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Automation and Predictive Analytics

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Administrator, Emergency Medicine, Mayo Clinic Rochester

March 17, 2026

Presenter Biography

- Master of Health Care Administration
University of Minnesota
- Fellow
American College of Healthcare Executives
- Mayo Clinic
18.5 years (11.5 as Administrator)
 - HIM
 - Psychiatry
 - Addictions
 - Ophthalmology
 - Primary Care
 - Neurology
 - Hyperbaric/Wound Care
 - Enterprise EHR
 - Emergency Medicine



in [gregorymdavis](#)

Learning Objective



Understand fundamentals of automation



Review Agentic AI and what makes it different



Review EM examples from Mayo Clinic



Identify 2–3 applications relevant to your own institution

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Why AI — Why Now for EM?



Volume + boarding + staffing constraints



Documentation burden



Throughput pressures



Quality + safety expectations



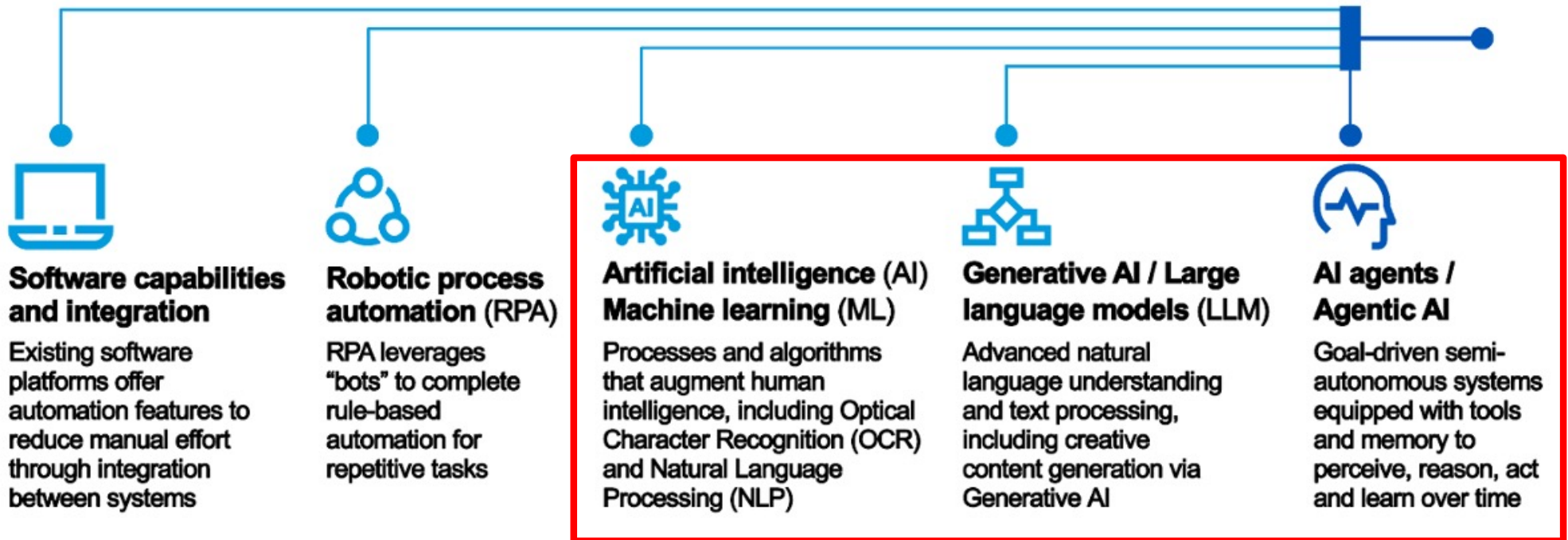
Workforce burnout



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Automation Spectrum

The emergence of agentic AI represents a paradigm shift where AI systems function as autonomous users of tools, rather than just being the tools themselves.



