

Predicting Patient No-Shows

Applying Machine Learning to Reduce Missed Visits

azara2026

USER CONFERENCE APRIL 13-15 | BOSTON, MA



Agenda

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Defining the Problem

Why No-Shows Matter

Predictive Modeling

Using Machine Learning To Predict No-Shows

Preliminary Model Results

Performance Summary

Turning Prediction Into Action

Prediction Alone Isn't Enough

Product Integration

Using No-Show Predictions



Defining the Problem

Why No-Shows Matter



The Scale of the Problem

No Shows cost the US Healthcare System an estimated:

\$150 Billion per year

That's a big number. Put in other terms, that is:

\$438.59
per capita

\$138,000
per healthcare
provider

In addition to monetary impacts, no shows **increase staff burnout and hamper continuity of care** efforts.



No Single Intervention Solves the Problem

It is easy to say:

Double book
high risk
patients!

- Somewhat punitive action
- Limits access to care

Send
reminder/
confirmation
messages!

Reminder fatigue 😞



Why No Shows are Hard

Humans are fickle. Some of this is indeed “I just don’t feel like going” but not all.

SDOH (and not just transit related SDOH) drive some unpredictability.



Not all no shows are lazy/voluntary



Real-World Constraints

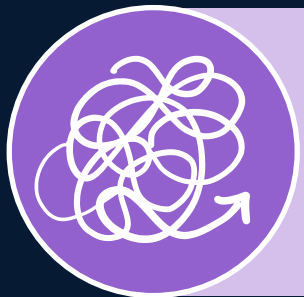
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Different scheduling workflows for different practices / service lines



Patterns vary by site, specialty, & population



Messy/non-standard EHR data – DRVS standardization helps with this!



Predictive Modeling

Using Machine Learning To Predict No Shows



What Are We Predicting?

**Categorical
risk**



We are not predicting *why* a patient may no show.

The goal is **NOT**:

- To replace staff judgement
- To deny care or overbook blindly

The goal **IS** to give staff the tools to prioritize outreach and confirmation, maximizing schedule time.



Data Sources



Appointment data



Patient-specific historical attendance patterns



Specific SDOH triggers



Limited patient-level demographics



Feature Engineering – Examples

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Appointment-Level:

- Visit Type (Primary Care, Specialty, etc.)
- Day/Time

Temporal Features:

- Lead Time
- Days Since Last Appointment

Patient History:

- No-Show History (both short and long-term)
- Selected SDOH Triggers (Transportation Issues, Childcare Issues, etc.)



Exclusions

Features we **did not** include:

- Race
- Ethnicity
- Location/ZIP of Patient

Features we **cannot** include (current state):

- Staff Outreach
- Appointment Reminders



Modeling Approach

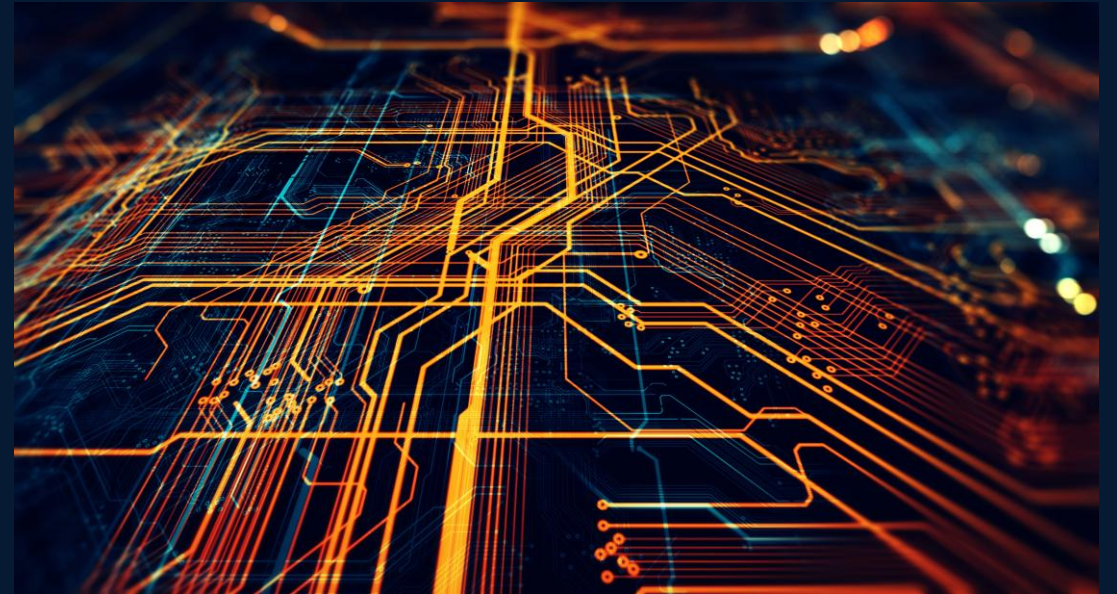
Why Machine Learning?

