27

RISK STRATIFICATION, SEGMENTATION, AND TIERING TRANSPARENCY DOCUMENT

APRIL 2026

TABLE OF CONTENTS

I. EXECUTIVE SUMMARY

1) Overview and Purpose

The Risk Stratification, Segmentation, and Tiering (RSST) Algorithm is a predictive analytics system developed by the California Department of Health Care Services (DHCS) as part of its Population Health Management (PHM) strategy. RSST provides a monthly, data-driven method for identifying Medi-Cal members who may be at increased risk of poor outcomes or underutilization of essential services, and who may benefit from additional outreach or care coordination. Each month, the system assigns each eligible member to a risk tier—low, medium-rising, or high—based on predicted likelihood of future outcomes, allowing for more proactive and equitable deployment of resources across the state.

RSST was designed to create a standardized and transparent method of risk tiering that can be applied uniformly across MCPs statewide. While the algorithm has been developed and validated for implementation, decisions about its formal policy adoption and integration into MCP operations are still forthcoming. The creation of this tool supports DHCS's broader objective to improve consistency, transparency, and equity in how risk is assessed across the Medi-Cal population, and it lays the groundwork for future phases of policy and program rollout.

One innovation of the RSST approach is the inclusion of a domain for underutilization of services. This domain focuses on identifying members who are predicted to not engage with recommended care despite known clinical or behavioral health risks. Unlike many risk models that target only high-utilizing or high-cost members, RSST explicitly seeks to surface members with unmet needs who may be overlooked in traditional frameworks because their lack of utilization makes them appear to be "low risk." In Version 1, underutilization is a significant driver of high-risk designation—particularly in the Adult population.

Importantly, RSST is an evolving algorithm that will be continuously updated and retrained on additional data to improve its accuracy, equity, and usefulness over time. While this initial launch represents a critical step forward, DHCS recognizes that it is an early version in an ongoing journey of refinement and learning.

2) Design Principles, Governance, and Stakeholder Engagement

DHCS's RSST approach sought to provide a consistent, statewide method to identify risk among Medi-Cal members, in order to make risk stratification more equitable across California. These guiding principles were chosen to ensure that the model would be fair, understandable, and adaptable across the state's varied populations and delivery systems. In that regard, the development of RSST was anchored in several core design principles: standardization, transparency, equity, and flexibility. The algorithm applies a statewide method to ensure that high-risk members are identified in a standardized method across all counties and health plans. Transparency was prioritized not only in the algorithm logic and model architecture, but also in the supporting documentation, thresholding approach, and validation methods. Equity was not treated as a one-time metric but as a continuous design consideration, influencing every stage of development—from the fine-tuning of outcomes and predictor variables to the way subgroup performance was evaluated, to the final tiering decisions. Flexibility was embedded by structuring the algorithm around multiple domains and subdomains of risk—physical, behavioral, social, and underutilization—so that future policies could adjust their emphasis across these areas without altering the core technical framework.

The RSST Work Group, led by DHCS, provided strategic direction and policy oversight throughout development. An Academic Work Group (AWG) composed of national experts in health equity, health outcomes, Medicaid analytics, and machine learning provided guidance on technical decisions and subgroup evaluation. A Scientific Advisory Council representing clinical and operational leaders from across the Medi-Cal delivery system helped ensure real-world applicability of the algorithm and supported stakeholder alignment. This multi-level governance approach created space for rigorous analysis, transparent debate, and deliberate policy design.

Development of the Birthing models included expanded engagement with clinical subject matter experts such as MFM OB/GYNs and DHCS Birthing policy leads.

3) Model Structure and Subdomain Organization

The RSST Algorithm is composed of thirteen predictive models to address specific areas risk identified by stakeholder consensus across the three populations (Adult, Pediatric, Birthing), five each for Adult and Pediatric members, and three for Birthing members. Each month, these models generate individual-level probability scores that are then translated into categorical risk tiers. Categories of risk were first divided into three risk domains: adverse events, underutilization, and social risk. The rationale for having multiple risk domains was to be able to target different types of risks, which may require different services, and to expand from traditional approaches that target healthcare adverse events and may miss members at risk of underutilizing systems or social adverse events. For each population, risk domains were further split into subdomains to address specific subcategories of risk. For Pediatric and Adult populations, adverse health events and underutilization domains were further subdivided into adverse physical health and adverse behavioral health subdomains, resulting in 5 models for each population: adverse physical health events, adverse behavioral health events, underutilization of physical health services, underutilization of behavioral health services, and social risk. For the Birthing population, the adverse event domain was split into three subdomains based on whether adverse events occurred during pregnancy versus post-partum: pregnancy, post-pregnancy physical, post-pregnancy behavioral. Underutilization and social risk models were not developed specifically for the Birthing population due to a mixture of factors, including gaps in data on prenatal care utilization and anticipated key drivers of social risk Future iterations of the RSST algorithm may incorporate more Birthing-specific underutilization and/or social elements. Subdomain tiers are rolled up into domain-level tiers and a single overall tier using a max-tier logic, ensuring that the highest relevant risk signal is preserved (Note: additional business logic applies for the Birthing domain. Subdomains roll up to Birthing domain only when there is a confirmed pregnancy-related claim, and the Birthing domain does not roll up to the overall RSST risk tier at V1.1 launch). This structure enables DHCS and MCPs to see not just who is at risk, but what type of risk is being predicted, allowing for differentiated program responses. By modeling each subdomain independently, the algorithm provides transparency in its predictions and enables future policy decisions to selectively emphasize or de-emphasize domains without disrupting the broader infrastructure.

The Birthing models differ structurally from Adult and Pediatric models in that they are trained and evaluated at the pregnancy-episode level rather than the person-month level, due to the episodic nature of pregnancy. Models were trained using repeated monthly observations within the same ongoing pregnancy episode, predictions were generated on each month, adverse outcomes apply to the entire span of the episode timeframe (episodes are different lengths for each member), and model technical performance was measured at the aggregate episode level (“best” of the repeated predictions).

4) Machine Learning Methods

The RSST models were developed using established machine learning methods widely adopted in health services research and public health contexts. These include gradient-boosted decision trees (e.g., LightGBM) and regularized logistic regression, both of which are known for their performance and interpretability in large, structured datasets. These approaches are supported by academic literature and have been applied in similar Medicaid-focused predictive modeling efforts.

Models were trained and retrospectively evaluated using eight years of Medi-Cal administrative claims and eligibility data from January 2016 through December 2023, covering more than 15 million individuals. Training was performed at the person-month level, with predictor variables constructed using “what was known when” logic. This ensured that when models were evaluated by retrospectively comparing predictions to known outcomes, the predictions from each model relied only on predictors that would have been available at the time of prediction. The evaluation therefore accounted for real claims processing delays and mimicked real-world deployment conditions to predicted risk of a poor outcome in the coming year._

Model performance was optimized using held-out validation data (e.g., to select hyperparameters). Independent test data (not used in model training) were used to evaluate performance and assess generalizability. In order to mitigate impacts of COVID-19, these test data, and all model performance metrics and tiering decisions, were restricted to index dates beginning January 2022 (after which COVID-19-associated disruptions had diminished).

The Birthing models were developed using gradient-boosted decision trees (XGBoost). This model choice was made due to the high level of performance seen in the Adult and Pediatric models. Models were trained and retrospectively evaluated using Medi-Cal administrative claims and eligibility data from January 2021 through March 2025. Training was performed at the pregnancy-episode level, with multiple index dates generated per episode. Predictor variables were constructed using "what was known when" logic, ensuring predictions relied only on information available at the time of prediction. Index dates for training and evaluation begin January 2022, driven by data availability.

5) Technical Performance

Area under the curve (AUC) scores ranged from 0.75 to 0.94 across the ten Adult and Pediatric models, which compared favorably to relatively similar models, with particularly strong performance in behavioral health and social risk domains. Additional performance evaluation took place during tiering (below).

Performance was also assessed using recall, and number-needed-to-treat (NNT) at the model, domain, and overall tier levels. For example, under the selected tiering configuration, the overall high-risk tier for Adults achieved a recall of 0.23 (meaning that, of members who experienced a relevant outcome in the next 12 months, 1 in 4 were identified as high risk), with an NNT of 1.75 (meaning that for every two members flagged as high-risk, approximately one experienced a relevant outcome in the next 12 months). Similar results were observed for Pediatrics, with a recall of 0.24 and NNT of 1.97. These metrics showed that the models could reliably support identification of members who went on to experience a relevant outcome in the subsequent year.

Three Birthing models were trained in total: Pregnancy Adverse Events, Post-Pregnancy Physical Health Adverse Events, and Post-Pregnancy Behavioral Health Adverse Events.

Across the three Birthing models, episode-level discrimination was moderate to strong, with AUC values ranging from 0.71 to 0.85, demonstrating reliable separation of higher and lower risk episodes, with the lowest AUC observed for the Pregnancy Adverse Events model (0.712). After review with cross-functional stakeholders, SMEs, and academic experts, the models were determined to be sufficiently performant to warrant inclusion.

Performance was further evaluated at the episode-level using recall and number-needed-to-treat (NNT) at domain-specific risk thresholds chosen to balance sensitivity and operational efficiency. Across the three Birthing models, episode-level recall ranged from approximately 44% to 51%, with NNT values ranging between ~2.0 and ~3.8, indicating that for every 2–4 pregnancy or postpartum episodes flagged as high risk, one went on to experience a modeled adverse event. Higher efficiency was observed for pregnancy and post-pregnancy physical health outcomes, while the post-pregnancy behavioral health model demonstrated meaningful performance despite lower outcome prevalence. Collectively, these results support the use of RSST risk stratification to reliably and efficiently identify pregnancy and postpartum episodes at elevated risk for clinically significant adverse outcomes.

6) Tiering Strategy and Option Evaluation

After model training and initial performance evaluation were completed, the RSST Work Group turned to the policy challenge of converting subdomain-level risk scores into tier assignments—particularly the high-risk tier, which may drive outreach or services in future phases of implementation. DHCS set a statewide target that no more than approximately 10 percent of the Medi-Cal population should be classified as high-risk, in order to align with existing MCP capacity and ensure policy feasibility. To implement this constraint, the team evaluated three approaches to setting model-specific thresholds.

Option 1 evenly distributed high-risk flags across all five models, regardless of model performance or outcome prevalence. Option 2 applied thresholds to equalize sensitivity (recall) across models, prioritizing balance in outcome capture. Option 3 optimized thresholds to maximize overall recall, favoring models with stronger technical performance. After evaluating the tradeoffs, the Work Group selected Option 2 for both Adults and Pediatrics. It offered the best alignment with policy goals by maintaining proportional contributions from each domain, supporting transparency in how risk was defined, and achieving strong subgroup performance.

Equity was central to this decision. Throughout the tiering analysis, the Work Group assessed model performance across subgroups defined by race, ethnicity, language, age, sex, and new enrollees. Option 2 was the only option that met or exceeded DHCS's equity performance threshold in all but one subgroup for each population. These deviations were closely examined and attributed to differences in outcome definitions—such as the use of female-only preventive care measures in Pediatric underutilization models, which resulted in slightly worse performance for males—rather than model bias. In both Adult and Pediatric populations, Option 2 also produced a meaningful number of net-new members who would not have otherwise been flagged under existing risk tools, many of whom went on to experience an RSST outcome. Technical performance was assessed using recall, NNT, and AUC.

These results confirmed that Option 2 offered the best combination of predictive value, equity performance, and explainability, and supported DHCS's broader objective to ensure that risk tiering is consistent, transparent, and actionable for this initial release. The overarching tiering methodology is explicitly designed to incorporate flexibility in tiering decisions, including refinement of the options above, as new data become available and the models are updated.

Tiering for the Birthing models was evaluated using a modified set of principles compared to Adult and pediatric models. Cost and net-new assessments were not primary decision criteria, as DHCS policy in 2025 already requires assessments of all pregnant members. Instead, tiering options were compared on the merits of their technical performance, balance of risk types across pregnancy and post-pregnancy/postpartum periods, equity, and operational explainability.

Based on this evaluation, the Work Group agreed to proceed with Option 2, using an approximately 27% episode-level high-risk reference point derived from observed adverse outcome prevalence. Option 2 was selected due to its consistency with Adult and Pediatric RSST decisions, comparable recall and NNT across options, and acceptable equity performance.

Given the natural lag in claims and other data, prediction of adverse events occurring during the post-pregnancy/postpartum period is more actionable for care management than prediction of adverse events occurring during the pregnancy period. Further, the

Work Group and clinical SMEs emphasized that 63% of maternal deaths occur during the post-pregnancy/postpartum period. Option 2 had the additional advantage of prioritizing this latter period, which the group agreed was the most operationally meaningful (see balance details below).

7) Maintenance, Monitoring, and Future Work

RSST risk tiers are refreshed monthly using the most recent data available and are delivered to MCPs via secure file transfer (SFTP) and API, then integrated into the longitudinal member record (LMR) in the PHM Portal. A separate dashboard is available to DHCS to support internal monitoring and policy evaluation. This dashboard enables detailed analyses of risk distribution over time, including subgroup comparisons aligned with the equity considerations emphasized throughout RSST development.

Validation tests confirmed that the RSST models and infrastructure performed as expected during productionization, with only minor, explainable differences across environments. Underutilization risk prevalence increased modestly when applied to 2024 data, but model logic and performance remained consistent with the original design.

Future updates to RSST may include model retraining on newer data, incorporation of additional predictors and outcomes, and refinement of tiering thresholds. DHCS is developing a formal process for reviewing and implementing such changes, ensuring that future updates preserve the technical integrity and policy alignment of the algorithm.

8) Assumptions and Limitations

RSST Version 1 includes several important limitations. The models rely entirely on Medicaid administrative claims and eligibility data. Clinical EHR data and broader social datasets are not currently integrated. Members enrolled in limited-benefit programs, such as GHPP, CCS, or Family PACT, were excluded due to incomplete data. Dual Medicaid–Medicare eligible members were included in all models except for underutilization, where lack of Medicare claims particularly limited the predictive power of the model. Note, Medicare claims data was not used to develop any of the models, so the reliability of the models for dual members is limited to their Medicaid benefits. Tier thresholds were set using predicted scores from January 2023 and remain fixed for Version 1, meaning the proportion of members flagged as high-risk may vary slightly over time. Internal data transfer lag within the PHM system was not explicitly modeled but is expected to be better understood and addressed in future releases.

9) Conclusion

The RSST Algorithm represents DHCS's commitment to building a modern, transparent, and policy-aligned approach to risk stratification for the Medi-Cal population. It introduces a replicable framework that can be applied statewide, supports more equitable targeting of care interventions, and lays the foundation for future enhancements. V1 (Adult and Pediatric models) and V1.1 (Birthing models) of RSST reflect a careful balance of technical rigor, operational feasibility, and policy vision. This document provides a comprehensive explanation of the algorithm's design, logic, and intended use, and is intended to serve as a transparent reference point for all stakeholders in the Medi-Cal system.

II. INTRODUCTION

Managed Care Plans (MCPs) in California are currently required to implement their own risk stratification methods as part of their Population Health Management programs. However, most MCPs have historically used disparate tools—many proprietary or commercially developed—resulting in wide variability in how members are identified for assessment or care coordination. To establish a statewide framework for risk tiering and address care gaps within the Medi-Cal program, DHCS developed the Risk Stratification Segmentation and Tiering (RSST) algorithm.

The RSST Algorithm was developed to address these gaps and establish a unified, statewide framework for risk tiering within the Medi-Cal program. This approach is distinct from many existing tools in both its technical design and its policy orientation. The RSST Algorithm is:

- Standardized across all MCPs and regions
- Transparent and interpretable
- Specifically tailored to the Medi-Cal population and benefit structure
- Built using supervised machine learning models that are maintainable and tunable over time
- Designed with equity in mind—including bias mitigation in model development and subgroup monitoring post-deployment

Unlike most traditional risk models, which often focus on prior cost and utilization, the RSST Algorithm is forward-looking. It estimates the risk of future adverse outcomes, underutilization, and social vulnerability. It also emphasizes transparency—both in how members are flagged and in how results are monitored at the population level by DHCS.

The following table summarizes the core challenges this approach aims to address, and the corresponding solutions implemented through RSST:

Table 1. Challenges of Existing Risk Identification Approaches and RSST Solutions

Challenge of Existing Risk Identification Approaches	RSST Response
Inconsistent stratification across plans	Statewide, standardized method applied to all members
Fragmented or incomplete data	Centralized data from the full Medi-Cal system, including sources not easily available to individual MCPs
Cost/utilization-focused models	Models include adverse events, underutilization, and social risk
Proprietary, opaque algorithms	Transparent and interpretable logic with monthly oversight
Limited attention to equity	Equity-informed model design and ongoing subgroup analysis
Retrospective risk score defined by past events or diagnoses	Forward looking Machine Learning models predict likelihood of future negative outcomes that have not yet occurred
Uniform treatment of risk across patient groups	Risk scores and tiers are differentiated across multiple domains
Static parametric models updated annually or less often	Built using supervised ML for ongoing refinement and updates

These principles also inform the operational model: RSST tier outputs are produced monthly using updated data and delivered for use in the PHM Service. Members in the highest risk tier are prioritized for outreach and assessment. An evolving dashboard and monitoring suite provides detailed visibility into tier distribution and subgroup patterns, supporting accountability and ongoing refinement.

Taken together, the RSST Algorithm provides a scalable, policy-aligned, and equitable foundation for identifying members most likely to benefit from proactive services and care coordination across the Medi-Cal program.

III. DESIGN PRINCIPLES

The RSST Algorithm was developed to support more equitable, consistent, and actionable risk stratification across the Medi-Cal program. Its design reflects both technical modeling objectives and broader policy values, including transparency, equity, and statewide standardization. This section outlines the key principles that guided the development of the algorithm.

Statewide Standardization with Population-Specific Design

A core goal of RSST is to establish a consistent, statewide approach to identifying Medi-Cal members at elevated risk—ensuring that risk stratification is applied equitably across Managed Care Plans (MCPs), regardless of regional or population differences. Standardization does not imply a one-size-fits-all model, but rather a shared framework that accommodates population-specific nuances while delivering consistent outputs for programmatic use.

Different populations experience risk differently—and face different consequences from being overlooked. RSST was designed from the outset to recognize the distinct needs of Adults, children, and Birthing people. Separate models were developed for each stratum to ensure that outcomes and predictors reflect the clinical context, service patterns, and risk factors relevant to each group. For example, children may be flagged for missed well-childcare, while Adults may be flagged for gaps in chronic disease or behavioral health care. Separate modeling enables the algorithm to better align with the populations DHCS serves while still promoting a standardized framework that can be applied consistently across all health plans.

Traditional risk models often identify only those who are already high-cost or high-utilizing. RSST was designed to also flag individuals who have clinical indicators suggesting unmet need. These may include, for example, a lack of primary care follow-up after an emergency department visit or a behavioral health diagnosis without a recent prescription refill. This “Underutilization” domain helps highlight members facing systemic barriers to care who may otherwise go unflagged.

Equity in Model Development

The ideal goal of equity in this context is to ensure that all Medi-Cal members—regardless of race, ethnicity, language, or gender—have a fair opportunity to be accurately identified for services and support. This approach aligns with DHCS's commitment to fostering an equitable, dignified Medi-Cal system that works for everyone. Equity was a guiding consideration throughout the RSST development process. This includes selecting outcomes and predictors with input on how risk manifests across populations and analyzing tier outputs by subgroup to detect any potential disparities. DHCS is not assuming this eliminates disparities but is committed to using equity-focused evaluation as a basis for future model refinement. Ongoing subgroup monitoring will continue as part of routine model oversight. Equity was considered at each stage of the model lifecycle—from defining outcomes and predictors, to model training and aggregation logic, to evaluation and ongoing monitoring. This framing helped ensure equity considerations were not siloed but embedded throughout the development and deployment process.

Transparency in Design and Structure

Transparency was a core reason for developing a custom RSST Algorithm. Many commercial risk tools function as black boxes—offering little visibility into how risk scores are calculated or how they relate to member needs. RSST was designed to be fully interpretable, with its logic, structure, and assumptions clearly documented. This document is part of that commitment—offering a public explanation of how the algorithm was designed, what it is intended to do, and how it is being monitored over time.

The RSST structure separates different types of risk into distinct subdomain models and aggregated domains (adverse events, underutilization, and social risk). This design was intentional: it allows for transparency in how each domain contributes to overall risk and creates the flexibility for policymakers to decide how to weight or prioritize each domain. As described in the Tiering Analysis section, this structure supported a policy decision-making process that considered how different types of risk should be elevated or balanced.

Interpretability and Flexibility

The RSST Algorithm uses supervised machine learning techniques that are designed to be flexible (provide as much information about risk as possible from available data), transparent (with all model inputs, outputs, and training procedures clearly defined), reproducible, and have interpretable outputs. This allows the algorithm to be updated over time as new data become available, additional models are introduced, or policy needs evolve. The algorithm's structure supports both transparency and ongoing refinement, ensuring it remains relevant and aligned with Medi-Cal program goals.

IV. LEADERSHIP AND GOVERNANCE

To guide the development of the RSST Algorithm, DHCS established a governance structure designed to ensure evidence-based methods, stakeholder input, and alignment with the needs of Medi-Cal beneficiaries. A dedicated leadership team was formed, with internal leads and sponsors overseeing strategy and execution. The RSST Work Group, under supervision of the Quality and Population Health Management (QPHM) division, led model design. A Scientific Advisory Council (SciAC) provided expert review on major decisions, including model principles, outcomes, predictors, and equity considerations. Subject Matter Experts (SMEs), specifically Maternal-Fetal Medicine (MFM) clinicians, national maternal-health experts and DHCS Birthing-policy leads,provided guidance on Birthing-specific data, inclusion criteria, and exclusion criteria, and helped to significantly shape the models. The PHM Advisory Group—composed of public stakeholders—helped ensure transparency and relevance throughout development. DHCS also received strategic support from external advisors to inform planning and execution.

A. Academic Work Group

The Work Group is charged with developing the RSST contextual design and approach of the algorithm. The Work Group (which was brought in 2023 to advise) consists of nationally recognized experts in health equity, health outcomes, Medicaid analytics, and machine learning.

Table 2. Academic Work Group Members

Name	Title	Organization
Maya Petersen – Lead	Professor, Biostatistics and Epidemiology	UC Berkeley
Jonathan Kolstad	Professor, Economic Analysis and Policy	UC Berkeley
Michael Barnett	Professor, Health Services Policy and Practice	Brown University
Alejandro Schuler	Asst. Professor, Biostatistics	UC Berkeley
Jacob Wallace	Assoc. Professor, Public Health (Health Policy)	Yale
Anna Zink	Asst. Professor, Community Health	Tufts University

B. Scientific Advisory Council

Established by DHCS in 2023 to support the RSST Work Group, the Scientific Advisory Council (SciAC) includes representatives from Medi-Cal Managed Care Plans, healthcare delivery systems, care management leaders, and medical academic institutions. Throughout the design and development of the RSST algorithm the SciAC served as key advisors providing input and guidance.

Introducing the PHM Initiative RSST Work Group Members and Scientific Advisory Council Members

C. Stakeholder Engagement

The RSST WG relied on the expertise of additional stakeholders through the development of the algorithm (e.g., design, structure, outcomes). This included extensive internal and external stakeholder engagement, consultation and consensus building.

1. Internal Stakeholders

Internal DHCS stakeholders were engaged and consulted through the design of the algorithm, particularly regarding the design and selection of outcomes. This included engagement with the following DHCS divisions and external groups:

Table 3. Internal Stakeholders

DHCS Divisions	External Groups
» Director's Office » Behavioral Health » Health Care Benefits and Eligibility » Enterprise Data and Information Management » Office of Medicare Innovation and Integration » Quality and Population Health Management » Health Care Financing » Health Care Delivery Systems	» Birthing Care Pathway » Children and Youth Advisory Council » Clinical Subject Matter Experts: Dr. Kim Gregory and Dr. Diana Robles » Social Risk experts » Further, MCPs were consulted on the RSST rationale and contextual algorithm design (i.e., framework, predictors, outcomes).

2. External Stakeholders

Adult and Pediatric Models (V1)

External stakeholders were actively engaged throughout the design of the algorithm, particularly through the Medi-Cal Connect Advisor process. These Advisors were MCPs that volunteered time and resources to review and validate Medi-Cal Connect on behalf of the broader Medi-Cal Plan community. The following MCPs participated in these activities:

- Health Net Community Solutions
- Inland Empire Health Plan
- Kaiser Permanente
- L.A. Care Health Plan

For RSST, Advisors compared 100 high-risk and 100 low-risk members from January 2023 against their internal risk assessments and care management activities conducted during the same year. They reported on concordance and discordance in tiering and shared insights from member assessments completed during that period. This comparison enabled DHCS to validate RSST tiers before launch and informed key policy decisions. Additionally, DHCS gathered feedback on RSST-related policy considerations, including reporting requirements, implementation timelines, and potential barriers from the Advisors as well as from the Medi-Cal Plan community. As the RSST algorithm is prepared for deployment and released, additional engagement will be required. This may include consultations regarding risk tiers, algorithm performance results, equity analyses, and how to improve the performance of the algorithm for marginalized, underrepresented and equity-deserving groups. The DHCS RSST and User and Stakeholder Engagement (USE) teams will work in partnership to engage MCPs post-release. The USE team will lead the engagement coordination, including outreach to additional MCPs beyond the original group of Advisors. The RSST team and project leads will contribute subject matter expertise to inform these efforts.