Predictive Analytics – Key Terms



ALGORITHM / MODEL

A set of rules a computer follows to make a prediction

"Given these vitals and labs, this patient has a 78% chance of admission"



TRAINING DATA

The historical records the model learned from

"Trained on 5 years of ED visits – their data is not your data"



AUROC / AUC

The model's score for how well it separates yes from no

0.5 = coin flip · 0.8+ = good · 1.0 = perfect



SENSITIVITY & SPECIFICITY

SENSITIVITY

How good the model is at catching true positives

High = rarely misses a sick patient (but may over-flag)

SPECIFICITY

How good the model is at ruling out false alarms

High = when it fires, it's usually right (but may miss some)



THRESHOLD

The score cutoff at which the model triggers an alert

"We set it at 0.65 – above that, the patient gets flagged for review"



MODEL DRIFT

Model becomes less accurate as the world changes

"Post-COVID patient patterns broke models trained before 2020"

Predictive Analytics – Core Concept

Using historical and real-time data to forecast outcomes and optimize care.

Observed Past & Present



Projected Future States



Probability-Based Estimates

Volume & Flow



“How busy will we be?”

Risk



“Which patients are at risk of deteriorating?”

Resources



“Where will bottlenecks emerge?”

Outcomes



“What is likely to happen if nothing changes?”



**Is your organization
using predictive
analytics?**

Responsible Adoption of AI



Human stays in the loop

AI recommends – a clinician decides



Validate before you deploy

Their data is not your data



Watch for bias

Does it work equally for all your patients?



Keep an audit trail

Log what the AI said and what you did



Name an owner

Someone clinical – not just IT

WHY THIS MATTERS

These aren't obstacles to AI.

They're what makes it **defensible when something goes wrong.**

Ask your vendors these five questions before you sign anything.

If they can't answer them clearly, keep looking.

LEARNING MADE EASY

Agentic AI

FOR
DUMMIES[®]

Learn to:

- Understand agentic AI concepts
- Explore applications and tools
- Consider benefits and risks

