Cognitive Computing Model Brief: Risk of Patient No-Show (Version 2)

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Epic | 1979 Milky Way | Verona, WI 53593 | Voice: 608.271.9000 | Fax: 608.271.7237 | www.epic.com | documentation@epic.com

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Cognitive Computing Model Brief: Risk of Patient No-Show (Version 2)

No-show appointments delay important patient care and can cause a major loss of revenue and time for your organization. In Epic, there are a few strategies to decrease the chance of no-shows or mitigate their impact. The Risk of Patient No-Show model is one of those strategies.

Version 2 of the Risk of Patient No-Show model is a cloud-based, random forest model. The model is localized on your patient population and predicts a patient's likelihood to no-show. By using Nebula, Epic's cloud-based platform, version 2 of the model has better performance because it uses a different model type and expanded feature set, and it includes patient-initiated late cancels in the definition of a no-show.

Version 1 of the Risk of Patient No-Show model is a Chronicles-based, Naïve Bayes model. The model is localized on your patient population and predicts a patient’s likelihood to no-show. Additional details about this model can be found in the Cognitive Computing Model Brief: Risk of Patient No-Show (Version 1) document.

Considerations
If you are licensed for Nebula, or plan to be in the near future, we strongly recommend using version 2 of the model. Cloud-based models have different licensing considerations than Chronicles-based models such as version 1. Your Cogito technical services representative can determine whether you have the licenses necessary to use version 2 of the model: 151-A and 151-B.

If this model brief doesn't answer all of your questions or you have any feedback about this model, contact us at predict@epic.com.

Workflow

Using information about past appointments in your system, the no-show predictive model can help identify appointments that are most likely to become no-shows. You can show these predictions to schedulers and clinic managers in Radar dashboard components or report columns in their existing workflows, giving them a way to prioritize outreach to the patients who are more likely to no-show.

Review the Ethics Review section of this document for additional considerations related to model workflows. Always consider the different workflows your model will be used in and the features that could drive those workflows before enabling the model in your system.

Measuring Success

Epic recommends using existing tools, such as reports and dashboard components to measure your organization's baseline metrics before implementing a new cognitive computing model and then continuing to use those same resources to monitor changes in those metrics after implementing the model. For the Risk of Patient No-Show model, we recommend using the following metrics to track your progress:

- ES No-Show Rate (Appt Based)
- ES Provider Utilization (With Exclusion)

Considerations

In making scheduling decisions based in part on the output of the Risk of Patient No-Show model, your organization should consider the effect of those decisions on groups who have historically had difficulties in receiving access to care.

Model Design

Version 2 of the Risk of Patient No-Show model uses a random forest algorithm to predict the likelihood that a patient will miss their upcoming appointment or cancel it with little notice based on trends in your patient population. This version of the model uses Nebula to localize the model on your patient population.

Population Statistics

To develop the model features, we used data from over 7 million appointments at two healthcare organizations between 2014 and 2017. The data set was split with 80% used for training and the remaining 20% for testing. The total number of appointments and no-shows for each site appear in the following table.

	Site 1	**Site 2**
Total Number of Appointments	4,048,917	3,571,586
Number of No-Shows	384,677	245,551
Prevalence Rate	9.5%	6.9%

Development Methodology

The dataset is comprised of appointments with statuses of Completed, No Show, or Canceled (as long as the appointment was canceled late and the cancellation was initiated by a patient). Walk-in appointments are excluded. An organization's late-cancel threshold is defined in the facility record, as described in the Define Late Cancellations and No-Shows for Your Organization topic. The initiator is determined by the cancel reason selected for the appointment. Refer to the Create Reasons for Schedulers to Choose from When Canceling Appointments topic for additional information.

We began feature development by extracting 57 features, including features previously used in version 1 of the model and weather features derived from an external API. This feature set was narrowed down to 34 features and did not include any weather features. We chose the top 34 features based on the Gini importances and removed features that did not result in a significant decrease in model performance. We later removed patient demographic features, bringing the total number of features included in the model to 22.

A grid search was performed to determine the following parameters: samples per leaf node, maximum tree depth, maximum number of features to consider at each split, and minimum number of samples required to split an internal node. At both sites we found the optimal values were 10, 10, square root, and 30, respectively. These values are held fixed when localizing the model.

