waymark

Beyond Risk Scores: Waymark's Signal Suite

Peer-Reviewed Precision Targeting for Better Outcomes and Lower Costs

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All Waymark results presented in this whitepaper have been independently validated through peer-reviewed publications in:

JAMA Network Open

NEJM Catalyst

npj | Digital Medicine

nature SCIENTIFIC REPORTS

AJMC

JMIR Publications Advancing Digital Health & Open Science

Executive Summary

Waymark Signal™ is a comprehensive suite of machine learning models that fundamentally transform how healthcare organizations identify, prioritize, and intervene with at-risk Medicaid populations. Our integrated platform reduces avoidable acute care by **22.9%**, delivers **$2,347 per member per year in savings** with a **3:1 return on investment** in the first year. These technologies also eliminate the racial bias inherent in traditional cost-based risk models, improving outcomes and equity for traditionally underserved populations [15].

This white paper presents our peer-reviewed, evidence-based approach to risk prediction across four key product lines: Signal for Rising Risk, Signal for Dual-Eligible Populations (Medicare–Medicaid beneficiaries), Signal for Quality Improvement, and Signal for Maternity. We also share how our technology improves effectiveness by **identifying patients most likely to benefit from interventions** through heterogeneous treatment effects (HTE) optimization, and reinforcement learning to **recommend next-best-action interventions** for care team members.

Identifying and Engaging Rising Risk Patients

Signal for Rising Risk

- **>90% accuracy**
  in predicting future avoidable hospital and ED visits
- **$250 in PMPM cost-savings**
  among activated patients compared to non-intervened cohort

Signal for Dual-Eligible Populations

- **80% accuracy**
  in predicting future avoidable hospital and ED visits
- **3x improvement**
  in cost prediction over standard models used for dual-eligible populations

Nature Scientific Reports, 2024; *BMJ Open*, 2025 (Under review)

Identifying and Engaging Patients with Quality Gaps & High-Risk Pregnancies

Signal for Quality Improvement

- **85% accuracy**
  in predicting patients who will benefit from outreach to close HEDIS quality gaps
- **35% improvement in gap closure**
  over traditional, non-predictive methods commonly used for HEDIS campaigns

Signal for Maternity

- **55-day earlier identification**
  of opportunities for proactive prenatal care coordination
- **4 out of 5 high-risk pregnancies**
  accurately identified while avoiding false alarms 95% of the time

npj Digital Medicine, 2025; *npj Digital Public Health*, 2025 (in press)

The Challenge: $50+ Billion in Avoidable Acute Care Costs

Our peer-reviewed analysis of national claims data reveals that approximately **40% of emergency department (ED) visits and hospitalizations in the Medicaid population are potentially avoidable** through better primary care coordination and proactive intervention [1]. This represents over **$50 billion annually in unnecessary healthcare spending**.

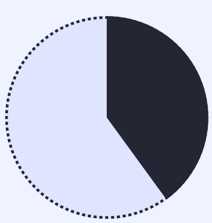
The problem extends beyond simple inefficiencies. Current approaches are fundamentally reactive—by the time patients appear on traditional high-cost/high-utilizer lists, patterns of crisis-driven care utilization have already been established. These patients have often experienced multiple emergency visits, hospitalizations, and gaps in medication adherence that could have been prevented with earlier intervention.

Additionally, traditional risk models systematically underestimate illness severity in minority populations, as documented by Obermeyer and colleagues in their seminal *Science* publication [2]. These models use healthcare costs as a proxy for health needs, but structural inequities lead to lower healthcare spending among minority populations despite equal or greater health needs. The result: in order to receive the same risk score, Black patients must be significantly sicker than white patients. This delays critical interventions and perpetuates health disparities.

The challenge for healthcare organizations is not merely identifying who is at risk, but understanding who will benefit most from intervention and when that intervention should occur.

40%

of hospitalizations and ED visits in the Medicaid population are potentially avoidable



The American Journal of Managed Care, 2024

50 billion

in unnecessary healthcare spending annually

Signal for Rising Risk: Multiplying Accuracy While Reducing Costs

Our Signal for Rising Risk algorithm employs advanced machine learning that processes over **2,700 features** from medical claims, pharmacy, and social determinants of health data. While traditional models assume linear relationships between risk factors, our machine learning approach captures how factors interact in the real world—when housing instability compounds diabetes management, or when mental health affects medication adherence, for example. The system learns from millions of patient interactions to identify patterns traditional statistical models miss.

