

WHITE PAPER

Signal-Action Framework & Urgency Score



Table of Contents

Signal-Action Framework & Urgency Score	_2
Abstract	2
Goals	2
Definitions	4
Insights	4
Signals	4
Suggested Actions	5
Urgency Score	6
Severity Score	6
Signal Status	6
Overview of the Signal-Action Framework	7
Signal Research	7
Predictive Model Development	
Building Predictive Model Accuracy	8
Turning ML Models Into Signals	9
How We Study the Effectiveness of ML-Based Signals	10
Signal Prioritization	12
Hexagon Colors	
Signal Ranking	13
Calculating Urgency Score	14
Objective	14
Calculating Urgency Score	14
Authors	15
About Pearl Health	16

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Signal-Action Framework & Urgency Score

Abstract

The <u>Pearl Platform</u> 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

- Create a scalable, data-driven method of surfacing tailored insights to practices to drive desired patient outcomes.
- 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.
- Deliver Suggested Actions in a patient- and provider-centric way, prioritized for engagement 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.



Fictionalized Patient Information

OUTCOMES

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, Admission, Discharge, and Transfer (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 to make hierarchical condition category (HCC) coding more accurate.

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, ADT notifications, and opportunities identified by clinicians.

Examples of approaches Pearl takes to surface actionable opportunities via Signals

Machine learning: <u>Preventable ED</u> <u>Visit</u>: A predictive algorithm that forecasts future episodes of avoidable ED visits and enables PCPs to take proactive action that may help avoid those visits.

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% 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.**²

- Event-based: <u>Transitional Care</u> <u>Management (TCM)</u>: An alert that highlights discharged patients eligible for TCM, which has been proven to reduce complications, improve outcomes, and save thousands in care costs.
- Preventative care reminders: AWVs: An alert that indicates when a patient is eligible to complete their Annual Medicare Wellness Visit.
- Manual clinical review: High-Risk Patient: Targeted Signals curated by Pearl's Clinical Strategy team, focused on highlighting 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 improve Signals and their Suggested Actions, ensuring that our recommendations are constantly improving and tied to guantifiable impact in our patient population.

2 For more information on our approach to model development, see Section II.

• Urgency Score³

Quantitative measure that helps practices prioritize patients based on the significance of care coordination opportunities.

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.

Quantitative measure of how chronically sick/at risk the patient is. While this is out of scope for this document, **Severity Score** is determined 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**.⁴

Signal Status

The state of a Signal (which could be acted 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 <u>Patient View</u>, which provides holistic, longitudinal insights into patient care.

As a Signal is surfaced and acted on, 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). 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 the outstanding "to-do"s, feel the progress they are making in impacting patient outcomes, and complete the feedback loop to the system.

³ For more information on how the Urgency Score is calculated, see Section IV: Calculating Urgency Score

⁴ For more information on risk adjustment and the RAF, see this educational piece from the American Academy of Professional Coders: What is risk adjustment?

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 finetune 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. This blending of wide-reaching academic rigor with hyper-local application has the power to create healthcare solutions that are both cuttingedge and community-focused.

The result of our approach to marrying datadriven 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: <u>Transitional Care Management</u>

(TCM): Pearl's research on TCM identified an actionable opportunity to reduce postdischarge spend by \$3,000 over the 90 days after each discharge by completing a TCM visit, which helps to reduce skilled nursing facility (SNF) and inpatient hospital utilization. This led Pearl to create a focused TCM Signal following discharges for Sepsis and Hypertension as the diagnoses most strongly correlated with improved outcomes via TCM, empowering PCPs to improve post-discharge outcomes and lower healthcare costs.

Predictive Model Development

Pearl uses predictive modeling to provide Signals to practices about patients that may be at risk for high cost due to acute utilization like unplanned admissions and preventable ED visits.

1 Building Predictive Model Accuracy

Our research models are trained on three to 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 backtesting. 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: 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.⁵ Our model, when tested, performed around 30% 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 examples:

- 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.

⁵ 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.

2 Turning ML Models Into Signals

To derive Signals from our predictive models, we apply a risk score threshold to the output of the models to choose a list of patients for whom the Signal should be fired. Predictive models can have some false predictions, so when we pilot a predictive model, we apply a very high threshold and only flag a small proportion of beneficiaries to get initial feedback on whether or not the Signal is useful to providers.

Once we have evidence that the Signal is useful (based on provider engagement and feedback), we want to deploy it to as many high priority patients as possible. We select a threshold to optimize both the positive predictive value of our model and the true positive rate of our model. Using the harmonic mean of these two scores at different thresholds, we determine what threshold will maximize these two values. This allows us to flag as many true positives for our model (as many patients who truly are at risk of the outcome occurring) as we can without introducing too many false positives.

See below an example of a graph we would use to evaluate which risk score threshold to apply.