Model Performance

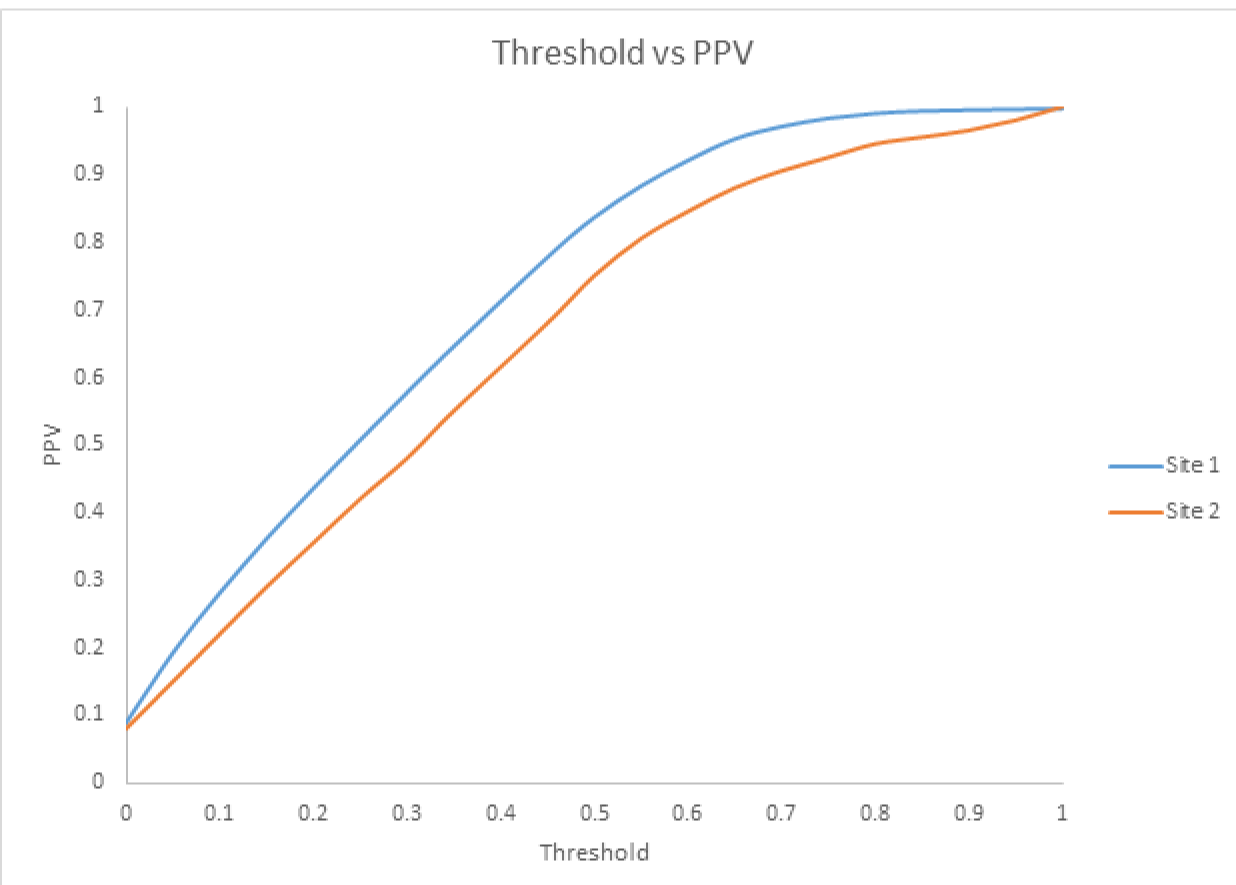
> The performance statistics shown here were calculated using the original feature set of the model, which included patient demographic variables. However, as of calendar month February 2022, we removed all demographic features from the model. This change affects the performance of the model, which means that model performance after this change does not exactly match the performance shown here.

C-Statistic

A model's C-statistic (also known as its AUC, the area under the receiver operating characteristic curve) measures the model's ability to discriminate between positive and negative cases. A C-statistic of 0.5 is no better than chance, while a C-statistic of 1.0 represents perfect accuracy. In the industry, no-show models with a C-statistic of 0.7 are respectable and 0.8 are outstanding. Version 2 models localized at our two testing sites had C-statistics (95% confidence interval) of 0.83 (0.824, 0.836) and 0.87 (0.865, 0.874).

Positive Predictive Value (PPV)

PPV is a measure of how often an appointment identified as meeting certain criteria (predicted no-show) does, in fact, meet those criteria (is a no-show). We want to be correct when labeling an appointment as a no-show according to the model to minimize additional time spent on appointments that won't become no-shows.



