WHITE PAPER

Signal-Action Framework & Urgency Score

October 2023

pearl

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Signal-Action Framework & Urgency Score

Abstract

The Pearl Platform is a technology solution purpose-built to help primary care organizations proactively manage patient panels, identify opportunities to provide timely care, and achieve better financial outcomes through value-based performance.

This document explains the "Signal-Action Framework" and Urgency Score Algorithm that power the insights surfaced within the Pearl Platform, the mechanics of our current algorithm, and our vision for how this functionality will continue to evolve in 2024 and beyond.[1]

Goals

1. Create a scalable, data-driven method of surfacing tailored insights to practices to drive desired patient outcomes.

2. Establish how actions and outcomes make their way back into the platform to generate new Signals and inform future suggested care coordination actions, allowing us to continuously learn and prioritize the most impactful **Signals** and **Suggested Actions**.

3. Deliver **Suggested Actions** in a patient- and provider-centric way, prioritized to engage with the patients that most need attention.

1 For more information about how we think about the evolution of our product, read this article by our Chief Product Officer, Jennifer Rabiner, on Pearl's Product Principles.


Commodity Data
EMR
ADT
SDoH
Claims
Demo
Appts.
Machine Learning
Urgency Score vs. Recommended Follow-up
ADMISSION
DISCHARGE
RECOMMENDED FOLLOWUP WINDOW
TOUCHPOINT
1.0
Frail Elderly
Healthy
0
30
60
90
120
SIGNALS
OUTCOMES
Actions
Aligned Patient Map
Higher Urgency
Lower Urgency
TO
Severity
0
60
120
180
240
300
360+
Days Since Last Touchpoint
O'Connor, Tobin
View Profile
Demographics
M, 1/11/1958 - 65YO
Last Touchpoint
02/03/23 (101D)
Diagnoses (Showing 2 of 5)
Cardio-Respiratory Failure and Shock
Early Onset Dementia
Potential Future ED Visit
Note: Patient identified by Pearl's algorithm as potential risk for a preventable future ED visit. Suggest review chronic conditions and contact patient within 14 days to discuss possible indications that could warrant a PCP f/u. Please refer here for additional resources.
Actions
-Select-
Comments
Requires "Actions" Selection
Save
Close

SECTION I

Definitions

Insights

Any new information that causes the Pearl Platform to (1) update our view of the patient, and/or (2) prompt new Suggested Actions for care coordination (e.g., user activity in the app, the arrival of new lab results, ADT alerts, etc.).

Insights can be generated from events (something happening, e.g., ADT message informing of hospital discharge) or more passively learned information about a patient through any number of channels. A variety of data sources including claims, EMR, labs, social determinants of health (SDOH), and more can be used to generate insights.

Insights can also be generated via model outputs driven by machine learning. Model outputs can be predictive, such as determining that a patient is at high risk of a preventable ED visit in the future, or retrospective, such as identifying an opportunity for hierarchical condition category (HCC) capture.

Signals

Actionable, time-sensitive care opportunities for a patient surfaced via the Pearl Platform highlighting potential need for attention. Signals are paired with Suggested Actions intended to improve patient outcomes and/or lower costs.

Signals are created when Pearl detects a combination of one or more Insights that creates an ***actionable*** opportunity for improved care. **Signals** may be related to a disease state, recent care utilization patterns, or a predicted outcome. They can be powered via machine learning algorithms, heuristics, or manual clinical review. These **Signals** are informed by a wide set of data, including patient demographics, patterns of health care utilization, regional context, and manually identified opportunities pushed through the platform by Pearl Clinical Ops.

Surfacing Actionable Opportunities via Signals

- **Machine learning — Preventable ED Visit**: A predictive algorithm that forecasts future episodes of avoidable ED visits and enables PCPs to take proactive action that can help avoid those visits.[2]

  Our differentiated approach to model development allows our Signals to improve performance over widely-accepted best practices. For example, **our preventable ED visits Signal performs 30-40% better than the commonly-used clinical rule of targeting patients who have visited the ED a certain number of times in the last 6-12 months**.[3]

- **Event-based — Transitional Care Management (TCM)**: An alert that highlights discharged patients eligible for TCM, which has been proven to reduce complications, improve outcomes, and save thousands in care costs.[4]

- **Manual clinical review — High-Risk Patient**: Targeted Signals curated by Pearl's Clinical Strategy team, focused on highlighting bespoke actionable care opportunities for our most at-risk patients to help improve outcomes.

VISION: In the future, we will continue to incorporate new sources of data, such as Rx fill, Health Information Exchange (HIE) data, lab data, and patient/caregiver communications. We'll also continue to build cutting-edge predictive and opportunity-surfacing models to drive Signal generation based on opportunities we see emerge. Our goal is to optimize the ROI of our practices' time to ensure they have the information they need to maximize impact and improve outcomes.

Suggested Actions

The specific care coordination steps (and timing) recommended to improve patient outcomes, generated in response to signals. Suggested Actions are determined based on clinical guidelines and collaboration between Pearl's clinical strategy and data science teams.

Suggested Actions are specific and differentiated for each signal. These actions focus on tactical activities associated with scheduling, outreach, etc. to increase efficiency and optimize outcomes over time. The impact of **Suggested Actions** is continuously assessed within the Pearl population, and we have established clear attribution between many of our **Suggested Actions** and tangible impact on patient outcomes, healthcare costs, and/or practice performance in value-based care. We will continue reinforcing this feedback loop to measure impact and

2 To learn more about how Pearl is equipping providers with cutting-edge data science to help predict future preventable ED visits, read this article by our EVP of Clinical Strategy, Dr. Cameron Berg, on Predicting and Preventing Future ED Visits.