Birthing Models (V1.1)

For the Birthing models, external stakeholders were engaged in the comparison exercise using a similar process and format as conducted prior. The following MCPs participated in this activity:

- Health Net Community Solutions
- Inland Empire Health Plan
- L.A. Care Health Plan

For the RSST Birthing Models, MCP Advisors compared 50 pregnant members, 50 postpartum members who delivered, and 50 post-pregnancy members who had a loss as of December 2022 against their internal risk assessments and care management activities conducted during the same period. They reported on concordance and discordance in tiering and shared insights from member assessments completed during that period.

Table 4. RSST/USE Stakeholder Engagement

Engagement Type	Purpose	MCPs	MCP Rationale
May 2024 - USE Discovery	Engage a small subset of MCPs to validate, understand, and refine initial assumptions on the five identified value propositions and core elements of Medi-Cal Connect.	» Health Net » IEHP » LA Care	Selected for engagement from early adopter list and per the recommendation of GWTs strategic advisor.
Sept 2023 - MCP Engagement	Engage a small subset of MCPs to collect input on how RSST may be used at	» Health Net » HPSM » Kaiser	Selected a small group with diverse representation of

Engagement Type	Purpose	MCPs	MCP Rationale
	the MCP for purposes of developing the algorithm.	» LA Care » Partnership	technology/analytic abilities.
RSST Lead Outreach Sarah Lopez	Introduce Sarah to MCPs and get a sense of the "state of the art" and advanced Plan approaches to understand how the RSST effort's work compares.	» Central California Alliance for Health » HPSM » IEHP » Partnership	Selected for engagement due to maturity of population health and tiering capabilities as well as access to advanced analytics.
Scientific Advisory Council	The Council serves as an advisory group to DHCS and the RSST WG with a goal of guiding the development of the PHM Service RSST algorithm.	» Contra Costa Health Services » LA Care » Partnership » IEHP » Health Net » Kaiser	The SciAC is comprised of individuals representing MCPs, health care delivery systems, care management leaders, and academic medical systems.
PHM Advisory Group	The Advisory Group was comprised of cross-sector stakeholders that provided feedback and made recommendations on the PHM Program and Service, including RSST.	» Health Net » HPSM » IEHP » LA Care » Kaiser » Kern Health Systems » Partnership	Members include a diverse set of leaders with representation from health plans, providers, counties, state departments, consumer organizations, and other groups.

V. MODEL DESIGN

A. Population Inclusion/Exclusion Criteria

The RSST algorithms were originally designed to produce monthly risk tiers on three subpopulations within California's Medi-Cal population – one risk tier for each subpopulation. These subpopulations included:

- **Adult population:** Any eligible Medi-Cal member, aged 18+
- **Pediatric population:** Any eligible Medi-Cal member, aged 4 months through 17 years of age
- **Birthing population:** Any eligible Medi-Cal member, who is currently pregnant or up to 12 months post-pregnancy/postpartum. Any infant, Medi-Cal member aged 0-3 months.

Eligible members were restricted to Medi-Cal members, not those who solely enrolled via FPACT, CSS, or GHPP. Members with Medicare dual eligibility were included, but their sub-domains of risk modeling were restricted to Adverse Events and Social Risk. Ages were calculated at the time of the most recent monthly data processing.

For the RSST V1 launch, modeling was restricted to the Adult and Pediatric populations only. The Birthing population was included in the V1.1 launch.

Birthing Population

At a high level, the Birthing population was defined as Medi-Cal members who were pregnant or up to 12 months post-pregnant/postpartum. Unlike Adult and Pediatric populations, however, pregnancy is episodic and must be inferred from claims data rather than directly observed. As a result, different methodologies were used to define the Birthing population for model training versus production inferencing, reflecting differences in data availability, timing, and operational requirements.

Model Training Population: Retrospective Pregnancy Episode Construction

For Birthing model training, RSST used a retrospective, episode-based approach leveraging the fact that pregnancy-ending events are more reliably observed in claims than pregnancy onset. This pregnancy episode identification methodology was adapted from a published claims-based pregnancy identification algorithm and enhanced using California-specific data sources and DHCS-provided code sets, including infant record linkage and additional validation logic.

- Pregnancy episodes were anchored on known pregnancy-ending events observed in claims data, including:
  - Vaginal delivery
  - Cesarean delivery
  - Induced abortion
  - Spontaneous abortion
  - Ectopic pregnancy
- Episodes were limited to members aged 15–49 years at the time of the event.

From each pregnancy-ending event, the model reconstructed the pregnancy episode by working backward in time to the first pregnancy-related diagnosis code that occurred between the estimated last menstrual period (LMP) and the pregnancy end date.

- Pregnancy-related diagnoses were identified using the Clinical Classifications Software (CCS) major category Pregnancy, Childbirth, and the Puerperium, supplemented with DHCS-provided diagnosis and procedure code sets.
- Gestational age was estimated using outcome-specific assumptions:
  - Standard gestational age defaults were applied by outcome type.
  - For deliveries, gestational age was refined when pregnancy-related diagnosis codes with gestational age information were present near the delivery date.
- An estimated last menstrual period (LMP) was calculated based on the estimated gestational age and pregnancy-ending date.

To prevent double-counting overlapping or closely spaced pregnancies, the model applied explicit interpregnancy gap rules:

- A 120-day gap following vaginal or cesarean deliveries.
- A 42-day gap following non-delivery outcomes.
- When overlaps occurred, pregnancy episodes were prioritized by outcome type (e.g., cesarean before vaginal delivery, delivery before abortion).

After reviewing first-iteration results with the Work Group, pregnancy episodes with a start date and end date in the same calendar month were excluded from Pregnancy model training dataset. Because these episodes would typically end before the model could generate even one monthly prediction in production—often due to episode timing and claims processing lag—excluding them ensured the model was trained on episodes with sufficient pre-outcome history to support actionable, prospective identification aligned with the monthly RSST cadence. This had the effect of removing 78% of loss episodes and 1% of delivery episodes, while still leaving reasonably large samples of both types of episodes included in the training data.

Post-pregnancy Training Episodes

- A fixed 12-month post-pregnancy window was applied to the pregnancy-ending event date.
- The same episode construction logic was used across physical and behavioral health models, with the following distinction: the post-pregnancy physical health model required successful parent-child linkage for inclusion, while the post-pregnancy behavioral health model did not require this linkage, because the physical health model included infant outcomes, whereas the behavioral health model outcomes included only parent-based outcomes.

Production Inferencing Population (Prospective, Indicator-Based)

In production, the Birthing population was identified monthly using claims-based indicators designed to operate prospectively with rolling lookback windows.

A member was flagged as pregnant in a given month if they met each of the following criteria:

- Female, ages 15–49
- No evidence of hysterectomy in available claims data
- Pregnancy-related service occurred within the last 40 weeks (from the last day of the month)
    - Service included CPT/HCPCS codes from:
        - DHCS Pregnancy: Per-Visit Billing Codes
        - DHCS Pregnancy: Global Billing Codes
        - DHCS Pregnancy: Comprehensive Perinatal Services (CPSP) List of Billing Codes
    - Service also included a pregnancy diagnosis where CCS Group = "Pregnancy, Childbirth, and the Puerperium"
- No pregnancy-ending event (delivery or loss) since the last pregnancy service
- No delivery in the past 120 days
- No pregnancy loss in the past 42 days

- Clinical plausibility refinement: After examining real-world data, additional constraints were added to reduce false positives. These refinements ensure that implausibly early post-pregnancy codes do not incorrectly reclassify members as pregnant.
    - If a pregnancy service occurs within ≤56 days of a delivery, the pregnant flag is set to 'U' (Unknown)
    - If a pregnancy service occurs within ≤42 days of a loss, the pregnant flag is set to 'U' (Unknown)

A member was flagged as post-pregnancy in a given month if they met each of the following criteria:

- Female, ages 15–49
- No evidence of hysterectomy in available claims data, with the exception if the hysterectomy occurred within the last 12 months and the member is still with a clinically valid post-pregnancy period, as hysterectomies can occur as complications of delivery
- Claims indicated a pregnancy-ending event (delivery or loss) within the last 12 months (from the last day of the month)
- When both a loss and delivery occurred, the most recent event determined status

Pregnancy-ending events for post-pregnancy flagging included:

- Delivery events: vaginal delivery and cesarean delivery (identified via procedure codes; note: includes non-live births)
- Loss events: Spontaneous abortion, induced abortion, and ectopic pregnancy (identified via procedure codes, diagnosis codes, and medication records)

For any given month, a member was included in the Birthing population only if at least one indicator (pregnancy or post-pregnancy) was active. Members with neither indicator active were excluded from Birthing population counts for that month.

Descriptive characteristics of the Birthing model training population and a point-in-time snapshot of the production inferencing population (December 2022) are presented in Table 5A below.

Table 5: Characteristics and demographics in Jan 2023

	Adult	Pediatric
Sex – no. (%)		
Male	3,945,095 (44.5%)	2,329,503 (51.2%)
Female	4,930,234 (55.5%)	2,219,539 (48.8%)
Age		
Mean (sd)	43 (18.40)	9 (5)
Race/Ethnicity – no. (%)		
Am. Indian or Alaska Native	35,939 (0.4%)	13,830 (0.3%)
Asian	912,370 (10.3%)	252,153 (5.5%)
Black or African American	651,099 (7.3%)	285,213 (6.3%)
Native Hawaiian or Pacific Islander	107,863 (1.2%)	39,400 (0.9%)
Other	3,783,527 (42.6%)	2,508,718 (55.1%)
Two or More Races	515,482 (5.8%)	299,658 (6.6%)
Race Unknown	1,057,495 (11.9%)	543,973 (12.0%)
White	1,811,554 (20.4%)	606,097 (13.3%)
Language – no. (%)		
Primary Language English	6,085,288 (68.6%)	3,073,996 (67.6%)
Primary Language Spanish	2,028,567 (22.9%)	1,323,350 (29.1%)
Primary Language Other	761,474 (8.6%)	151,696 (3.3%)
Enrollee Status – no. (%)		
Dual Eligible	1,524,937 (17.2%)	104 (0.0%)
Not Dual Eligible	7,350,392 (82.8%)	4,548,938 (100.0%)

Table 5A: Characteristics and demographics of the Birthing Population in the Tiering Analysis and Dec 2022 Inference Populations

	Tiering Sample	Dec 2022 Birthing*	Dec 2022 Potential Birthing*
Age			
Mean (sd)	28 (6.2)	29 (6.3)	30 (9.9)
Age 18 and Under	2,977 (4.1%)	5,982 (2.4%)	580,098 (14.2%)
Age 40 and Over	3,225 (4.4%)	15,041 (6.1%)	928,637 (22.7%)
Ethnicity			
Hispanic or Latino	39,956 (54.5%)	138,291 (56.1%)	1,996,867 (48.9%)
Not Hispanic or Latino	33,404 (45.5%)	108,358 (43.9%)	2,086,706 (51.1%)
Race			
American Indian or Alaska Native	258 (0.4%)	738 (0.3%)	15,738 (0.4%)
Asian	2,705 (3.7%)	9,042 (3.7%)	265,301 (6.5%)
Black or African American	5,064 (6.9%)	19,873 (8.1%)	270,222 (6.6%)
Native Hawaiian or Pacific Islander	569 (0.8%)	1,958 (0.8%)	35,552 (0.9%)
Other Race	38,046 (51.9%)	129,562 (52.5%)	1,901,733 (46.6%)
Two or More Races	7,998 (10.9%)	26,640 (10.8%)	351,358 (8.6%)
Unknown Race	9,985 (13.6%)	30,122 (12.2%)	555,555 (13.6%)
White	8,735 (11.9%)	28,714 (11.6%)	688,114 (16.9%)
Language			
Primary Language English	51,594 (70.3%)	176,684 (71.6%)	2,833,679 (69.4%)
Primary Language Spanish	19,332 (26.4%)	63,004 (25.5%)	1,063,949 (26.1%)
Primary Language Other	2,434 (3.3%)	6,961 (2.8%)	185,945 (4.6%)
Residence Location			
Rural	1,006 (1.4%)	2,565 (1.0%)	49,316 (1.2%)
Urban	62,242 (84.8%)	212,615 (86.2%)	3,388,736 (83.0%)

*Birthing = known pregnancy status via claims data

*Potential Birthing = Females, 15-49, unknown pregnancy status via claims data.

B. Data Sources

Restricted to data available at the time of model training, the RSST models (V1.0) used data from two core sources: Medicaid Administrative Claims Data and Eligibility Data. Both data sources were formatted by DHCS to conform to the All-Payer Claims Data Common Data Layout (APCD-CDL).

Historic data files were delivered in bulk for training, and monthly incremental files are to be delivered on a monthly cadence post launch:

- An extract of all Medi-Cal claims, including professional, facility, dental, and pharmacy claims
- An extract of Medi-Cal eligibility/enrollment data, including demographic and product enrollment information
- A supplemental member eligibility (SUME) extract, which was used to extract death date (used for mortality prediction) and create a dual-enrolled status indicator (Note: future model iterations will draw more information from SUME)

Representing eight years of data from 2016-2023, these data files were passed through an MPI engine that grouped multiple CIN values into a single Person ID, allowing the data to be modeled at the person-level. We partitioned data into non overlapping time-based windows with index dates spanning January 2019 to January 2023. See 'Data Splitting' section for details on specific splits across datasets.

For Birthing models, the same data sources were leveraged, with the following changes:

- An additional year of claims (2024 with runout through March 2025) was available for use during model training.
- Historic vital birth certificate records became available midway through model design and were used as part of parent-child linkage logic in order to assign risk tiers to infants 0-3 months old, and also to code one outcome (Early preterm and/or very low birthweight), based on data included in birth certificate records.
- SUME data was utilized as part of parent-child linkage logic on historic claims and eligibility data, to enable inclusion of infant adverse outcomes tied back to the Birthing parent's claims history.

C. Outcomes

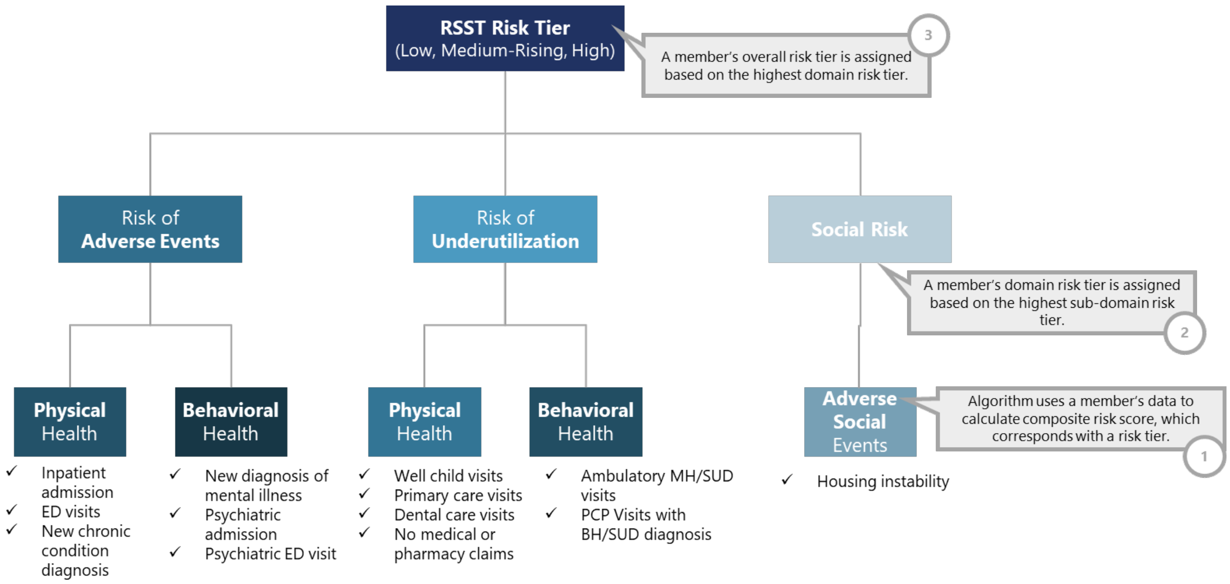
Adult and Pediatric Outcomes (V1)

For RSST V1, binary outcomes were developed for the Adult and Pediatric Medi-Cal populations. Each subdomain-level model predicts whether a member will experience one or more of these outcomes in the 12 months following a defined index date. If a member experienced at least one outcome, they were assigned a composite outcome value of 1; otherwise, they were assigned a value of 0.

Outcomes were organized within three overarching domains: Risk of Adverse Events, Risk of Underutilization, and Social Risk. Within each domain, outcomes were grouped into clinically and programmatically relevant subdomains, including physical health, behavioral health, and adverse social events such as housing instability.

The RSST Work Group led the design of these outcomes, supported by analytic staff and with consultation from subject matter experts across DHCS, including the Enterprise Data and Information Management (EDIM) Division and the Data Services Branch (DSB). The Work Group sought to align outcome definitions with existing DHCS business logic and ensure outcomes could be implemented consistently across the Medi-Cal population. Wherever possible, definitions were based on data elements and rules already in use at the state level.

Each proposed outcome was tested in historical Medi-Cal data to confirm feasibility, appropriate prevalence, and clarity of construction. Prevalence rates were reviewed by DHCS and academic SMEs to confirm that results were reasonable and interpretable, and subgroup breakdowns (e.g., by race, ethnicity, sex, language, enrollment type) were used to identify potential data quality issues. These equity-focused reviews helped flag patterns to be aware of but did not lead to major structural changes at the outcome level.



Note: A complete listing of RSST V1 outcomes with definitions can be found below in the Outcomes Detail section.

Birthing Outcomes (V1.1)

A similar approach was used to define outcomes for the Birthing models as for the Adult and Pediatric models, with key differences reflecting the pregnancy context. The Birthing models do not include Underutilization or Social subdomains; all outcomes were therefore classified as Adverse Events.

Underutilization and social risk models were not developed as standalone components for the Birthing population in V1.1, due to data limitations. One key data limitation is the way prenatal care is commonly billed in claims data. Prenatal services are frequently submitted as global or bundled claims, often spanning multiple months or submitted after delivery, which limits our ability to measure, individual service use patterns during pregnancy. This makes it challenging to reliably measure, and thus to train models to predict, underutilization of indicated prenatal services. The decision not to include a social risk domain was driven largely by limited ability to link to data sources needed to derive meaningful social risk adverse outcomes for the Birthing population.

The decision not to develop Birthing-specific underutilization or social risk models reflects a prioritization of clinical relevance and analytic feasibility for the initial Birthing release. The primary focus of the Birthing models was on adverse pregnancy-related and infant outcomes, where claims-based signals are more clearly defined and temporally aligned. Future iterations of the RSST algorithm may incorporate more Birthing-specific underutilization and/or social elements, particularly as data availability, billing practices, and policy guidance evolve, and as clearer definitions of actionable underutilization during pregnancy are established.

Outcomes were drawn from multiple sources, including select Adverse Events reused from the Adult and Pediatric V1 models, new infant adverse event outcomes requiring parent–child linkage, pregnancy- and delivery-specific diagnosis-based outcomes, and one outcome derived from vital birth certificate records, a data source that became available partway through model design. Candidate outcomes were reviewed by the Work Group, analytic staff, and clinical subject matter experts, with coding logic and observed prevalence examined before finalizing each composite outcome basket.

Unlike the Adult and Pediatric V1 models, the Birthing V1.1 models were not subject to a strict top-down constraint on proportion of the population classified as high risk, given the smaller size of the Birthing population and existing policy context requiring assessments of all pregnant members. Thus, clinical means were allowed to drive outcome selection as long as total outcome prevalence remained within reasonable guidelines defined by DHCS leadership. As a result, outcome prevalence and the number of outcomes vary across the three Birthing subdomain models.

Note: A complete listing of RSST V1.1 outcomes with definitions can be found below in the Outcomes Detail section.

D. Predictors

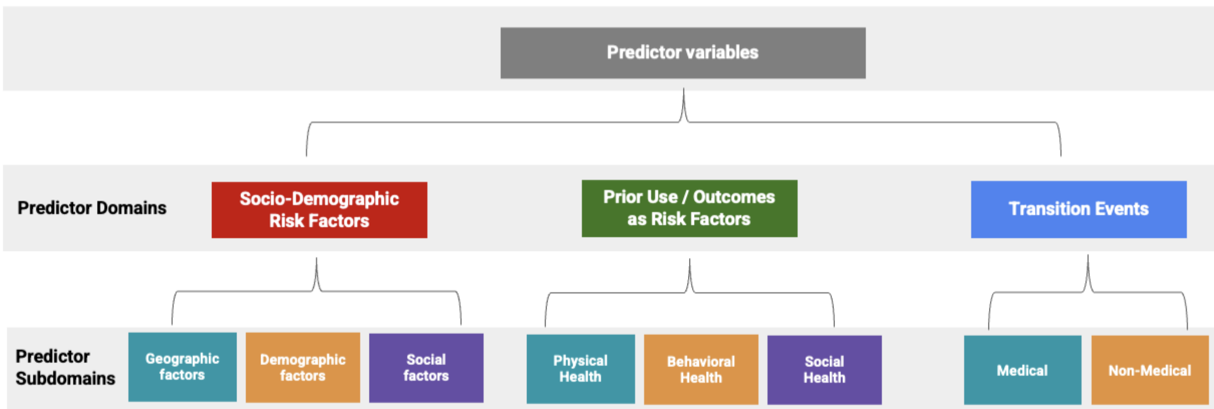
Adult and Pediatric Outcomes (V1)

Predictors were developed using lookback windows prior to the defined index date. Depending on the predictor, the lookback window was defined in the past 3 months, 12 months, or “ever”, where “ever” incorporates the full available history, which extends back no earlier than January 2016. Lookback window information for each predictor can be found in the “Predictor Details” section. Predictors were grouped into one of four domains:

- Socio-Demographic Risk Factors
- Prior Use
- Transition Events
- Outcomes as Risk Factors

Socio-Demographic Risk Factors were grouped in geographic, demographic, and social subdomains and included information such as age, race, gender, employment status, etc. **Prior Use** risk factors were grouped into physical, behavioral, and social health subdomains and included indicators and counts on attributes such as chronic condition diagnoses and healthcare service utilization. **Transition Events** were grouped into medical and non-medical subdomains and included indicators such as switching Medicaid plans, moving counties, aging into the Adult population, etc.

Outcomes as Risk Factors is a special case where the outcomes we are predicting were adapted for use as prior period predictors. In many cases this involved transformation from a binary outcome (e.g. Indicator of any ED visits in the next 12 months) to a continuous predictor (e.g. Count of ED visits in the past 3mo, 12mo, or "ever" – full available history).



Birthing Outcomes (V1.1)

For the Birthing models, the same V1 set of predictors were used, but with a few key enhancements:

- Additional pregnancy-related predictors with 3-, 12-, and 60mo lookbacks (Note: 60mo lookbacks dipped into historic data from pre-2021 where possible).
- Additional "Outcomes as Risk Factors" derived from Birthing model outcomes.
- V1 Adult/Pediatric 3mo and 12mo lookback predictors were incorporated into Birthing models (Not the "ever" lookback variants, given data availability).

For consistency between training and production runs of these models, and because the production data warehouse includes data from 2021 onwards, Birthing model predictors were capped at 60 months lookback prior to the index date as opposed to "ever". Predictor windows end on the last day of the month before the index date, ensuring predictor and outcome windows never overlap.

The new pregnancy-specific predictors (diagnosis-based and service-based) were added based on reviewing with the Work Group and clinical SMEs what could be reliably gleaned from administrative claims data, considering the impact of global billing, which is common for prenatal care. Claims lag also factored into determining whether a given feature was better suited as a predictor or an outcome. In some cases (e.g. Ectopic pregnancies, prenatal ultrasound) features originally intended as outcomes were better suited as predictors given our reliance on claims data.

Note: A complete list of the RSST V1 and V1.1 predictors can be found below in the Predictors Detail section.

E. Model Training Methods

Machine learning models were used to provide flexibility in learning complex patterns from the data. We evaluated three supervised learning algorithms, selected for their balance between performance, scalability (up to 100s of millions of rows), and interpretability.

1. Models

a. Regularized Logistic Regression (LR)

Logistic regression with elastic net penalty was implemented with stochastic gradient descent optimization, allowing tuning over a wide range of regularization strengths (C) and mixing parameters (l1_ratio).

b. XGBoost

A high-performance implementation of gradient boosting, optimized for parallel training. Hyperparameters included number of estimators, learning rate, and tree depth.

c. LightGBM

A leaf-wise histogram-based gradient boosting algorithm, selected for its speed and memory efficiency on large datasets. Similar hyperparameters were explored as in XGBoost for comparison.

