Predicting Patient No-Shows

Applying Machine Learning to Reduce Missed Visits

azara 2026
USER CONFERENCE APRIL 13–15 | BOSTON, MA

Agenda

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.

Source: https://curogram.com/blog/how-much-each-year-do-no-shows-cost-the-u.s.-healthcare-system

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

- 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 **<u>not</u>** 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

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

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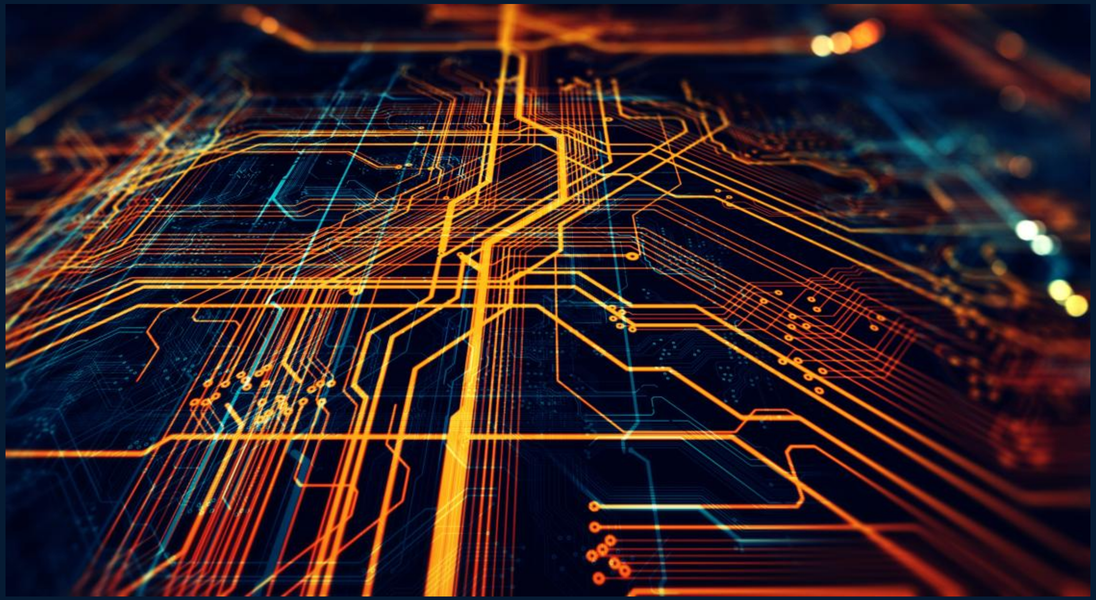
Why Machine Learning?

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:

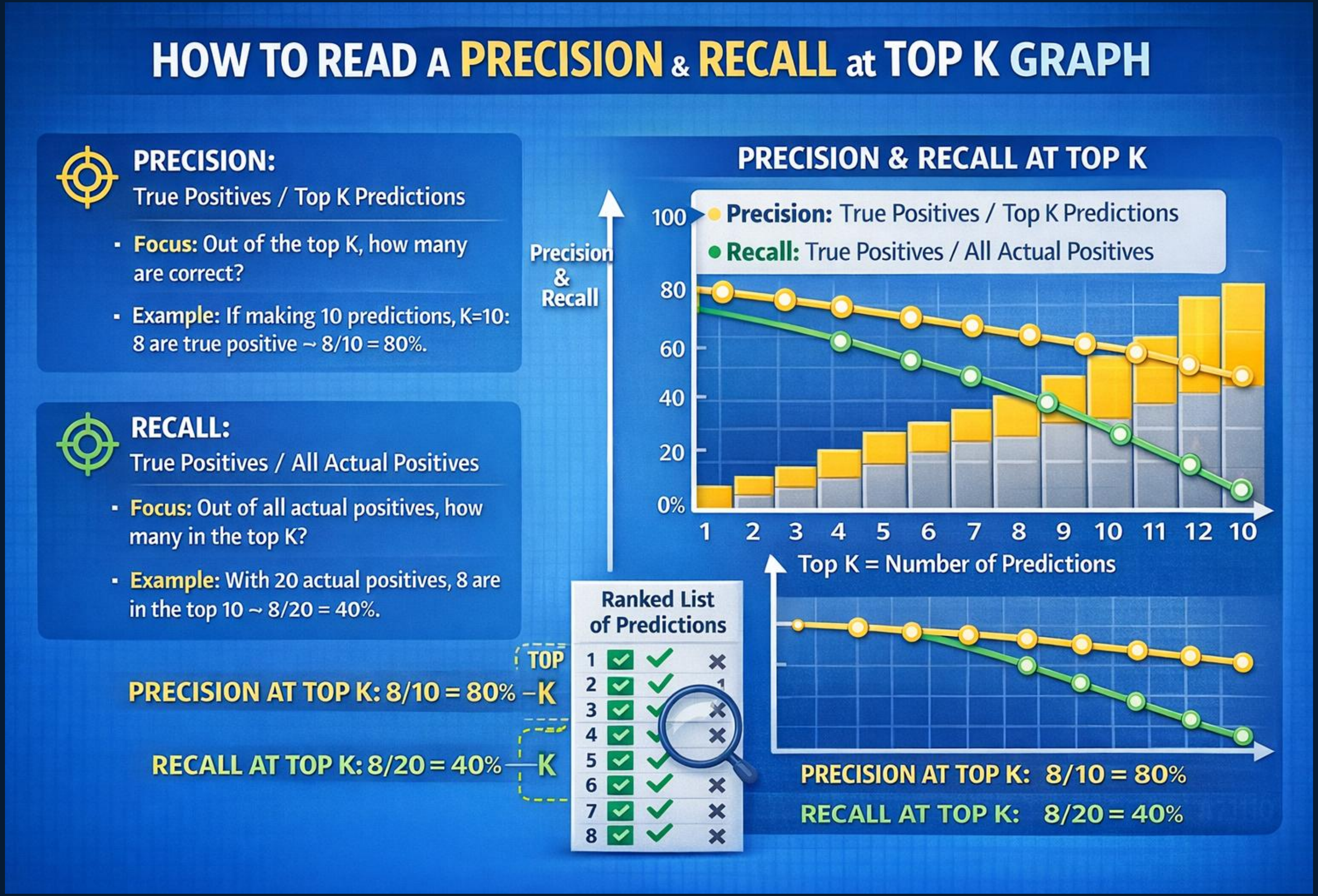
- Train/Validation/Test by Date

Model Evaluation

Accuracy is not a good metric.

Metrics Used:

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



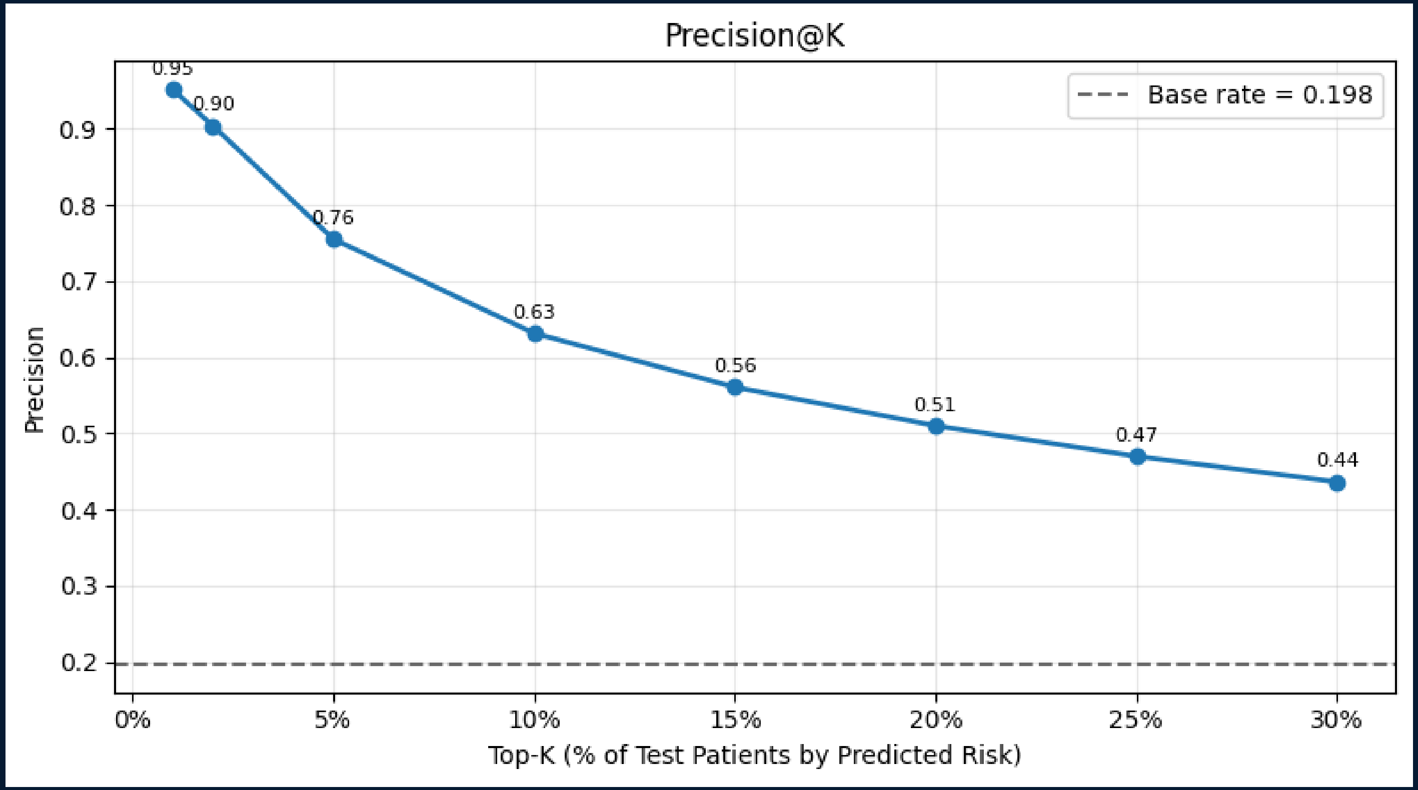
Preliminary Model Results

Performance Summary

How Did We Do?

One Example:

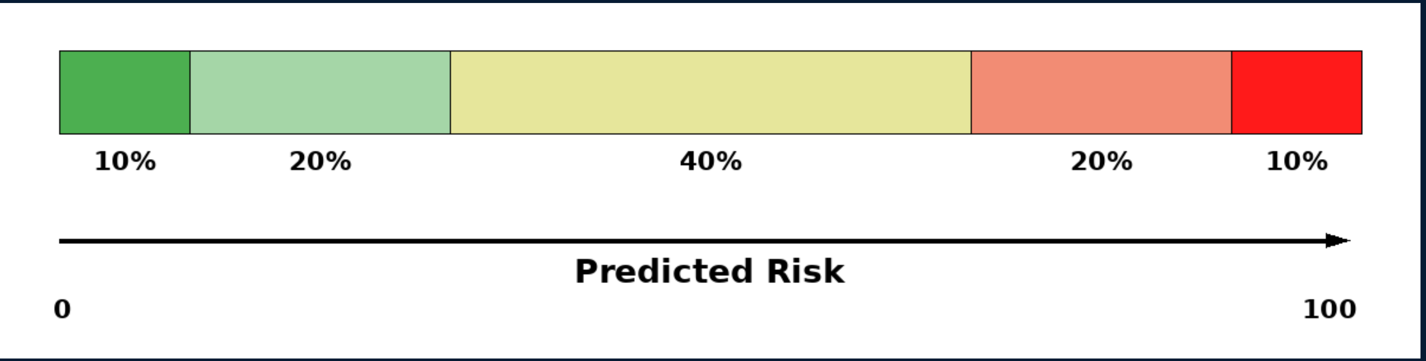
- Base No-Show Rate: 19.8%
- PR AUC = 0.554
- Precision @ Top 10% = 0.63
- Recall @ Top 10% = 0.31
- Lift @ Top 10% = 3.16