3 For more information on our approach to model development, see Section V: Building Predictive Model Accuracy.

4 To learn more about the benefits of managing transitions of care and how to drive adoption of TCM, read this article by Devon Brackbill, Staff Data Scientist, and Rebecca Kee, Data Analyst, on Revolutionizing Post-Discharge Care With Transitional Care Management.

improve **Signals** and their **Suggested Actions**, ensuring that our recommendations are constantly improving and tied to quantifiable impact in our patient population.

Urgency Score[5]

Quantitative measure that helps practices prioritize patients based on the importance of action(s) due.

> **VISION:** Over time, the Urgency Score will increasingly optimize for the ROI of taking action on a particular patient, which is driven by factors such as: how much the proposed actions are expected to affect outcomes (clinically/financially); who needs to take action; how quick the action is to complete; how important it is to happen in a timely manner; and how reliable the Signal is.

Severity Score

Quantitative measure of how chronically sick/at risk the patient is.

While this is out of scope for this document, **Severity Score** is informed by the Risk Adjustment Factor (RAF) and is intended to indicate high likelihood of poor outcomes and events, and functions as an input to **Urgency Score**.[6]

Signal Status

The state of a Signal (which could be actioned on by a practice user, a Pearl user, or, in the future, an automated process).

The history of these **Signal** actions appears in the timeline of **Patient View**, which provides holistic, longitudinal insights into patient care.[7]

As a **Signal** is surfaced and acted upon, a feedback loop is created. The action updates the **Signal Status**, which may cause new **Signals** to be generated and, in turn, modify the next set of **Suggested Actions** surfaced in the platform's **Panel View**, (which gives PCPs high-level visibility across their patient panels to quickly and easily identify who is most likely to need attention).[8] For example, when an action is completed or dismissed, the patient urgency de-escalates, the patient hexagon color updates and the patient falls on the priority list until a new opportunity arises. This helps the practice coordinate on the outstanding "to-do"s, feel the progress they are making in impacting patient outcomes, and complete the feedback loop to the system.

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5 For more information on how the Urgency Score is calculated, see Section III: Calculating Urgency Score.

6 A risk score is the numeric value an enrollee in a risk adjustment program is assigned each calendar year based on demographics and diagnoses (HCCs). For more information on the risk adjustment methodology and the significance of risk scores, see this educational piece from the American Academy of Professional Coders: **What is risk adjustment?**

7 Patient View distills clinical and administrative patient data across providers and facilities down to what's essential for providers to stay up to date on patients over time. To learn more, read this article by our Senior Product Manager, Alana Levy, on Patient View: Holistic, Longitudinal Insights into Patient Care.

8 Panel View provides simple visibility to quickly identify the patients most in need of attention. To learn more, read this article by our VP of Product, Lana Cohen, on Panel View: Using Data to Drive Proactive Care.

SECTION II

Overview of the Signal-Action Framework

Signal Research

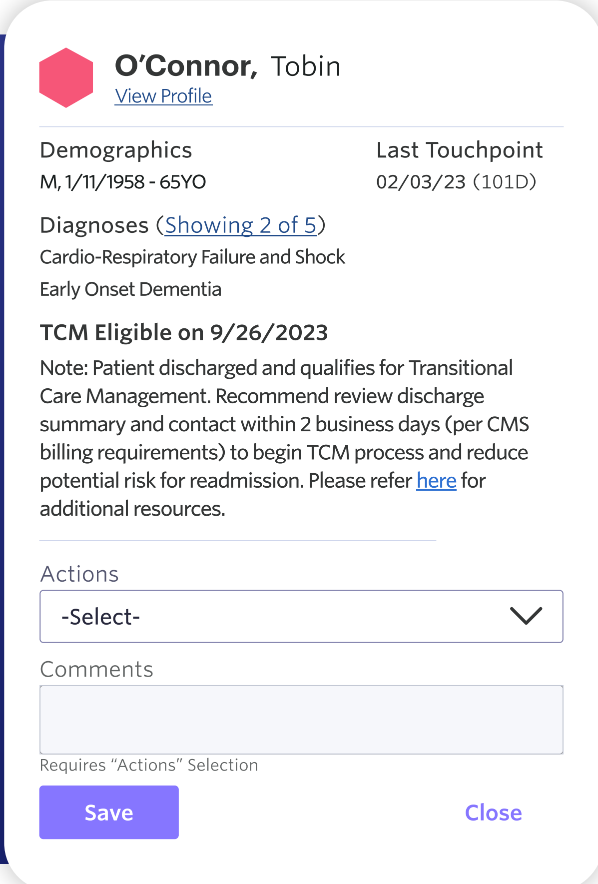
Signal research at Pearl involves a multidisciplinary approach where data scientists and clinicians collaborate to find actionable Signals to improve health outcomes. Incorporating research literature into the process sets a strong academic foundation for Pearl's work, but the real innovation comes from customizing this information for the unique patient populations within our Accountable Care Organizations (ACOs). Our data scientists and clinicians not only extract insights from broader scientific research, but they also contrast these insights with specific demographic, medical history, and SDOH data from our ACO population. This targeted approach allows us to fine-tune clinical models and identify Signals that are particularly relevant to our community.

By tailoring the research to the needs and characteristics of our own patient population, we ensure that the strategies we develop are not only based on the best existing evidence but also directly applicable and optimized for those under our partner practices' care. This blending of wide-reaching academic rigor with hyper-local application has the power to create healthcare solutions that are both cutting-edge and community-focused.

> By tailoring the research to the needs and characteristics of our own patient population, we ensure that the strategies we develop are not only based on the best existing evidence but also directly applicable and optimized for those under our partner practices' care.