All models were trained to generate probabilistic predictions for binary outcomes in a multi-label setting.

2. Data Splitting

Adult and Pediatric Models (V1)

The data were partitioned into training, validation, and test sets, with a buffer window to ensure that no individuals appeared with an outcome label that overlapped with the test set. The data were partitioned into the following distinct time-based windows:

- **Tuning and Hyperparameter Search Set** (Jan 2019 – Jan 2020): Used to explore hyperparameter configurations across all models and train initial models for validation and model selection.
- **Validation Set** (Feb 2020 – Jan 2021): Used to perform model selection between models trained on the Search Set and for sensitivity analyses to investigate model stability & generalizability.
- **Buffer Window** (Feb 2021 – Dec 2021): Excluded from all training and evaluation to prevent label leakage. This window ensures that no individual appears with an outcome label that overlaps into the test set.
- **Test Set** (Jan 2022 – Jan 2023): Held out for final evaluation only, simulating real-world performance in a temporally shifted future.

These dates reflect the index dates; historical predictor data before (3 months, 12 months, and "ever") and outcome data after (12 months) the index dates were included in the datasets. This structure was designed to ensure that all model comparisons and selections were based on realistic future-facing performance, and to avoid contamination of future labels during training. In order to mitigate impact of the COVID-19 pandemic on the generalizability of results to current settings, the independent Test Set that was used for all tiering decisions and final performance evaluations used data from a period when COVID-related disruptions to the health care system had substantially decreased. In additional sensitivity analyses, sub-domain-specific model AUCs were stable when evaluated on the Test Set compared to the Validation Set (which included the period of maximal COVID-19 impact), supporting stability of model performance.

Logistic Regression was implemented with elastic net penalty and stochastic gradient descent optimization and was tuned over a wide range of regularization and mixing parameters. Models were trained using a GPU-accelerated implementation of logistic regression from the cuML library, with the 'qn' solver (quasi-Newton optimization) and a maximum of 100 iterations per trial. Optimization was performed using Optuna, with single-threaded tuning and early stopping and pruning conditions, consistent with the tree-based models.

The XGBoost model used gradient boosting, optimized for parallel training, while the LightGBM model used a leaf-wise gradient boosting algorithm. The number of estimators, learning rate, and tree depth were tuned as hyperparameters. Training and evaluation for the XGBoost Model were performed using DaskQuantileDMatrix to support GPU-native batching. The gradient based sampling method was enabled to stabilize learning under class imbalance. For the LightGBM model, hyperparameter trials were parallelized using Dask, and tuning was conducted using Optuna with the same early stopping and pruning strategies.

Birthing Models (V1.1)

For the Birthing models, a randomized member-based split was used instead of a time-based split. This approach was selected for the following reasons:

- The available data range is shorter, leaving insufficient room for clean temporal partitions.
- For the Birthing population, most individuals will not reappear across long horizons, diminishing the benefit of forward-looking evaluation.
- Laws, policies, and political dynamics affecting pregnancy and postpartum care shifted during the data range, meaning a time-based split could confound performance evaluation by embedding these external changes.

The data were partitioned at the person-level into training (70%), validation (15%), and test (15%) sets. All pregnancy episodes belonging to the same individual remain in the same split set, ensuring independence across splits, while preventing outcome information from leaking across training, validation, and test sets. For the Pregnancy model, valid pregnancy start dates span January 2022 through December 2023. For the post-pregnancy models, valid pregnancy start dates span January 2022 through December 2022, constrained by the longer 12-month post-delivery outcome window.

To account for differential contributions by month, row-level weights were derived as the inverse of each pregnancy episode's length and applied as sample weights to ensure that each episode contributed proportionally to model training, accounting for the multiple index dates generated per episode. We exclusively used XGBoost due to its performance observed from the Adults and Pediatric models.

Overall model performance (AUC, Accuracy, Precision, Recall, Specificity), and the performance across a set of pre-defined Equity Subgroups (see next section), was calculated and reviewed for each subdomain model for each training iteration and used by the Work Group to guide iterative changes. Calibration curves were developed to compare predicted probabilities with observed outcome rates within each subgroup. NNT, Precision, and Recall were also calculated across the range of possible tiering thresholds to evaluate model performance, and SHAP values were generated for the top predictors to evaluate feature importance.

F. Bias and Sensitivity Testing Methods

Equity was identified by DHCS as a key principle of the model development process, and academic leaders in the space were consulted for their opinions and recommendations at several stages such as outcome development, model training, tiering, and monitoring.

Before model training commenced, the WG evaluated prevalence rates of individual outcomes by subgroup, and consulted with DHCS subject matter experts, available literature, and clinical experts on these prevalence rates.

The Work Group approached model training and tiering evaluation from two angles: (1) whether models performed consistently across demographic subgroups (e.g., similar recall, AUC), and (2) whether high-risk flags were equitably distributed across those subgroups to reach members with relevant outcomes across models, to support equitable prioritization of members for services. During model training, model performance results were reviewed for each subgroup and evaluated by the WG.

During Tiering Analysis, the Work Group assessed model performance across equity subgroups using a relative benchmark. The general guidance adopted by DHCS was that subgroup recall values should fall within ±20% of the statewide average recall. This threshold was used as a screening tool to highlight meaningful differences and inform decision-making around tiering options. While not a definitive standard for fairness, this approach supported a consistent, interpretable evaluation of subgroup-level variation during the selection process.

Adult and Pediatric Models (V1)

Equity Subgroups for the Adult and Pediatric models (V1) were considered across Race, Ethnicity, Sex, Language, and Access:

- New Medicaid Enrollee
- Primary Language English
- Primary Language Spanish
- Female
- Male
- Hispanic or Latino
- Asian
- Black or African American
- Native Hawaiian or Pacific Islander
- Other Race
- Unknown Race
- White

- American Indian or Alaskan Native

Note: Medicare dual eligible members and housing insecure members were initially considered for inclusion in the formal equity evaluation during the Tiering Analysis but were ultimately excluded for different reasons.

Medicare dual eligible members were excluded from the formal equity subgroup evaluation across all models and were also excluded entirely from scoring in the two Underutilization subdomain models. This decision was driven by data availability limitations rather than clinical considerations. Most inpatient, outpatient, and prescription drug utilization for dual eligible members is captured in Medicare claims rather than Medi-Cal claims, and Medicare claims data were not available for use in RSST. As a result, including dual eligible members in underutilization modeling could have led to systematic overclassification of underutilization, simply due to incomplete visibility into their true utilization patterns. This exclusion does not imply that dual eligible members are lower risk; rather, it reflects a deliberate choice to avoid biased signals arising from missing data. Dual eligible members remained included in RSST overall for the remaining subdomains, and the Work Group remains open to future updates as additional data sources become available.

Housing insecurity was excluded from the formal equity evaluation for a separate reason. Housing insecurity is the sole outcome in the Social Risk domain in V1, and prior housing insecurity was a strong predictor of future housing insecurity. As a result, members identified as housing insecure were, by design, more likely to be classified as high risk, and including this subgroup in the equity evaluation would have reflected outcome definition rather than differential model performance. When subgroup-level disparities were identified during development, the Work Group considered several remediation options, including refining outcome definitions. Work group evaluation of disparities and selection of remediation approach, if any, was based on case-by-case evaluation incorporating contextual understanding, recognizing that not all disparities in performance reflect algorithmic bias. For example, the inclusion of a Pediatric Chlamydia screening measure improved predictive performance for females but was not applicable to males. After reviewing the data and model outputs, the Work Group concluded this pattern reflected real-world clinical relevance and chose to retain the outcome.

Birthing Models (V1.1)

The Birthing models followed the same bias and sensitivity evaluation approach as the Adult and Pediatric V1 models to maintain methodological consistency. Equity considerations were reviewed throughout model training and tiering analysis with input from the Work Group and clinical subject matter experts, and the same relative benchmark was applied: subgroup recall values were assessed against the statewide average using the ±20% threshold as a screening tool.

Equity subgroups were modified to reflect the Birthing population and available data. Sex-based subgroups were removed because the models are restricted to female members. Additional subgroups were added following review:

- Housing Instability (not an outcome in the Birthing models),
- Age 18 and under,
- Age 40 and over,
- Rural residence based on ZIP code–level 2020 USDA RUCA classifications
- Urban residence based on ZIP code–level 2020 USDA RUCA classifications.
- Note: All other equity subgroups were consistent with V1.

Subgroup-level performance was reviewed during model training when available and reassessed during tiering analysis when Birthing subdomain models were combined into a single domain. Additional analyses based on timing of initial high risk classification within a pregnancy episode were explored during training but were not included in the formal tiering equity evaluation, as they were intended to inform model understanding rather than equity assessment.

G. Tiering Analysis Methods

1) Goals of Tiering – Adult and Pediatric Models (V1)

The RSST Algorithm was developed to help DHCS identify Medi-Cal members who are most likely to benefit from proactive services and outreach. To support implementation, DHCS established an initial high-risk tier ceiling: no more than 10% of the total Medi-Cal population should be classified as high risk in Version 1. This target was informed by policy guidance and stakeholder input and reflects what is operationally feasible for managed care plans to assess and engage. Over time, this ceiling may be adjusted as additional tiering strategies and capacity are introduced.

To ensure a consistent definition of high risk across plans and regions, the algorithm outputs a numeric risk score for each of five subdomain models, separately for Adults and Pediatrics. These scores are translated into tier assignments—low, medium, or high—using fixed threshold values. In total, 20 thresholds are applied: one for each subdomain across the two population strata. This structure enables a common definition of “high risk” that is applied uniformly, supporting alignment in how resources and services are allocated statewide.

To define these thresholds, the RSST Work Group used predicted risk scores from January 2023—the most recent month in the training environment for which subsequent 12-month outcomes were knowable. High-risk thresholds were set at the subdomain level such that, in combination, they would flag approximately 10% of the Medi-Cal population as high risk. Given that this was done on historic data, but launching on the current population, an extra step was taken to translate 2023 subdomain-level high risk rates to 2025 corresponding risk score thresholds.

After that adjustment, these values are held fixed over time rather than recalculated each month, allowing the definition of high risk to remain stable even as population characteristics shift. This means that the flagged proportion may vary slightly in future months and monitoring and adjustments will be needed on a regular basis for operational continuity.

In contrast, the medium-risk threshold was set using a simpler method—at the point corresponding to 50% recall in each subdomain model. The selection of high-risk thresholds was treated as a key policy decision—just as impactful as the model design itself—because it is eventually intended to determine which members are prioritized for outreach and assessment.

Note: The placement of “medium” risk threshold should be considered a pre-decisional placeholder, while the team conducts further analyses to refine this simple approach.

1.1) Goals of Tiering – Birthing Models (V1.1)

Tiering for the Birthing models differs from the Adult and Pediatric approach in several important ways driven by policy context and population size. The Birthing models include only two tiers—medium and high—rather than low, medium, and high, reflecting existing DHCS policy to engage all pregnant members and reducing the need for an additional lower-risk cutoff. The Birthing models were also not subject to the top-down 10% high-risk ceiling used for the full Medi-Cal population. Instead, a data-informed reference point was derived from the observed prevalence of the three Birthing outcome baskets, resulting in an approximate 27% high-risk benchmark within the Birthing population rather than across the total Medi-Cal population. In other words, tiering was conducted with the goal of classifying approximately 27% of Birthing episodes as high risk (Note that this results in less than 27% of Birthing population being classified as high risk in any one particular month of predictions). Birthing members fully overlap the Adult or Pediatric strata and may also be independently flagged as high risk by any of the V1 RSST models. As with the Adult and Pediatric models, once selected, Birthing tier thresholds are held fixed over time to support stability and consistent operational use, with ongoing monitoring to assess alignment with policy and capacity.

2) Tiering Options Considered

Because the RSST Algorithm produces separate model outputs for each of the five subdomains, the RSST Work Group considered multiple options for how to define "high risk" at the subdomain (i.e. model) level, and the implications of each of these options for member-level high risk tiers. Each option prioritizes a different principle for how high risk tiers were determined across the subdomains and members flagged for assessment.

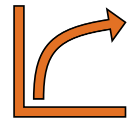
Option 1 flagged the same percentage of members as high risk from each subdomain. This was the most straightforward and interpretable approach but did not adjust for model performance and tended to over-represent members flagged by models predicting less common outcomes. As a result, more members flagged as high risk under this option may not go on to experience an adverse outcome.

Option 2 aimed to balance risk tier performance across subdomains by ensuring each model flagged high-risk members at the same level of recall (sensitivity)—that is, flagging a similar share of members who actually go on to experience a poor outcome in that subdomain. This resulted in different proportions of members flagged across models, providing a more complete representation of how effectively each model identifies true cases.

Option 3 prioritized overall recall (for at least one outcome in any subdomain) by concentrating high-risk flags in the models with the highest model performance. This option pulled more high-risk members from models that were better able to identify future adverse outcomes, potentially maximizing the number of members flagged who would go on to need services, but allowing the share of members flagged who actually go on to experience a poor outcome in that subdomain to vary across subdomains.

Each of these options was evaluated for performance (recall and NNT) under fixed resource constraints, such as targeting approximately 10% of the population as high risk. While the total number of members flagged was consistent across options, the distribution of who was flagged and why varied significantly, with tradeoffs in equity, interpretability, and predictive value.

Table 6. Summary of Tiering Options Considered

	Option 1	Option 2	Option 3
			
Highest Priority	Having the same percentage of members flagged as high risk from each subdomain	Balancing the level of recall (sensitivity) across all subdomains	Maximizing total level of recall (sensitivity) across all subdomains
Because outcomes across subdomains are not equally common and each algorithm has different performance…			
Implications	» Comparatively over-weights less-common outcomes among those identified as high risk » May result in more people flagged as high risk who do not go on to have a poor outcome	» Results in different percentages of members flagged as high risk in each domain	» May identify more overall people flagged as high risk who would go on to have a poor outcome

Birthing Model Tiering Options

The same three tiering options were evaluated for the Birthing models using the same performance metrics as the Adult and Pediatric models (recall and NNT), with adaptations reflecting the clinical and policy context of pregnancy. Unlike Adult and Pediatric tiering, Option 1 for Birthing did not begin by flagging the same percentage of members from each model. Instead, initial high-risk rates were informed by the observed prevalence of each Birthing outcome basket, reflecting substantial differences in outcome frequency across the three models. This approach was used to empirically establish an overall high-risk reference point of approximately 27% when the three models were combined at the pregnancy episode level.

This episode-level benchmark was then applied as the top-down constraint for Options 2 and 3, analogous to the 10% ceiling used in Adult and Pediatric V1 tiering. DHCS did not specify a fixed resource constraint for Birthing; instead, guidance was to allow observed outcomes to inform reasonable thresholds. Consistent with how Birthing models were trained, the Birthing models were tiered and evaluated at the episode-level rather than for any one month of data, reflecting how pregnancy-related care management is expected to be delivered.

a. Tiering Technical Methods

1. Option 1

To implement Option 1, we operationalized a thresholding strategy that applied a fixed top-K approach within each subdomain model. This strategy aimed to flag a consistent percentage of individuals—such as the top 1%, 5%, or 10%—as high-risk each month in the test set.

We began by calculating monthly risk score rankings for each subdomain. For every person-month, individuals were ranked in descending order of predicted risk. A fixed proportion of individuals (e.g., top 1%) were designated as high-risk based on this rank. The lowest risk score within the flagged group was extracted to serve as the month-specific cutoff. These cutoffs were then averaged across months to produce a stable threshold per subdomain model. This step ensured temporal smoothing and reduced volatility in the high-risk designations over time. Once the subdomain thresholds were computed, a member was flagged as high-risk within a subdomain if their subdomain predicted risk score met or exceeded the corresponding threshold.

To support implementation under multiple policy configurations, we ran this process using three global targeting constraints: 5%, 8%, and 10% of the total Medi-Cal population. For each setting, the appropriate top-K percentages were applied per subdomain to ensure that cumulative high-risk designation across the state remained within the specified constraint.

2. Option 2

To operationalize Option 2, we implemented an iterative threshold selection process designed to achieve consistent recall across subdomains while adhering to a global constraint on the total size of the high-risk tier. This approach directly supported the goal of equitable identification across risk domains, ensuring that no single model disproportionately influenced high-risk designation due to differences in outcome prevalence or model performance.

The implementation proceeded in two stages. First, we estimated the risk threshold required to achieve a target recall value using a binary search algorithm for each subdomain model. Candidate thresholds were sampled from the range of predicted risk values within each model, and recall was computed based on true positives and false negatives. The search continued until the threshold produced recall within a pre-specified tolerance of ±2% of the target recall.

In the second stage, we calculated the percent of members flagged as high-risk using the selected subdomain thresholds. If the total exceeded or fell short of the global target (e.g., 5% of all members), the recall target was adjusted, and the process was repeated. This loop continued iteratively, adjusting the recall target in small increments and re-running the binary search for each subdomain model until the final selected set of thresholds collectively satisfied both the balanced recall constraint and the population-level targeting constraint (±0.5% of the specified 5%, 8%, or 10% total).

This approach yielded a threshold set that provided uniform recall across domains, supported transparent documentation of tradeoffs, and served as a strong candidate for policy options focused on equity and broad-based targeting.

3. Option 3

To implement Option 3, we operationalized a strategy designed to identify the combination of subdomain thresholds that would maximize overall recall while ensuring that the total number of flagged individuals remained within a global targeting constraint (e.g., 10% of the Medi-Cal population).

Threshold selection was performed using Optuna, which systematically searched over combinations of pre-defined candidate thresholds. In each optimization trial, thresholds were set for each subdomain. These thresholds were applied to generate binary flags indicating whether each individual was predicted to be high-risk in each subdomain. These subdomain-level flags were then coalesced to create a composite high-risk designation across subdomains, and this designation was compared to observed outcomes to calculate recall. The primary objective of the optimization was to maximize this recall score.

Every trial was also subject to the initial hard constraint: the proportion of members flagged as high-risk must fall within a fixed margin (±0.5%) of the specified global target (e.g., 5%, 8%, or 10%). Trials that produced target rates outside this range were pruned early to avoid unnecessary computation. This combination of constraint-based pruning and performance-driven scoring allowed the optimization algorithm to efficiently converge toward high-recall configurations that remained operationally feasible with the global targets. The final result of this process was a set of optimized subdomain thresholds that jointly produced the highest recall achievable under the imposed constraint.

4. Computing Final Metrics

After identifying thresholds and assigning high risk flags among all members enrolled in Medi-Cal in January 2023, we created a derived variable to indicate whether the member had experienced an outcome in the following 12 months. This enabled us to compute the empirical measures used for tiering evaluation such as recall, NNT, and distribution of risk by across risk domains.

For the Birthing models, tiering options were implemented using the same technical framework described above, with targeted modifications to Option 1. Rather than applying a uniform top-K percentage across subdomains, Option 1 thresholds used prevalence-informed top-K values specific to each Birthing subdomain, based on observed outcome frequencies in the training data. Thresholds and performance metrics were derived using all pregnancy episodes available in the training environment, subject to the limits of the underlying data window, rather than a single monthly cross-section.

All Birthing thresholds were computed at the pregnancy episode level rather than monthly. Episode-level risk scores were ranked and aggregated to derive stable subdomain thresholds, consistent with the smoothing principles used in V1. These thresholds were first used to establish a combined episode-level high-risk reference point and were then applied as the population-level constraint for Options 2 and 3. Final evaluation metrics, including recall and NNT, were calculated using the same definitions as in the Adult and Pediatric analyses.

3) Tiering Analysis Evaluation Criteria

Options were evaluated and scored based on five key principles and associated empirical measures laid out ahead of time (see below) to drive selection of tiers most aligned with the DHCS vision for the RSST algorithm. These principles were used to assess the advantages and disadvantages of each option to drive policymakers' decision of which option to select for the V1 release. While the measures in the list are objective, the relative balancing of these principles was a subjective policy decision that required iterative, data-informed discussions.

Principle	Description	Empirical Measure
Technical Performance	The predictive performance of the RSST algorithm overall, compared with industry standards and subject matter expertise.	• **AUC (Area Under the ROC Curve):** Measures the trade-off between the model's recall and its specificity (true negative rate) across different thresholds. • **Recall:** Percent of members with an adverse event who are flagged as high-risk. • **NNT**: Number needed to treat before identifying a member who had an adverse event.
Balance of Risk Types	The balance across adverse events, underutilization, and social domains.	• **Distribution of domains among high-risk members**: Among members who are flagged as high-risk, what percent of members are flagged because of each domain.
Equity	The predictive performance of the RSST algorithm by subgroups of interest.	• **Distribution of high-risk by subgroup:** Among subgroups, what percentage of members would be flagged as high-risk. • **Comparative recall by subgroup:** Compared to the overall State Weighted Average, who recall performs across each subgroup.
Potential Benefits	The possible benefits of driving improved health outcomes, timely interventions, and better resource allocation.	• **Net new assessments:** Number of members who would receive a net new assessment who would not have received one otherwise. • Count of net new needs assessments on members who went on to have an event.
Potential Costs and Impacts	The estimated costs of RSST needs assessments and possible direct impacts to stakeholders.	• **Estimated Costs Overall and by Plan:** Estimate the net-new needs assessments and high-risk TCS events that would have been triggered by the RSST algorithm, in the context of 2023 experience.

Note: For the Birthing models Tiering Analysis, we did not assess Potential Costs. We did assess the variance of impact on plans as well as the overlap in high risk flags with existing RSST Adult and Pediatric models at a historic point in time cross section.

VI. MODEL RESULTS

A. Outcomes Detail

1) Adult and Pediatric Models (V1) Outcome Development Process

Each outcome proposed for RSST V1 was evaluated for feasibility of construction, consistency across populations, and overall utility in supporting meaningful risk stratification. Several outcomes were ultimately excluded due to data limitations or incomplete logic at the time of model development. For example, colorectal cancer screenings and influenza vaccinations require additional clinical data and could not be reliably identified solely through the available claims data.

DHCS subject matter experts were consulted throughout the process to ensure that outcome definitions were consistent with internal measurement logic and program standards. For example:

- The primary care visit outcome used a DHCS-specified taxonomy of provider types to reflect established definitions.
- The dental outcome logic was refined in collaboration with a DHCS dental SME to ensure appropriate coding of fluoride and preventive care.
- Housing insecurity was defined using a DHCS-supplied list of address strings associated with shelters and transitional housing programs.

Several outcomes also underwent significant revision to improve specificity. The underutilization domain in particular required substantial refinement. Initial definitions were too broad, capturing large portions of the population and limiting the ability of the models to distinguish higher-risk members. The Work Group introduced more targeted eligibility criteria for specific underutilization outcomes to better facilitate identification of clinically relevant subgroups. For example:

- The Adult primary care visit underutilization outcome was narrowed to include only members with recent hospital or ED use who did not have a follow-up visit.

- The Pediatric dental care underutilization outcome was limited to children with elevated clinical risk, including those with cardiac conditions, developmental delay, autism spectrum disorder, or recent ED or inpatient visits for dental concerns, who did not have a dental visit.
- The Adult care disengagement outcome was defined as Adults with no claims history in the two years prior to the index date who also had no claims in the following year.

These adjustments helped ensure that the outcomes used in RSST V1 were both actionable and appropriate for use in predictive modeling across the Medi-Cal population. Definitions for each outcome are provided below, grouped by strata, domain, and subdomain.

1.1) Birthing Models (V1.1) Outcome Development Process

Outcome development for the Birthing models followed the same principles as RSST V1 Adult and Pediatric models—feasibility, clinical relevance, and actionability—while reflecting the unique clinical context of pregnancy and the postpartum period. Because the Birthing models do not include Underutilization or Social domains, all outcomes were classified as Adverse Events and organized into three composite subdomains: Pregnancy, Post-Pregnancy Physical Health, and Post-Pregnancy Behavioral Health.

DHCS engaged multiple clinical subject matter experts throughout outcome development to support coding logic, prevalence “gut checks,” and clinical rationale. SME input directly informed several key decisions. For example:

- Gestational Diabetes was initially identified as highly prevalent and insufficiently discriminative; based on clinical guidance, the outcome definition was refined to require both diagnosis codes and evidence of injectable insulin use, narrowing the outcome to a more clinically severe and actionable subset.
- SMEs also guided the use of all-cause inpatient admission, which was reviewed as a candidate outcome for both pregnancy and post-pregnancy periods but was ultimately retained only for the Pregnancy subdomain and removed from the Post-Pregnancy Physical model to better reflect clinical relevance.
- Several additional candidate outcomes were reviewed but ultimately excluded based on clinical guidance and data considerations, including Ectopic Pregnancy, Placenta Previa, selected congenital anomalies, short interpregnancy interval, and certain infections, due to concerns about accurate identification, given the available data, interpretability, or suitability for predictive modeling.

Unlike V1 Adult and Pediatric models, Birthing models were not constrained by a fixed top-down prevalence target during outcome selection. Given the smaller population size and current policy context, clinically meaningful outcome definitions were allowed to drive observed prevalence within reasonable bounds, resulting in differing prevalence and outcome counts across the three Birthing subdomains.