Proven Performance and Cost Reduction

Peer-reviewed validation across 30.6 million Medicaid patients demonstrates dramatic improvements over existing approaches:

- **Identifies 3x more at-risk patients** than standard models [3]
- **Maintains 98% specificity**—no flood of false positives that waste care team time [3]
- **Predicts future costs 10x more accurately** than traditional risk models [3]

The superior performance stems from the model's ability to identify subtle interactions between medical conditions and social determinants that traditional models cannot capture. For instance, air pollution exposure combined with asthma diagnosis increases risk for acute exacerbations, while food insecurity paired with diabetes increases the risk of hypoglycemia.

Key Innovation: Medication Denial Early Warning System

Our research shows that procedural medication denials serve as powerful predictors of acute events. In our study of 19,700 Medicaid patients, those experiencing specific procedural prescription denials had significantly higher risk of physiologically-related emergency visits within 60 days—with net medical spending increases ranging from $624 to $3,016 per patient per year [4].

This insight led to development of an automated system that flags high-risk medication denials and triggers pharmacy team outreach, preventing emergencies like weekend seizures when prescriptions are rejected Friday but won't be resolved until Monday.

Eliminating Bias While Improving Outcomes

Rather than just predicting costs, our model directly predicts avoidable hospitalizations and ED visits by incorporating social determinants of health. This approach **eliminated systematic bias against minority populations** while establishing superior predictive accuracy. The model achieved equalized odds across racial groups and was actually slightly more sensitive at identifying at-risk Black patients than white patients [3].

Advanced Targeting: Identifying Patients Who Will Benefit Most From Interventions

Traditional risk models excel at identifying who is at risk but fail to answer the critical question: **who will benefit most from a specific intervention**? A comatose ICU patient may be high-risk but unlikely to benefit from care management calls, while a lower-risk patient with inappropriate blood thinner dosing before a camping trip may benefit greatly from pharmacist outreach. These scenarios illustrate why predicting risk alone is insufficient—what matters is intervention benefit.

Heterogeneous Treatment Effects: Precision Intervention

Our heterogeneous treatment effects (HTE) framework addresses this critical gap by predicting who is most likely to benefit from an intervention. Waymark's HTE framework was evaluated in a prospective cohort analysis across 9,600 Medicaid patients randomized to receive either risk-based or benefit-based care team prioritization. The benefit-based prioritization approach resulted in:

- **49% reduction in acute events** versus traditional risk-based targeting [8]
- **92 fewer acute care visits per 1,000 member-months** in intention-to-treat analysis
- **Similar engagement rates** (not "cherry-picking" easier patients)
- **$123 additional PMPM cost savings** beyond base risk prediction [8]

Patient archetypes with highest benefit potential include those with early-stage chronic disease progression, recent medication changes, recent Medicaid enrollment with prior coverage gaps, and young adults with first mental health diagnoses who haven't yet established crisis utilization patterns.

49%
reduction
in acute events versus traditional risk-based targeting*

92
fewer care visits
per 1,000 member-months in intention-to-treat*

$123
additional PMPM savings
beyond base risk prediction*

**Health Services Research*, 2025 (Under review)

(Section continued on next page)

Advanced Targeting: Identifying Patients Who Will Benefit Most From Interventions (cont.)

Next Best Action Recommendations Through Machine Learning

Most Medicaid beneficiaries present with multiple chronic conditions, creating complex scenarios where optimal intervention sequence remains unclear. Should care teams focus first on diabetes management, mental health stabilization, or pain control when a patient has all three conditions?

Our **reinforcement learning system** addresses this challenge by learning from thousands of physician-supervised care team decisions to **identify next best actions and optimal intervention sequences**. The system employs a State-Action-Reward-State-Action (SARSA) algorithm that learns from both successful and unsuccessful intervention attempts to build a nuanced understanding of what works for different patient profiles.

Peer-reviewed clinical impact:

- **12 percentage point reduction** in acute care events (20.7% relative reduction) [9]
- For every 8 patients engaged, **we prevent 1 costly acute event** (NNT=8.3) [9]
- **Improved equity outcomes** with reduced disparities across gender and racial groups [9]

Real-world example: A patient with uncontrolled schizophrenia and hypertension presents Friday afternoon with limited intervention time. Traditional approaches might follow disease-specific guidelines. Our system, trained on similar scenarios, recognizes that weekend psychosis risk outweighs hypertension concerns and prioritizes completing long-acting antipsychotic authorization before the weekend.