Demographics M, 1/11/1958 - 65YO Diagnoses (<u>Showing 2 o</u> Cardio-Respiratory Failure and Early Onset Dementia TCM Eligible on 9/26/2 ^d Note: Patient discharged and Care Management. Recomm summary and contact withir billing requirements) to begi potential risk for readmission additional resources.	Last Touchpoint 02/03/23 (101D) f_5) Shock 023 I qualifies for Transitional nend review discharge n 2 business days (per CMS n TCM process and reduce n. Please refer <u>here</u> for	Illustrative Examples We see that Tobin O'Connor was just discharged from the hospital, which activates a Signal for Transitional Care Management based on his admission and overall Severity Score. Tobin will also already have known opportunities for Frail Elderly patients. All patients will also receive a Signal to schedule an Annual Wellness Visit (AWV).
-Select-	\checkmark	
Comments		
Requires "Actions" Selection	Close	
Fictionalized P	atient Information	

3 How We Study the Effectiveness of ML-Based Signals

After deploying a Signal for some time, we use causal inference methods to conduct observational studies of our data to measure the impact of engaging with the Signal in the Pearl Platform. We examine the association between patient outcomes and actions taken in the Pearl Platform. but we also account for holistic information about patients, like chronic conditions and prior utilization. This informs us of the causal impact, i.e. how many of the positive outcomes are attributable to our Signals vs other factors. These observational studies inform Pearl of which Signals are effectively driving positive impact to clinical outcomes, and allows us to best prioritize Signals for providers based on their clinical impact.

FIGURE 1.2 shows a series of potential events, Signals, and Actions before and after Tobin's discharge from the hospital. Signals may be triggered on a set schedule, assuming nothing changes in our logic, his health, or the practice's activity in the Platform — but of course, Signals will be revised based on recent info and activity.

The table in FIGURE 1.3 provides 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 reduce work where possible.

Figure 1.2: Example of Signals Throughout Patient Journey



Figure 1.3: Example Signals and Suggested Actions

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

This example uses fictionalized patient information and includes functionality that is not yet available in the Pearl Platform.

Signal Prioritization

Hexagon Colors

The Pearl Platform enables clinical staff to drill down into the highest priority patient alerts by categorizing Signal opportunities into four color-coded buckets.

Do Now

Interventions for provider's consideration that are predicted to provide the most benefit from proactive outreach it is recommended that these alerts are addressed within 2 business days

Do Next

Actionable interventions for provider's consideration that are predicted to provide meaningful benefit from proactive outreach, but may not be as sensitive to timing as "Do Now" actions

Awareness

New information or activity, but Pearl hasn't identified actionable activities for provider's consideration that are predicted to provide special benefit from proactive outreach

No Pending Action

No pending activity identified, or recently completed action

Aligned Patient Map

Do Now **Internet** No Pending Action



everity

O'Connor, Tobin <u>View Profile</u>

Demographics M, 1/11/1958 - 65YO Last Touchpoint 02/03/23 (101D)

Diagnoses (<u>Showing 2 of 5</u>) 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 <u>here</u> for additional resources.

Comments	
Requires "Actions" Selection	

Fictionalized Patient Information

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pearlhealth.com 12

Pearl uses a combination of clinical knowledge and data science research to determine which opportunities belong to which buckets. For example:

- Discharge alerts are categorized into the "Do Now" bucket since proactive outreach is most impactful immediately after discharge. Signals for Timely Follow-Up and Transitional Care Management, which have time-sensitive requirements, also fall into "Do Now".
- Admission avoidance alerts, which are predictive alerts to head off potentially avoidable admission events with outsized TME impact, are also categorized into the "Do Now" bucket, as the sooner they are addressed the more likely the costly event is avoided.
- Chronic Care Management alerts are categorized into the "Do Next" bucket given the different levels of urgency and appointment timelines for these patients, providing the practice additional time to conduct review and scheduling of appointments.
- Annual Wellness Visit alerts for patients who are due for an AWV in the next month are categorized into the "Awareness" bucket to let the practice know a visit should be scheduled soon, but not necessarily immediately. If the visit is not scheduled and becomes overdue, the alert moves into the "Do Next" bucket.

By making it clear whether a Signal is a 'Do Now', 'Do Next', or 'Awareness' opportunity, we allow our providers to approach their panel with confidence, knowing where to start on their patient list and what situations are most in need of their attention.

Signal Ranking

An important part of surfacing the right Signal at the right time is determining which Signals should take priority over others. Even within the above hexagon color buckets, not all care opportunities are created equal if a practice has multiple red-hex patients, or a single patient has multiple red-hex opportunities, practice staff need to know where to start. This is clearly critical for a single patient who might have multiple care opportunities, but It's also necessary when looking across a patient panel.

To accomplish this, Pearl builds a 'Priority Score' for each Signal type. This score combines two primary factors — the **urgency** of the Signal (how quickly is attention recommended in order to create impact), and the **value** of the Signal (how large is the cost savings if this opportunity is captured). The Pearl Platform uses this score in multiple places:

- In the Panel View to display the active Signals across a practice's patient panel
- In the Prioritized Patient List to rank patients within the priority buckets and highlight the highest opportunity Signal for patients with more than one active Signal

Applying clinical expertise and researchbacked opportunity sizing allows us to rank Signals against each other to optimize efficiency and impact, channeling attention to the best place at all times and keeping from overwhelming clinical staff.

SECTION IV 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 ranking of the Signal on the Prioritized Patient List.

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,⁶ Severity Score (January 2024 normalized RAF score), claims data, and ADT feeds.

Calculating Urgency Score

To start, 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;

6 Joynt KE, Figuero JF, Beaulieu N, et al. "Segmenting high-cost Medicare patients into potentially actionable cohorts," Healthcare. 2017; 5(1–2): 62–67

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.

Figure 2.1: Urgency Score with Severity = 1

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





Figure 2.2: Urgency Score with Varying Severity Scores

This chart demonstrates how Urgency Scores are changed by differences in severity.

Authors



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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.



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.



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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 innovative shared savings models in traditional Medicare.

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.

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