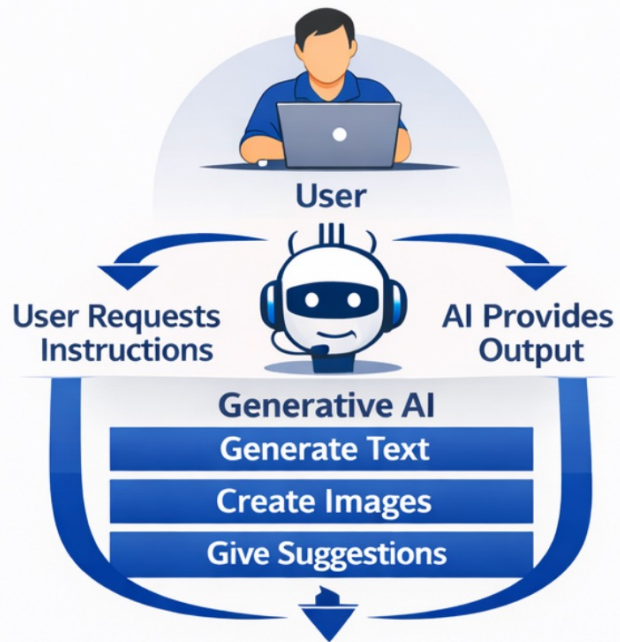


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AGENTIC AI

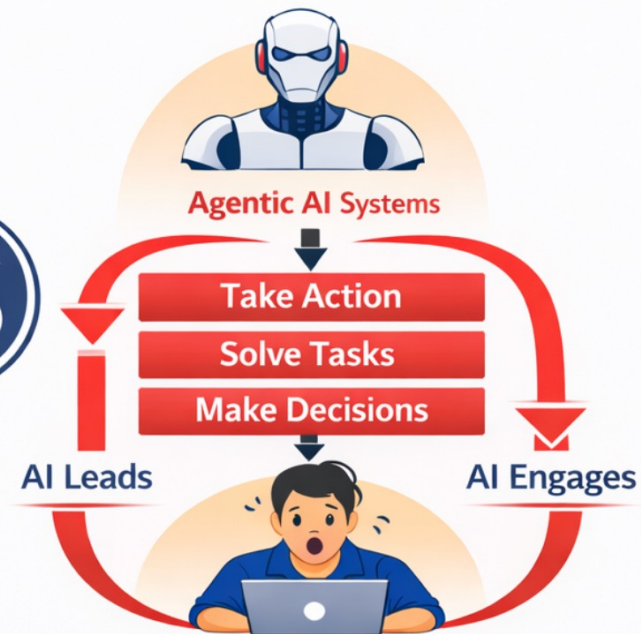
Traditional vs. Agentic AI

Traditional Generative AI



VS

Agentic AI Systems



Legacy Workflows

Agentic Workforce

1 Go digital

Data and inputs need to be where future agents can access them.

2 Standardize & systematize

Take inventory of work and identify efficient processes for agents to support.

3 Reshape work

Identify tasks for agents and upskill staff for new workflows.