Physician validation: Independent board-certified physicians confirmed that our models choose the same interventions as clinicians but identify intervention opportunities earlier in disease trajectories, suggesting improved predictive capability and more proactive support [17].

12
percentage point reduction
in acute care events*

8.3 NNT
For every 8 patients engaged, we prevent 1 costly acute event*

Improved equity outcomes
with reduced disparities across gender and racial groups*

**JMIR AI*, 2025

Signal for Dual-Eligible Populations: Mastering Medicare-Medicaid Complexity

Medicare–Medicaid dual-eligible beneficiaries represent the most medically and socially complex population. Despite this, traditional risk models focus narrowly on patient demographics while overlooking the delivery systems shaping their care. This gap limits accuracy and perpetuates inequities.

Improved Cost Prediction and Risk Adjustment

Signal for Dual-Eligible Populations integrates patient, provider, facility, market, and area-level social determinants within an advanced ensemble model to capture contextual drivers of cost and utilization:

- **Predicts future costs 75% more accurately** than traditional risk models [18]
- **Captures patient complexity with 89% accuracy for risk adjustment,** vs. 56% for standard approaches [18]
- **Identifies 30% more patients heading towards acute events** while keeping false positives under 3% [18]

61.5%
more accurate at predicting future costs than traditional risk models [18]

36%
more patients identified as at-risk of an acute care visit compared to standard approaches [18]

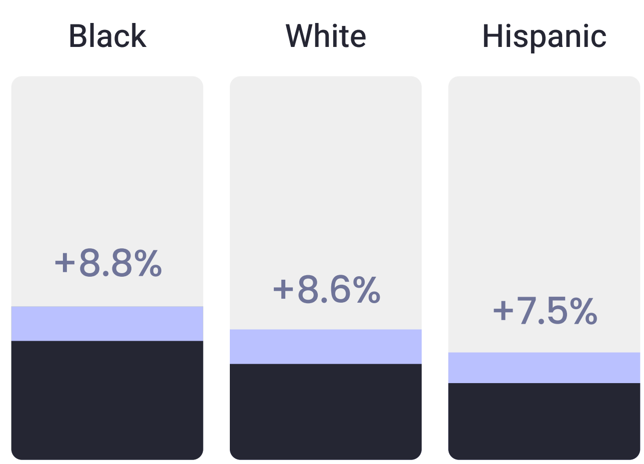
Eliminating Prediction Disparities

The system achieved comparable sensitivity in predicting future acute care across racial groups, without sacrificing specificity:

- **Black patients**: sensitivity improved from 30.9% to 39.7% (95.9% specificity) [18]
- **White patients:** sensitivity improved from from 25.4% to 34.0% [18]
- **Hispanic patients:** sensitivity improved from 20.4% to 27.9% [18]

By quantifying context-attributable risk, Signal for Dual-Eligible Populations enables health plans to identify not only who is at risk but why and where—identifying neighborhood-level and systemic factors that drive health outcomes. This enables more targeted interventions and equitable resource allocation.

Improvement in sensitivity across racial groups



Signal for Quality: Driving Improved HEDIS Performance

Healthcare organizations face fundamental resource allocation challenges in achieving HEDIS quality measure targets. Traditional approaches either attempt universal outreach to all patients with open quality gaps (which is inefficient given resource constraints) or focus only on the sickest patients (thus missing crucial prevention opportunities among those who could benefit most).

Precision Quality Targeting

Our Signal for Quality Improvement model identifies the patients who are unlikely to complete preventive care and close HEDIS quality gaps without assistance. This enables strategic resource allocation and reflects:

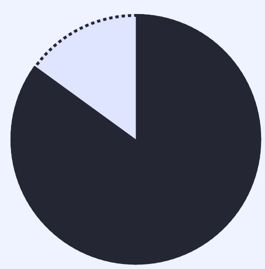
- **33 percentage points improvement in accuracy** over standard approaches without incorporating social needs [5]
- **85% overall accuracy** when incorporating social needs alongside clinical data [5]
- **35% increase in preventive care gaps closure** through precision targeting including social needs [5]

We find that many patients complete preventive care independently if given sufficient time, while others face barriers preventing completion without assistance. Patients with stable transportation and established primary care complete measures at higher rates without intervention, while those with recent address changes, insurance gaps, or limited English proficiency show very low spontaneous completion rates.