PPV - Sites 1 and 2

Data Definitions

Population

To be included in the training population, an appointment must meet the following criteria:

- Appointment status of one of the following:
    - Completed
    - No Show
    - Canceled, within your organization's late-cancel threshold and with a cancellation reason indicating that the patient initiated the cancellation
- Not a walk-in appointment

We did not include early cancellations in the population because it dilutes the training set and does not provide information on a patient's likelihood to show up to their new appointment, as we do not know what their behavior would have been without the cancellation.

Target Definition

We define a patient's outcome based on the appointment status, and, if it is canceled, the time and initiator of the cancellation. If the appointment's status is No Show or is Canceled within your organization's late-cancel threshold and with a cancellation reason indicating that the patient initiated the cancellation, the outcome is noted as a no-show. Otherwise, the target is a show.

Variables

The following approaches were used for missing data:

- Numerical variables were imputed to the mean of the training set values.
- Categorical variables were imputed to the most common value.
- Binary variables were imputed to 0.

Demographics/Patient Characteristics

In May 2022, in February 2022 with special update E10101732, in November 2021 with special update E9906683, in August 2021 with special update E9808731, in May 2021 with special update E9710234, and in February 2021 with special update E9612142 all demographic variables have been removed to mitigate the risk of potential adverse impacts to groups that have been marginalized.

Variables
Age
Has Medicaid
Has Medicare
Has PCP
Has Specialty Care Team
Marital Status
MyChart Status
State
Uses Alcohol
Uses Drugs
Uses Tobacco

Appointment Characteristics

Variables
Appointment Changed
Appointment Day of Week
Appointment Hour of Day
Appointment Month of Year
Appointment ZIP Code
Confirmation Status
Department ID
Department Specialty
Last Communication
Lead Time
Patient Called
Referral Exists
Referral Required
Rescheduled
Service Area ID
Visit Type

Appointment History

Variables
No-Show Rate
Number of Past Appointments
Number of Past Canceled Appointments
Number of Past ED Visits
Number of Past Hospitalizations
Number of Scheduled Appointments

Additional Considerations

Ethics Review

As we sought design feedback for version 2 of the Risk of Patient No-Show predictive model, we received some interest from the Epic community in overbooking workflows that incorporated our model. Overbooking is typically a controversial topic and using a predictive model to aid overbooking might present additional ethical concerns. In our original model brief for version 2 of the model, we cautioned organizations to be thoughtful about the use of the model for overbooking workflows, to consider the potential for discrimination and the ethical impact of your model, and to guide your organization on addressing concerns before putting the model into your end users' workflows.

What Are the Considerations and How Did Epic Address Them?

We evaluated a large set of demographic features, some of which were included in version 1 of the Risk of Patient No-Show model. We concluded that some demographic features that were both ethically ambiguous (in part because they might lead to differences in access to care across these classes) and had insignificant impact on model performance should be excluded from the model. However, our approach to ethics continues to evolve. To further mitigate the risk of potential adverse impacts to groups that might have been adversely affected, we removed all demographic features from the model.

Another consideration was evaluation of presenting relative feature importances to end users, particularly with demographic features included in the model. We decided, unlike other use cases, to not show feature importances by default in the model's hover bubble.

Finally, performance of the model has a large impact on the success of an outreach workflow. Evaluating the PPV at various thresholds of intervention is important, and Epic chose to heavily emphasize PPV in defining the final algorithm and features.

Health disparities do exist in medicine. We encourage organizations considering the Risk of Patient No-Show model to look critically at the workflow the model will be used in to ensure that it is having a positive impact on communities rather than perpetuating potential disparities in access to care.

Implementation Considerations for Your Organization

Before implementing the Risk of Patient No-Show model, we recommend the following steps to evaluate the model.

1. Document workflows where the model will be deployed. Establishing workflows will guide further discussion around ethics.
2. Review the features in the model. Consider the different workflows your model will be used in and the considerations that certain features could drive. Think about how the model can be used to increase access to care, particularly by historically disadvantaged groups.
3. With the help of your Cadence TS, validate the model to ensure the accuracy of the model is sufficient for the workflow you are planning. The performance of the model is paramount for the success of the models use.
4. Ensure the right conversation about ethics, effect on a patient population, and performance take place before your organization decides to use the no show model.

If you have additional concerns about the model or its use case, please reach out to your Cadence TS.