Spectrum of Agents and Tools

Simple /
no code



Advanced /
pro code

1

Retrieval agents

Retrieve information from provided data. Can reason, summarize and answer user questions.

For end users



Copilot Studio Lite

2

Task agents

Take actions when asked, automate workflows and replace repetitive tasks for users.

For makers



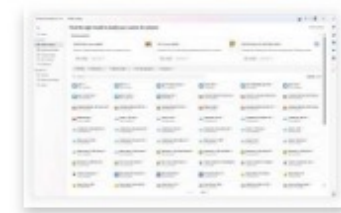
Copilot Studio

3

Autonomous agents

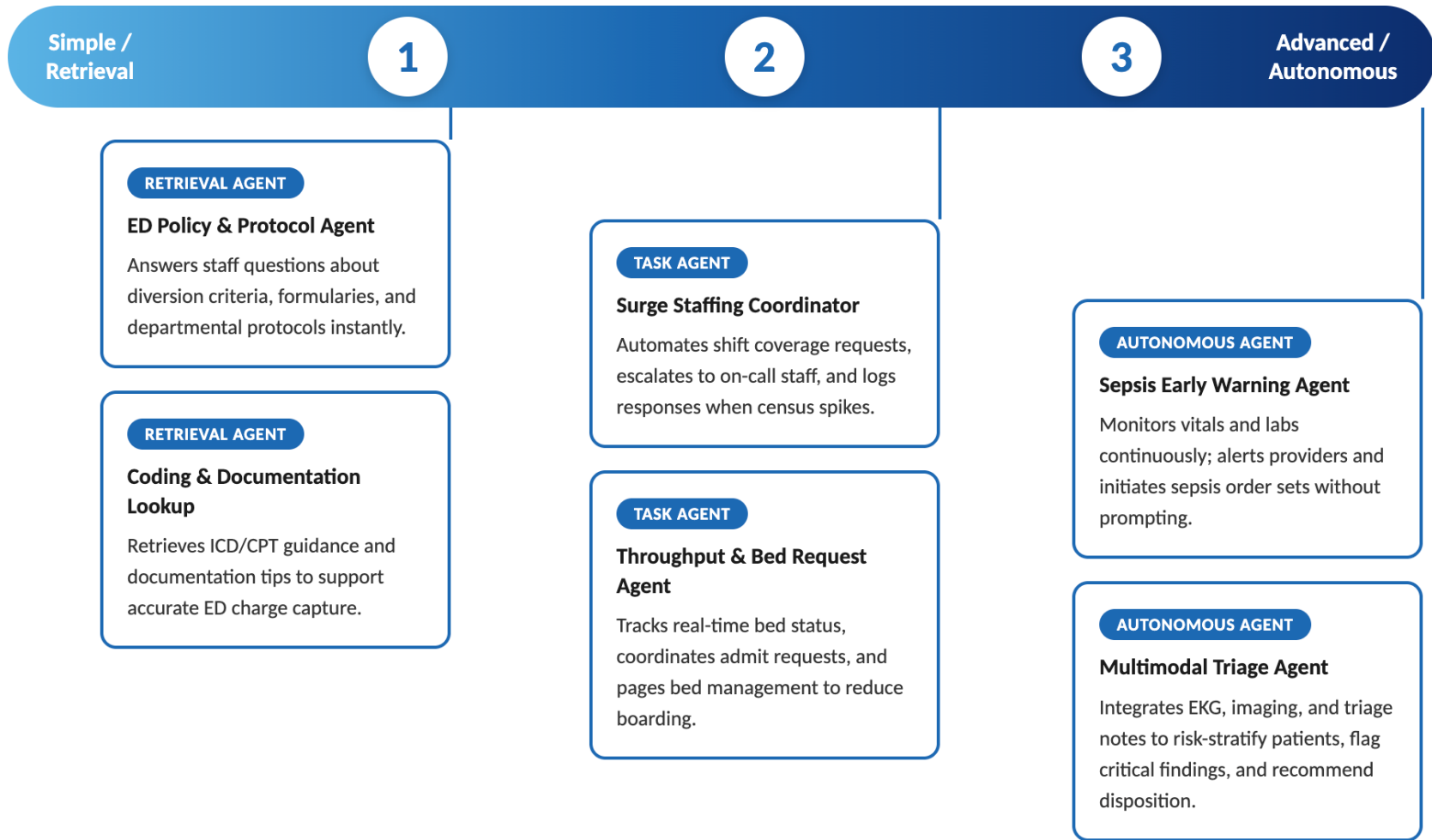
Operate independently, dynamically plan & orchestrate other agents, learn and escalate.