Resource optimization impact: In our analysis of 14 million Medicaid enrollees, targeted outreach based on our predictions would increase preventive care gap closure by over one-third compared to traditional approaches [5].

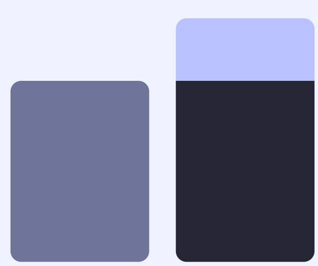
85% overall accuracy

when incorporating social determinants of health*



35% increase

in preventive care gap closure through targeted outreach*



npj Digital Medicine, 2025

Signal for Maternity: Early Detection of High-Risk Pregnancies

The United States faces a maternal mortality crisis, with significant disparities across racial groups. Traditional prenatal risk assessment relies on data that often arrives too late for effective intervention—by the time clinical risk factors become apparent in prenatal visits, critical intervention windows have already passed.

Advanced Warning System for Better Outcomes

Our Signal for Maternity model leverages pre-conception and early pregnancy signals to identify high-risk pregnancies significantly earlier than conventional approaches:

- **55 days earlier identification** for prenatal care coordination—nearly two months of additional intervention time [7]
- **Catches 81% of patients heading towards adverse delivery outcomes** when incorporating social determinants of health
- **94% specificity with zero racial bias**-performs equitably across all patient populations [7]

The model holistically incorporates comprehensive data sources: pharmacy claims for fertility medications, emergency visits for early pregnancy symptoms, historical pregnancy outcomes that predict recurrence risk, and social support indicators derived from family coverage patterns.

Preventing Cascading Care Failures

Our analysis reveals that many adverse maternal outcomes stem from cascading failures in prenatal care access. A missed first trimester appointment due to insurance confusion can lead to delayed prenatal vitamin initiation, increasing neural tube defect risk. Transportation barriers in the second trimester can result in missed glucose screening, allowing gestational diabetes to progress undetected.

By identifying these failure points before they occur, health plans can implement proactive interventions that break the cascade and prevent downstream complications threatening both maternal and infant health.

55

days earlier identification compared to standard methods*

81%

sensitivity when incorporating social determinants of health*

86%

accuracy using demographic and clinical data alone*

94%

specificity while eliminating algorithmic disparities between racial groups*

**npj Digital Public Health*, 2025 (In press)

Implementation Science: From Models to Measurable Impact

Optimized Trial Design for Faster Learning

We deploy Sequential Multiple Assignment Randomized Trials (SMART) to optimize interventions with greater efficiency than traditional A/B tests can provide. SMART trials adapt randomization based on intermediate outcomes, which mimics clinical practices where treatment adjustments follow patient response.

For example, rather than comparing static text message vs. phone call outreach, SMART trials first randomize patients to initial virtual modalities, then re-randomize non-responders to intensified interventions like door-to-door visits. This identifies optimal intervention sequences for different patient types while requiring fewer participants.

Efficiency advantage: For detecting small effect sizes, SMART designs achieve 72.7% power compared to 20.1% for traditional A/B tests with identical sample sizes [12].

Scalable Deployment Across State Populations

Our models successfully generalize across different state Medicaid populations through transfer learning techniques. Rather than training from scratch for each population, we begin with models trained on millions of patients and fine-tune using local data—similar to how physicians apply medical knowledge across populations while adjusting for local factors [13].

Meta-learning framework analyzes patterns across multiple state deployments to understand how population density, provider composition, and coverage patterns affect model performance, enabling rapid deployment to new populations with minimal local training data.

Turning Missing Data Into Predictive Intelligence

Traditional models handle missing healthcare data through imputation, replacing absent values with statistical estimates. Our innovative approach treats missing data as informative signals rather than noise. Missing lab values often indicate low healthcare engagement; missing address updates signal housing instability more reliably than any single indicator.

Our Integrated Missingness-and-Time-Aware Multi-task XGBoost (IMT-XGB) framework creates representations for observed values, missingness indicators, and interaction patterns. This approach improves prediction accuracy precisely for the most vulnerable populations who most need proactive intervention [14].

