Medical Center, Houston, Texas, <sup>2</sup>Section of Infectious Diseases, Department of Medicine, Baylor College of Medicine, Houston, Texas, <sup>3</sup>Geriatric Research Education and Clinical Center (GRECC) at the VA Pittsburgh Healthcare System, Pittsburgh, Pennsylvania, <sup>4</sup>Division of Geriatric Medicine, Department of Medicine, School of Medicine, University of Pittsburgh, Pittsburgh, Pennsylvania and <sup>5</sup>Section of Health Services Research, Department of Medicine, Baylor College of Medicine, Houston, Texas

Amenta EM, Jump RL, Trautner BW. Bacteriuria in older adults triggers confusion in healthcare providers: A mindful pause to treat the worry. Antimicrobial Stewardship & Healthcare Epidemiology. 2023 Jan;3(1):e4.





### Source: ChatGPT 4 Plus. 2024



# Case Scenario Output

### **Patient Profile:**

- Age: 79 years old
- Sex: Female
- Past Medical History:
- Type 2 Diabetes Mellitus
- Hypertension
- Chronic Kidney Disease (Stage 3)
- History of urinary tract infections (UTIs)
- Current Medications:
- Metformin
- Lisinopril
- Calcium supplements

### History of Presenting Illness:

- The patient is a resident in a long-term care facility. She was noted by the nursing staff to be slightly more confused than usual this morning, without other new specific symptoms. Her confusion did not have an apparent trigger and resolved within a few hours.

- A well-meaning nurse, concerned about a potential UTI given the patient's past history, ordered a routine urinalysis and urine culture without the presence of urinary symptoms like dysuria, frequency, or urgency.

### **Relevant Laboratory Information:**

- Urinalysis:
- Cloudy urine
- Negative for nitrite
- Positive for leukocyte esterase
- Moderate bacteria
- Urine Culture:
- Escherichia coli >100,000 CFU/mL
- Blood Tests:
- Normal white blood cell count
- Slightly elevated C-reactive protein

### Interdisciplinary Communication:

- \*\*Nursing Notes:\*\* Documented the patient's temporary confusion and the lack of urinary symptoms, initiated urine tests based on past medical history.

- \*\*Physician Review:\*\* A physician reviewed the results the next day, noted the absence of urinary symptoms, but decided to prescribe antibiotics fearing potential repercussions of an untreated UTI, especially given the patient's history and the high bacterial count in the culture.

- \*\*Pharmacy Consult:\*\* The pharmacist questioned the necessity of antibiotic treatment given the asymptomatic presentation and suggested reviewing the case. However, the physician decided to proceed with antibiotics due to concern over the patient's age and comorbidities.





### Source: ChatGPT 4 Plus. 2024

- https://consensus.app/ •
- https://scholarai.io/
- https://elicit.com
- https://www.perplexity.ai/

## Literature Search

PROMPT: Provide a list of diagnostic stewardship intervention studies that aim to reduce unnecessary urine culturing for asymptomatic bacteriuria.

### Example Response (CSV Output):

Title	Takeaway	Authors	Year	Citations	Abstract	Study Type	Journal	DOI
Applying Diagnostic Stewardship to Proactively	Diagnostic	Faiza Mor	2022	8	A urinary	systematic	Antibiotics	10.3390/a
Effectiveness of an Antimicrobial Stewardship A	An antimi	B. Trautne	2015	163	IMPORTA		JAMA inte	10.1001/ja
The Use of Clinical Decision Support in Reducing	Clinical de	S. Keller, L	2017	31	Clinical de	non-rct ex	Journal of	10.12788/
Asymptomatic bacteriuria: Impact of an antimic	An antimi	Matthew I	2021	1	PURPOSE	non-rct ex	American	10.1093/a
Impact of a Stewardship Initiative to Decrease	A multi-fa	J. Smith, J.	2017	1	Abstract B	non-rct ex	Open Foru	10.1093/C
1853. Impact of Antimicrobial Stewardship Inte	Interdiscip	P. Shah, C.	2018	0	Abstract B	non-rct ex	Open Foru	10.1093/o
1592. SHEA Featured Oral Abstract: Reducing U	Diagnostic	Valerie M.	2022	0	Abstract B	ackground	Open Foru	10.1093/o
219. Characteristics Associated with Inappropri	Inappropr	M. Bixby, I	2020	0		non-rct ob	Open Foru	10.1093/o
Reducing antimicrobial therapy for asymptoma	No longer	J. Leis, Gal	2014	134	This proof	-of-concep	Clinical inf	10.1093/c
Impact of Antimicrobial Stewardship Intervention	Interdiscip	P. Shah, C.	2019	2	Backgrour	non-rct ex	Hospital P	10.1177/0



Al Literature Search Tools

### Source: Consensus.app. 2024



## Literature Search

PROMPT: Provide a list of diagnostic stewardship intervention studies that aim to reduce unnecessary urine culturing for asymptomatic bacteriuria. Create a summary table with headings of citation, year, country, strategy, and outcomes. Include up to ten articles. Think step by step about articles to include based on relevance, and think step by step about the appropriate information to include under each heading.