ML can model complex relationships between variables that rules-based and traditional approaches cannot.

ML models are fast once trained.

Trade-Offs

Interpretability



Training Strategy

Record Count:

- One Calendar Year (plus an additional calendar year for individual no-show history)

Splits:

- Train/Validation/Test by Date



Model Evaluation

Accuracy is not a good metric.

Metrics Used:

- Precision and Recall (PR-AUC)
- Precision & Recall at Top K
- Lift

HOW TO READ A PRECISION & RECALL at TOP K GRAPH



PRECISION:

True Positives / Top K Predictions

- **Focus:** Out of the top K, how many are correct?
- **Example:** If making 10 predictions, K=10: 8 are true positive ~ $8/10 = 80\%$.



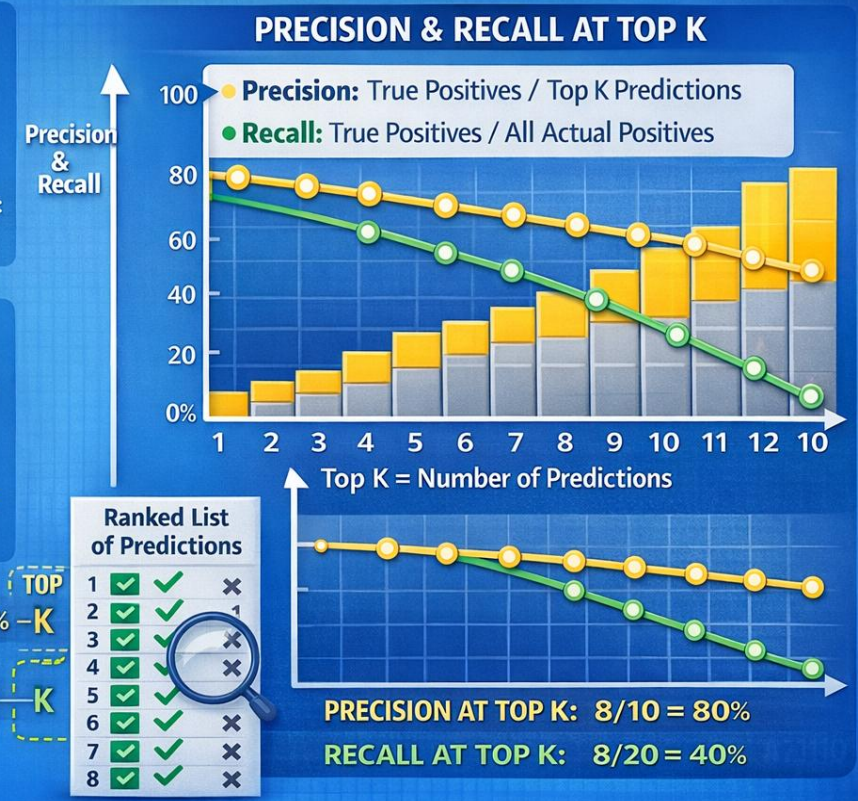
RECALL:

True Positives / All Actual Positives

- **Focus:** Out of all actual positives, how many in the top K?
- **Example:** With 20 actual positives, 8 are in the top 10 ~ $8/20 = 40\%$.