For developers



Copilot Studio, Visual Studio Code, Azure AI Foundry

Continuum of Solutions for EM





APPLICATIONS IN EMERGENCY MEDICINE @ MAYO CLINIC PREDICTIVE ANALYTICS

EM Data Team

Predictive Analytics

Operational Integration

Advanced Modeling

Day to Day Reports & Analytics

Dashboard Visualizations

Data Infrastructure & Delivery



Derick D. Jones, M.D., M.B.A.
Chair

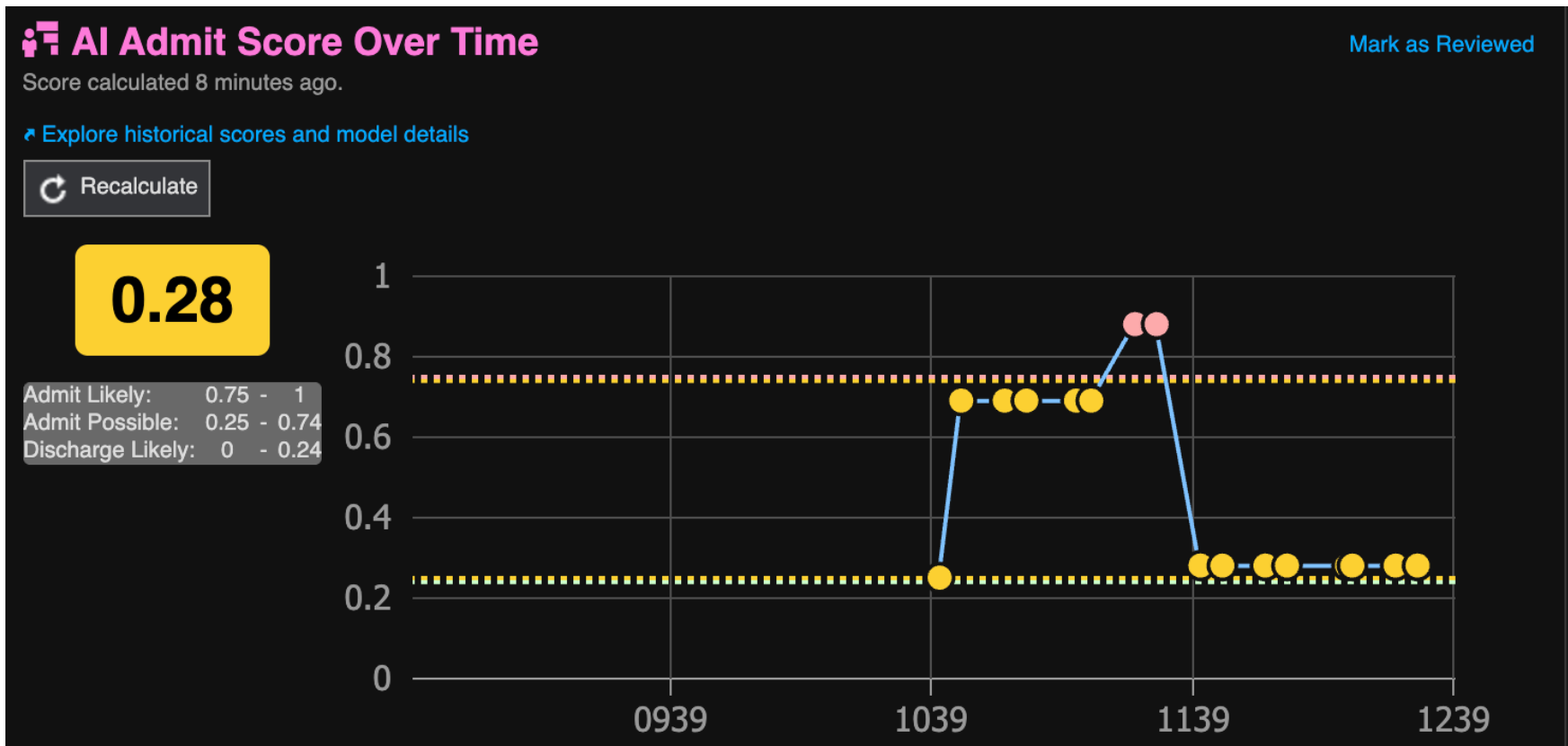


Ryan Schoer
Principal Business Analyst



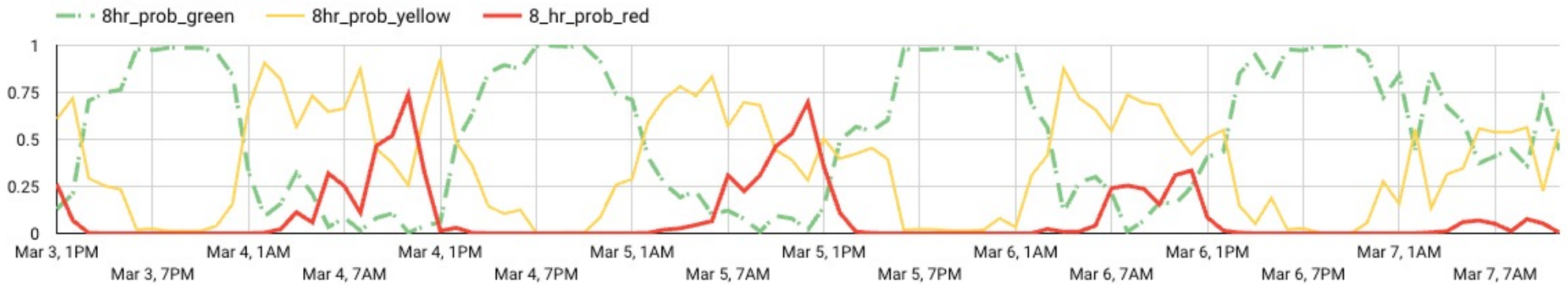
Admission Prediction Model

Score is used in collaboration by HIM/ED to complete advanced review of patients to prevent avoidable admissions