A complete list of Birthing outcomes and definitions is provided in the Outcomes Detail section below.

2) Adult Outcome Detail

a. Adverse Events: Physical

Outcome	Description	Data Source(s)
Mortality	The occurrence of death for an individual.	Supplemental Member Eligibility
Morbidity	Y/N Indicator of a net new increase of ≥1 in Charlson Comorbidity Index (CCI) count indicating an individual's departure from a state of physiological or psychological well-being. The CCI includes 17 conditions including diabetes, chronic pulmonary disease, congestive heart failure, cancer, and liver disease.	Medical Claims
All Cause Inpatient Admission	Y/N Indicator of any unplanned hospital admission, regardless of diagnosis or reason for admission.	Medical Claims
3 or More All Cause ED Visits	Y/N indicator that member had 3 or more visits to an ED or ED setting in a 12 month period, regardless of primary reason for the visit.	Medical Claims

b. Adverse Events: Behavioral

Outcome	Description	Data Source(s)
Care for Unintentional Drug Overdose	Healthcare encounter for care related to unintentional drug overdose.	Medical Claims
Injection Drug Related Adverse Event	Healthcare encounter for complications typically related to injection drug use within 90 days of an event with a confirmed opioid diagnosis.	Medical Claims
Care for Intentional Self Harm	Healthcare encounter for care related to intentional self-harm.	Medical Claims
Psychiatric Admission	Hospitalization where primary diagnosis is a psychiatric disorder (i.e., inpatient admission with primary diagnosis of mental health conditions).	Medical Claims

Outcome	Description	Data Source(s)
Two or More Psychiatric ED Visits	Two or more visits in ED or ED setting where primary reason for the visit is a psychiatric condition.	Medical Claims
Co-Occurring High ED Utilization and MH/SUD Care	Members with one or more Short Doyle visits and three or more all cause ED visits for any condition.	Medical Claims, Supplemental Claims

c. Underutilization: Physical

Outcome	Description	Data Source(s)
Underutilization of Primary Care Visit (among members with hospital usage)	Among Adult members who had at least 1 ED Visit or Inpatient Admission in the 12 months prior to index date, Y/N Indicator that the member did not have at least 1 outpatient visit to a primary care provider, based on DHCS definition of a PCP visit in the next 12 months.	Medical Claims
Underutilization of Dental Care (among a subset of members with prior dental related usage)	Members who had a visit with a dental diagnosis in a non-dental setting or have diagnoses indicating higher risk (i.e. cancer, cardiac) in prior year who did NOT have 1+ dental care visit.	Medical Claims
Underutilization of STI Screening (Chlamydia) Among Females 16-24 Years	Among female members aged 16–24 years as of the index month, Y/N Indicator that the member did NOT receive a chlamydia screening in the 12 month period post-index month. Note for Adult population this is 18-24 yr olds.	Medical Claims
Underutilization of Appropriate Pharmacotherapy for Common Indications (among members taking medications for those conditions)	Among Adult members who had at least 1 relevant diagnosis code and 1 disease-specific medication fill in the year pre-index date, separately for Hypertension and Diabetes, this is a Y/N indicator of sub-optimal medication days covered (<80% PDC) in the year post-index date for those medications.	Medical Claims, Pharmacy Claims
Underutilization of Asthma Controller Medications (among members with Asthma)	Y/N Indicator that members who were diagnosed with Asthma in the 12 months prior to index date, did NOT have a ratio of controller medications to total asthma medications of 0.50 or greater during the 12 months post index date.	Medical Claims, Pharmacy Claims

Outcome	Description	Data Source(s)
No Medical or Pharmacy Claims (among members with no claims history)	Y/N Indicator that an Adult member with no medical or pharmacy claims in the 2 years prior to index date will also have no medical or pharmacy claims in the 12 months post index date.	Medical Claims, Pharmacy Claims

d. Underutilization: Behavioral

Outcome	Description	Data Source(s)
Underutilization of MH/SUD Office Visits (among members with BH/SUD)	Members with an established MH/SUD diagnosis in prior year who did NOT have an ambulatory or preventive office visit (with any provider) with a diagnosis of MH/SUD.	Medical Claims
Underutilization of MH/SUD-Related Primary Care (among members with MH/SUD conditions)	Members with an established MH/SUD diagnosis in prior year who did NOT have a PCP visit with a diagnosis of MH/SUD.	Medical Claims
Underutilization of Antidepressant Medications (among members with the condition and past medication fills)	Among Adult members with a Major Depression diagnosis code and an Antidepressant Medication fill in the year prior to the index date, this is an indicator that the member had <180 days supply of those medications in the year post-index date.	Medical Claims, Pharmacy Claims
Underutilization of Antipsychotics (among members with schizophrenia)	Indicator of whether Adult members who had a schizophrenia diagnosis code AND who were dispensed any antipsychotic medications in the prior 12 months, remained on those medications, defined as having <80% PDC (<292/365d) within the prediction period by any antipsychotic medication (oral or long lasting injection) in the 12 months post-index date.	Medical Claims, Pharmacy Claims
Underutilization of Opioid Agonist Therapy (among members with OUD)	Y/N indicator of those who do NOT fill any prescription for an appropriate opioid agonist in the 12 months post-index date, among Adult members with an OUD diagnosis and a relevant medication fill in the 12 months pre-index date.	Medical Claims, Pharmacy Claims

e. Social: Adverse Events

Outcome	Description	Data Source(s)
Housing Instability	DHCS business logic measuring a proxy of housing instability using a combination of ICD10 z-codes, as well as how an individual's address is classified upon Medi-Cal enrollment, and the type of address used (e.g. homeless shelter, group housing).	Medical Claims (z-codes), Eligibility (street address)

3) Pediatric Outcome Detail

a. Adverse Events: Physical

Outcome	Description	Data Source(s)
All Cause Inpatient Admission	Y/N Indicator of any unplanned hospital admission, regardless of diagnosis or reason for admission.	Medical Claims
3 or more all cause ED visits	Y/N indicator that member had 3 or more visits to an ED or ED setting in a 12 month period, regardless of primary reason for the visit.	Medical Claims
New Diagnosis of common chronic illness	Y/N Indicator of a Pediatric patient increasing their rolling count of chronic illnesses anytime during the post-index 12 months	Medical Claims
Morbidity	Y/N Indicator of a Pediatric patient's movement to a level of higher medical complexity sometime during the rolling 12-month post-index period, as defined by the Pediatric Medical Complexity Algorithm (PMCA), such as moving from no chronic disease to a noncomplex chronic disease (NC-CD) state, or from a noncomplex chronic disease to complex chronic disease (C-CD) state.	Medical Claims

b. Adverse Events: Behavioral

Outcome	Description	Data Source(s)
New Diagnosis of mental illness	Y/N indicator that a member with no MH diagnoses (based on Claims based) in the 12 months prior to index date, had a claim with a MH diagnosis code in the 12 months post index date.	Medical Claims
New diagnosis of developmental delay	Y/N indicator that a member with no DD diagnoses (based on CDPS mapping table) in the 12 months prior to index date, had a claim with a DD diagnosis code in the 12 months post index date.	Medical Claims

Outcome	Description	Data Source(s)
New diagnosis of SUD	Y/N indicator that a member with no SUD diagnoses (based on Claims based and F10-F19 ICD10Dx codes) in the 12 months prior to index date, had a claim with a SUD diagnosis code in the 12 months post index date.	Medical Claims
Psychiatric Admission	Hospitalization where primary diagnosis is a psychiatric disorder (i.e., inpatient admission with primary diagnosis of mental health conditions).	Medical Claims
Psychiatric ED Visit	One or more visits in ED or ED setting where any diagnosis code on the claim for the visit indicates a psychiatric condition.	Medical Claims
Care for Drug Overdose	Healthcare encounter for care related to unintentional drug overdose.	Medical Claims
Care for Intentional Self Harm	Healthcare encounter for care related to intentional self-harm.	Medical Claims

c. Underutilization: Physical

Outcome	Description	Data Source(s)
Underutilization of STI Screening (Chlamydia) among females 16- 24 years	Among female members aged 16–24 years as of the index month, Y/N Indicator that the member did NOT receive a chlamydia screening in the 12-month period post-index month. Note that for Pediatric population this is 16-17yr olds.	Medical Claims
Underutilization of Well child visits (for children in the first 30 months of life)	Members aged 16 to 30 months at the end of the outcome period who did NOT have at least 2 well-care visits. Note: Members less than 16 months of age at the end of the outcome period were not eligible to be included in this measure as they were not included in the Pediatric population (due to being 0 to 3 months of age) at the beginning of the outcome period.	Medical Claims
Children and Adolescents with no claim's utilization	Among members aged 30 months to 17 years old with no medical or pharmacy claims in the year prior to index date, this is a Y/N Indicator that the member also had no medical or pharmacy claims in the year post index date.	Medical Claims, Pharmacy Claims
Underutilization of Topical Fluoride and/or Dental Care	Among a subset of Pediatric members with any of the following conditions in the year prior to the index date, 1) a cardiac diagnosis (based on PMCA body systems), 2) an ED visit or Inpatient admission with a dental diagnosis code (primary or secondary position), 3) an autism spectrum disorder diagnosis,	Medical Claims, Dental Claims

Outcome	Description	Data Source(s)
	4) a developmental delay diagnosis, This is a Y/N indicator that those members will NOT receive at least one topical fluoride application (CPT/CDT codes) or at least one dental claim (CDT codes) in the 12 months post-index date,	
Underutilization of Immunizations	Members aged 0 to 12 months at the start of the outcome period who did NOT have at least one dose of 6 different immunizations recommended for this age bracket.	Medical Claims, Pharmacy Claims
Underutilization of Asthma Controller Medications (among members with Asthma)	Among members with an Asthma diagnosis code in the 12 months prior to index date, this is a Y/N Indicator that the member did NOT have a ratio of controller medications to total asthma medications of 0.50 or greater during the 12 months post index date.	Medical Claims, Pharmacy Claims

d. Underutilization: Behavioral

Outcome	Description	Data Source(s)
Underutilization of PCP Visits (among members with BH/SUD)	Patients with an established MH/SUD diagnosis in prior year who did NOT have a PCP visit in the prior year or the current year.	Medical Claims
Underutilization of MH/SUD related office visits (among members with MH/SUD conditions)	Members with an established MH/SUD diagnosis in prior year who did NOT have an ambulatory or preventive office visit (with any provider) with a diagnosis of MH/SUD in the prior year or the current year.	Medical Claims
Underutilization of Metabolic Screenings (among members with Antipsychotics)	Among members with 2 or more antipsychotic prescriptions in the 12 months prior to the index date, this is a Y/N indicator that the member DID NOT receive the appropriate metabolic monitoring (both cholesterol and glucose tests) services in the 12 months post index date.	Medical Claims, Pharmacy Claims
Underutilization of Follow-up visits (among members with an admission or ED visit for MH/SUD)	Among members with a psychiatric ED visit or psychiatric admit, this is a Y/N indicator that the member DID NOT have any appropriate follow-up visits within 30 days of the hospital visit, in the 12 months post index date.	Medical Claims
Underutilization of ADHD follow-up care (among members	Among members who had at least 210 days supply of ADHD medications in the 12 months prior to index date, this is a Y/N indicator	Medical Claims, Pharmacy Claims

Outcome	Description	Data Source(s)
taking ADHD medications)	that the member DID NOT receive an adequate follow up visit in the 12 months post index date.	

e. Social: Adverse Events

Outcome	Description	Data Source(s)
Housing Instability	DHCS business logic measuring a proxy of housing instability using a combination of ICD10 z-codes, as well as how an individual's address is classified upon Medi-Cal enrollment, and the type of address used (e.g. homeless shelter, group housing).	Medical Claims (z-codes), Eligibility (street address)

4) Birthing Outcome Detail

a. Pregnancy Adverse Events

Outcome	Description	Data Source(s)
Care for Unintentional Drug Overdose	Healthcare encounter for care related to unintentional drug overdose.	Medical Claims
Care for Intentional self-harm	Healthcare encounter for care related to intentional self-harm.	Medical Claims
Injection Drug Related Adverse Event	Healthcare encounter for complications typically related to injection drug use within 90 days of an event with a confirmed opioid diagnosis	Medical Claims
Care for Maltreatment/abuse	Healthcare encounter for care related to Maltreatment/abuse	Medical Claims
Psychiatric ED Visit	One or more visit in ED or ED setting where primary reason for the visit is a psychiatric condition.	Medical Claims
All cause inpatient admissions	Y/N Indicator of any unplanned hospital admission, regardless of diagnosis or reason for admission.	Medical Claims
Thromboembolism	Healthcare encounter for care related to thromboembolism during pregnancy	Medical Claims
Maternal Mortality	The Birthing member has a recorded death during the post-pregnancy window (from enrollment/death data and/or claims), using the reported date of death as the event date.	Medical Claims; Enrollment data
Gestational diabetes requiring insulin	Healthcare encounter for care related to gestational diabetes with evidence of administration of insulin during pregnancy	Medical Claims; Pharmacy Claims
Placental abruption	Healthcare encounter for care related to placental abruption during pregnancy	Medical Claims
Severe fetal outcome	Pregnancy ending in a non-live birth	Medical Claims

Outcome	Description	Data Source(s)
Severe maternal morbidity composite	Delivery with evidence of one or more of the severe maternal morbidity diagnoses	Medical Claims
Unplanned C-Section	Cesarean delivery with evidence of anesthesia/epidural administration for a vaginal delivery first	Medical Claims
Neonatal NICU	Healthcare encounter indicating ICU/NICU care during delivery event or on the infant's record within the first 28 days of life	Medical Claims; (Matching only: Vital Birth Records; SUME)
Neonatal mortality	The linked infant has a recorded death within 28 days of birth (from vital birth/enrollment data), using the infant's death date as the event date	Medical Claims; (Matching only: Vital Birth Records; SUME)
Neonatal Abstinence Syndrome	Healthcare encounter for care related to neonatal abstinence syndrome on the infant's record within the first 28 days of life	Medical Claims (Matching only: Vital Birth Records; SUME)
Early preterm and/or very low birthweight	Infant birth record indicating early preterm birth before 34 weeks gestation or birthweight less than 1,500 grams	Vital Birth Records; SUME

b. Post-Pregnancy Physical Adverse Events

Outcome	Description	Data Source(s)
Post-pregnancy hypertensive disorders	Any medical claim in the post-pregnancy window carries a diagnosis for hypertensive disorders of pregnancy (e.g., gestational hypertension, preeclampsia/eclampsia)	Medical Claims
Post-pregnancy hemorrhage	Any medical claim with a hemorrhage ICD-10 diagnosis code starting with "O72.X" with service-date in the post-pregnancy window	Medical Claims
Thromboembolism (DVT/PE)	Any medical claim in the post-pregnancy window contains diagnosis/procedure codes indicating DVT or pulmonary embolism.	Medical Claims
Maternal mortality	The Birthing member has a recorded death during the post-pregnancy window (from enrollment/death data and/or claims), using the reported date of death as the event date.	Medical Claims; Enrollment Data
Infant mortality	The linked infant has a recorded death within 28 days of birth (from vital birth/enrollment data), using the infant's death date as the event date	Medical Claims; Enrollment Data; (Matching only: Vital Birth Records; SUME)
Infant NICU	The linked infant is admitted to a neonatal intensive care unit within the first month of life, captured via NICU revenue codes	Medical Claims; (Matching only: Vital Birth Records; SUME)

c. Post-Pregnancy Behavioral Adverse Events

Outcome	Description	Data Source(s)
Care for Unintentional Drug Overdose	Healthcare encounter for care related to unintentional drug overdose.	Medical Claims
Care for Intentional self-harm	Healthcare encounter for care related to intentional self-harm.	Medical Claims
Injection Drug Related Adverse Event	Healthcare encounter for complications typically related to injection drug use within 90 days of an event with a confirmed opioid diagnosis	Medical Claims
Care for Maltreatment/abuse	Healthcare encounter for care related to Maltreatment/abuse	Medical Claims
Psychiatric ED Visit	One or more visit in ED or ED setting where primary reason for the visit is a psychiatric condition.	Medical Claims
Psychiatric Admission	Hospitalization where primary diagnosis is a psychiatric disorder (i.e. inpatient admission with primary diagnosis of mental health conditions).	Medical Claims

B. Predictors Detail

1) Socio-Demographic Risk Factors

Predictor	Description	Data Source	Population	Lookback
months_enrolled	Total number of distinct Medi-Cal enrolled months per unique member, in the full history ("ever"), and within a rolling 3- and 12-month lookback from index date.	Eligibility	Adult, Pediatric, Birthing	3mo, 12mo, ever
disability_status	Composite Y/N indicator of a member having either ABD (Age Blind Disabled) or SPD (Senior and Persons with Disability) flags in their data in the 12 months prior to the index date.	Eligibility	Adult, Pediatric	ever
gaps_in_enrollment	Number of distinct, continuous gaps in eligibility of at least 1 month in duration within a rolling 12-month lookback prior to the index date.	Eligibility	Adult, Pediatric, Birthing	12mo, ever
age	Whole number age as of the last day of the index month, based on date of birth value.	Eligibility	Adult, Pediatric, Birthing	

Predictor	Description	Data Source	Population	Lookback
primary_language indicators (n= 30 languages + missing)	Latest recorded primary member language as included in the APCD-CDL Member Eligibility layout, as of the index month.	Eligibility	Adult, Pediatric, Birthing	
race_category indicators (n=8)	Latest recorded member race as included in the APCD-CDL Member Eligibility layout, as of the index month, with DHCS code mapping logic applied.	Eligibility	Adult, Pediatric, Birthing	
ethnicity_category (n=2)	Latest recorded member ethnicity as included in the APCD-CDL Member Eligibility layout, as of the index month, with DHCS code mapping logic applied.	Eligibility	Adult, Pediatric, Birthing	
sex (M, F, U)	Latest recorded sex as of the index month, as included in the APCD-CDL Member Eligibility layout CDLME018 provided by DHCS	Eligibility	Adult, Pediatric	
county of residence indicator (n=58)	Latest recorded member county of residence as of the index month	Eligibility	Adult, Pediatric, Birthing	
aid_code_category indicators (n=8)	Each member's aid code category was used as a categorical predictor, reflecting eligibility classification, and was one-hot encoded into binary indicators representing categories such as ACA expansion, adoption/foster care, CHIP, long-term care, parents/caretaker relatives and children, seniors and persons with disabilities, undocumented, and unknown.	Eligibility	Adult, Pediatric, Birthing	
is_medicare_dual	Indicator of Medicaid/Medicare Dual enrollment via appearance of Medicare ID	Supplemental Member Eligibility	Adult, Pediatric, Birthing	
line_of_business_non_medicaid	Y/N indicator if member was enrolled with DHCS via a non-MEDICAID line of business or "product id" in the 12 months prior to the index date (e.g. GHPP, CCS, FPACT).	Eligibility	Adult, Pediatric, Birthing	
avg_persons_per_housing_unit	Average number of people per housing unit, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	
median_income	Median annual income, based on member's ZCTA of residence (ACS 2017).	American Community	Adult, Pediatric, Birthing	

Predictor	Description	Data Source	Population	Lookback
		Survey (ACS), 2017		
pct_25_hs_degree	Percentage of residents age 25+ with at least a high school diploma, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	
pct_Adults_employed	Percentage of Adults (age 16+) who are employed, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	
pct_bach_degree	Percentage of residents with a bachelor's degree or higher, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	
pct_hh_w_2_parents	Percentage of households with children that have two parents, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	
pct_hh_w_automobile	Percentage of households with access to at least one vehicle, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	
pct_income_over_2x_poverty	Percentage of families with income at or above 200% of the federal poverty level, based on member's ZCTA of residence (ACS 2017).	American Community Survey (ACS), 2017	Adult, Pediatric, Birthing	

Note: "Ever" lookbacks do not apply to Birthing models

2) Transition Events

Predictor	Description	Data Source	Population	Lookback
moving_different_address	Indicator for the month that a member moves to a different address than where they lived in the prior month (for model purposes, this will be a Y/N if member moved in a 12 month pre-index period)	Eligibility	Adult, Pediatric, Birthing	12mo

Predictor	Description	Data Source	Population	Lookback
moving_different_county	Indicator for the month that a member moves to a different geographic county than where they lived in the prior month (for model purposes, this will be a Y/N if member moved in a 12 month pre-index period)	Eligibility	Both Adult, Pediatric, Birthing	12mo
new_medicaid_enrollee	Indicator of the earliest Medi-Cal enrollment three month period for the member, looking back to the full available history up to 1/1/2016	Eligibility	Adult, Pediatric, Birthing	12mo
returning_medicaid_enrollee	Indicator for the first three months of a member regaining Medi-Cal enrollment after an Enrollment Gap of any duration 1 month or more	Eligibility	Adult, Pediatric, Birthing	12mo
snf_indicator	Y/N indicator of any SNF claims utilization in the 12mo prior to the index date	Medical Claims	Adult, Pediatric, Birthing	12mo
switch_aid_category	Y/N indicator if member switches their Medicaid aid category in the last 12 months	Eligibility	Adult, Pediatric, Birthing	12mo
switch_lob	Y/N indicator if member switches their line of business (product id) in the last 12 months	Eligibility	Adult, Pediatric, Birthing	12mo
switch_medical_plans	Y/N indicator that a member has changed which Medi-Cal Managed Care Plan (MCP) "Parent" they are managed by during the 12 month period prior to the index date; for Fee for Service (FFS) members, we flag if a member moves between FFS and managed care.	Eligibility	Adult, Pediatric, Birthing	12mo
transition_to_ihss	Y/N indicator that a member has any in home supportive services (IHHS) provided to them in the 12 months prior to index date, using aid codes available on the APCD-CDL medical claims layout from DHCS.	Medical Claims	Adult, Pediatric, Birthing	12mo
Pediatric_to_Adult	Indicator for the month that a member aged into the Adult population strata. For the purposes of modeling this will result in a Y/N indicator applied to the entire pre-index 12 month lookback period if member turned 18 within that pre-index period	Eligibility	Adult	12mo

Note: “Ever” lookbacks do not apply to Birthing models

3) Prior Use

Predictor	Description	Data Source	Population	Lookback
ip_claims	Count of Inpatient visits on distinct service dates, within three overlapping lookback periods: 3 months, 12 months prior to index date, as well as a full "ever" lookback to earliest data available pre index date. Based on place of service (POS) codes in claims data.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
office_claims	Count of Office visits on distinct service dates, within three overlapping lookback periods: 3 months, 12 months prior to index date, as well as a full "ever" lookback to earliest data available pre index date. Based on place of service (POS) codes in claims data.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
op_claims	Count of Outpatient visits on distinct service dates, within three overlapping lookback periods: 3 months, 12 months prior to index date, as well as a full "ever" lookback to earliest data available pre index date. Based on place of service (POS) codes in claims data.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
bh_claims	Y/N indicator if member has at least 1 Short Doyle / Behavioral Health claim in a rolling 12 month lookback pre-index date.	Medical Claims	Adult, Pediatric, Birthing	12mo
ccs diagnosis & procedure code groupings binary flags (n=365)	Diagnosis: CCS groupings of a member's diagnosis codes, primary and secondary, in 12 month lookback period prior to index month (without regard to clinical setting). This flags for each member a Y/N indicator for each of the ccs minor categories. Procedure: CCS groupings of a member's procedure codes, in 12 month lookback period prior to index month (without regard to clinical setting). This flags for each member a Y/N indicator for each of the ccs minor categories specific to procedure codes.	Medical Claims	Adult, Pediatric, Birthing	12mo
count_of_rx_fill	Count of prescription fills in the prior 12 months	Pharmacy Claims, Medispan	Adult, Pediatric, Birthing	12mo
dme_use	Y/N indicator of "any" DME/Devices claims in the 12 months prior to index date	Medical Claims	Adult, Pediatric, Birthing	12mo

Predictor	Description	Data Source	Population	Lookback
rx Medispan drug class indicators (n=144)	Y/N Indicator of each distinct Medispan drug class that member has a filled prescription claim for in the 12 months prior to the index date.	Pharmacy Claims, Medispan	Adult, Pediatric, Birthing	12mo
rx_fill_hit_2000; rx_fill_hit_500	Two binary Y/N indicators of Total insurance paid amounts on prescription fills in the 12 months prior to the index date hits a) $500 and b) $2000 respectively.		Adult, Pediatric, Birthing	12mo

Note: "Ever" lookbacks do not apply to Birthing models

4) Outcomes as Risk Factors

Predictor	Description	Data Source	Population	Lookback
all_cause_ed_visits	Count of distinct Emergency Department person-claim-service-dates in the 12 months prior to index date, using the same underlying logic as the all cause ED outcome.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
all_cause_inpatient_admission	Count of distinct inpatient admission dates in the past 12 months, regardless of diagnosis.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
dental_care	Binary indicator for whether the member had any dental care encounter in the past 12 months.	Medical Claims, Dental Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
drug_overdose	Count of distinct drug overdose event dates in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
intentional_self_harm	Binary indicator for whether there was any intentional self-harm event recorded in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
mh_sud_visits	Count of distinct outpatient or professional visits for mental health or substance use diagnoses in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
pcp_visits_bh_sud_diagnosis	Count of primary care visits with a behavioral health or substance use diagnosis in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
psychiatric_admission	Count of distinct psychiatric inpatient admissions in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever

Predictor	Description	Data Source	Population	Lookback
psychiatric_ed_visit	Count of distinct emergency department visits with psychiatric diagnosis in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	3mo, 12mo, ever
housing_instability	Binary indicator for any evidence of housing instability in the past 12 months, using DHCS business logic for address string values and ICD10 z-codes.	Medical Claims, Eligibility	Adult, Pediatric, Birthing	12mo
std_screening_chlamydia	Binary indicator for whether the member received chlamydia screening in the past 12 months.	Medical Claims	Adult, Pediatric, Birthing	12mo
Adult_morbidity	Count of distinct service dates for selected Adult morbidity diagnoses in the past 12 months. Specifically diseases within the Charlson Comorbidity Index logic.	Medical Claims	Adult, Birthing	3mo, 12mo, ever
injection_drug_related_adverse_event	Count of distinct events indicating injection drug use complications in the past 12 months.	Medical Claims	Adult, Birthing	3mo, 12mo, ever
primary_care_visit	Count of distinct primary care visits in the past 12 months.	Medical Claims	Adult, Birthing	3mo, 12mo, ever
antidepressant_medication_use	Count of distinct antidepressant medication fill dates in the past 12 months.	Pharmacy Claims	Adult, Birthing	12mo
antipsychotics_schizophrenia_use	Count of distinct antipsychotic medication fills for schizophrenia-related treatment in the past 12 months.	Pharmacy Claims	Adult, Birthing	12mo
opioid_agonist_therapy_oud	Count of distinct fill dates involving opioid agonist therapy for opioid use disorder in the past 12 months.	Pharmacy Claims	Adult, Birthing	12mo
pharmacotherapy_diabetes	Count of distinct fill dates for diabetes treatment in the past 12 months.	Pharmacy Claims, Medical Claims	Adult, Birthing	12mo
pharmacotherapy_hypertension	Count of distinct fill dates for hypertension treatment in the past 12 months.	Pharmacy Claims, Medical Claims	Adult, Birthing	12mo
glucose_cholesterol_screenings	Count of distinct screening events for glucose or cholesterol in the past 12 months.	Pharmacy Claims, Medical Claims	Pediatric, Birthing	3mo, 12mo, ever

Predictor	Description	Data Source	Population	Lookback
new_diagnosis_developmental_delay	Binary indicator for any new developmental delay diagnosis first appearing in the past 12 months.	Medical Claims	Pediatric	3mo, 12mo, ever
new_diagnosis_mental_illness	Binary indicator for any new mental illness diagnosis first appearing in the past 12 months.	Medical Claims	Pediatric	3mo, 12mo, ever
new_indicator_diagnosis_sud	Binary indicator for any new substance use disorder diagnosis first appearing in the past 12 months.	Medical Claims	Pediatric	3mo, 12mo, ever
pmca_body_systems_progressive	Count of distinct progressive body systems flagged by PMCA logic in the past 12 months.	Medical Claims	Pediatric	3mo, 12mo, ever
well_child_visits	Count of distinct well-child visit dates in the past 12 months.	Medical Claims	Pediatric, Birthing	3mo, 12mo, ever
asthma_medication	Binary indicator for any asthma medication dispensed in the past 12 months.	Pharmacy Claims	Pediatric, Birthing	12mo, ever
immunization_count	Count of distinct immunization events recorded in claims history.	Pharmacy Claims, Medical Claims	Pediatric, Birthing	ever
net_new_autism_diagnosis	Binary indicator for any new autism diagnosis first appearing in the past 12 months.	Medical Claims	Pediatric	12mo, ever
net_new_neurological_diagnosis_no_autism	Binary indicator for any new neurological diagnosis (excluding autism) first appearing in the past 12 months.	Medical Claims	Pediatric	12mo, ever
topical_fluoride	Binary indicator for whether topical fluoride treatment was provided in the past 12 months.	Medical Claims, Dental Claims	Pediatric, Birthing	12mo, ever

Note: "Ever" lookbacks do not apply to Birthing models

5) Birthing-Specific Predictors (Including Outcomes as Risk Factors)

In addition to the V1 predictors, the following Birthing-specific predictors were added to all three Birthing models.

Predictor	Description	Data Source	Lookback
Diagnosis of Anemia (OCSS)	Count of encounters with specified diagnosis as determined by the ICD-10-CM diagnosis codes from the Diagnosis codes for comorbidities in relation to severe maternal morbidity (SMM)	Medical Claims	3mo, 12mo

Predictor	Description	Data Source	Lookback
	and non-transfusion SMM table from Obstetric Comorbidity Scoring System		
Diagnosis of Asthma, Acute or Moderate/Severe (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Bleeding Disorder (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Cardiac Disease (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Chronic Hypertension (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Chronic Renal Disease (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Connective Tissue or Autoimmune Disease (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Gastrointestinal Disease (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of HIV/AIDS (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Major Mental Health Disorder (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Neuromuscular Disease (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Diabetes Mellitus (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Pulmonary Hypertension (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Substance Use Disorder (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Thyrotoxicosis (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Uterine Fibroids (OCSS)	TBD	Medical Claims	3mo, 12mo
Diagnosis of Gestational Diabetes Mellitus (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Placenta Accreta Spectrum (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Placenta Previa, Complete or Partial (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Placental Abruption (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo

Predictor	Description	Data Source	Lookback
Diagnosis of Preeclampsia With Severe Features (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Preeclampsia Without Severe Features or Gestational Hypertension (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Postpartum Hemorrhage (OCSS)		Medical Claims	3mo, 12mo, 60mo
Diagnosis of Preterm Birth (<37 Weeks) (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Previous Cesarean Birth (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Twin or Multiple Pregnancy (OCSS)	TBD	Medical Claims	3mo, 12mo, 60mo
Diagnosis of Syphilis	Count of encounters with a diagnosis code for syphilis	Medical Claims	3mo, 12mo
Diagnosis of Herpes Simplex Virus (HSV)	Count of encounters with a diagnosis code for herpes simplex virus (HSV)	Medical Claims	3mo, 12mo
Diagnosis of HIV	Count of encounters with a diagnosis code for HIV/AIDS	Medical Claims	3mo, 12mo
Diagnosis of Chlamydia	Count of encounters with a diagnosis code for chlamydia	Medical Claims	3mo, 12mo
Diagnosis of Gonorrhea	Count of encounters with a diagnosis code for gonorrhea	Medical Claims	3mo, 12mo
Diagnosis of Trichomoniasis	Count of encounters with a diagnosis code for trichomoniasis	Medical Claims	3mo, 12mo
Diagnosis of Hepatitis B or C	Count of encounters with a diagnosis code for hepatitis B or C	Medical Claims	3mo, 12mo
Diagnosis of Other Sexually Transmitted Infection	Count of encounters with evidence of a sexually transmitted infection not otherwise specified in the above indicators	Medical Claims	3mo, 12mo
Aneuploidy Screening Received	Binary indicator if member had a prior aneuploidy screening performed	Medical Claims	3mo, 12mo, 60mo
Prenatal Care Visit Received	Binary indicator if member had a prior prenatal care visit	Medical Claims	3mo, 12mo, 60mo
Prenatal Ultrasound Received	Binary indicator if member had a prior prenatal ultrasound	Medical Claims	3mo, 12mo, 60mo

Predictor	Description	Data Source	Lookback
Maltreatment or Abuse Indicator	Healthcare encounter for care related to Maltreatment/abuse	Medical Claims	3mo, 12mo, 60mo
Severe Fetal Outcome Indicator	Pregnancy ending in a non-live birth	Medical Claims	3mo, 12mo, 60mo
Unplanned Cesarean Delivery	Cesarean delivery with evidence of anesthesia/epidural administration for a vaginal delivery first	Medical Claims	3mo, 12mo, 60mo
Gravida	Number of prior pregnancies, regardless of outcome	Medical Claims	3mo, 12mo, 60mo
Parity	Number of prior deliveries, including live and non-live births	Medical Claims	3mo, 12mo, 60mo
Prior Vaginal Delivery	Number of prior vaginal deliveries	Medical Claims	3mo, 12mo, 60mo
Prior Cesarean Delivery	Number of prior Cesarean deliveries	Medical Claims	3mo, 12mo, 60mo
Prior Ectopic Pregnancy	Number of prior pregnancies identified as ectopic	Medical Claims	3mo, 12mo, 60mo
Prior Induced Abortion	Number of prior pregnancies ended with the support of medical intervention	Medical Claims	3mo, 12mo, 60mo
Prior Spontaneous Abortion	Number of prior pregnancies ended prior to delivery without medical intervention (miscarriage)	Medical Claims	3mo, 12mo, 60mo

C. Technical Environments Setup

For the Adults and Pediatric models, training and evaluation were performed using a distributed GPU compute environment, optimized for large-scale data processing, including 96 vCPUs, 768 GiB system memory, 8 NVIDIA V100 GPUs (32GB each), and 100 Gbps bandwidth. For Birthing models, model training and evaluation were performed using a single GPU-accelerated compute (ml.g6.16xlarge), with 1 NVIDIA L4 GPU (24GB). The reduced compute configuration relative to Adults and Pediatrics reflects the smaller Birthing population dataset.

Parallel execution and resource orchestration were handled by Dask (version 2024.7.1), which enabled distributed scheduling, spill control, and GPU-to-GPU communication at scale. GPU-backed computation was managed using the RAPIDS ecosystem (RAPIDS AI, 2024), specifically cuDF for dataframe operations and CuPy for array computations. RAPIDS provides a suite of GPU-accelerated libraries for data science workflows, enabling efficient manipulation of large datasets and seamless integration with Python-based machine learning pipelines.

D. Model Tuning Results

To identify high-performing configurations across multiple model architectures, we implemented an adaptive and parallelized hyperparameter optimization framework using Optuna, in combination with Dask and GPU-accelerated training backends. The optimization objective was to maximize the area under the ROC curve (ROC-AUC) on a held-out validation set. This tuning strategy was applied independently to each model and for each outcome, enabling architecture-specific configurations tailored to individual risk signals.

All tuning experiments were conducted using consistent validation data drawn from a fixed temporal window (Feb 2020 – Jan 2021), ensuring fair comparisons under conditions of temporal drift. Training data (the "search set") for the putative models with different hyperparameters were drawn from a separate subset of the training period (Jan 2019 – Jan 2020).

To support efficient search across high-dimensional hyperparameter spaces while maintaining tractability, we randomly sampled 10–30% of the training data (depending on overall size) to create a search set. The sampled data were split into a search dataset, which included data from Jan 2019-Jan 2020, and a validation dataset drawn from a 30% random sample from Feb 2020-Jan 2021. This structure ensured that models were tuned on a reduced but representative subset of earlier data and evaluated on temporally newer data—effectively testing their ability to generalize under real-world deployment conditions.

Trials were distributed across multiple GPUs using Dask, and all computation was orchestrated through a central Dask distributed client to manage task execution, memory allocation, and GPU scheduling.

Birthing Models: Unlike Adults and Pediatrics, the Birthing models used a randomized train/validation/test split rather than time-based partitioning, so tuning and validation data were drawn from the same temporal range but separated at the person level to prevent leakage. Additionally, to deal with differential time contribution, models were trained using weighted and unweighted methods. After assessment, it was determined that using weighted models would be the most appropriate.

1) Optimization Framework

Optuna's Tree-structured Parzen Estimator (TPE) sampler with multivariate optimization was used to guide the sampling process. Early stopping and resource-aware pruning were implemented using the HyperbandPruner, enabling efficient allocation of computational effort toward the most promising regions of the search space.

All trials were managed through Dask's distributed client, allowing for parallel trial execution across 8 GPUs. Models were evaluated using ROC-AUC computed on the validation set, with each trial's results logged and persisted.

Key trial management techniques included:

» Timeout-based stopping: Each tuning session was limited to one hour (3600 seconds).

» Performance-based early stopping: Tuning was terminated if no improvement was observed over 10 consecutive trials.

» Pruning-based termination: Studies were halted if 5 consecutive trials were pruned, suggesting convergence.

2) Model-Specific Search Spaces

a. XGBoost (Gradient Boosted Trees)

XGBoost was trained using the GPU-accelerated histogram method (tree_method='hist', device='cuda'). The hyperparameter space included:

» n_estimators: 1 to 3000

» learning_rate: 10 log-spaced values from 0.001 to 0.1

» max_depth: {2, 4, 6, 8, 10, 12, 14, 16}

Training and evaluation were performed using DaskQuantileDMatrix to support GPU-native batching. To stabilize learning under class imbalance, sampling methods and max delta steps were determined (i.e. sampling_method='gradient_based' and max_delta_step=1).

Validation AUC was computed using cuML's roc_auc_score to ensure consistency with the RAPIDS pipeline.

For the Birthing models, row-level weights were derived as the inverse of each pregnancy episode's length and applied as sample weights to ensure that each episode contributed proportionally to model training, accounting for the multiple index dates generated per episode.

b. LightGBM

LightGBM was optimized using its GPU-enabled training backend, with similar hyperparameter settings to XGBoost for consistency:

- n_estimators: 1 to 3000
- learning_rate: 10 log-spaced values between 0.001 and 0.1
- max_depth: {2, 4, 6, 8, 10, 12, 14, 16}

The model was configured with boosting_type='gbdt' and tree_learner='data', enabling distributed gradient boosting suitable for large datasets. Although LightGBM supports GPU training, explicit GPU device settings (e.g., device='gpu') were not enforced. Hyperparameter trials were parallelized using Dask with n_jobs=2, and tuning was conducted using Optuna with the same early stopping and pruning strategies as in XGBoost. Validation followed the same protocol, using probabilistic predictions on a time-split validation set.

c. Logistic Regression (Quasi-Newton with Elastic Net)

We tuned logistic regression was using an elastic net penalty, enabling regularization along the full spectrum between L1 (lasso) and L2 (ridge). The search space consisted of:

- C: log-uniform from 1e-5 to 1e5
- l1_ratio: categorical values in {0, 0.01, 0.5, 0.99, 1.0}

Models were trained using a GPU-accelerated implementation of logistic regression from the cuML library, with the 'qn' solver (quasi-Newton optimization) and a maximum of 100 iterations per trial. Optimization was performed using Optuna with single-threaded tuning (n_jobs=1) and the same early stopping and pruning conditions as for the tree-based models.

Due to its relative computational efficiency, logistic regression was able to support a larger number of trials within the same time budget, making it a robust and interpretable baseline across outcomes. Performance was evaluated using ROC-AUC on a held-out validation set.

3) Final Model Selection

For each model and outcome in the Adult and Pediatric models, the trial with the highest ROC-AUC on the validation set was selected. The selected hyperparameters were then used to retrain the model on the combined training and validation periods (Jan 2019 – Jan 2021). This retrained model was evaluated on the temporally held-out test set (Jan 2022 – Jan 2023) for final performance reporting. Lastly, XGBoost consistently demonstrated the highest performance across most of the subdomain models. In a few cases where it did not perform best, LightGBM yielded slightly superior results. However, given the marginal differences in performance and the superior scalability of XGBoost for multi-GPU inference, XGBoost was selected as the final model for all subdomains. For the Birthing models, only XGBoost model was trained.

E. Model Performance

Each subdomain model was reviewed using a standardized evaluation framework developed by the academic Work Group. This framework assessed models across key performance domains:

- **Calibration:** Visual inspection of calibration curves to evaluate alignment between predicted risk and observed outcomes.
- **Discrimination:** Metrics such as AUC, as well as precision, recall, and specificity—particularly at the top 5% risk threshold—were used to assess model separation and baseline operational utility.
- **Feature Interpretability:** Review of feature importances to confirm that models prioritized clinically and contextually relevant inputs.
- **Risk Distribution:** Assessment of risk score distributions and outcome co-occurrence to understand model behavior across the population.
- **Hyperparameter Tuning:** Review of tuning results and parameter sensitivity to ensure performance gains were both robust and reproducible.

Models were approved for use only after meeting minimum thresholds for performance, calibration, and interpretability as defined by the Work Group.

Table 7. Summary of Model Performance Metrics Across Subdomains[1]

Model (Top %)[3]	AUC	Accuracy	Precision	Recall	Specificity
Adult Behavioral Health Adverse Events	0.938	0.955	0.173	0.697	0.958
Adult Physical Health Adverse Events	0.879	0.928	0.595	0.367	0.978

[1] For the underutilization subdomains, these metrics are calculated only among persons eligible for at least one underutilization outcome.

Model (Top %)[3]	AUC	Accuracy	Precision	Recall	Specificity
Adult Social Risk Adverse Events [2]	0.936	0.959	0.343	0.689	0.966
Adult Behavioral Underutilization	0.805	0.316	0.961	0.066	0.993
Adult Physical Health Underutilization	0.769	0.421	0.941	0.075	0.992
Pediatric Behavioral Health Adverse Events	0.754	0.915	0.274	0.218	0.961
Pediatric Physical Health Adverse Events	0.775	0.919	0.341	0.261	0.965
Pediatric Social Risk Adverse Events [2]	0.923	0.952	0.080	0.700	0.954
Pediatric Behavioral Underutilization	0.782	0.254	0.969	0.062	0.993
Pediatric Physical Health Underutilization	0.763	0.466	0.933	0.081	0.992[3]
Birthing Post-Pregnancy Behavioral Health[4] (5%)	0.849	0.946	0.262	0.436	0.962
Birthing Post-Pregnancy Physical Health[4] (15%)	0.773	0.8516	0.345	0.507	0.891
Birthing Pregnancy Adverse Events[4] (30%)	0.712	0.701	0.508	0.502	0.788

1) Adult Adverse Events (Physical Health)

The composite outcome for Adult physical health adverse events had a prevalence of 8% in the Adult population (N = 8,875,329). This composite included key drivers such as

[2] The selected models were not the top performers in terms of AUC but were retained due to their close performance to the best (LightGBM) and the scalability benefits of XGBoost, which supports multi-GPU training and inference at production scale.
[3] For V1 Adult and Pediatric models, all metrics except AUC were calculated using each model's specific top 5% risk threshold, representing the highest-risk individuals in the population.
[4] All Birthing model performance metrics were calculated on the weighted version of the model, and at an episode-level, in line with Work Group expectations that care management resources would be allocated not at a month-level but at the pregnancy episode level.

all-cause inpatient admissions (8%) and all-cause emergency department visits (6%). Additional outcomes included mortality (1%) and new morbidity, as measured by a rise in the Charlson Comorbidity Index (1%).

The final model selected was XGBoost, with n_estimators = 1210, learning_rate = 0.0359, and max_depth = 12. The model displayed excellent calibration. Predicted probabilities closely tracked observed event rates across all bins, with minimal deviation from the ideal diagonal line. The consistent fit supports the reliability of the risk scores for use in tiering and prioritization (see Appendix for calibration curves).

The model achieved an AUC of 0.879 and, at the model-specific top 5% risk threshold, a precision of 0.595, recall of 0.367, specificity of 0.978, and accuracy of 0.928, indicating high model performance and sufficient discrimination for a relatively common composite outcome (See Table 7).

Subgroup performance was stable across demographic segments. Recall was similar between males (38%) and females (36%) and remained consistent for the English (40%) language group. Higher recall was observed among American Indian or Alaska Native (42%) and Black or African American (43%) subgroups, with strong performance across race and ethnicity categories more broadly. Reductions in recall were observed among Spanish-speaking (31%) and new Medicaid enrollees (30%), potentially reflecting patterns of historical utilization and data availability. Full subgroup results are available in the Appendix.

2) Adult Adverse Events (Behavioral Health)

The composite outcome for Adult behavioral health adverse events had a prevalence of 1% in the Adult population. It encompassed multiple rare but clinically significant outcomes. Psychiatric admissions and having three or more all-cause ED visits and at least one Short-Doyle encounter were the most common, each with a prevalence of approximately 1%. Other components—intentional self-harm, drug overdose, and injection-related adverse events—were less frequent (all <1%).

The final model selected for this subdomain was XGBoost with n_estimators = 2833, learning_rate = 0.0599, and max_depth = 6. The model demonstrated strong calibration across the full range of predicted probabilities. Predicted risks tracked closely with observed event rates, with most points aligning with the diagonal line of perfect calibration. Mild overprediction was observed in mid-to-high probability bins, but the overall fit supports the model’s use for risk stratification and downstream tiering decisions (see Appendix for calibration curve).

The model achieved an AUC of 0.938 and, at the model-specific top 5% risk threshold, a precision of 0.173, recall of 0.697, specificity of 0.958, and accuracy of 0.955, demonstrating high model performance and effective discrimination of high-risk individuals within a low-prevalence outcome space.

Subgroup analysis at the top 5% risk threshold showed consistent performance across demographic strata. Recall was comparable between males (71%) and females (68%). Performance remained strong among Hispanic (65%) and non-Hispanic (72%) populations. Recall exceeded 73% among American Indian or Alaska Native (73%) and Black or African American (73%) individuals. We observed reduced recall among Spanish-speaking (49%) and newly enrolled Medicaid members (53%), most likely consistent with patterns of data availability and historical utilization.

3) Adults Underutilization (Behavioral Health)

The composite outcome for Adult behavioral health underutilization had a prevalence of 7% among the total Adult strata (N = 8,875,329) and a prevalence of 72% among Adults (N = 861,901) eligible for at least one underutilization outcome. The remainder of metrics reported are among the eligible population. This composite was designed to flag gaps in behavioral health care and included: visits to primary care providers with behavioral health or substance use diagnoses (24%), ambulatory mental health or substance use treatment visits (52%), and pharmacologic management such as antidepressants (16%), antipsychotics for schizophrenia (5%), and opioids for opioid use disorder (2%). These individual outcomes were assessed against a shared denominator defined by the composite inclusion criteria.

The final model was XGBoost, with n_estimators = 552, learning_rate = 0.0359, and max_depth = 16. The model demonstrated strong overall calibration, with predicted probabilities closely matching observed event rates across the risk spectrum. While slightly underestimating risk at the lower end, the model's predictions aligned well with observed frequencies across most bins, indicating good reliability for identifying underutilization patterns.

The model achieved an AUC of 0.805 and, at the model-specific top 5% risk threshold, a precision of 0.961, recall of 0.066, specificity of 0.993, and accuracy of 0.316.

Subgroup performance for the behavioral health underutilization model remained stable across demographic groups, with precision consistently above 95% and recall ranging from 4.7% to 8.9%. Recall was highest among Spanish-speaking individuals (8.9%), American Indian or Alaska Native (8.7%), and Black or African American (7.9%) subgroups. Female individuals exhibited lower recall (5.5%) compared to males (7.9%), while English and Spanish speakers performed comparably overall. The model maintained specificity above 99% across all groups.

4) Adults Underutilization (Physical Health)

The composite outcome for Adult physical health underutilization had a prevalence of 31% among the total Adult strata (N = 8,875,329) and a prevalence of 63% among eligible individuals (N = 4,290,776). The remainder of metrics reported are among the eligible population. This composite identified gaps in routine and preventive care delivery, including missed primary care visits (18%), lack of any claims (17%), and insufficient dental care (8%). Additional measures included gaps in chlamydia screening (14%), pharmacy fills for hypertension (8%) and diabetes (5%), and suboptimal asthma medication use (3%). These outcome-specific rates reflect a shared denominator, as inclusion criteria were applied at the composite level.

The final model selected was XGBoost, with n_estimators = 1671, learning_rate = 0.0359, and max_depth = 10.The calibration curve revealed slight underprediction across the probability range, with observed event rates consistently exceeding predicted probabilities.The model achieved an AUC of 0.769 and, at the model-specific top 5% risk threshold, a precision of 0.941, recall of 0.075, specificity of 0.992, and accuracy of 0.421.

Subgroup analysis demonstrated consistent performance across demographic strata, with precision above 93% for all groups and recall ranging from 4% to 11%. Recall was highest among American Indian or Alaska Native (11.6%), Black or African American (10.0%), and White (8.6%) populations. Lower recall was observed among new Medicaid enrollees (4.4%) and Hispanic or Latino individuals (6.6%). Performance across sex and language groups remained similar, with recall for females at 7.6% and English speakers at 7.7%. The model preserved high specificity (≥ 99%) across all subgroups.

5) Adults Social Risk (Adverse Events)

The composite outcome for Adult social risk adverse events had a prevalence of 3% in the Adult population. This outcome is defined entirely by a single event: documented housing insecurity, which, accordingly, accounts for the full composite.

The final model selected was XGBoost, with n_estimators = 1868, learning_rate = 0.0359, and max_depth = 10. The model demonstrated excellent calibration, with predicted probabilities closely aligned with observed event rates across the probability spectrum.

The calibration curve shows minimal deviation from the diagonal, indicating well-calibrated scores even at the highest risk ranges.