No-Show Risk Scores & Bands

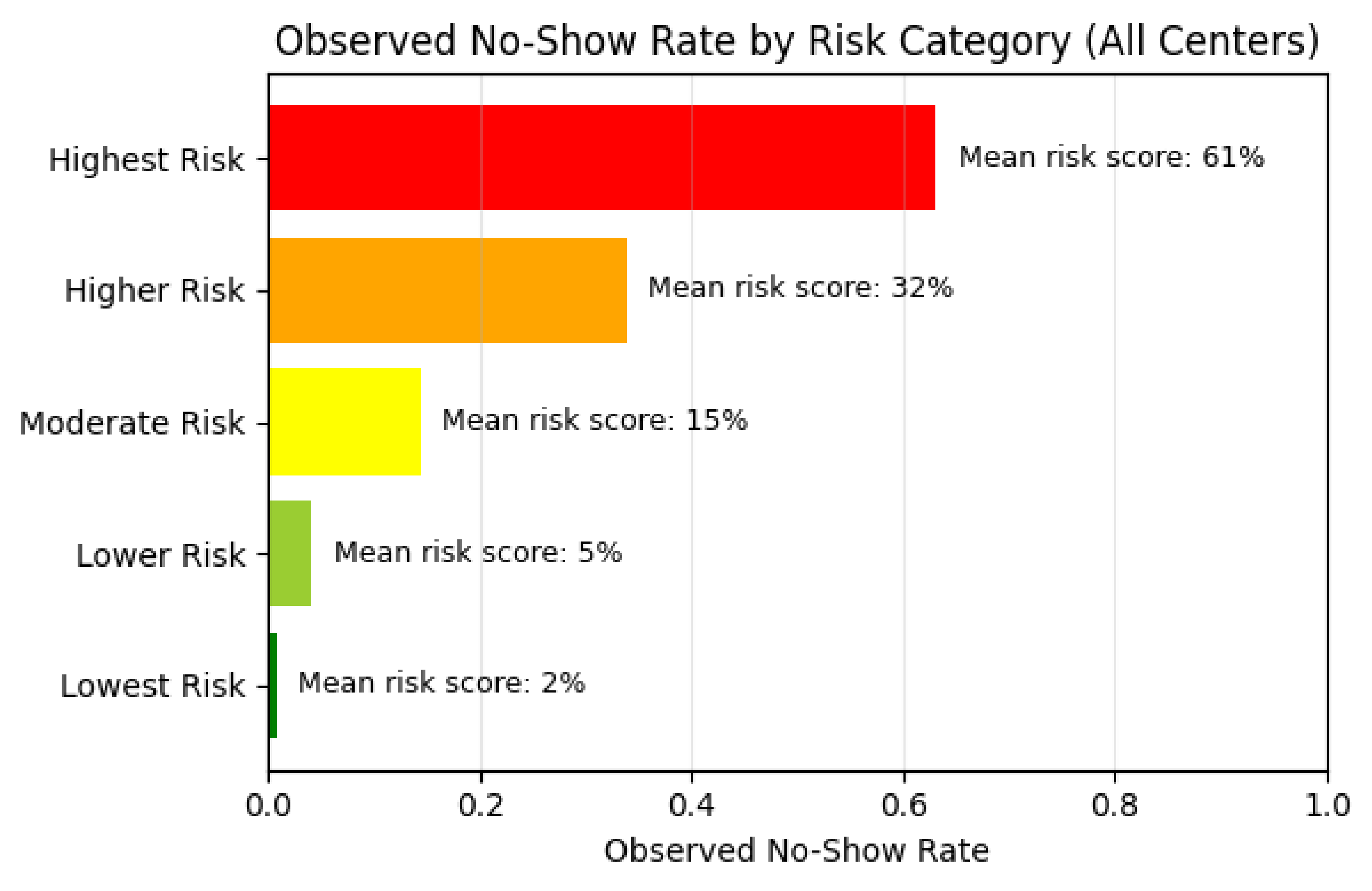
The model will assign appointments to categories:

- 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.