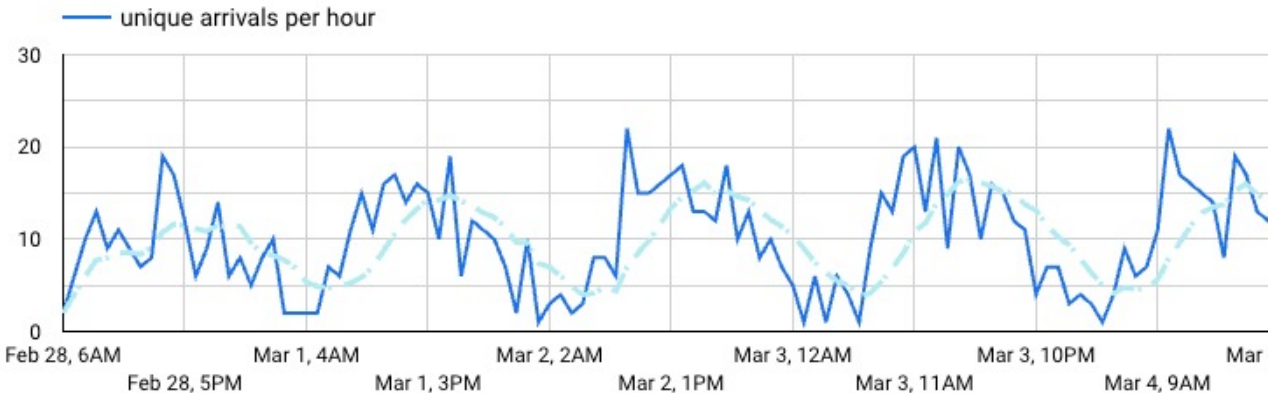


3 Class RST ED Surge Prediction

Light Status Prediction



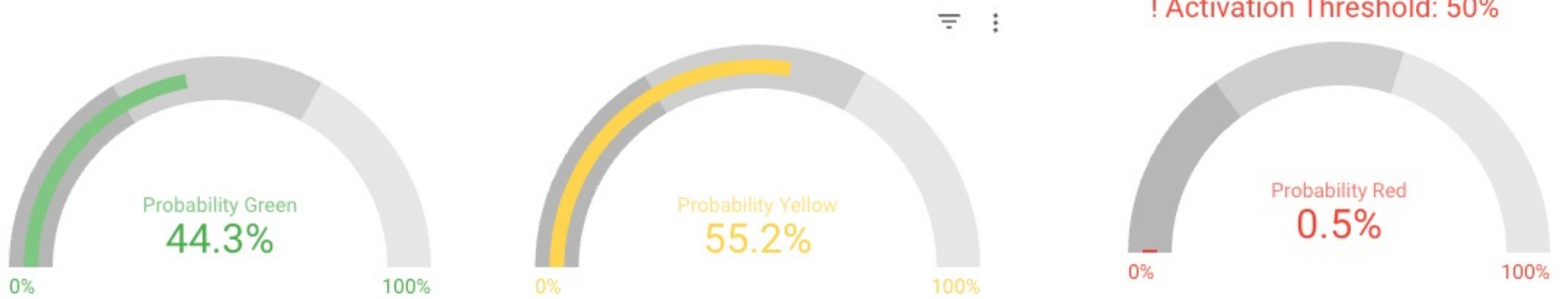
Hourly Arrivals



Bottom Line: Predicting Light Status in advance with approximately 80% accuracy

Next Step: Bottleneck Detection

Waiting Room Census Prediction in 8 hours at: Mar 7, 2026, 8:37 PM



Predicting Short LOS

Mayo Clinic Research: ML Model to Predict Short LOS Patients (Room to Discharge) - 2024

67K

Adult ED visits analyzed
2023-2024 dataset

84%

AUC accuracy for ≤ 1 hr LOS
Fast Track candidates

80/20

Train/test split
Rigorous validation

84%

AUC Accuracy
For predicting Fast Track
candidates (≤ 1 hr LOS)
at time of rooming