PRECISION AT TOP K: $8/10 = 80\%$ - K

RECALL AT TOP K: $8/20 = 40\%$ - K



Preliminary Model Results

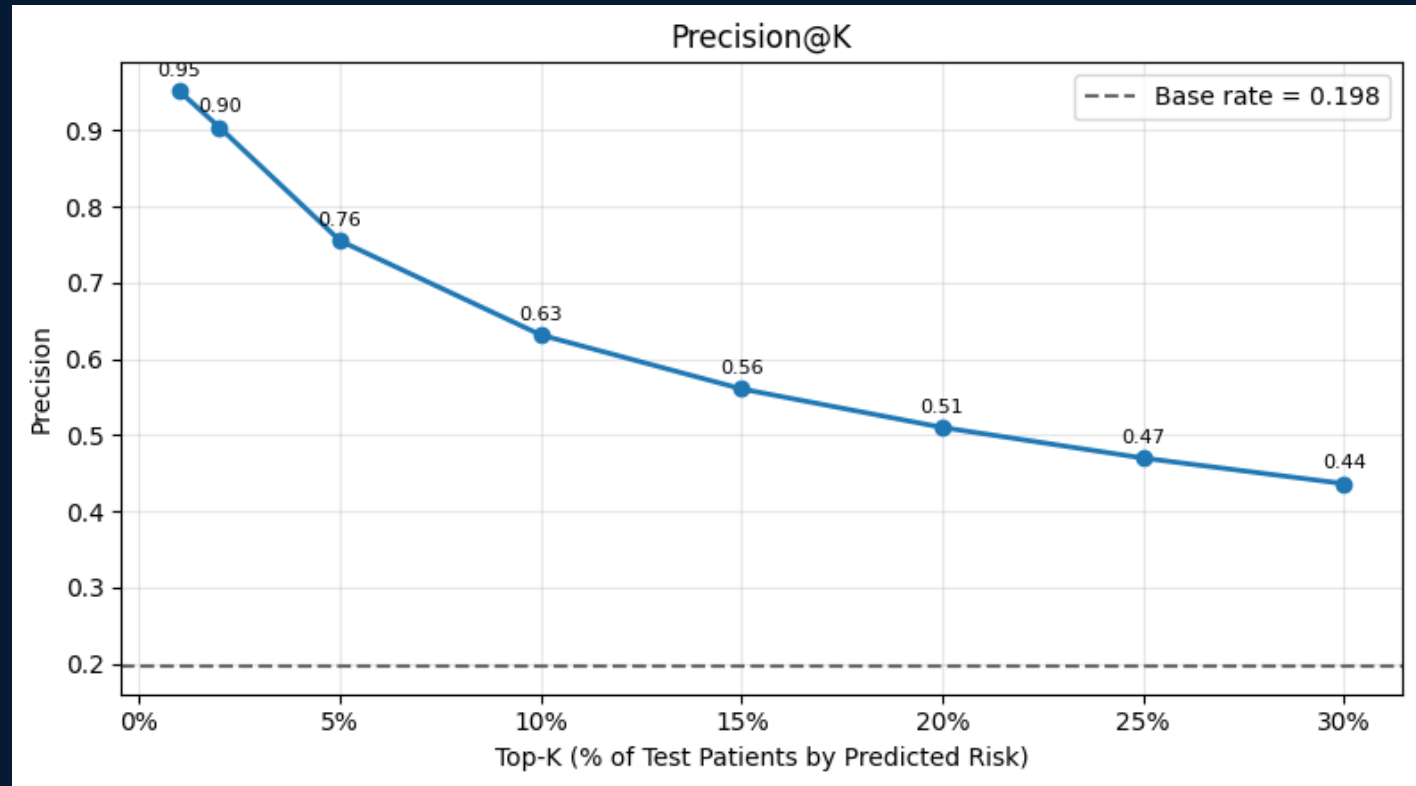
Performance Summary



How Did We Do?