The result of our approach to marrying data-driven methodologies with clinical expertise is the creation of new Signals to drive healthcare interventions that improve clinical outcomes, lower costs, and transform patient care.

Example – Transitional Care Management (TCM): Pearl's research on TCM identified an actionable opportunity to reduce post-discharge spend by $3,000 over the 90 days after each discharge by reducing skilled nursing facility (SNF) and inpatient hospital utilization. This led Pearl to create a focused TCM Signal following



Illustrative Examples

We see that Tobin O'Connor was just discharged from the hospital, which activates a 30-Day Action Plan based on his admission and overall Severity Score. Tobin will also already be on the Action Plan for Frail Elderly patients. All patients will also be on the Action Plan for having an Annual Wellness Visit (AWV).

The result is a series of potential Actions for Tobin that are all queued to happen on a set schedule, assuming nothing changes in our logic, his health, or the practice's activity in that app. Of course, Actions will be revised based on recent info and activity.

discharges for Sepsis and Hypertension that empowers PCPs to improve post-discharge outcomes and lower healthcare costs.

Functionality

Insights are combined to create **Signals** via rules — sets of logic that determine which combinations of Insights lead to actionable, impactful **Signals**. These Signals can be generated via either simple ETL processes (e.g., has_diabetes) or more sophisticated approaches like machine learning (e.g., probability_of_readmission). Each **Signal** has tailored **Suggested Actions** for the unique patient situation identified.

> **VISION:** While the core of this functionality is already in place, the work that we are doing in 2023 and the years ahead will cause this framework to evolve and position the Pearl Platform to identify and surface increasingly valuable Signals — and to make a greater impact on patient outcomes with less work from our partner practices.

The chart in **FIGURE 1.2** and the table in **FIGURE 1.3** provide examples of how potential Signals and Actions could evolve over this year and beyond. It illustrates how patients may be prioritized based on Urgency Score and the range of actions due. On the workflows side, we'll continue our efforts to make it easier for practices to triage, escalate and delegate activities and put automation in place to remove work where possible.