### Example Response (Google Sheets Output):

Citation	Year	Country	Strategy	Outcomes					
A Statewide Qua	2003	USA	Compared reduc	Decreased ASB	ecreased ASB-related antibiotic use associated with decline in unnecessary cultures				s
Applying Diagno	2019	Not specified (R	Analyzed studies	Reduced urine o	educed urine cultures through clinician education & EMR prompts for appropriate orderin				rdering
Implementing an	2016	USA	Guidelines for in	Indirectly promo	ndirectly promotes diagnostic stewardship by focusing on appropriate testing				
Controlled Quas	2015	Multi-national	Educational outr	Reduced rates of	Reduced rates of inappropriate antibiotic use for ASB, potentially impacting culture reques				quests
Downstream Imp	2014	USA	Analyzed impact	Demonstrated h	Demonstrated high rates of negative cultures, highlighting unnecessary resource use				1
Reflex Urine Cul	2012	USA	Implementation	Reduced costs a	associated with ur	nnecessary cultur	es for ASB		
Electronic Memo	2011	USA	Electronic alerts	Reduced rates of inappropriate antibiotic use and potentially unnecessary cultures					

Source: Gemini. 2024







# **Chat with Guidelines**

PROMPT: What is the recommended antibiotic treatment for bronchitis?

Many foundational model platforms allow users to customize responses with domainspecific information.

A custom GPT <u>"Virtual Antibiotic Steward"</u> was built using GPT builder in ChatGPT with instructions to only respond with information from the WHO AWaRe handbook

> ChatGPT 4 Plus. 2024 WHO AWaRe Handbook. 2022

### **RESPONSES:**

### AI in Antibiotic Stewardship Opportunities

- Consider creating fine-tuned infectious diseases/antimicrobial stewardship GPTs
- GPTs can be tailored for different audiences (e.g., clinician vs. patient)
- Compare fine-tuned ASP/ID models with those for general use
- Explore options for integration into existing resources (website, EHR)







# GENERATIVE AI AND ANTIMIC ROBIAL STEWARDSHIP Practical Use Cases



## **DEVELOP GUIDANCE**

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## EDUCATE

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## SUMMARIZE

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# Artificial Intelligence Disruption of the Infectious Disease Workforce



# **AI Disruption**



# **ID** Adaptation

### Prediction

Early identification of patients at risk for infection; prediction of optimal empiric therapy; detection and evaluation of outbreak scenarios

### **Decision Making**

Focus on leadership and change management. ID expertise needed for nuanced clinical judgement and empathetic patient interaction

# 

### Synthesizing Data

Summarizing data in textual and graphical format; writing notes, reports, and preparing presentations

### Increased Efficiency

More efficient development of reports, consult notes, and presentations; Free up time for tasks requiring human interaction; mitigating burnout



### **Development of Novel Tools**

With increasing data points and model sophistication, functionality of AI will increase; use cases will continue to emerge

### **Planning and Evaluation**

Subject matter expertise is needed for needs assessment, development, validation, and evaluation of patient-centered AI tools



### **Uncertain Future**

The full impact of AI on infectious disease, infection control, antimicrobial stewardship and public health is not yet known

### **Advocacy and Training**

ID experts should advocate for their involvement in AI development, workforce protection, and training to adapt to new automation

### Langford BJ, et al. OFID. 2024

# **Take-Home Messages and Future Steps**

- Artificial intelligence includes many subfields, most of which are applicable to antimicrobial stewardship
- High quality models require access to high quality data
- Take a **cautiously optimistic** approach to AI in stewardship understanding both the benefits and limitations
- Generative AI holds promise but technology is nascent
- To keep up with rapid advancement in AI, antimicrobial stewards and hospital epidemiologists can participate in training and advocate for ID specialist involvement in model development and testing

## "Once a new technology rolls over you, if you're not part of the steamroller, you're part of the road." -Stewart Brand

Non LR. Antimicrobial Stewardship & Healthcare Epidemiology. 2023.







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