Limitations

"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

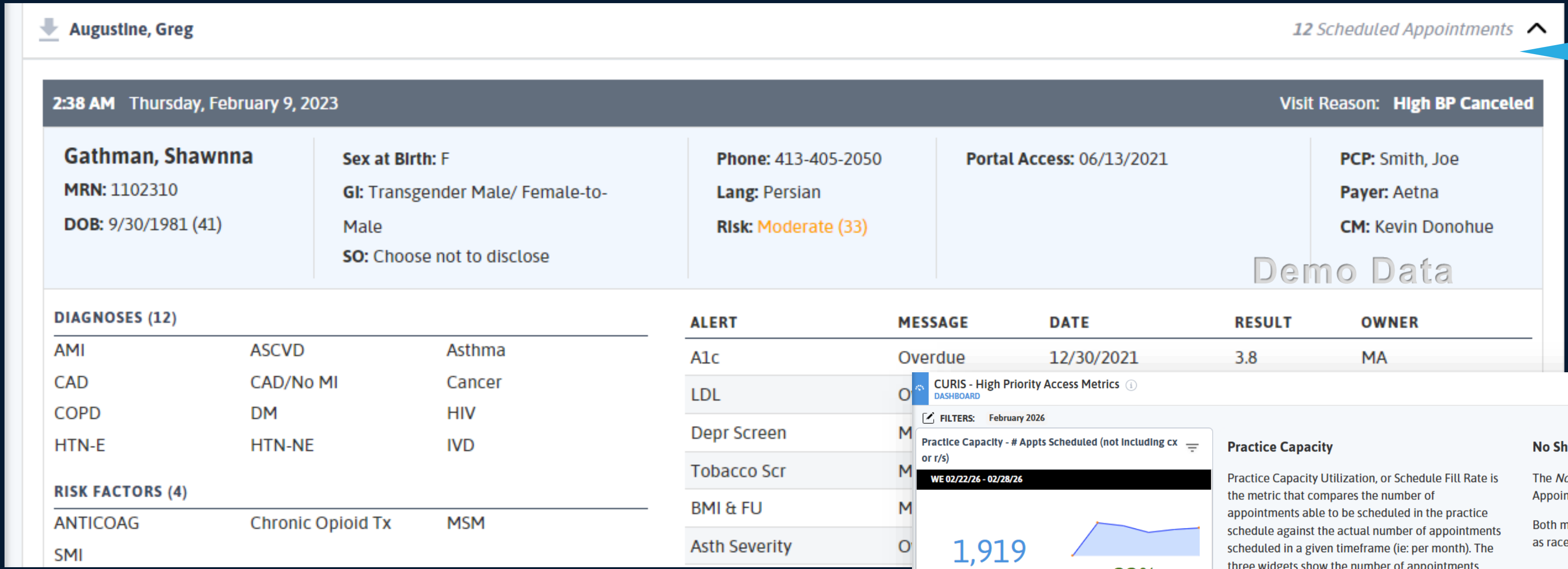
Example Operational Use Cases

- ☑ Targeted Outreach
- ☑ Reminder Escalation
- ☑ Careful Schedule Optimization

Measuring Impact

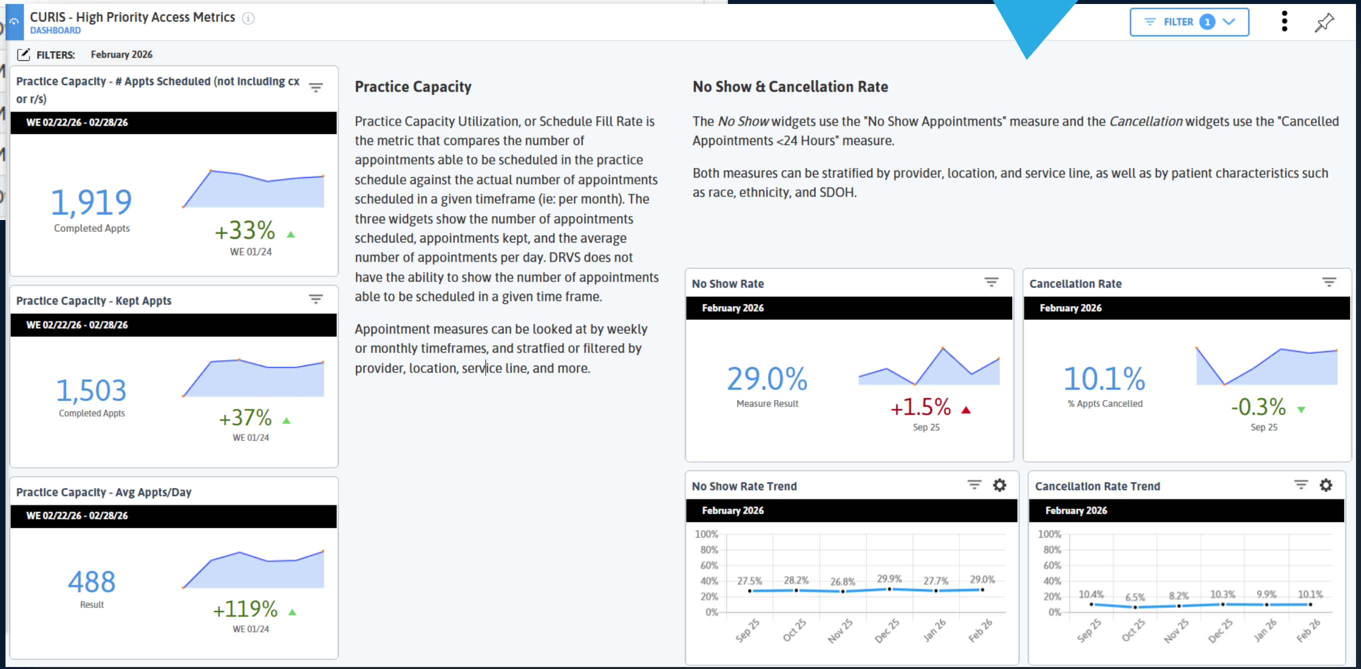
- Reduction in No-Show Rates
- Staff Time Savings
- Improvements in Access

How No-Show Predictions Fit Into DRVS