The model achieved an AUC of 0.936 and, at the model-specific top 5% risk threshold, a precision of 0.343, recall of 0.689, specificity of 0.966, and accuracy of 0.959, indicating strong performance in identifying individuals experiencing housing instability.

Subgroup performance showed particularly strong recall among American Indian or Alaska Native (81%), White (76%), and male (74%) populations. Recall remained above 61% across most other subgroups, including Black or African American (66%), Hispanic (62%), and individuals reporting English as their primary language (70%). Slightly lower precision and recall were observed among Spanish-speaking individuals, but specificity exceeded 99% in that group, as in several others.

6) Pediatrics Adverse Events (Physical Health)

The composite outcome for Pediatric physical health adverse events had a prevalence of 6% in the Pediatric population (N = 4,549,042). This composite was primarily composed of all-cause inpatient admissions (3%) and all-cause emergency department visits (3%). Less common but clinically significant components included diagnoses of common chronic illnesses (1%) and new onset morbidity (<1%). Together, these outcomes reflect a range of acute and chronic physical health burdens relevant to Pediatric populations.

The final model selected was XGBoost, with n_estimators = 1671, learning_rate = 0.0359, and max_depth = 10.

The model for physical health adverse events in Pediatrics displayed excellent calibration. Predicted probabilities closely tracked observed event rates across all bins, indicating strong reliability of the risk scores for guiding tier assignment.

The model achieved an AUC of 0.775 and, at the model-specific top 5% risk threshold, a precision of 0.341, recall of 0.261, specificity of 0.965, and accuracy of 0.919, reflecting solid overall model performance and discrimination in identifying children at highest risk for adverse physical health outcomes.

Subgroup analysis revealed consistent performance across most demographic groups. Recall was slightly higher among new Medicaid enrollees (36%), English-speaking (27%) and White children (27%), while performance across sex, ethnicity, and language groups remained balanced. Spanish-speaking and Asian subgroups showed slightly lower precision, potentially reflecting variation in prevalence or care patterns. Specificity remained high (≥91%) across all subgroups.

7) Pediatrics Adverse Events (Behavioral Health)

The composite outcome for Pediatric behavioral health adverse events had a prevalence of 6% in the Pediatric population. The most common components included new diagnoses of mental illness (5%) and emergency department visits for psychiatric reasons (1%). Less frequent but critical components included new diagnoses of developmental delay (<1%), substance use disorders (1%), psychiatric admissions (<1%), and rare events such as intentional self-harm and drug overdose (both <1%). These outcomes capture both early identification and escalation of behavioral health needs in Pediatric care.

The final model selected was XGBoost, with n_estimators = 1050, learning_rate = 0.0359, and max_depth = 12.

The model exhibited moderate overcalibration, particularly in the higher predicted risk ranges. As shown in the calibration curve (see appendix), predicted probabilities above 0.5 consistently overestimate the true outcome frequency. Still, model predictions remain directionally correct and actionable for prioritizing high-risk individuals.

The model achieved an AUC of 0.754 and, at the model-specific top 5% risk threshold, a precision of 0.274, recall of 0.218, specificity of 0.961, and accuracy of 0.915, reflecting a focused ability to identify Pediatric patients at risk for emerging or severe behavioral health needs.

Subgroup analysis showed balanced performance across most demographic groups. Recall was slightly higher among male children (23%) and Black or African American children (25%), with notably strong precision among American Indian or Alaska Native (27%) and White children (26%). Spanish-speaking and Asian subgroups showed lower recall (18% and 18%, respectively), though specificity remained high (≥93%) across all subgroups.

8) Pediatrics Underutilization (Behavioral Health)

The composite outcome for Pediatric behavioral health underutilization had a prevalence of 5% among the total Pediatric strata (N = 4,549,042) and a prevalence of 78% among eligible children (N = 299,096). The remainder of metrics reported are among the eligible population. This composite reflects insufficient engagement with behavioral health services, including ambulatory mental health or substance use treatment (71%) and primary care visits with behavioral health or substance use diagnoses (20%). Less frequent components included metabolic screenings (3%), follow-up care after admissions or ED visits for behavioral health (3%), and ADHD-specific follow-up (<1%). These outcome rates are calculated using a shared denominator, consistent with the composite inclusion criteria.

The final model selected was XGBoost, with n_estimators = 2090, learning_rate = 0.0129, and max_depth = 10.

The model's calibration curve shows that predicted probabilities are generally undercalibrated, particularly in the lower to mid-range. In these bins, observed outcome rates exceed predicted probabilities, indicating underestimation of risk. Calibration improves in the upper range, where predictions align more closely with actual event frequencies.

The model achieved an AUC of 0.782 and, at the model-specific top 5% risk threshold, a precision of 0.969, recall of 0.062, specificity of 0.993, and accuracy of 0.254, demonstrating high precision in identifying members with likely behavioral care gaps, albeit with limited sensitivity in a high-prevalence context.

Subgroup performance was generally consistent, with precision consistently above 95% across all groups. Recall was highest among new Medicaid enrollees (18.3%), American Indian or Alaska Native (11.7%), Native Hawaiian or Other Pacific Islander (8.8%), and Asian (6.8%) subgroups, possibly reflecting lower historical system contact. The model maintained high specificity (≥98%) across all subgroups.

9) Pediatrics Underutilization (Physical Health)

The composite outcome for Pediatric physical health underutilization had a prevalence of 20% among the total Pediatric strata (N = 4,549,042) and a prevalence of 59% among eligible children (N = 1,559,019). The remainder of metrics reported are among the eligible population. This composite reflects unmet preventive and routine care needs, including adolescent and well-child visits (23%), chlamydia screening (15%), and topical fluoride or dental care (10%). Other components included immunization status (4%) and asthma medication indicators (5%). These outcomes were assessed against a common denominator, reflecting inclusion criteria applied at the composite level.

The final model selected was XGBoost, with n_estimators = 1909, learning_rate = 0.0215, and max_depth = 12.

The calibration curve shows that the model is slightly undercalibrated in the lower- to mid-range predicted probabilities, where observed event rates exceed the model's estimates. However, it becomes well-aligned above a predicted probability of 0.60 and closely tracks the diagonal through the mid-to-high ranges.

The model achieved an AUC of 0.763 and, at the model-specific top 5% risk threshold, a precision of 0.933, recall of 0.081, specificity of 0.992, and accuracy of 0.466, reflecting a conservative but precise strategy for identifying children at highest risk of care underutilization.

Subgroup analysis showed consistently high precision across all demographics, with modest variation in recall. Asian (13%), Native Hawaiian or Other Pacific Islander (11%), and female (10%) subgroups showed relatively higher recall, while male children (5.1%) and Black or African American children (5.8%) showed lower sensitivity. Specificity exceeded 98% for all subgroups, underscoring the model's reliability in filtering lower-risk populations.

10) Pediatrics Social Risk (Adverse Events)

The composite outcome for Pediatric social risk adverse events had a prevalence of 1% in the Pediatric population (N = 4,549,042). This outcome was defined entirely by the presence of housing instability.

The final model selected was XGBoost, with n_estimators = 2090, learning_rate = 0.0129, and max_depth = 10.

The model exhibits strong calibration across most of the prediction range, with slight underestimation of risk in mid-range (0.25–0.55) predicted probabilities. Calibration improves at both extremes, particularly for higher-risk members.

The model achieved an AUC of 0.923 and, at the model-specific top 5% risk threshold, a precision of 0.080, recall of 0.700, specificity of 0.954, and accuracy of 0.952, indicating strong discriminatory power for a rare outcome and suitability for flagging individuals with elevated social risk.

Subgroup performance remained consistent across most demographics. Recall exceeded 70% for English speakers, and both male and female children. Higher recall values were observed among American Indian or Alaska Native (91%), White (82%), and multiracial (80%) subgroups. In contrast, recall was lower among Spanish-speaking children (33%) and Asian children (51%). Specificity remained high (≥93%) for most groups.

11) Post-Pregnancy Behavioral Health (Adverse Events)

Across the Post-Pregnancy Behavioral Health cohort, 2,071,461 person-months of observation time were observed. Composite outcome prevalence was 2.68% at the episode-month level, driven primarily by prior psychiatric ED visits (2.31% at the episode-month level). The next most frequent component was maltreatment/abuse (0.29% at the episode-month level). See Appendix Table A.2A for additional detail.

The final model selected was a weighted XGBoost model with best hyperparameters n_estimators = 1285, learning_rate = 0.0046416, and max_depth = 16. We used episode-based weighting (inverse of event-count per episode) to better balance episodes of different lengths.

Calibration was strong, with the calibration curves showing predicted probabilities tracking the observed event rates closely (i.e. near the diagonal), with a slight over-estimation at the high end (>0.8), supporting reliability of the risk scores for tiering.

At the top 5% risk threshold, performance was strong. From an episode-month lens, the model achieved ROC-AUC = 0.8275, with precision = 0.2199, recall = 0.4035, and specificity = 0.9599. When performance was assessed at the episode level, discrimination improved further with ROC-AUC = 0.8495, precision = 0.2623, recall = 0.4361, and specificity = 0.9620.

Subgroup performance was generally stable, at the episode level. There was a decrease in AUC for Black women, those with housing instability, and younger women, but all saw AUC values over 0.788. Recall remained similar between loss vs. delivery subgroups at the episode level (0.440 vs 0.433), but some subgroups saw variations in recall, including Spanish language speakers (0.178) and housing instability (0.943).

12) Post-Pregnancy Physical Health (Adverse Events)

Across the Post-Pregnancy Physical Health cohort, 1,640,968 person-months of observation time were observed. Composite outcome prevalence was 10.37% at the episode-month level, driven primarily by post-pregnancy hypertensive disorders (7.07% at the episode-month level). The next most frequent component was infant NICU (2.30% at the episode-month level). See Appendix Table A.2A for additional detail.

The final model selected was a weighted XGBoost model with best hyperparameters: n_estimators = 2151, learning_rate = 0.0077426, and max_depth = 10.

Calibration was very strong: the curve followed very closely with the diagonal showing almost perfect calibration, indicating usable probability estimates for stratification.

At the top 15% risk threshold, performance was solid and operationally useful for outreach/tiering. On the episode-month view, the model achieved ROC-AUC = 0.7388, with precision = 0.2985, recall = 0.4356, and specificity = 0.8827 (Overall). On the episode-level rollup, performance was stronger: ROC-AUC = 0.7730, precision = 0.3456, recall = 0.5077, and specificity = 0.8907 (Overall).

Subgroup performance was broadly consistent. There was a decrease in AUC for the American Indian or Alaskan Native subgroup, likely driven by very small sample size in the population. Subgroups with higher-than-average AUC for this model included those with housing instability, members over 35 years old, and Black women.

Episode-level recall remained in a similar range for loss vs delivery (≈48% vs 52%), and performance was also relatively stable across language and race/ethnicity groups, with most subgroups near the overall recall of 0.508. There was some variability by subgroup. For example, the Spanish speaking subgroup saw a small drop in recall (0.438), while the housing instability subgroup saw the highest recall (0.857), the under 21 subpopulation saw the lowest recall (0.291).

13) Pregnancy Adverse Events

Across the Pregnancy cohort, 1,854,155 person-months of observation time were observed. Composite outcome prevalence for adverse events was 31.13% at the episode-month level, driven primarily by all-cause inpatient admissions (13.13% at the episode-month level). The next most frequent component was neonatal NICU (10.96% at the episode-month level). See Appendix Table A.2A for additional detail.

The final model selected was a weighted XGBoost model with best hyperparameters n_estimators = 2981, learning_rate = 0.0046416, max_depth = 16.

Calibration was very strong: the episode-level calibration curve stayed close to the diagonal for most bins, indicating that predicted probabilities are broadly well-aligned with observed rates.

At the top 30% risk threshold, the episode-month model saw reasonable performance of for a wide range of metrics, including ROC-AUC (0.6617), precision (0.4605), recall (0.4497), and specificity (0.7664). At the episode-level, performance improved for ROC-AUC (0.7118), precision (0.5084), recall (0.5024), and specificity (0.7882).

Subgroup results were generally stable with expected variation. For example, in the episode-level model, the Spanish language subpopulation showed higher precision (0.560) but lower recall (0.402), compared to English language subpopulation's precision (0.498) and recall (0.543). Other equity subgroups had similar recall values, except the housing instability subpopulation (0.767), American Indian or Alaskan subpopulation (0.419), and Asian subpopulation (0.420).

F. Tiering Analysis Results

Adult and Pediatric Models (V1)

After the completion of the modeling phase, members were assigned into risk tiers based on the framework decided upon by the Work Group. As mentioned in the Tiering Analysis Evaluation Criteria section above, the framework prioritized the following 5 principles, each with a set of quantitative metric(s) that the Work Group translated into a qualitative scorecard to weigh the 3 options from a policy and feasibility lens:

- Technical Performance
- Balance of Risk Types
- Equity
- Potential Benefits
- Potential Costs and Impacts

A review of potentially comparable studies was conducted to determine an appropriate benchmark for AUC performance, and eight studies were summarized and used as part of the Work Group's tiering decision-making process.

Table 8. Summary of Studies Used in Tiering Decision-Making Process

Study	Outcome	Population	Strata	Domain/ Subdomain	AUC
Yu et al. (2022)	Avoidable ED Visits (Psychiatric factors)	NHAMCS incl. 35% using Medicaid	Pediatric; Adults (mean age - 37.06)	Risk of Adverse Events / Behavioral Health	0.677 (Medicaid - only AUC)
Rahman et al. (2022)	Intentional Self-Harm Prediction	NY Medicaid mental health clients	Pediatric; Adult (ages 10 to 64)	Risk of Adverse Events / Behavioral Health	0.86
Lo-Ciganic (2021)	Predicting risk of opioid	Medicaid beneficiaries (n = 237,259) in	Pediatric; Adult (mean age - 38±18)	Risk of Adverse Events / Behavioral Health	0.885

Study	Outcome	Population	Strata	Domain/ Subdomain	AUC
	overdose among Medicaid beneficiaries	Allegheny County, Pennsylvania			
Lo-Ciganic (2022)	Predict opioid overdose in Medicaid beneficiaries in two US states (Pennsylvania and Arizona)	Pennsylvania Medicaid beneficiaries	Adult (18-64)	Risk of Adverse Events / Behavioral Health	0·828 (external valid.), 0.841 (internal valid.)
Gao et al (2021)	Predicting Opioid Use Disorder and Associated Risk Factors in a Medicaid Managed Care Population	Medicaid enrollment, medical, pharmacy, and care management administrative data from January 1, 2016, to December 31, 2018. Included data from the District of Columbia, Florida, Louisiana, Michigan, Pennsylvania, and South Carolina	Adult (18+)	Risk of Adverse Events / Behavioral Health	0.914
Patel et al. (2024)	All-Cause Acute Care Visits	10 million Medicaid patients from 26 states and Washington DC	Pediatric; Adult (64.7% under 18)	Risk of Adverse Events / Physical Health	0.807 - 0.829
Pourat et al. (2023)	Homelessness identification via Medicaid admin data	Medicaid (California WPC program)		Social Risk / Adverse Events	0.95
Holcomb et al. (2022)	Prediction of health-related social needs incl. housing	Medicaid (85.4%) and Medicare (22.8)	Pediatric; Adult (mean age - 35.5)	Social Risk / Adverse Events	0.68

Birthing Models (V1.1)

Tiering analysis results for the Birthing models were reviewed using a modified version of the RSST evaluation framework, reflecting differences in policy context and analytic approach. For Birthing, the scorecard emphasized technical performance, balance of risk types, equity, and operational feasibility, while cost and benefit considerations were not evaluated given the existing policy to assess all pregnant members. Aligned with training, tiering analysis was conducted at the episode-level, rather than a month-level view, to align with pregnancy-centered risk assessment.

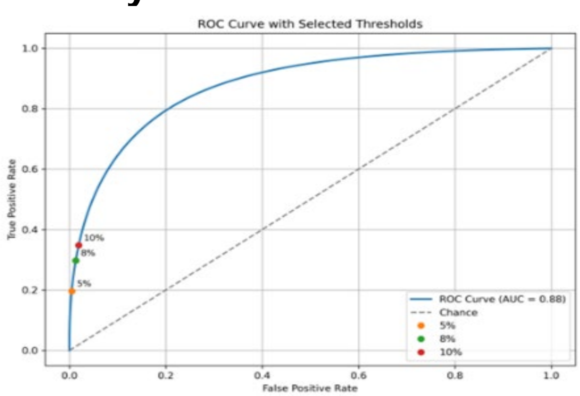
1) Adult Tiering: Technical Performance

All subdomain models were assessed for technical performance, equity, and appropriateness of predictive outcomes in the Adult population. AUC values ranged from 0.879-0.938, with the highest discrimination statistic approaching 0.938.

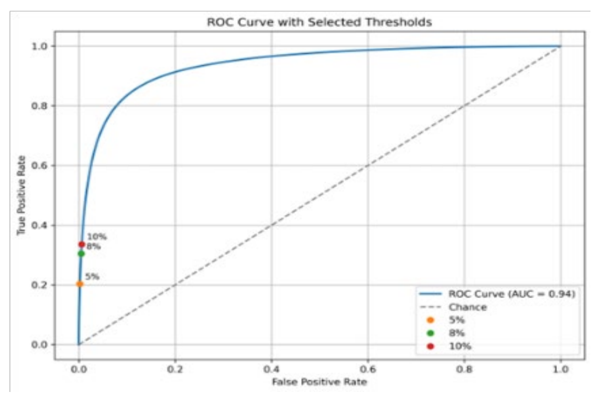
Domain	Adverse Events		Underutilization		Social Risk
Subdomain	Physical Health	Behavioral Health	Physical Health	Behavioral Health	Adverse Social Events
AUC	0.879	0.938	0.769	0.805	0.936

None of the AUC curves demonstrated atypical patterns, with all five models exhibiting patterns consistent with standard model behavior:

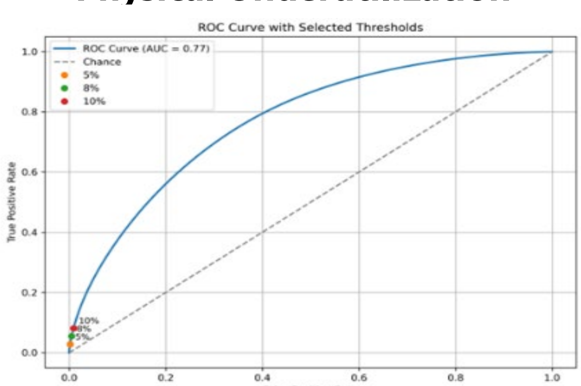
Physical Adverse Events



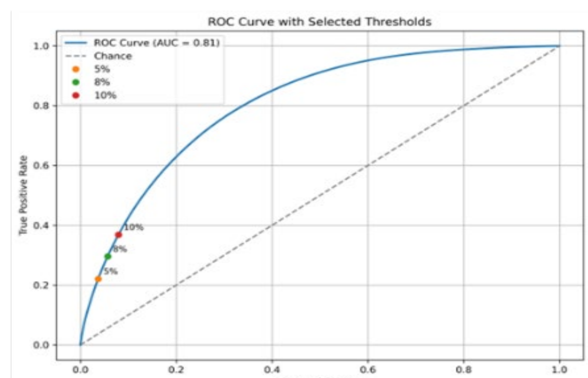
Behavioral Adverse Events



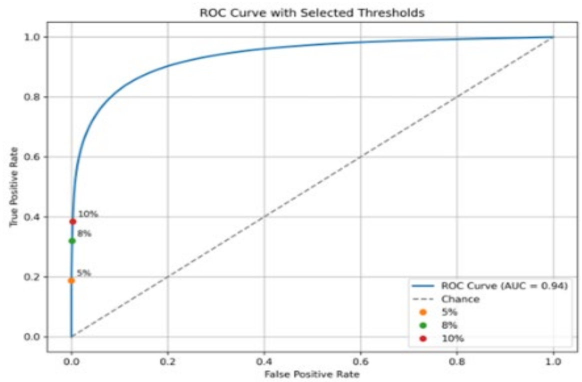
Physical Underutilization



Behavioral Underutilization



Social Risk

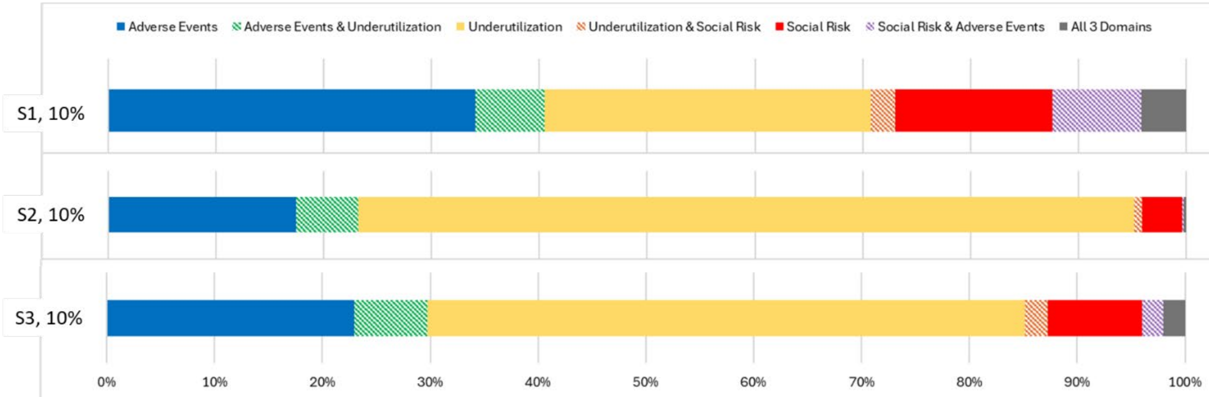


Finally, the Work Group reviewed NNT and Recall for each of the 3 options. Option 2, which was ultimately selected, had overall recall of 0.23 and NNT of 1.75. In other words, approximately 1 in 5 of all Adult state members who went on to have at least one RSST adverse outcome were flagged as high risk, and over half of members flagged as high risk went on to have at least one adverse RSST outcome. More details on these numbers can be found in the Equity section below.

Tiering Option (Adults)	Recall	NNT
Option 1	0.216	2.012
Option 2	0.226	1.751
Option 3	0.233	1.799

2) Adult Tiering: Balance of Risk Types

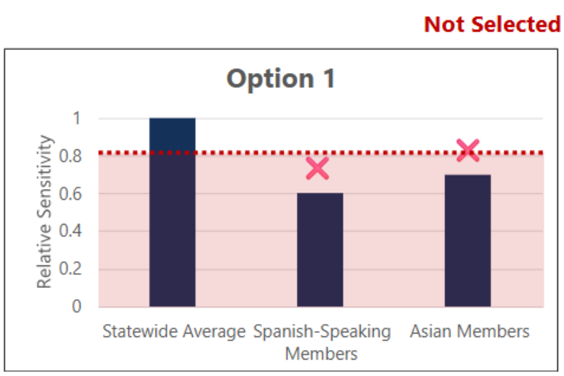
In determining the relative contribution of all risk types to the overall high-risk population, we calculated member counts by which domain (or combination of domains) drove the high-risk designation under each option. As expected, Option 1 was found to have the most even balance across all five models. Notably, Options 2 and 3 indexed heavily on the Underutilization models in determining who was High Risk. This was deemed appropriate given the extent to which many population subgroups have barriers to accessing care, and the priorities of DHCS leadership.

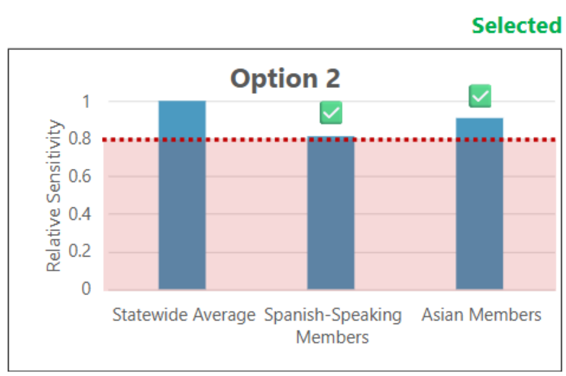


3) Adult Tiering: Equity Assessment

The goal of RSST is to ensure that the algorithm performs consistently across all member subgroups, without systematically under- or over-identifying risk for any particular population. DHCS prospectively considered equity by evaluating model performance stratified by demographic factors such as race, ethnicity, gender, and new enrollment.

In practice, this was implemented by evaluating recall (sensitivity) for each subpopulation, with a target of ensuring that subgroup-specific recall was no worse than 80% of performance of overall statewide average recall (0.23), an approach and benchmark used in this field.





Representative but not actual tiering data on adult Medi-Cal members

In Option 1, primary Spanish-speakers and Asian subgroups fell below the threshold, with recall values of 0.13 and 0.11 respectively, compared to 0.22 overall. Similarly in Option 3, Spanish-speakers and Asian subgroups fell below the threshold, with recall values of 0.16 and 0.15 respectively, compared to 0.23 overall. In Option 2, however, almost all subgroups fell within 80% relative threshold, and this factored into DHCS decision to approve Option 2. New Medicaid Enrollees fell below the threshold in all three options, very likely due to lack of data history available on those members. The Work Group found this to be an acceptable limitation of the predictive models.