One Example:

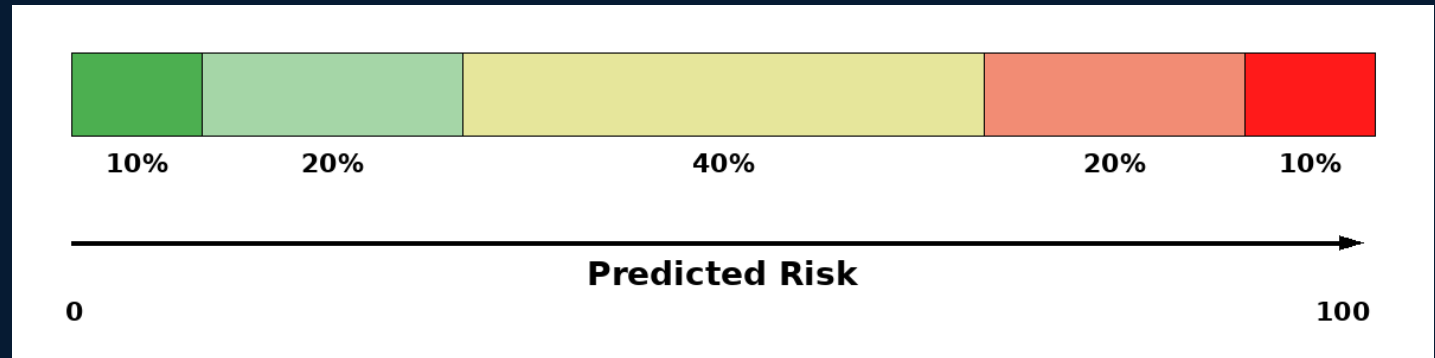
- Base No-Show Rate: 19.8%
- PR AUC = 0.554
- Precision @ Top 10% = 0.63
- Recall @ Top 10% = 0.31
- Lift @ Top 10% = 3.16



No-Show Risk Scores & Bands

The model will assign appointments to categories:

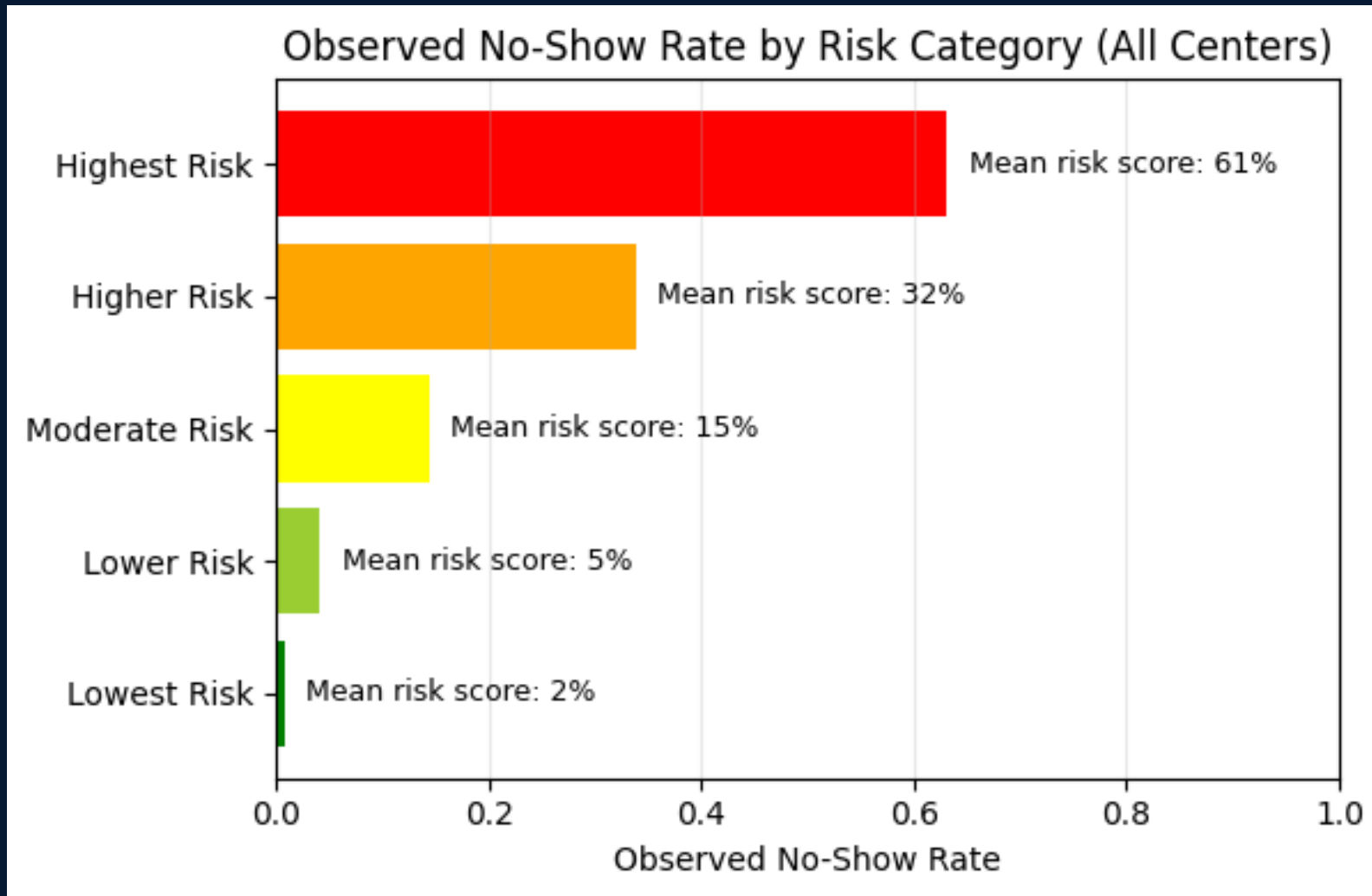
- Highest Risk (Top 10% of predicted risk)
- Higher Risk (Next 20%)
- Moderate Risk (40%)
- Lower Risk (20%)
- Lowest Risk (Bottom 10%)



Risk Scores will be on a scale from 0-100.



A Ranking Model



This chart will vary widely by practice.

Some practices with lower historical no-show rates.



“All models are wrong, but some are useful”

- George E.P. Box



Reality is messy!



Mid-range muddiness



Missing & Unknowable Variables



Turning Prediction Into Action

Prediction Alone Isn't Enough



Example Operational Use Cases

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- Targeted Outreach
- Reminder Escalation
- Careful Schedule Optimization



Measuring Impact



Reduction in No-Show Rates



Staff Time Savings



Improvements in Access



How No-Show Predictions Fit Into DRVS



Augustine, Greg 12 Scheduled Appointments ^

2:38 AM Thursday, February 9, 2023 Visit Reason: High BP Canceled

Gathman, Shawwna	Sex at Birth: F	Phone: 413-405-2050	Portal Access: 06/13/2021	PCP: Smith, Joe
MRN: 1102310	GI: Transgender Male/ Female-to-Male	Lang: Persian		Payer: Aetna
DOB: 9/30/1981 (41)	SO: Choose not to disclose	Risk: Moderate (33)		CM: Kevin Donohue

Demo Data

DIAGNOSES (12)			ALERT	MESSAGE	DATE	RESULT	OWNER
AMI	ASCVD	Asthma	A1c	Overdue	12/30/2021	3.8	MA
CAD	CAD/No MI	Cancer	LDL				
COPD	DM	HIV	Depr Screen				
HTN-E	HTN-NE	IVD	Tobacco Scr				
RISK FACTORS (4)			BMI & FU				
ANTICOAG	Chronic Opioid Tx	MSM	Asth Severity				
SMI							

PVP/CMP/
EHR Plugin?