Figure 1.2: Patient-Centric Action Plan

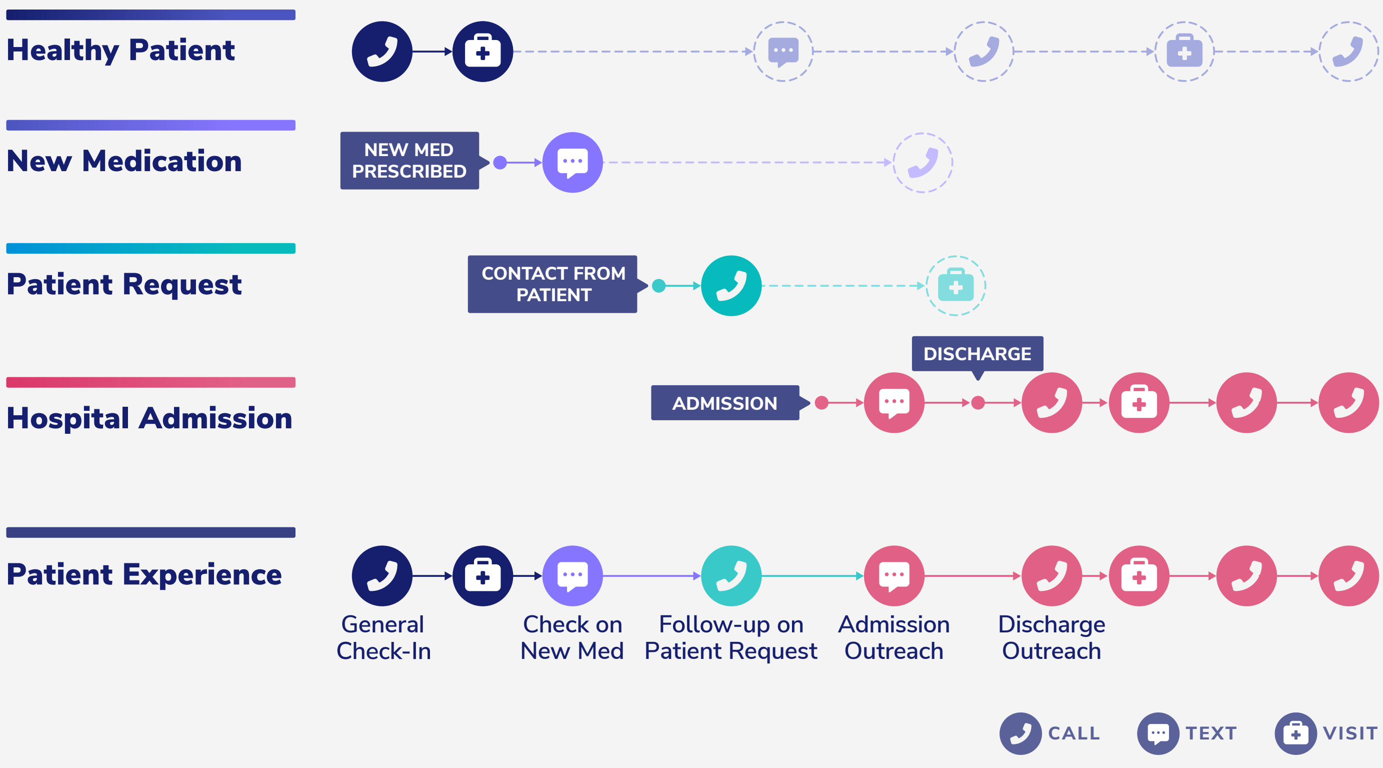


Figure 1.3: Example Signals and Suggested Actions

PATIENT	SIGNAL (filter)	ACTIONS DUE	TYPE OF ACTIVITY (filter)
Jenny Smith (8/3/1952)	Discharge first response	**1.** Call to reconcile hospital discharge from Mercy Hospital **3 days ago** (5/19/23)	Call Patient (clinical)
	Discharge first response	**2.** Schedule discharge follow-up visit by 5/31/23 for timely follow-up	Schedule
	AWV Due	**3.** Schedule AWV (eligible 3/1/23)	Schedule
Robert Jones (3/4/1945)	Recent Discharge check-in	**1.** Call for 2 week check-in post discharge on 4/30/23, last contact 5/3/23.	Call Patient (clinical)
Joe Smith (2/1/1942)	ED visit	**1.** Call re recent (potentially avoidable) ED visit. Visits in past 6 months: 3.	Call Patient (clinical)
	Multi-chronic patient cadence	**2.** Call for monthly touchpoint	Call Patient (clinical)
Nina Tremble (5/3/1958)	New med prescribed	**1.** Text to check on new med	Text Patient (clinical)
Julio Madera (6/7/1953)	Contact from patient	**1.** Call to follow up on patient request	Call Patient (clinical)

Some of the platform functionality above is coming (e.g., automated texts, new medications and contact from patient) but is not yet live.

SECTION III

Calculating Urgency Score

Objective

Write a function that takes various inputs and creates a score for each patient to quantify how urgently a patient needs attention. This score will translate to a corresponding hexagon color in the Panel View.

Urgency should increase continuously as time passes, but will increase at a faster or slower rate dependent on the patient's complexity and current needs. The algorithm incorporates last touchpoint, Harvard Frailty Cohort,[9] Severity Score (January 2023 normalized RAF score), claims data, and ADT feeds. In the future, we will continue to incorporate new data sources to make this smarter and more up to date.

Algorithm

In the following, we explain the mechanics of the Urgency Score, starting with calculating an initial score based on the time since a patient's last visit and their Severity Score, and then layering on ADT data to refine that score. Urgency Score will continue to evolve and become more sophisticated over time. Last updated September 2023.

Calculating Urgency Score

As a starting point, Urgency Score is set to equal 1 when the number of days lapsed is equal to the maximum recommended number of days lapsed, and then increases above 1 as the number of days increases, maxing out at a year.

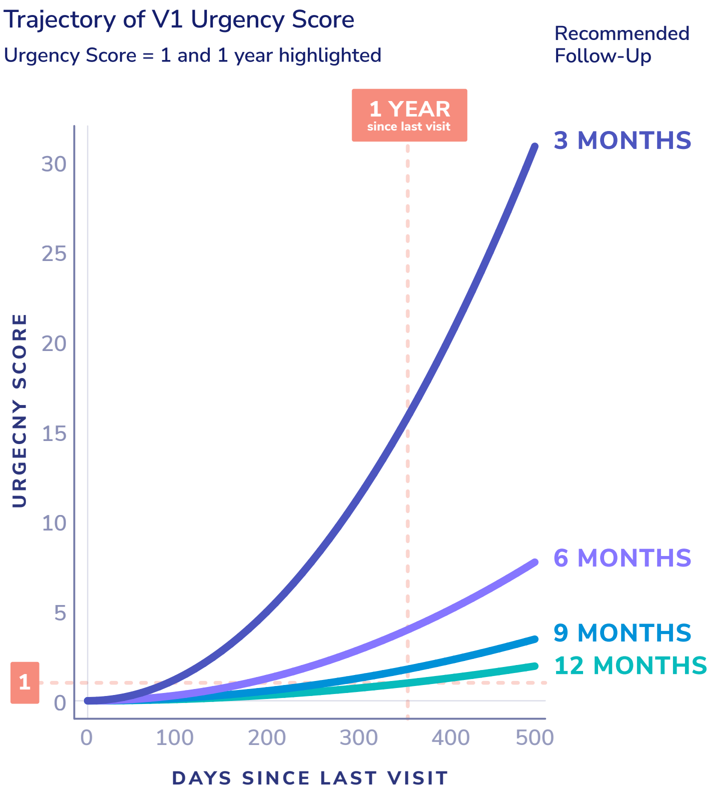
For example, if the recommended follow up time were 1-3 months, the Urgency Score would increase continuously so that it was 1 when it had been 90 days since the patient was last seen (a score of 1 indicates "urgently needs attention").

The trajectory of urgency is then modified by the multiplication of the Severity Score. This increases the growth rate of the Urgency Score for patients with **Severity Score >1**; however, the Urgency Score remains unchanged for patients with **Severity Score <1**. Severity Score impacts Urgency Score for patients with shorter follow-up times more than those with longer follow-up times.

9 Karen E. Joynt, Jose F. Figuero, et al. "Segmenting high-cost Medicare patients into potentially actionable cohorts." Healthcare, Volume 5, Issues 1–2. March 2017.

Figure 2.1: Urgency Score with Severity = 1

Note: This chart demonstrates how Urgency Scores grow without the influence of severity



Incorporating ADT Data Into Urgency Score

Next, the Urgency Score incorporates admit, discharge, and transfer (ADT) data from healthcare facilities in order to escalate the priority of patients who are undergoing a transition in care.