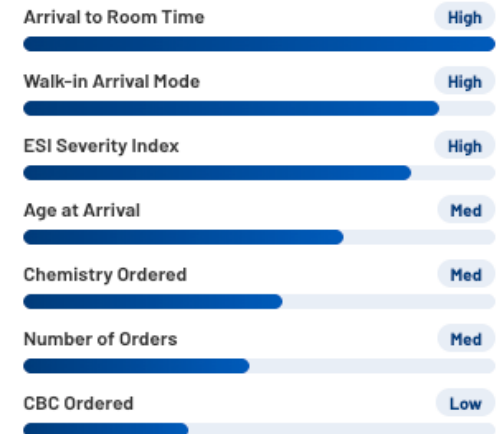
KEY PREDICTORS OF SHORT LOS

- ✓ **Lower ESI Scores**
Low-acuity presentations most predictive
- ✓ **Minimal Diagnostic Testing**
Fewer CT scans, labs, X-rays ordered
- ✓ **Walk-in / Wheelchair Arrival**
Arrival mode a strong signal
- ✓ **Younger Patient Age**
Age at arrival negatively correlated with LOS

CLINICAL APPLICATIONS

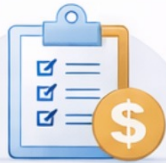
- Automatic Fast Track assignment at rooming
- Terminal Shift resource optimization
- Real-time capacity & flow planning
- Reduced waiting room burden

TOP INPUT FEATURES (RELATIVE WEIGHT)



⚡ Predict at time of rooming – enabling faster triage decisions, smarter staffing, and reduced door-to-discharge times.

Other Predictive Model Work



Professional Coding Automation

ML+NLP models assign ED billing levels from clinical documentation.

321K Encounters analyzed

0.95 AUC-ROC for Level 5

1.00 Critical care detection

- ✓ Reduce manual coding workload
- ✓ Improve coding consistency and accuracy
- ✓ Accelerate revenue cycle



Antibiotic Selection (UTI)

Predicts antibiotic sensitivity at the time of the ED encounter using available clinical data.

62,963 Encounters analyzed

21 Antibiotics modeled

0.82 Median AUROC

- ✓ Improve empiric antibiotic selection before cultures return
- ✓ Support antimicrobial stewardship programs



Return Visit Prediction

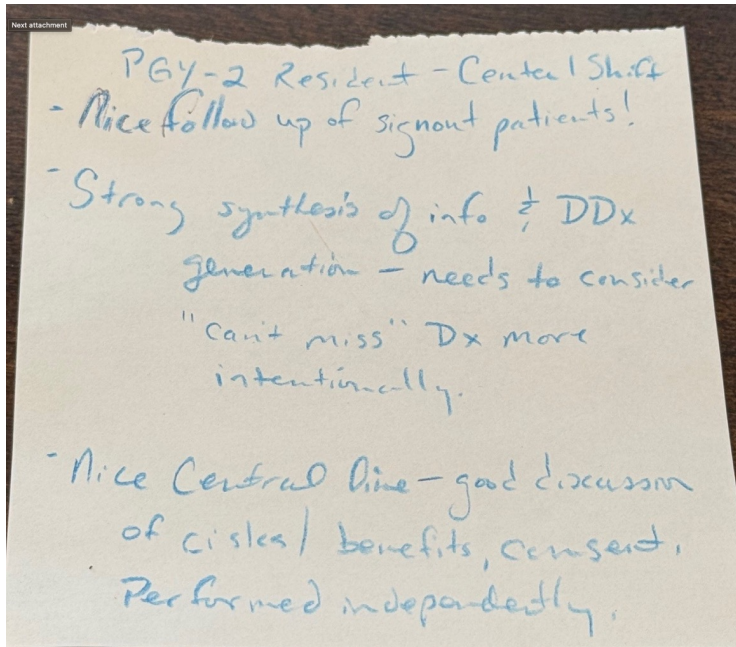
Predicts patients at high risk for ED return visits shortly after disch.

