waymark

What if we could predict which Medicaid patients will end up in the ER next month—and actually prevent it?

AI Designed with—and for—Medicaid Care Teams

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Waymark is a Medicaid ACO that wraps around PCPs to **expand their capacity** and **improve patient outcomes** through community-based teams.

Batniji , R., Agrawal, S., Ma, S., & Basu, S. (2023, October). A Social ACO for Medicaid Managed Care. Health Affairs . https://www.healthaffairs.org/content/forefront/social-aco-medicaid-managed-care

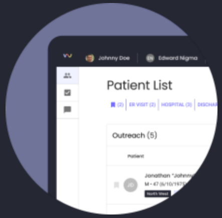
We wrap-around PCPs and serve their Medicaid patients in three ways

Community-based Care Teams

Local Waymark care teams engage with patients virtually and in-person, integrate with existing PCPs, helping patients access the resources to address clinical and social needs

Evidence-based Care Pathways

AI assisted tools guide our care teams to the patient and specify the right intervention to perform, lowering ED and hospital use by 25%[1]



Optimized Targeting & Engagement

Continuous population health monitoring of the dynamic rising risk population to enable care team members to intervene at the right place and time

1. Kangovi S, et al. Evidence-Based Community Health Worker Program Addresses Unmet Social Needs And Generates Positive Return On Investment. Health Aff. 2020; 39(2):207-213.; Powers BW, et al. Impact of complex care management on spending and utilization for high-need, high-cost Medicaid patients. Am J Manag Care. 2020; 26(2):e57-e63. ; Brown DM, et al. Effect of Social Needs Case Management on Hospital Use Among Adult Medicaid Beneficiaries : A Randomized Study. Ann Intern Med. 2022; 175(8):1109-1117.

Our Approach

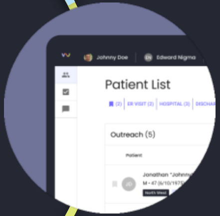
Our ***Data Science and AI*** vision addresses four key areas

1. Predictive Intelligence

See risk before it escalates

2. Autonomous Navigation

Guide the right action at the right time



3. Operational Automation

Remove friction from care delivery

4. Continuous Learning

Improve with every interaction

Our Problem

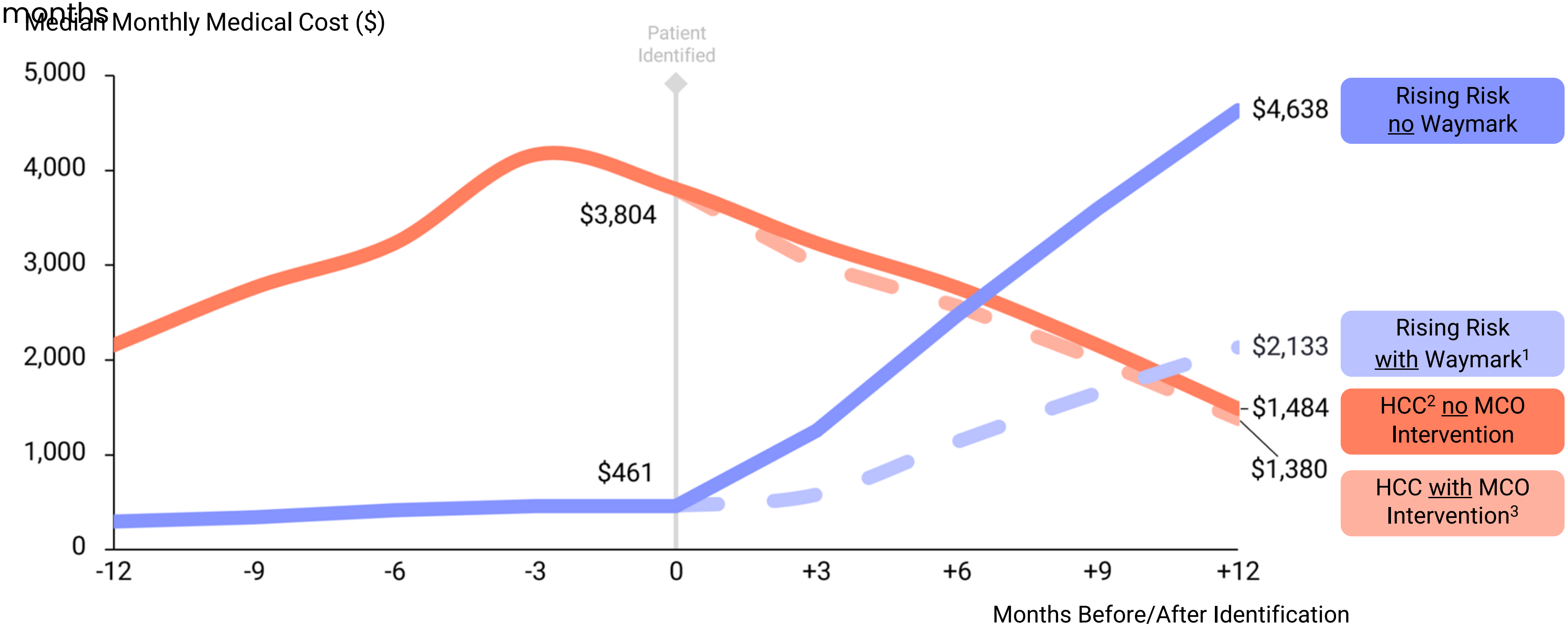
Challenges We’re Addressing with Data Science