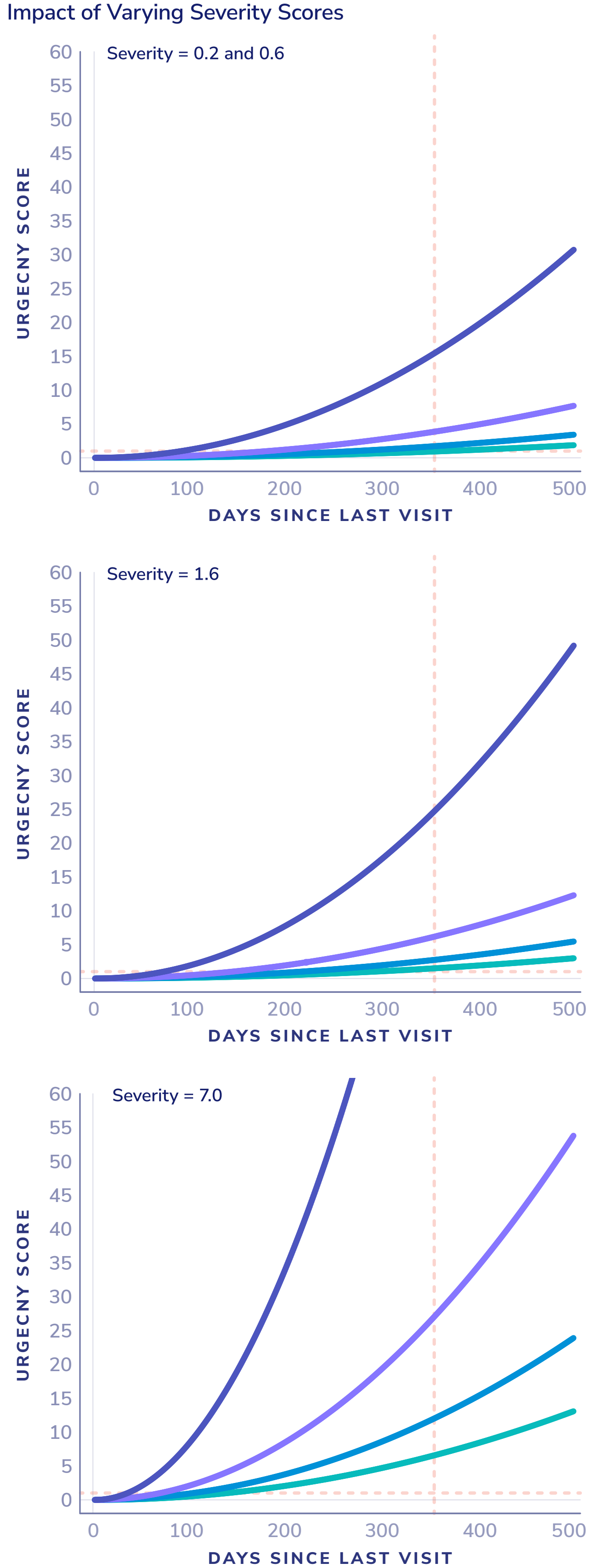
We consider a recommended follow-up time for the ADT event (β_y) as well as an ADT time window in which the ADT event is relevant (α). All ADT events will be relevant for 30 days. Whether or not a given ADT event spikes urgency is dependent on properties of that ADT, such as the facility type and the event type.

β_y is defined as:

- A03 (Discharge): 10 Days
- Otherwise, a function of the start score and predefined recommended

Figure 2.2: V1.1 with Varying Severity Scores

Note: These charts demonstrate how Urgency Scores are changed by differences in severity.



follow-up time for the event

ADT events which will spike urgency are:

- A01 (Admission)
- A02 (Transfer)
- A03 (Discharge)
- A04 (Presenting to the ED)

How ADT Events Impact Current Algorithm

If no ADT event has occurred, ADT events have no impact.

If an ADT event has occurred for a relevant facility type, and there has not been a touchpoint after the ADT event, we effectively add a score of 1 to the Urgency Score, which ensures that the patient's hexagon will turn red and that the Urgency Score will keep escalating over time. (**SEE FIGURE 2.3**)

If an ADT event has occurred, and there has been a touchpoint after the ADT event, we first calculate how long after the ADT event the touchpoint was (y-x). If y-x is greater than or equal to α, this will be 30 days. Since there has been a touchpoint and it has been more than 30 days, the ADT event is no longer relevant, so it has no impact on the Urgency Score. (**SEE FIGURE 2.4**)

If a touchpoint after an ADT event occurs in less than 30 days (y-x *is less than* α), we use the Urgency Score calculated without accounting for ADT plus a score calculated on the base score x and y. This additional score is designed to ensure that the score doesn't go to 0 after a touchpoint within the 30 days. (**SEE FIGURE 2.5**)