Note: Underutilization drives risk disproportionately among Spanish-speaking and Asian Members. Prioritization of equitable predictive performance resulted in relatively more people flagged as high-risk due to underutilization. Because many existing RSS methodologies largely focus on utilization and prevention of costly adverse events, DHCS's RSST approach flags people who may have been missed by existing approaches.

4) Adult Tiering Potential Benefit Assessment

Potential benefits of Adult tiering options were assessed by estimating the number of net new needs assessments at a historical reference point (January 2023). In this context, "net new" refers to members who would have been identified as high risk under the RSST algorithm but would not have been designated as high risk under existing DHCS policy, which governs how members are currently prioritized for assessment and outreach. At the time of analysis, RSST had not yet been mandated for operational use.

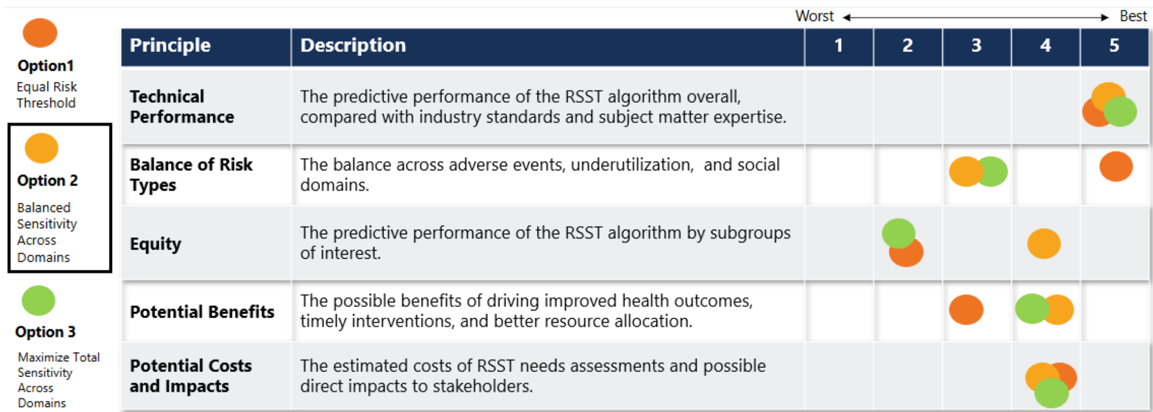
In addition to total counts, we evaluated how many of these net new members went on to experience an RSST outcome in the subsequent 12 months, using historical data where future outcomes were observable. Among the options evaluated, Option 2 identified the largest number of net new members for needs assessment (n = 629,247). Underutilization was the primary driver of high-risk identification, accounting for the largest share of members newly flagged by RSST. Separately, across all RSST domains, a high proportion of net new members identified as high risk (approximately 87–94%) went on to experience a corresponding outcome in the following year. Together, these findings supported DHCS's conclusion that RSST both expands identification beyond current policy and effectively prioritizes members with meaningful unmet needs.

5) Adult Tiering Potential Costs and Impacts

As part of the tiering analysis, the RSST Work Group considered the potential downstream impact of different tiering options on managed care plans. This included estimating how many members might qualify for additional assessments or transitional care services, and how those numbers—and associated costs—might vary across MCPs. While no new service requirements will be implemented at RSST V1 launch, this analysis helped inform understanding of how different design choices might translate into operational and resource implications across the state. These considerations supported decision-making but did not serve as the primary driver in option selection. Prior to policy being updated and enforced, additional analysis looking at benefits and feasibility including costs will be considered.

6) Adult Tiering Summary

The Work Group's evaluation of the different options resulted in agreement that Option 2 was the most appropriate path forward for the V1 launch in the Adult population. It satisfied all evaluation criteria laid out by the group, with high technical performance and contribution across domains. It was the option with the strongest equity result, with only new enrollees falling below the 80% benchmark relative to the state average recall. The scorecard below was used by the Work Group to compare the relative performance of each of the 3 options on the 5 key evaluation principles we set.



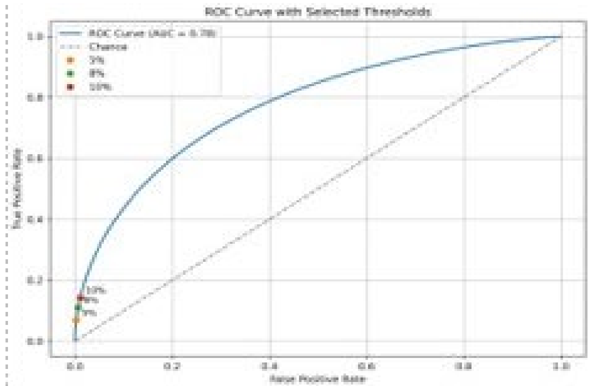
7) Pediatric Tiering: Technical Performance

All subdomain models were assessed for technical performance in the Pediatric population. The models achieved sufficient levels of performance and effectively predicted member risk scores. AUC values ranged from 0.75-0.92, with the highest discrimination statistic approaching 0.92 in the Social Risk model. These results compared favorably to models predicting similar adverse events in similar populations (see above comparative studies).

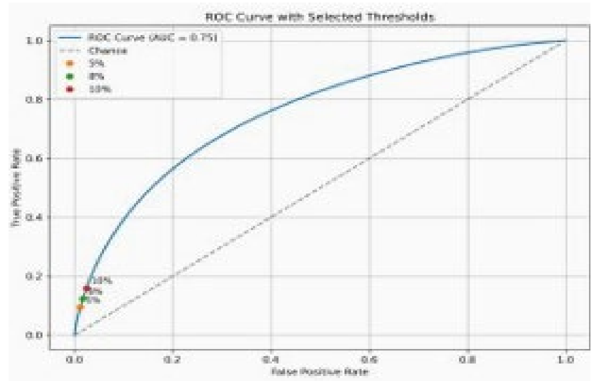
Domain	Adverse Events		Underutilization		Social Risk
Subdomain	Physical Health	Behavioral Health	Physical Health	Behavioral Health	Adverse Social Events
AUC	0.77	0.75	0.76	0.78	0.92

None of the AUC curves demonstrated atypical patterns, with all five models exhibiting patterns consistent with standard model behavior:

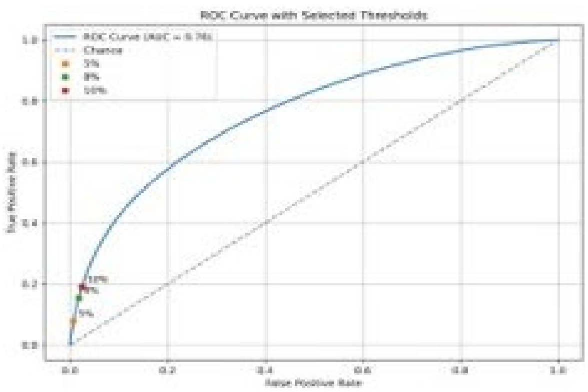
Physical Adverse Events



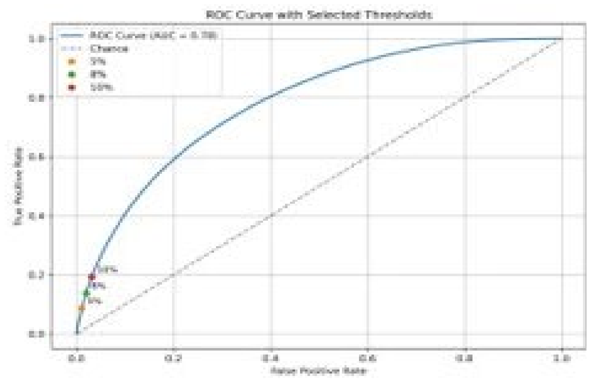
Behavioral Adverse Events



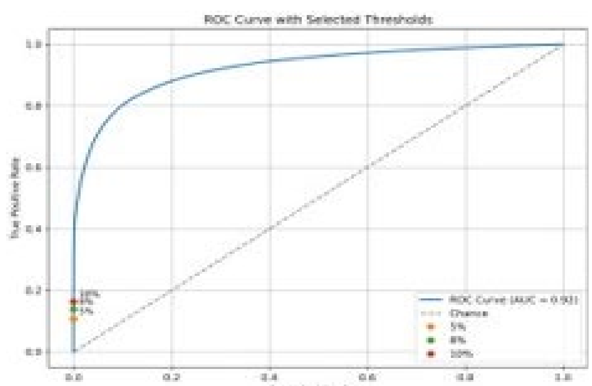
Physical Underutilization



Behavioral Underutilization



Social Risk

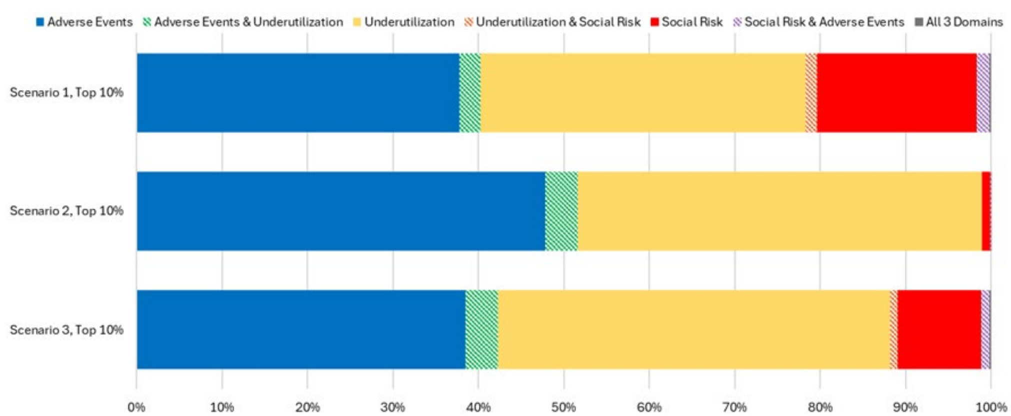


Finally, the Work Group reviewed NNT and Recall for the overall RSST tier for the Pediatric strata, with a state average recall of 0.24 and a NNT of 1.97 (Option 2). In other words, approximately 1 in 4 of all Pediatric state members who went on to have at least one RSST adverse outcome were flagged as high risk, and over half of Pediatric members flagged as high risk went on to have at least one adverse RSST outcome.

Tiering Option (Pediatrics)	Recall	NNT
Option 1	0.215	2.207
Option 2	0.241	1.966
Option 3	0.245	2.001

8) Pediatric Tiering: Balance of Risk Types

The Pediatric models showed less balance of risk types, with Options 2 and 3 generating many members for Underutilization domain due high level of underutilization in the Medi-Cal population, and an appropriately small number of members due to Social Risk. Option 1 was designed to balance the proportion of members flagged as high-risk at the subdomain level, which as expected resulted in greater balance than other options at the domain level. However, the Work Group determined that it over-emphasized Social Risk, which is based on only one rare Pediatric outcome (Housing Instability).



9) Pediatric Tiering: Equity Assessment

When comparing all subgroups to the statewide average, all three options nearly met the 80% relative recall threshold, with a few exceptions.

In Options 1 and 3, the American Indian or Alaska Native subgroup had higher-than-average recall (0.39 vs. 0.22 for Option 1 and 0.39 vs. 0.25 for Option 3), exceeding the 120% threshold. Likewise, in Option 2, the American Indian or Alaska Native subgroup had higher-than-average recall (0.30 vs. 0.24), exceeding the 120% threshold. The Work Group agreed this positive outlier was acceptable given the small subgroup size. As in the Adult models, New Medicaid Enrollees had lower than average recall (0.17 in Option 1 and 0.15 in Option 3), however this was not the case for Option 2.

Option 2 also showed lower recall for males (0.19 vs. 0.24), driven by the inclusion of chlamydia screening underutilization among 16–17-year-old females in the Physical Health Underutilization composite. This outcome applied only to females and thus disproportionately improved recall for females in that model. A review of all other model outcomes found this to be the only such case. DHCS determined the result reflected real underutilization patterns and that sex-based differences in model performance were justified by the underlying data.

10) Pediatric Tiering: Potential Benefit Assessment

Potential benefits of Pediatric tiering options were assessed by estimating the number of net new needs assessments at a historical reference point (January 2023). "Net new" refers to Pediatric members who would have been identified as high risk under the RSST algorithm but would not have been designated as high risk under existing DHCS policy. At the time of analysis, RSST had not yet been mandated for operational use.

In addition to total counts, we evaluated how many of these net new members went on to experience an RSST outcome in the subsequent 12 months, using historical data where future outcomes were observable. Option 2, which was ultimately selected, identified 351,177 net new Pediatric members for needs assessment, slightly fewer than Option 3 (n = 364,032). Across options, the majority of net new members flagged (approximately 73–75%) went on to experience an adverse event, underutilization, or social risk outcome in the following year. While this rate was lower than that observed for Adults, it still demonstrated meaningful predictive value in identifying Pediatric members who may otherwise be missed under current policy.

Impacts related to TCS were excluded from this analysis, as these members were not considered net new for care identification purposes, even if associated costs were newly observed. Additional analyses evaluating benefits, feasibility, and cost considerations may be conducted as policy implementation progresses.

11) Pediatric Tiering: Potential Costs and Impacts

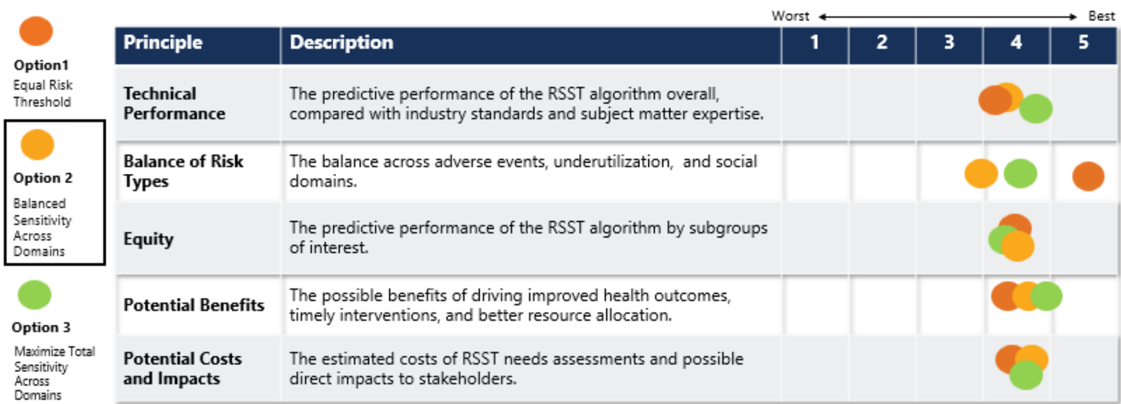
See Adults section above.

12) Pediatric Tiering Summary

The Work Group's evaluation of the different options resulted in agreement that Option 2 was the most appropriate path forward for the V1 launch in the Pediatric population.

Both Option 2 and Option 3 performed well across the evaluation criteria, and the decision between them was closer than in the Adult analysis. Option 2 demonstrated recall and NNT values of 0.24 and 1.97, respectively similar to or higher than the other Options. It also performed best on the equity analysis, with all subgroups meeting or exceeding the 80% benchmark relative to the statewide average—aside from a single sex-specific underperformance in males, which was reviewed and determined to reflect real-world data patterns.

Given the importance of transparency and explainability to stakeholders, it was important to DHCS to select the same tiering option for both Adult and Pediatric populations, provided that no major equity or performance tradeoffs were present. Option 2 satisfied that condition, offering the clearest path for consistent statewide implementation in Version 1.

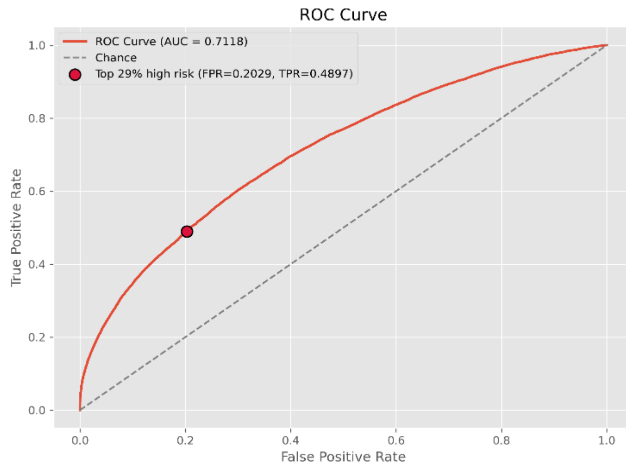


13) Birthing Tiering: Technical Performance

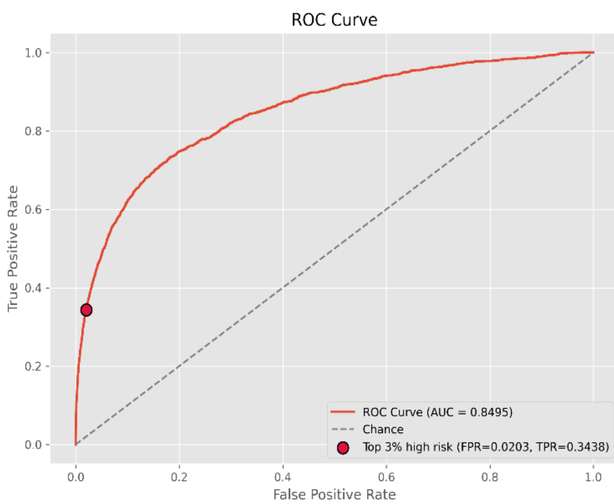
All three Birthing subdomain models were assessed for technical performance and appropriateness for use in tiering at the episode-level. Model discrimination was consistent with that of the V1 Pediatric models. Episode-level AUC values ranged from approximately 0.71 to 0.85 across the three Birthing subdomains, with no evidence of atypical ROC behavior (see Appendix A).

Domain	Birthing Adverse Events		
Subdomain	Pregnancy Adverse Events	Post-Pregnancy Physical Adverse Events	Post-Pregnancy Behavioral Adverse Events
AUC	**0.7118**	**0.7730**	**0.8495**
Outcome Prevalence	**29%**	**10%**	**3%**

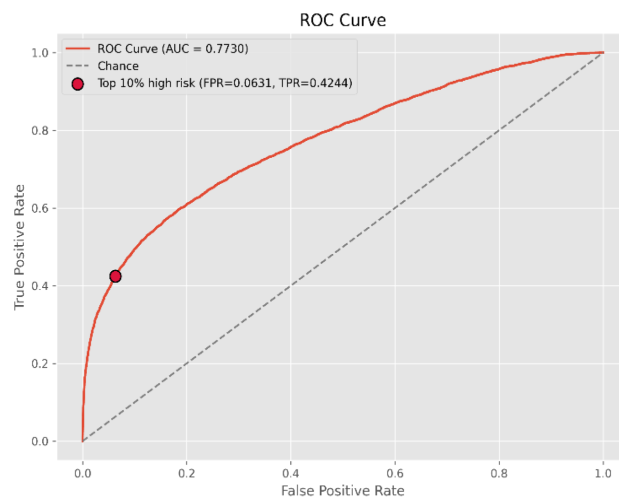
Pregnancy Adverse Events



Post-Pregnancy Behavioral Health



Post-Pregnancy Physical Health



Overall Performance (All 3 Birthing Models, Recall and NNT) by Tiering Option

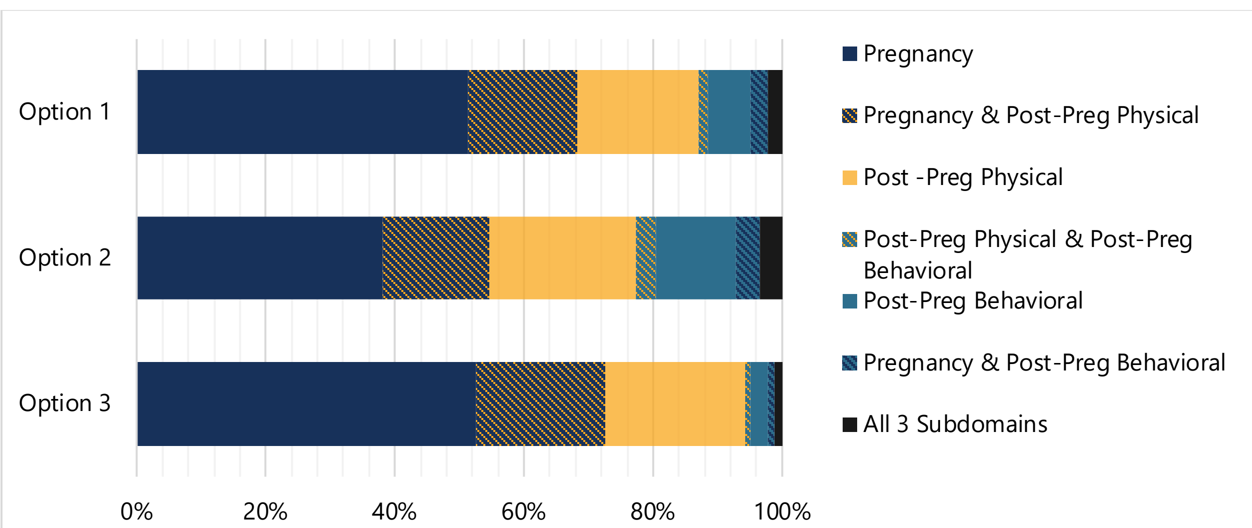
Tiering Option (Consistent Target of 27% High Risk Episodes)	Recall	NNT
Option 1 – Outcome-Driven Thresholds Across subdomains	0.56	2.47
Option 2 – Balanced Recall Across subdomains	0.56	2.56
Option 3 – Maximize Overall Recall (at the domain level)	0.57	2.47

The Work Group reviewed Recall and NNT across the three tiering options. Across options, overall recall (all 3 models combined) clustered tightly around ~0.56, and NNT ranged from approximately 2.47 to 2.56, indicating that for every ~2.5 Birthing members outreached, one member would have experienced at least one adverse outcome. Differences in recall and NNT between options were modest, with no option demonstrating a clear technical advantage.

14) Birthing Tiering: Balance of Risk Types

To assess balance across the three Birthing subdomains—Pregnancy, Post-Pregnancy Physical, and Post-Pregnancy Behavioral—among all episodes designated as high-risk the Work Group examined the distribution of which subdomain (or combination of subdomains) drove the high-risk designation under each option.

Options 1 and 3 produced pregnancy-heavy distributions, reflecting direct alignment with observed outcome prevalence (29%). Option 2 resulted in a more even distribution across Pregnancy, Post-Pregnancy Physical, and Post-Pregnancy Behavioral risk types, and this emphasis on Post-Pregnancy risk was viewed as favorable by the Work Group given the lagged timing of claims and the opportunities for care management intervention being more realistically in the post-pregnancy/postpartum period.

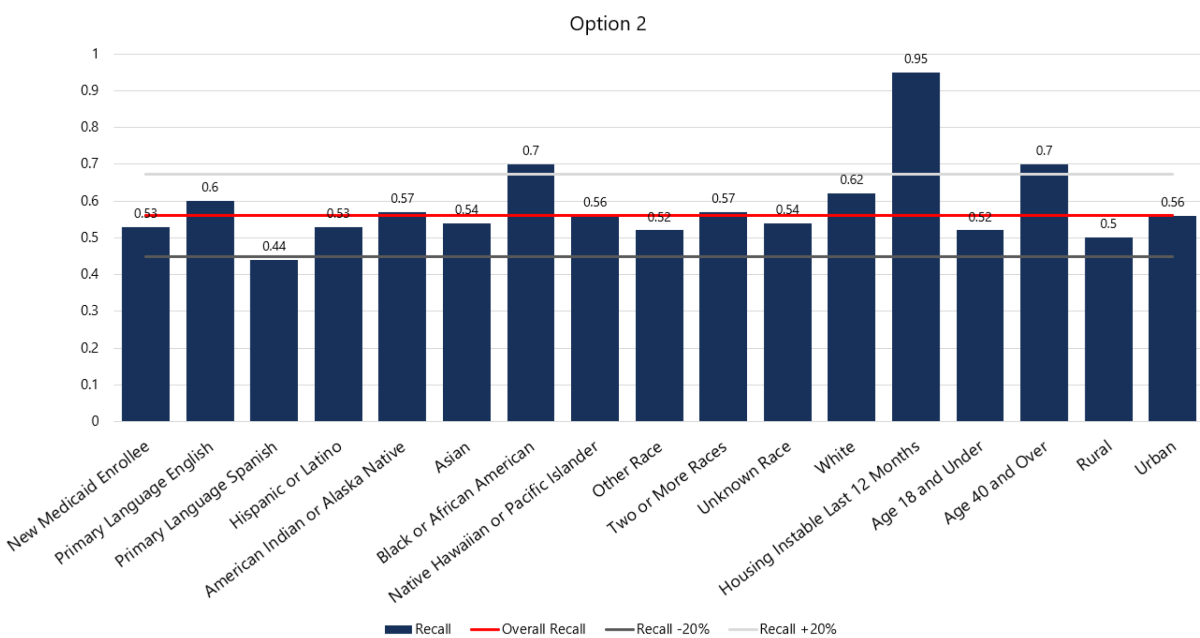


15) Birthing Tiering: Equity Assessment

Equity was evaluated by comparing subgroup-specific recall against the overall statewide average recall, using the same ±20% relative threshold applied in prior RSST tiering decisions. Overall, equity patterns were similar across all three options, with modest subgroup variation and no option exhibiting widespread or systematic underperformance.