- 40% of ED/hospital visits among Medicaid patients are preventable; we identify upstream risk and intervene earlier.
- This presents over $50 billion annually in unnecessary healthcare spending

Who We Target

We target ‘rising risk’ patients, to prevent High Cost Claimants

Unlike typical models, we target rising risk patients who will become High Cost Claimants (HCCs) in 6-12 months



Note: Data shown above is sourced from the TMSIS dataset for all Medicaid MCOs for 2019, 2021, and 2022 (excluding COVID year 2020) with a sample size of 49.4M Medicaid patients

1. Baum, A et al. Supporting Rising Risk Patients In Medicaid Through Technology-Enabled, Proactive Community-Based Early Intervention . NEJM Catalyst; accepted; in press.
2. HCCs are defined as greater than $50k in allowed amount claims per person per year [standard actuarial definition] cumulative in any 12 month period for people with >3 months of eligibility
3. Meta-analytics population-weighted average reduction (https://pubmed.ncbi.nlm.nih.gov/36121357/, https://pubmed.ncbi.nlm.nih.gov/21993059/, https://pubmed.ncbi.nlm.nih.gov/32672916/, https://pubmed.ncbi.nlm.nih.gov/20860506)

Our Values and Co-Design Process

Our Data Science and AI Guiding Principles:

- Tech equity: Medicaid patients deserve digital health tools on par with commercially insured populations
- Participatory design: We co-build with care teams to ensure relevance, trust, and adoption
- SDoH integration: Social needs account for up to 50% of Medicaid outcomes—our models reflect that
- Equity-first mindset: Our tools aim to reduce disparities, not reinforce them

How We Co-Design:

- Co-defined tool goals and model explainability with care team input
- Frontline-led decisions on what information to surface
- Built evaluation plans with operations leads using natural experiments
- Integrated regular feedback loops to refine tools in real-world settings

Implementation Challenges

- **Building** Medicaid-specific, population-level models that improve accuracy and equity
- **Embedding** tools into workflows via natural experiments to prove ROI
- **Unifying** fragmented data across health plans
- **Building** trust with care teams on model relevance and fairness
- **Layering** new risk models on top of Signal without disrupting operations

Our Risk Models

Effectiveness solutions across the patient engagement journey

Patient Targeting

Signal

Identify Rising Risk patients with 90%+ accuracy

Activation

Time-to-event

Identify which patients are more acute

Performance Optimization

Most Likely to Benefit

A second indicator trained from engagement data to further improve patient targeting

Next-Best-Action

Equip care teams with the right action and order when a patient has multiple needs

Our Approach

Waymark Signal identifies rising risk with >90% accuracy

Peer-reviewed results show best-in-class performance

Waymark Signal™

Rising risk prioritization tool

- ML algorithm that incorporates SDOH into risk prediction
- 90% accuracy in predicting avoidable ER/IP visits (also: 81.1% PPV, 90.5% NPV)
- Prioritizes outreach based on critical window of opportunity to redirect ED use to PCP

nature
SCIENTIFIC REPORTS

- 3x higher probability of predicting a non-emergent visit ahead of time, compared to the next-best algorithm
- 10x better prediction of care cost than the standard CDPS model used by states and MCOs
- Validated on data from 30.6 million patients on Medicaid, nationwide, the largest such Medicaid-specific risk algorithm
- Neutralized the Black-White prediction bias (under-predicting Black health needs) in common cost-based risk models
- Impact of Signal: 9.5-fold improvement in reducing acute care events than before Signal

Our Approach

Why Signal Works?