PVP/CMP/ EHR Plugin?

Dashboards?



- Updated daily
- Configurable categories?

Wrap Up

Key Takeaways and Q&A

Key Takeaways

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

Questions?

Celebrating 15 Years of Partnership & Progress

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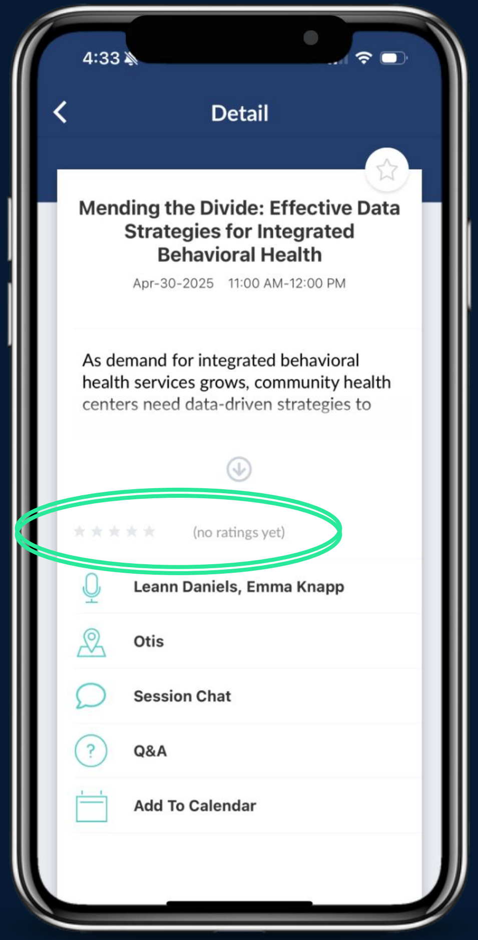

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