62,963 Encounters

0.82 Median AUC-ROC

- ✓ Identify high-risk patients before ED discharge
- ✓ Enable targeted follow-up and care coordination
- ✓ Reduce avoidable return visits and hospital admissions

Resident Feedback Agent (Pilot)



- ACGME milestone aligned
- Structured: Strengths & Growth
- Comment-box length output
- Bias-resistant design
- Faculty time reduction

9:20 97

Resident Feedback in MedH... > [share icon] [more icon]

9:16 97

Resident Feedback in MedH... > [share icon] [more icon]

Strengths:
During this central shift, the Postgraduate Year 2 resident demonstrated strong ownership of patient care, including reliable follow-up on signed-out patients. They consistently synthesized clinical information effectively and generated thoughtful differential diagnoses, reflecting solid clinical reasoning skills. The resident independently performed a central line with appropriate discussion of risks, benefits, and consent, demonstrating procedural competence appropriate for this stage of training.

Opportunities for Growth:
At this stage in training, it is expected that the resident consistently and intentionally considers high-risk "can't miss" diagnoses when formulating differentials. As a next step, the resident should work on explicitly verbalizing and prioritizing these diagnoses during presentations and care planning to further strengthen diagnostic accuracy and patient safety. Continued deliberate practice in this area will support progression toward higher-level diagnostic reasoning milestones.

Based on the handwritten notes provided, here is milestone-aligned written feedback appropriate for a Postgraduate Year 2 emergency medicine resident on a central shift, formatted for the concise MedHub comment box and aligned with the ACGME Emergency Medicine Milestones (Patient Care, Medical Knowledge, and Procedural Skills) 🌐.

Strengths:
During this central shift, the Postgraduate Year 2 resident demonstrated strong ownership of patient care, including reliable follow-up on signed-out patients. They consistently synthesized clinical information effectively and generated thoughtful differential diagnoses, reflecting solid clinical reasoning skills. The

+ Message Resident Feedb... [share icon] [voice icon]

+ Message Resident Feedb... [share icon] [voice icon]

Other Analytics and Agents



Patient Grievance Response

- 1 Source Material**
Complaints & responses from the past several years
- 2 Agent Response**
Complete clinical review (if needed), and formulate the response.



Change Management Plans

- 1 Input**
Provide Briefing Document or Project Plan
- 2 Agent Builds Plan**
Determine "size" needed (tiered model) and build deliverable.



Administrative Support

- ✓ Scheduling
- ✓ Expense & membership tracking
- ✓ Award submissions



Data

- ✓ Self-serve
- ✓ Ad hoc data pulls



Knowledge

- ✓ Emergency medicine app

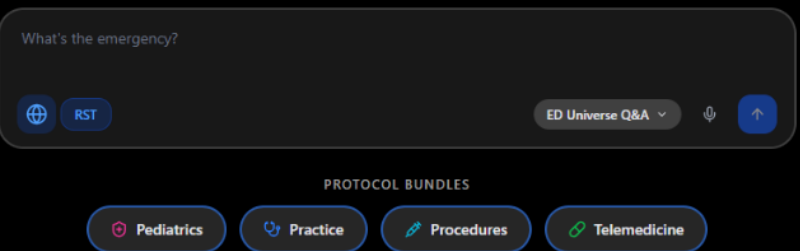


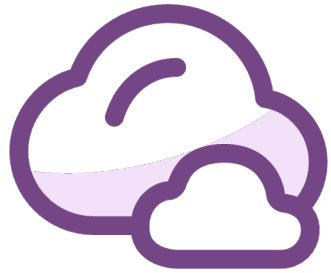
Clinical

- ✓ Admission (Bed Center)
- ✓ Predictive LOS
- ✓ Triage

emergency medicine app

AI-powered emergency medicine clinical decision support





What types of opportunities do you see for routine tasks in your departments to be handled by an agent?

THE STRATEGIC QUESTION FOR EM LEADERS

NOT THIS

~~"Should we use AI?"~~



BUT THIS

"How **quickly** can we
responsibly integrate AI
into our workforce model?"

• The tools exist today

• The evidence is building

• Your peers are moving

• The workforce needs this



Audience Q&A