Figure 2.3: Urgency with an ADT event, no follow-up

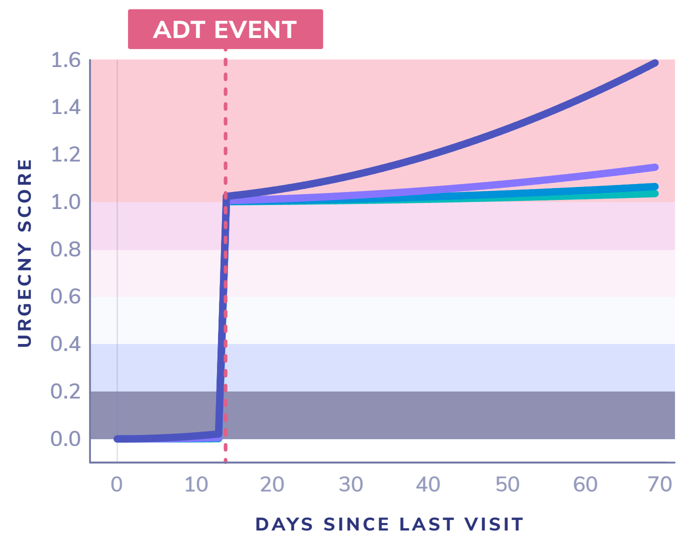


Figure 2.4: Urgency with an ADT event, follow-up after 30 days

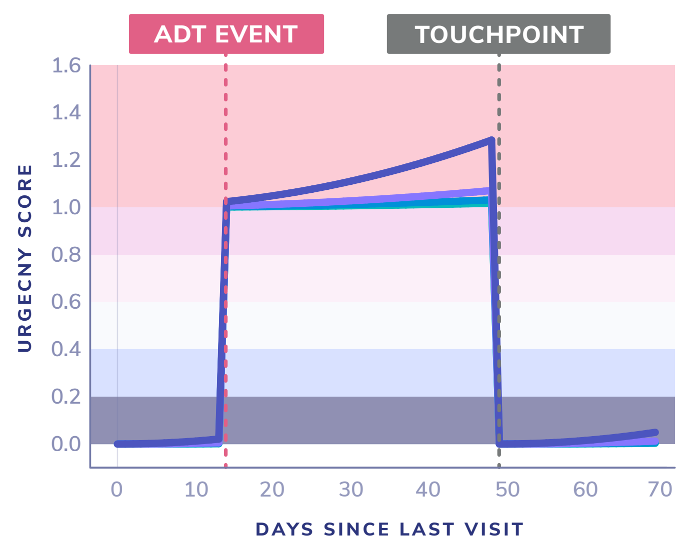
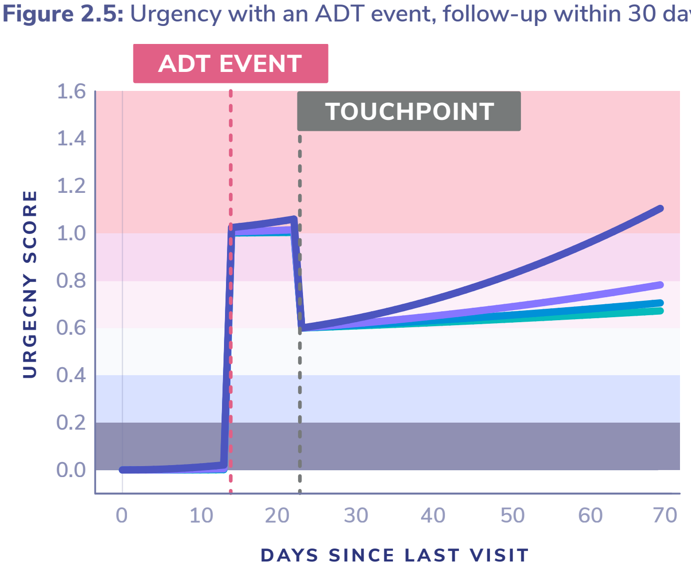


Figure 2.5: Urgency with an ADT event, follow-up within 30 days



In addition to the foundational definition described previously, we are continuously refining our Urgency Score algorithm based on learnings from our patient population. Recent examples of this refinement include:

- Lowering urgency for specific types of ADT events (Facility-specific Admits)
- Increasing urgency for discharges that are detected to be eligible for the Timely Followup QM measure
- Increasing urgency for discharges that are detected to be eligible for Transitional Care Management billing

Urgency Score Definition

$$x = \textit{days since last visit}$$
$$\beta_x = \textit{recommended follow up}$$
$$\gamma_x = \min(\beta_x, 365)$$
$$c_x = \gamma_x^{-2}$$

$$y = \textit{days since last ADT event}$$
$$h = \textit{base score (using 0.6 for v2.0)}$$
$$\beta_y = \begin{cases} 10 & \textit{ADT event is a discharge} \\ (1-h) * \beta_x & \textit{otherwise} \end{cases}$$

$$\alpha = \textit{ADT time window}$$
$$\beta_{y_{adj}} = \begin{cases} \max\left(0, \beta_y + \frac{((1-h) * \beta_x) - \beta_y}{\beta_y}(y - x)\right) & \textit{if } x < y \\ \beta_y & \textit{otherwise} \end{cases}$$

$$\gamma_y = \min(\beta_{y_{adj}}, 365)$$
$$c_y = \gamma_y^{-2}$$

$$\lambda = \max(\textit{severity score}, 1)$$

$$p = \begin{cases} 1 & \textit{if ADT event has occured} \\ 0 & \textit{otherwise} \end{cases}$$

$$g(t, \beta, h) = \beta\sqrt{h} + (1 - \sqrt{h})t$$
$$d = \begin{cases} \frac{1}{c_y} & \textit{if } p = 1 \textit{ and } x > y \\ 0 & \textit{if } p = 0 \textit{ or } (x < (y - \alpha) \textit{ and } y > \alpha) \\ g(x, h, \beta_{y_{adj}})^2 & \textit{otherwise} \end{cases}$$
$$f(x, y) = \lambda c_x x^2 + c_y d$$

SECTION IV

Hexagon Colors in Panel View

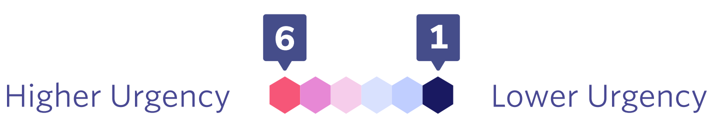
For translating the Urgency Score to one of 6 colors (numbered 1-6), we are currently using the following logic:

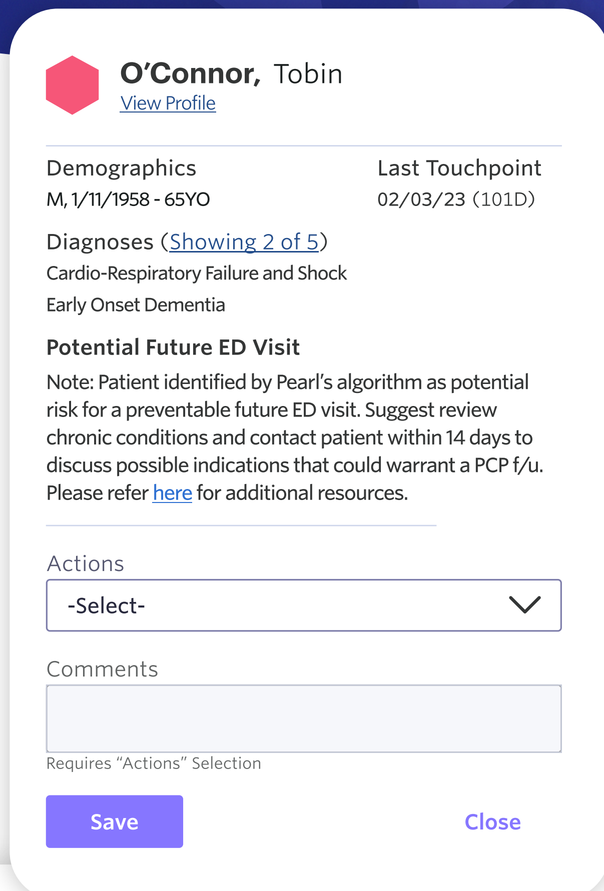
> *6 if urgency >= 1*
> *else math.ceil(urgency * (6 - 1))*

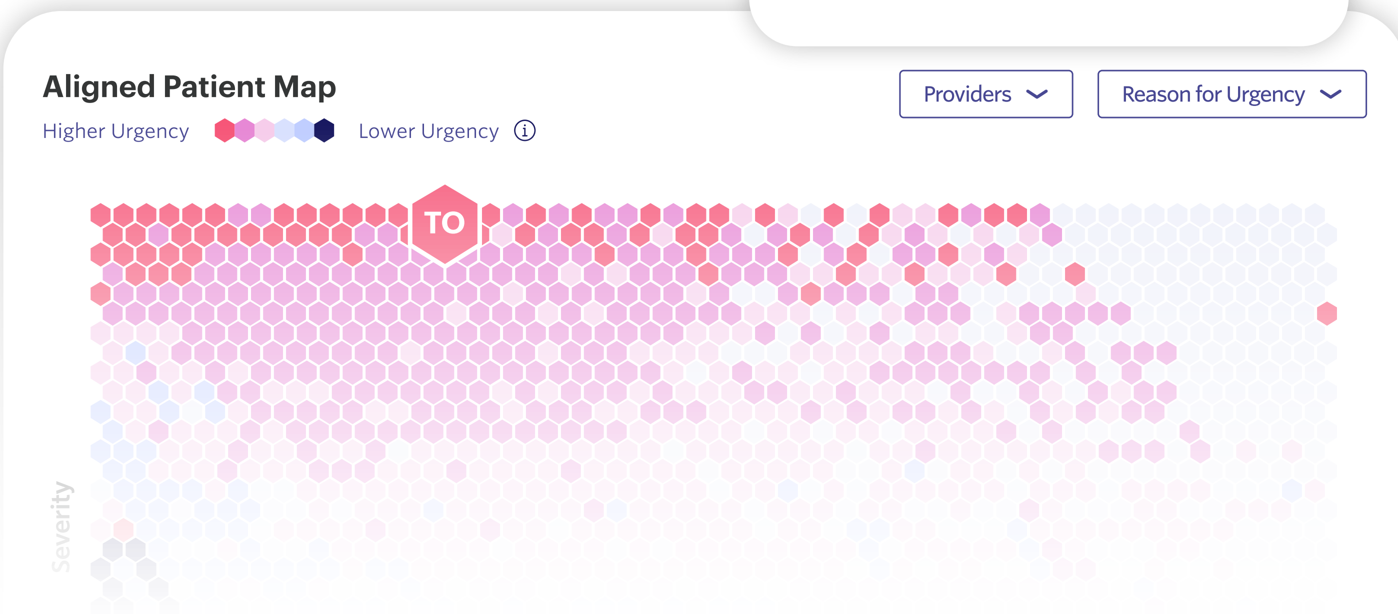
For example, if the Urgency Score is 0.2, then the color will be color 1

If the score is 0.18, the color will also be 1

If the score is 0.99 the color will be 5







Expected Behavior[10]

For any change made to the Urgency Score, the following expected behaviors must be verified before making the change.

1. If any patient, regardless of Severity Score or cohort has not been seen in 365 days or more, their Urgency Score should be 1.
2. Ensure that patients in more urgent cohorts have higher Urgency Scores than less urgent cohorts for the same number of days since last visit.
3. Patients with an ADT event will have hexagons turn red and remain red until an action has been taken.
4. Patients with an ADT event and an action has been taken within 30 days will have hexagons turn hot pink and escalate to red in a shorter time window than normal (this time window is between 30 days and the recommended follow-up time, depending on when the Action is taken in the 30 day window).
5. Patients with an ADT event and an action taken after 30 days will have hexagons turn dark blue, after which the hexagon will escalate to red within the patient's recommended follow-up window.

Validation Tasks for Algorithm Development

1. Visualize trajectories of scores for different cohorts to ensure they are reasonable.
2. Verify expected behaviors above are satisfied.

Validation Results

As of September 14, 2023.

Distribution of Urgency Scores where days since last visit is greater than 365:

>365	
mean	19.3435069
std	39.6409563
min	0.04450365922
p25	1.918737997
p50	5.76
p75	19.21723914
max	1069.220278

Distribution of Urgency Scores where days since last visit is less than 365:

<=365	
mean	0.7315172955
std	1.950134038
min	0
p25	0.06101537439
p50	0.2075308642
p75	0.6359223955
max	92.16651772

10 For more information on how we validate our results and the expected behaviors, see Section V: Building Predictive Model Accuracy.