Dashboards?

- Updated daily
- Configurable categories?

CURIS - High Priority Access Metrics

FILTERS: February 2026

Practice Capacity - # Appts Scheduled (not including cx or r/s)

WE 02/22/26 - 02/28/26

1,919 Completed Appts +33% ▲ WE 01/24

Practice Capacity - Kept Appts

WE 02/22/26 - 02/28/26

1,503 Completed Appts +37% ▲ WE 01/24

Practice Capacity - Avg Appts/Day

WE 02/22/26 - 02/28/26

488 Result +119% ▲ WE 01/24

Practice Capacity

Practice Capacity Utilization, or Schedule Fill Rate is the metric that compares the number of appointments able to be scheduled in the practice schedule against the actual number of appointments scheduled in a given timeframe (ie: per month). The three widgets show the number of appointments scheduled, appointments kept, and the average number of appointments per day. DRVS does not have the ability to show the number of appointments able to be scheduled in a given time frame.

Appointment measures can be looked at by weekly or monthly timeframes, and stratified or filtered by provider, location, service line, and more.

No Show & Cancellation Rate

The *No Show* widgets use the "No Show Appointments" measure and the *Cancellation* widgets use the "Cancelled Appointments <24 Hours" measure.

Both measures can be stratified by provider, location, and service line, as well as by patient characteristics such as race, ethnicity, and SDOH.

No Show Rate

February 2026

29.0% Measure Result +1.5% ▲ Sep 25

Cancellation Rate

February 2026

10.1% % Appts Cancelled -0.3% ▼ Sep 25

No Show Rate Trend

February 2026

Month	Rate
Sep 25	27.5%
Oct 25	28.2%
Nov 25	26.8%
Dec 25	29.9%
Jan 26	27.7%
Feb 26	29.0%

Cancellation Rate Trend

February 2026

Month	Rate
Sep 25	10.4%
Oct 25	6.5%
Nov 25	8.2%
Dec 25	10.3%
Jan 26	9.9%
Feb 26	10.1%



Wrap Up

Key Takeaways and Q&A



Key Takeaways

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- No Shows Are Predictable Enough To Take Action
- Data Quality Matters!
- Models Augment (not replace) Staff Judgement





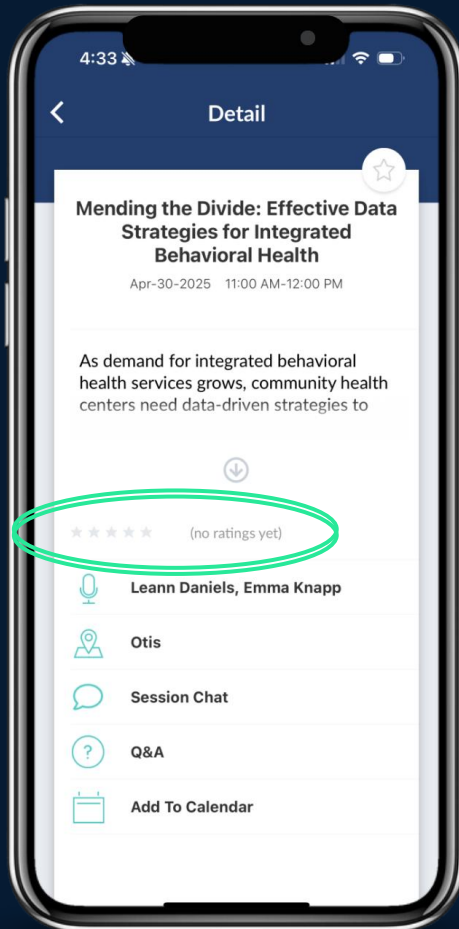
Questions?



We want to hear from you!

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