Proven Clinical and Economic Outcomes

Real-world impact has been validated through multiple peer-reviewed studies demonstrating substantial return on investment:

Clinical Impact

- **20% reduction** in avoidable ED visits [15]
- **48% reduction** in avoidable hospitalizations [15]
- **Equitable improvements** across all racial and ethnic groups [15]

Economic Returns

- **$2,347 per member per year** in savings [15]
- **3:1 return on investment** in the first year [15]

Engagement Success

Activation success rates are highest among Black and African American patients at 79.0%, compared to 66.5% for white patients [15]—demonstrating that culturally competent, trust-building approaches resonate particularly well with communities historically marginalized by healthcare systems.

$2,347
per member per year in savings*

3:1
return on investment in the first year*

20%
reduction
in avoidable ED visits**

48%
reduction
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***NEJM Catalyst Innovations in Care Delivery*, 2024

Safety, Governance, and Clinical Oversight

Waymark's comprehensive AI governance framework ensures that our risk prediction models are not only accurate but also safe, fair, and transparent, aligning with the National Institute of Standards and Technology (NIST) AI Risk Management Framework, and incorporating best practices from leading healthcare AI ethics guidelines.

Tiered Clinical Review System

- **Automated low-risk actions** (appointment reminders) proceed without manual review
- **Medication adherence interventions** require pharmacist review
- **Clinical pathway modifications** require physician approval
- **Weekly care management meetings** bring together clinical, operations, and front-line teams for ongoing collaborative efforts.

Bias Monitoring and Fairness

Rather than relying solely on technical metrics, we conduct monthly assessments to ensure that patients from minority backgrounds are activated into care management programs at rates that are at least proportional to their demographic composition in the eligible population. This approach ensures equity improvements in model predictions, which then translate to equity in care delivery.

Transparency and Explainability

Every prediction includes explainability features that support clinical decision-making. Care teams receive the top contributing factors, recommended next steps, and clear rationales for interventions. This enables appropriate clinical judgment in complex cases.

Automated low-risk actions proceed without manual review

Clinical pathway modifications require physician approval

Medication adherence interventions require pharmacist review

Care management meetings ensure ongoing collaboration

Conclusion: Transforming Medicaid Population Health Management

Waymark's Signal Suite represents a fundamental advancement in identifying and serving vulnerable populations while delivering measurable cost reductions. Our peer-reviewed research demonstrates that AI-powered risk prediction, when properly designed and implemented, can simultaneously reduce costs and eliminate health disparities.

The 20% reduction in avoidable ED visits, 48% reduction in avoidable hospitalizations, and $2,347 PMPM savings we have achieved represent thousands of health crises prevented, families kept stable, and healthcare dollars redirected to productive care rather than crisis intervention [15]. These improvements demonstrate that advanced technology, when thoughtfully applied with appropriate clinical oversight, can be a powerful tool for reducing healthcare waste while improving outcomes for vulnerable populations.

The technical innovations we have developed—from heterogeneous treatment effects to reinforcement learning for clinical decision support—address fundamental limitations in current approaches to population health management. By understanding not just who is at risk but who will benefit from intervention and what intervention sequence will be most effective, healthcare organizations can maximize the impact of limited resources while ensuring equitable care delivery.

As healthcare continues its transformation toward value-based care, health plans and providers will only be successful if they can identify risk early with predictive intelligence, act with precision through targeted interventions, learn continuously from outcomes, and scale equitably across all populations. Waymark stands ready to partner with forward-thinking health plans and health systems to deploy these capabilities at scale, creating measurable improvements in both clinical outcomes and total cost of care.

The question is no longer whether machine learning can reduce healthcare costs and improve outcomes, but how quickly we can scale these solutions to reach the patients who need them.

About the authors

Sanjay Basu, MD, PhD

Co-founder and Head of Clinical Product Development

Sanjay Basu, MD, PhD, is a physician and epidemiologist whose work focuses on the development and application of disease prevention models for low-income communities. As co-founder and Head of Clinical, he oversees Waymark's research and development function, including product, engineering, design, and clinical teams.

Sadiq Y. Patel, PhD, MS, MSW

Vice President of Data Science & AI

Sadiq Patel, PhD, MS, MSW, is a clinical social worker turned data scientist and health technologist whose work focuses on applying machine learning and generative AI to improve care for underserved populations. As Vice President of Data Science & AI, he leads Waymark's development and implementation of predictive models and AI tools that support care teams, streamline operations, and expand access to services for Medicaid recipients.

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