SECTION V

Building Predictive Model Accuracy

Our research models are trained on four years of historical claims data (for patients who have not opted out of data sharing).

In the development of our predictive models, we test how well the model would have performed in the past. This is known as back-testing. We do this by using historical data on patients to see if our model's predictions match what actually happened to each patient.

We then compare the performance of our model with existing methods commonly used by clinicians, which are often based on studies and academic literature.

Example of Predictive Model Development

For a Signal like Preventable ED, we're looking for patterns of classic ED misuse, combined with flare-ups in chronic conditions that could trigger future ED use in the next 3 months. This allows us to develop a high-performing model. For example, one commonly-used clinical rule identifies frequent ED users as patients who have visited the ED a certain number of times in the last 6-12 months.[11] Our model, when tested, performed 30-40% better than this rule.

What makes our model different and more effective? Instead of only looking at the number of ED visits a patient has had, we include a wider range of factors that give us a more comprehensive understanding of their health status. Here are some specifics:

- **Chronic Disease History:** We include data on whether a patient has chronic conditions like diabetes, heart disease, or asthma. This helps us better anticipate their healthcare needs.
- **Health System Utilization:** We look at the patient's history of using healthcare services — not just emergency visits but also hospital admissions, primary care visits, and so on.

By adding these additional pieces of information (and much more), we create a more holistic view of the patient, which means we consider multiple aspects of a patient's health, not just one or two indicators. This approach has proven to be more effective in predicting who will seek out preventable ED visits, making our model a more reliable tool for healthcare providers.

11 Krieg C, Hudon C, Chouinard MC, et al. "Individual predictors of frequent emergency department use: a scoping review," BMC Health Serv Res. 2016; 16(1): 594.

Authors

Lana Cohen

Vice President, Product

Lana Cohen is Vice President of Product at Pearl Health. Prior to joining Pearl, Lana spent over seven years at athenahealth as a Product Leader in the Platform division working on integration strategies and patient engagement solutions.

She is passionate about enabling physicians with the right information and tools at the right time and place to achieve better outcomes — and in empowering patients to be active agents in their care. At athena, she led the rollout of “login with athenahealth” credential for patients across the athena network and numerous patient and clinician-facing app integrations, including Apple Health and several Payor integrations. Prior to her MBA, she led Product for an early-stage fintech company.

Peter Jamieson

Head of Corporate Strategy

Peter Jamieson is the Head of Corporate Strategy at Pearl Health. Peter has extensive experience leading data science teams in both the healthcare and financial services industries. Prior to joining Pearl, he ran the DS team for Poloniex, a leading cryptocurrency exchange, focusing on issues related to security, risk, and financial performance. Before that, he worked as a consultant with BCG Gamma, Boston Consulting Group’s data science and advanced analytics practice, supporting clients in the pharmaceutical and insurance verticals, among others. In addition, he spent several years overseeing athenahealth’s population health and patient engagement data science efforts. He is passionate about helping businesses leverage cutting-edge technologies to make smarter decisions and serve their customers better.

Devon Brackbill

Staff Data Scientist

Prior to joining Pearl, Devon worked at Amazon Robotics, where he built ML systems to optimize warehouse performance, and designed autonomous robotic systems to sort packages. Before that, Devon worked at Meta where he built ML models and measurement systems to reduce the prevalence of harmful content on Instagram. Devon also worked at a health system in Camden, NJ to implement predictive models for commercial and CMS value-based care programs. Devon completed his PhD from Penn in Computational Social Science.

Nellie Ponarul

Sr. Data Scientist

Prior to joining Pearl, Nellie worked at Ankura Consulting where she performed data analytics on large healthcare claims and financial datasets for class action lawsuits. She also worked as a research assistant in the Onnela Lab at Harvard where she worked with smartphone data for biomedical research and oversaw collaboration with clinical research teams.

Morgan Lavine

Principal Product Manager

He is a healthcare boomerang – after starting his career as a software developer, he moved to Product at athenahealth on the Clinical Interoperability team. Morgan then moved to ecommerce at Wayfair, where he led the Search team and developed expertise creating data-driven scalable ML solutions. After a leadership stint at JuniperMarket, Morgan is excited to be back in healthcare, using cutting edge technology to ensure better care for both patients and their providers. Morgan holds a B.S. in Electrical and Computer Engineering from Franklin W. Olin College of Engineering.

Khrisendat Persaud

Manager, Software Engineering

Khrisendat is a Manager of Software Engineering at Pearl Health. Before joining Pearl, he served as the technical lead of the data warehousing and analytics team at ListenFirst. There he helped to design and build the data warehouse and external analytics APIs. Khrisendat holds a Bachelors in Biomedical Engineering from CCNY.

About Pearl Health

We help primary care organizations succeed in value-based care

We're a team of doctors, technologists, and health plan specialists with a passion for enabling our provider partners to deliver better care and reduce health system costs. Our executive team has deep experience in payor and provider technology, in addition to diverse industry backgrounds offering fresh perspectives.

At Pearl Health, our mission is to democratize access to value in healthcare. We seek to empower primary care practices to deliver better quality care for their patients at a lower cost via a physician enablement technology platform and a value-based payment model — starting with Medicare's ACO REACH Model.

Our platform and services are designed to make it easy for providers to continue delivering quality care for their patients while maximizing revenue for their practices. We do this by providing simple financial reporting, visibility into patient panel health, and recommendations to allocate time and resources to deliver care to patients who need it most.

Learn more at pearlhealth.com

www.pearlhealth.com

info@pearlhealth.com

220 5th Avenue, 17th Floor,
New York, NY 10001