Signal Training Data | **Claims & Encounter** + **Local SDoH**

Built on TMSIS Medicaid Data

- Signal was trained initially on national[1] claims data for 30.6 million patients on Medicaid
- Largest sample size for a Medicaid-specific risk algorithm

Medical and Pharmacy Claims

- Last 12 months of claims incl. all medical, behavioral, and pharmacy, shared monthly

Patient Eligibility Data

- Latest patient Medicaid eligibility data, shared monthly

ADT Feed Access

- Real-time acute care visit notifications (no claims lag)

Geographic-level SDoH Data

- Availability of healthcare resources (behavioral health, SUD, PCPs)
- Neighborhood conditions (poverty, housing, high school graduation rates)
- Environment factors (e.g. air pollution)

Patient-level SDoH Data

- Social services (TANF, SSI, SSDI)
- Household income
- Environmental exposures

Signal is trained on national data and calibrated specifically to the patients we are assigned to

1. TMSIS training data includes the full Medicaid population across 26 states and Washington, D.C.

Our Approach

NEJM Catalyst

Leveraging Signal, Waymark significantly lowers acute care events

Peer-reviewed clinical results show statistically significant reductions in events versus a matched control group[1]

Outcome (N = 1,652)	**Relative Change in Event Rate vs. Control Group** *(all P<0.05)*
Outpatient Visits	▲ 16.2% *(59 More Events / 1000 Patients)*
All Acute Events	▼ 22.9% *(438 Fewer Events / 1000 Patients)*
Hospitalizations	▼ 39.4% *(149 Fewer Events / 1000 Patients)*
Emergency Visits	▼ 19.1% *(293 Fewer Events / 1000 Patients)*
Ambulatory Care Sensitive Acute Events	▼ 24.7% *(242 Fewer Events / 1000 Patients)*
Ambulatory Care Sensitive Hospitalizations	▼ 48.3% *(80 Fewer Events / 1000 Patients)*
Ambulatory Care Sensitive Emergency Visits	▼ 20.4% *(166 Fewer Events / 1000 Patients)*

$253 in total cost savings per intervened patient per month

Note: "Ambulatory Care Sensitive" means an acute event that could have been avoided per NYU and AHRQ definitions
1. Baum, A et al. Supporting Rising Risk Patients In Medicaid Through Technology-Enabled, Proactive Community-Based Early Intervention . NEJM Catalyst
Notes: Data through 1/04/2024. Number of ED visits or IP stays (including observation stays) is based on ADT feed data. Results were estimated using a propensity score-matched logistical difference-in-differences analysis, which controls for secular trends in utilization and time-invariant unmeasured confounding differences between the intervention (N = 1,652) and comparison (N = 21,631) groups, with additional control variables of age, sex, patients' baseline risk score and mean acute care utilization, and time period fixed effects. Avoidable hospitalizations defined by AHRQ PQIs, https://qualityindicators.ahrq.gov/measures/pqi_resources. Avoidable emergency visits defined by NYU Patch, Johnston KJ, Allen L, Melanson TA, Pitts SR. A "Patch" to the NYU Emergency Department Visit Algorithm. Health Serv Res 2017;52(4):1264–76. 10.1111/1475-6773.12638.

Opportunity ID

Which patients benefit most from care management? Results of our prospective matched cohort study:

Research Question

- How do we not just target ‘rising risk’ patients but the subset who actually benefit most from our specific care model? Over time, can we match each patient to the right intervention or care team member?

Finding

- Use a novel set of machine learning called heterogeneous treatment effect (HTE) analysis to identify which subset of rising risk patients benefit the most from Waymark services resulted in lower ED visits and hospitalizations in a prospective matched cohort study.

Overview	**9,266** Patients	**8** Months	**80%** ML Model Accuracy

Prioritization Approaches	**Risk Based**	vs	**Benefit Based**

Generalized Random Forest Methodology

Historical Data Training → **Individual Treatment Effects** → **Benefits - Based Ranking** → **Targeted Outreach**

Results: Acute Care Visits per 1,000 member months

-92.4 Fewer visits (intention-to-treat)	**-208.4** Fewer Visits (among engaged)	**$123** Lower cost per member/month

Key Learnings	In a prospective matched cohort in our WA population, acute care events lowered by nearly half when patients were ranked by ‘most likely to benefit’ versus just ‘rising risk’

Integrated Care

JMIR Publications
Advancing Digital Health & Open Science

New research Spotlight | What's the right order of tasks when you have competing priorities & multiple suggestions to choose from?

Research Question

- How can we improve the current practice which heavily relies on individual judgment about what order to implement actions suggested in our playbooks, creating potential risks to delivering the right care at the right time.

Findings

- Assess if a AI method called SARSA (State-Action-Reward-State-Action) reinforcement learning model improved intervention recommendations compared to standard practices in a causal inference study comparing AI-recommended actions to standard practice.

Overview	**3,175** Patients	**2023 - 2024**	**WA & VA**

SARSA Methodology

Patient State Assessment → **AI Action Summary** → **Outcome Measurement** → **Model Learning**

Key Findings

12%	**8.3**	**20.7%**
Absolute reduction in Acute Care Events	Number Needed to Treat	Relative Risk Reduction

Key Learnings	AI-guided care management would substantially reduce acute care events, enhances fairness, and effectively prioritize complex medical-social interventions.

Thank You