Option 3 was the only option in which no subgroup fell at or below the −20% relative recall threshold. In Options 1 and 2, primary Spanish-speaking members were near the −20% threshold, though results were viewed as directionally consistent with known epidemiologic and clinical context provided by our SMEs that the Hispanic population often has better health outcomes despite facing socioeconomic disadvantages (e.g. Hispanic/Latino paradox). Across all options, Black/African American members, members with housing instability, and members age 40 and over performed at or above the +20% relative threshold.

The Work Group generally agreed that equity results were acceptable and aligned with expectations for this population, and that no option presented a material equity risk that would preclude selection.



16) Birthing Tiering: Potential Impacts

Birthing tiering impacts were assessed using historical data from December 2022, translating episode-level results to member-level impacts. While approximately 27% of pregnancy episodes were associated with a Birthing outcome over the full episode window, only ~10–16% of members were flagged in any given month. The Birthing models identify mostly net-new high risk members over and above the V1 Adult/Pediatric models, but there is also significant overlap in the high risk tiers. About 35% of the high-risk Birthing members identified by these new models overlap with those already identified as high risk under the Adult and Pediatric V1 models, and 65% of them are net-new. Overall, given the proportionally smaller size of the Birthing population at any time, when layering the Birthing models on top of the Adult/Pediatric models, there is a resulting net increase in overall RSST high risk prevalence from ~10% to 10.2% of the total Medi-Cal population in the reference month used. The Work Group concluded that Birthing tiering would enhance pregnancy-related risk identification while having a modest impact on statewide and MCP-level high-risk volumes.

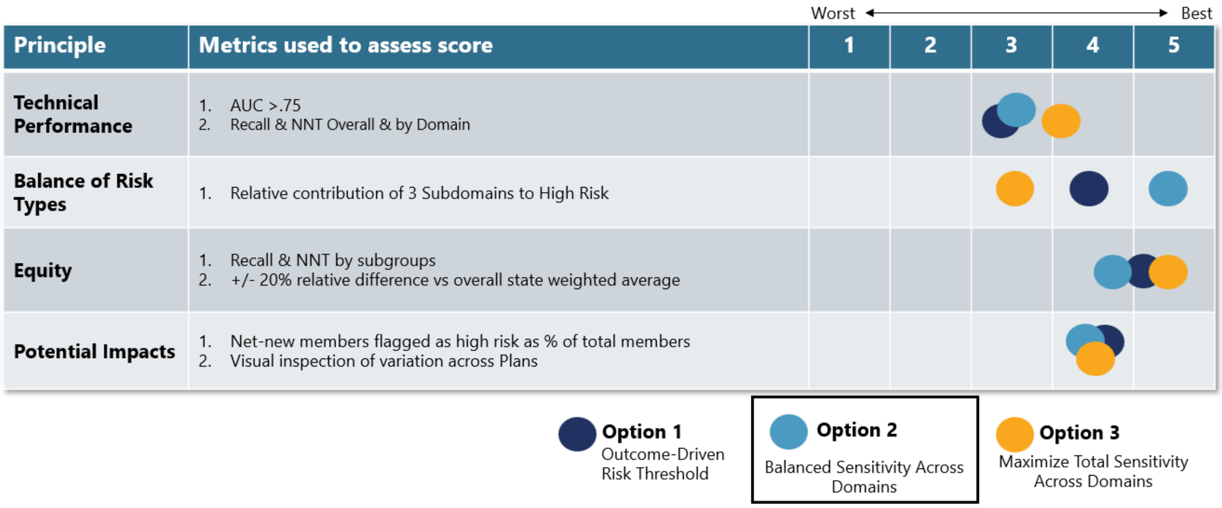
17) Birthing Tiering Summary

The Work Group's evaluation of the three tiering options resulted in agreement to proceed with Option 2, using an approximately 27% episode-level high-risk reference point derived from observed adverse outcome prevalence, and to lock in the corresponding thresholds for initial release.

Option 2 was selected because it:

- Maintains consistency with prior RSST decisions for Adults and Pediatrics, supporting continuity, explainability, and MCP familiarity.
- Provides the most balanced representation of risk types across Pregnancy, Post-Pregnancy Physical, and Behavioral subdomains, without overly restricting post-pregnancy risk.
- Performs comparably to the other options on recall, NNT, and equity, with no clear technical downside relative to Options 1 or 3.
- Avoids additional delay or scope expansion, as exploring alternate top-line prevalence targets or further optimization would require re-running analyses and visuals without materially improving decision-making for V1.1.

While Option 3 demonstrated slightly more favorable equity characteristics and marginally higher recall, the incremental gains were limited. Given the close performance across options and the value placed on consistency and operational clarity, the Work Group determined that Option 2 represented the most appropriate and stable path forward for the Birthing V1.1 launch.



G. Validation Results

Adult and Pediatric Models (V1)

After model tuning, training, and tiering were approved by DHCS, several steps were taken to productionize the RSST V1 predictive models (n=10) for routine monthly inference generation. The models were originally trained in the Training environment using historical data stored in an AWS Redshift SQL database. To support production go-live (target: July 2025), the models were migrated to run in the Production environment, with all data transformation and input files generated through the AWS Data Lake using Spark SQL.

Because this transition involved both code refactoring and changes to underlying data environments (including differences in available data by year), a structured series of validation exercises was conducted to ensure consistency, correctness, and readiness:

- Tests 1–3 evaluated model alignment at the person-level across the full ~15 million-member population, verifying consistency in high-risk designations and risk scores.
- Test 4 was conducted at the subdomain level, assessing broader differences in high-risk prevalence between historical and current populations.

Test 1: Input Code Refactor Validation – Redshift SQL to Spark SQL

Objective: Confirm that the model input logic was correctly refactored from Redshift SQL to Spark SQL when moving from Training to Production pipeline.

Approach:

- Model inputs for IndexDate January 2023 were generated using Spark SQL in the AWS Data Lake (Training environment).
- Outputs were compared at the PersonID level to the original model training inferences.
- High-risk designations were used as the key comparison point across all 10 RSST models.

Results Summary:

Strata	Model Name	Percent Agreement
Adult	physical_adverse_events	99.2%
Adult	behavioral_adverse_events	99.8%
Adult	physical_underutilization	94.2%
Adult	behavioral_underutilization	92.6%
Adult	social_adverse_events	99.9%
Peds	physical_adverse_events	98.9%
Peds	behavioral_adverse_events	98.5%
Peds	physical_underutilization	95.7%
Peds	behavioral_underutilization	92.9%
Peds	social_adverse_events	100.0%

Findings:

- Agreement between Redshift and Spark-generated inputs was high across models, confirming successful logic migration.
- The behavioral_underutilization model showed the largest variation (92.6%), driven by changes in the bh_claims_12_months predictor, which relies on Short Doyle claims.
- The discrepancy is expected: the Spark pipeline does not apply a received_date limit as in training. Additionally, Short Doyle claims are known to have long runout delays, which were communicated after model training was completed.

Test 2: Environment Shift Validation – Training to Production

Objective: Assess whether differences in model inference outputs arise when shifting from the Training to Production environment, using the same IndexDate and Production inference code.

Approach:

- Inferences were generated using the Production codebase in both the Training and Production environments for IndexDate January 2023.
- PersonIDs were converted back to CIN, and comparisons were made only for CINs present in both environments (11.56M Adults, 5.03M Pediatrics).

Results Summary:

Strata	Model Name	Percent Agreement
Adult	physical_adverse_events	99.3%
Adult	behavioral_adverse_events	99.8%
Adult	physical_underutilization	94.1%
Adult	behavioral_underutilization	87.6%
Adult	social_adverse_events	99.6%
Peds	physical_adverse_events	99.1%
Peds	behavioral_adverse_events	97.8%
Peds	physical_underutilization	97.0%
Peds	behavioral_underutilization	95.3%
Peds	social_adverse_events	99.9%

Findings:

- Agreement across environments was generally high, particularly for adverse event models.
- The behavioral_underutilization model again showed the lowest alignment, likely due to runout differences in Short Doyle claims.
- Key known difference: Training includes claims through Dec 2023, while Production includes claims through Dec 2024.
- The differences are consistent with expectations and considered acceptable.

Test 3: Inference Logic Validation – Training to Production

Objective: Confirm that the Production inference code produces consistent model outputs compared to the original training process when run on identical input data.

Approach:

» Production inference code was run in the Training environment using January 2023 inputs—the same data used for model training.

» Continuous risk scores were compared for all 10 models.

Findings:

» Risk score outputs were effectively identical across all models.

» Minor rounding differences (<0.01%) were observed but are not material.

» This confirms the Production inference logic accurately reproduces the model training logic.

Test 4: Data Timeframe Shift – From Historical to Most Recent Data

Objective: Assess whether RSST model outputs differ when applied to the latest Medi-Cal population compared to the population used during development and determine whether any action was needed before go-live.

Approach:

» Compared the percent of members flagged as high-risk in January 2023 (based on 2022 data used for Tiering Analysis) to December 2024 (the go-live month using 2024 data).

» Examined trends at the subdomain, domain, and overall RSST tier level for both Adult and Pediatric strata.

» Analysis was conducted using the fixed thresholds derived from model development, applying them to the updated 2024 population.

Findings:

» Across most subdomains, percent of members flagged high-risk remained stable, with variation generally under 0.5%.

» The exception was the Underutilization domain, where the proportion of members flagged increased by 2–3 percentage points, driving an increase in the overall RSSTTier prevalence from 10.0% to 12.1% in Adults and 10.1% to 11.5% in Pediatrics.

- This increase was likely attributable to a combination of known limitations in behavioral health claims runout (e.g., Short Doyle data lag), and real population-level shifts in access patterns, potentially related to post-COVID care trends.

Decision and Action Taken:

To address this, the team performed a one-time rebasing of the subdomain-level thresholds. Rather than retrain the models, which was deemed unnecessary, the original top-K subdomain percentile thresholds from 2023 were reapplied to the December 2024 population. This realignment restored the RSSTTier high-risk prevalence to approximately 10% at go-live, consistent with DHCS's original guidance.

Decision Context:

In discussions with DHCS and RSST leads, consensus emerged that adjusting thresholds prior to go-live was preferable to allow RSST to launch close to the 10% target. Re-training was considered unnecessary, and this approach was viewed as a straightforward mitigation strategy that maintained alignment with the original tiering analysis. The team acknowledged that the prevalence of high-risk designations will still vary in future months and recommended continued monitoring (see next section).

Implications and Future Considerations:

- The adjusted high risk threshold values will remain static for RSST Version 1, meaning future monthly prevalence may drift depending on population changes.
- However, starting from a rebased 10% high-risk population ensures alignment with DHCS policy expectations at launch.
- A broader re-tiering analysis is expected in 2025–2026 to revisit thresholds, cost impact, and equity results ahead of any formal policy mandate for MCPs to act on high-risk flags.
- The table below summarizes the pre- and post-rebaselining results across strata and domains:

	Adults			Peds		
	Jan 2023 Tiering	Dec 2024 Prod	Diff	Jan 2023 Tiering	Dec 2024 Prod	Diff
RSSTTier	10.0%	12.1%	2.1%	10.1%	11.5%	1.4%
AdverseEventDomainTier	2.4%	2.1%	-0.3%	5.2%	4.8%	-0.4%
AdversePhysicalSubdomainTier	2.1%	2.0%	-0.1%	2.2%	2.0%	-0.2%
AdverseBehavioralSubdomainTier	0.5%	0.2%	-0.3%	3.5%	3.2%	-0.3%
UnderuseDomainTier	7.9%	10.4%	2.5%	5.2%	7.0%	1.8%
UnderusePhysicalSubdomainTier	6.7%	9.4%	2.7%	4.2%	6.1%	1.9%
UnderuseBehavioralSubdomainTier	1.6%	1.5%	-0.1%	1.0%	1.0%	0.0%
SocialRiskDomainTier	0.5%	0.3%	-0.2%	0.1%	0.1%	0.0%
SocialAdverseEventsSubdomainTier	0.5%	0.3%	-0.2%	0.1%	0.1%	0.0%

Conclusion

The four validation tests confirm that the RSST models approved by DHCS have been accurately migrated to the production environment. Tests 1–3 demonstrated strong consistency in logic, scoring, and data handling across environments and refactored code, with only minor, explainable differences. Test 4 identified a modest increase in high-risk prevalence—primarily in underutilization models—consistent with known data limitations and shifts in population-level care patterns.

Overall, the productionized RSST models remain aligned with those originally approved, and the system is ready for go-live. Outputs can be used with confidence, supported by ongoing monitoring and maintenance.

Looking ahead, future iterations of RSST models are expected to run within the same production environment and data pipelines, reducing the need for cross-environment validation. This streamlining will simplify future retraining and re-validation efforts while maintaining confidence in model continuity.

Birthing Models (V1.1)

Consistent with the direction outlined above, the Birthing models did not require the same cross-environment validation performed for the Adult and Pediatric models. Birthing model development, training, testing, and deployment were all conducted within the same production environment, using the same member identifiers, data sources, and SQL-based implementation. As a result, validation activities related to environment migration, data translation, or code refactoring were not applicable. Model development included internal quality assurance checks, including re-running training using alternate data splits to confirm stability of results. While formal, standalone machine learning validation was not conducted for the Birthing models, ongoing RSST monitoring is being developed to track model inputs, outputs, and distributions over time. This monitoring framework will support early detection of data issues or model drift and inform future decisions about model refresh or retraining, including for the Birthing models.

VII. MAINTENANCE AND MONITORING

The RSST Algorithm is operational in the production environment and supports a recurring monthly process for generating and distributing risk tier outputs across the Medi-Cal population. Ongoing activities include monthly delivery of member-level tier files, monitoring via a dashboard available to DHCS, and structured maintenance of the algorithm and its underlying models.

A. Monthly RSST Tier File Generation

Each month, a member-level RSST tier file is generated and delivered through secure channels for integration into the PHM Service. The tier file includes consistent, structured information to support use in MCP workflows, the longitudinal member record, and care management tools.

Each record contains:

- Member identifier (CIN)
- Strata indicator (Adult, Pediatric, Infant)
- Risk tier variables representing:
    - Eight individual subdomain model outputs, five for V1 Adult and Pediatric models and three for V1.1 Birthing models
    - Aggregated domain-level tiers for Adverse Events, Underutilization, Social Risk, and Birthing
    - A single overall RSST tier value (Note: at V1.1 launch, the Birthing domain does not rollup into this overall RSST tier value, except for Infants included in the file as they have no other risk tiers available).
- Two categorical indicators for pregnancy status (- = N/A, U = Unknown, Y = Yes) and post-pregnancy/postpartum status (- = N/A, U = Unknown, L = Loss, D = Delivery). Females 15-49 will be provided Birthing subdomain tier values each month, but only

when one of these categorical indicators is triggered do those subdomain tier values roll up into the Birthing domain tier value.

» Infants are either matched to their Birthing parent and given the parent's risk tier values (post-pregnancy subdomains, Birthing domain, and overall RSST) or they are not successfully matched and are defaulted to High risk overall RSST.

Tier values are reported as integers (1 = Low, 2 = Medium, 3 = High). The file format and contents are consistent across months to support comparability and integration.

B. Dashboard-Based Monitoring

A secure monitoring dashboard is available to the RSST leadership team at DHCS, to be shared with a broader audience as appropriate determined by DHCS. The dashboard allows for ongoing tracking of tier distribution patterns, system behavior, and potential signals of change in the Adult, Pediatric, and Birthing models performance.

Key features of the dashboard include:

» Statewide and county-level tier distributions

» MCP-level summaries

» Subgroup breakouts (e.g., race/ethnicity, language, age group, dual eligibility)

» Month-over-month trend tracking at the domain and subdomain levels

» The dashboard also supports subgroup analysis using the same demographic variables examined in the Tiering Analysis, enabling DHCS to monitor monthly results for key populations and compare subgroup trends to statewide averages.

The dashboard is updated monthly and is designed to support oversight and decision-making. Unusual shifts in tiering patterns or subgroup variation may trigger further review and potential model updates.

C. Ongoing Maintenance of the RSST Algorithm

The RSST Algorithm will be maintained through a structured review and release process. Ongoing activities include:

» Periodic retraining of underlying models using updated data

» Adjustments to model logic, input features, or risk tiering methodology

» Integration of additional models, including future iterations focused on Birthing populations

» Monthly review of outputs using the monitoring dashboard

- Version tracking and documentation of changes over time

These processes ensure that the RSST Algorithm remains aligned with Medi-Cal program goals and continues to reflect changes in data, policy, and population characteristics.

VIII. ASSUMPTIONS AND LIMITATIONS

The RSST Algorithm operates within known constraints related to data availability, model design choices, and system infrastructure. These limitations should be considered when interpreting tier outputs and planning future development.

- **Data availability:** The models are trained using Medicaid administrative claims and eligibility data. These sources provide broad statewide coverage but do not include clinical records (e.g., EHR data) or many non-health social factors. Social risk features are currently limited in scope. EHR data is not available and is not expected to be included in future RSST versions. Medicare claims and encounter data is not included in any of the models.
- **Excluded populations:** Members with only partial Medi-Cal coverage (e.g., GHPP, Family PACT, CCS) are excluded from RSST tiering due to data limitations, and dual-eligible members (enrolled in both Medicaid and Medicare) are excluded from receiving Underutilization tier values as Medicare claims are not accessible and that model is particularly sensitive to the lack of Medicare data. These exclusions are detailed in the Population Definition section.
- **Claims lag:** RSST models were intentionally designed to account for the natural delays in claim submission and processing. During model training, inputs were constructed using a “what was known when” approach: only data with a processing date prior to the index date was included as a predictor. If a claim had not yet been processed at the prediction time, it was excluded—even if the service occurred earlier. This mirrors real-world data availability conditions and helps ensure that model performance reflects how the algorithm would function in practice.
- **Data transfer lag within PHM Service:** In addition to claims runout, data must pass through several systems within the PHM Service before it is available for tiering. These delays were not quantified at the time of model development and were not incorporated into Version 1. Future retraining is expected to account for this lag explicitly.

- **Fixed thresholds:** High-risk tier thresholds were set using January 2023 predicted scores—the most recent month with complete follow-up data. After a one-time correction to a more current population, these thresholds will remain fixed for consistency, but the share of members flagged as high risk may vary over time as populations shift. This will require active monitoring, a cadence for re-training when population shifts occur, and/or a change to tiering methodology.
- **Model generalizability over time:** Models are based on historical data and may become less predictive as care patterns, access, or population characteristics change. Ongoing monitoring and periodic retraining will be necessary to maintain performance.
- **Assumptions around service capacity:** The 10% high-risk flagging rate was informed by estimates of what managed care plans could reasonably manage under future policy scenarios. These assumptions may not align with actual MCP capacity and will be revisited over time, at which point additional analytics will be conducted to support a new high-risk rate.
- **Medium-risk tiering:** Medium-risk thresholds were set using a uniform 50% recall cutoff across V1 Adult and Pediatric subdomains for simplicity. These thresholds do not currently influence service requirements and were not optimized for operational outcomes. They are to be considered pre-decisional placeholders while the team refines the analytical approach to medium threshold setting. Birthing models have two tiers (High vs Medium). There is no Low tier for Birthing models at V1.1 launch.
- **Evaluation scope:** The Tiering Analysis included key performance and equity metrics, but not all possible subgroup or policy simulations. The analysis is meant to inform policy choices, not prescribe them.
- **Rare subgroups:** For smaller or underrepresented populations—such as certain race/ethnicity categories or low-volume counties—model performance and equity statistics may be less stable due to limited sample size.

IX. APPENDIX

A. Glossary of Key Policy Terminology Used

Admission, discharge, and transfer (ADT) feed is a standardized, real-time data feed sourced from a health facility, such as a hospital, that includes members' demographic and healthcare encounter data at time of admission, discharge, and/or transfer from the facility.

Assessment is a process or set of questions for defining the nature of a risk factor or problem, determining the overall needs or health goals and priorities, and developing specific treatment recommendations for addressing the risk factor or problem. Health assessments can vary in length and scope.

Basic Population Health Management (BPHM) is an approach to care that ensures that needed programs and services are made available to each member, regardless of their risk tier, at the right time and in the right setting. BPHM includes federal requirements for care coordination (as defined in 42 C.F.R. § 438.208).

Care manager is an individual identified as a single point of contact responsible for the provision of care management services for a member.

Care Management Plan (CMP) is a written plan that is developed with input from the member and/or their family member(s), guardian, authorized representative, caregiver, and/or other authorized support person(s), as appropriate, to assess 86 strengths, risks, needs, goals, and preferences, and make recommendations for service needs.

Complex Care Management (CCM) is an approach to care management that meets differing needs of high-and rising-risk members, including both longer-term chronic care coordination and interventions for episodic, temporary needs. Medi-Cal Managed care plans (MCPs) must provide CCM in accordance with all NCQA CCM requirements.

Early and Periodic Screening, Diagnostic, and Treatment (EPSDT) is a federal entitlement that states are required to provide to all children under age 21 enrolled in Medicaid. This includes any Medicaid-coverable service in any amount that is medically necessary, regardless of whether the service is covered in the state plan. [5]

[5] EPSDT in Medicaid. Medicaid and CHIP Payment and Access Commission. DHCS specific requirements on EPSDT is outlined in APL 23-010.

Enhanced Care Management (ECM) is a whole-person, interdisciplinary approach to care that addresses the clinical and nonclinical needs of high-cost and/or high- need members who meet ECM Populations of Focus eligibility criteria through systematic coordination of services and comprehensive care management that is community-based, interdisciplinary, high-touch, and person-centered.

Health Information Form (HIF)/Member Evaluation Tool (MET) is a screening tool that is required to be completed within 90 days of MCP enrollment for new members. It fulfills the federal initial screening requirement. [6]

Health Risk Assessment (HRA) is an assessment required for Seniors and Persons with Disabilities. Effective January 1, 2023, HRA assessment requirements for Seniors and Persons with Disabilities are simplified, while specific member protections are kept in place.

Initial Health Appointment(s) previously called Initial Health Assessment, now refers to appointment(s) required to be completed within 120 days of MCP enrollment for new members and must include a history of the member's physical and behavioral health, an identification of risks, an assessment of need for preventive screens or services and health education, and the diagnosis and plan for treatment of any diseases.[7]

Long-Term Care (LTC) includes specialized rehabilitative services and care provided in a Skilled Nursing Facility, subacute facility, Pediatric subacute facility, or Intermediate Care Facilities (ICFs). [8]

Long-Term Services & Supports (LTSS) includes services and supports designed to allow a member with functional limitations and/or chronic illnesses the ability to live or work in the setting of the Member's choice, which may include the Member's home, a worksite, a Provider-owned or controlled residential setting, a nursing facility, or other institutional setting. LTSS includes both LTC and HCBS and includes carved-in and carved-out services. [9]

Risk stratification and segmentation (RSS) is the process of separating member populations into different risk groups and/or meaningful subsets using information

[6] 42 CFR 438.208(b)(3)-(4)

[7] These required Initial Health Appointment(s) elements are specified in 22 C.C.R. § 53851(b)(1).

[8] 2024 Re-Procurement. Exhibit A, Attachment I, Definitions and Acronyms

[9] 2024 Re-Procurement. Exhibit A, Attachment I, Definitions and Acronyms

collected through population assessments and other data sources. RSS results in the categorization of members with care needs at all levels and intensities.

Risk tiering is the assigning of members to standard risk tiers (i.e., high, medium- rising, or low), with the goal of determining appropriate care management programs or specific services.

Population Health Management (PHM) is a whole-system, person-centered, population-health approach to ensuring equitable access to health care and social care that addresses member needs. It is based on data-driven risk stratification, analytics, identifying gaps in care, standardized assessment processes, and holistic care/case management interventions.

The Population Health Management (PHM) Service collects and links Medi-Cal beneficiary information from disparate sources and performs risk stratification and segmentation (RSS) and tiering functions, conducts analytics and reporting, identifies gaps in care, performs other population health functions, and allows for multiparty data access and use in accordance with state and federal law and policy.

DHCS Population Health Management Strategy (PHM) Deliverable is an annual deliverable that MCPs submit to DHCS to demonstrate that it is responding to identified community needs, to provide other updates on its PHM program as requested by DHCS, and to inform the DHCS quality assurance and Population Health Management program compliance and impact monitoring efforts.

Screening is a brief process or questionnaire for examining the possible presence of a particular risk factor or problem to determine whether a more in-depth assessment is needed in a specific area of concern.

Social drivers of health (SDOH) are the environments in which people are born, live, learn, work, play, worship, and age that affect a wide range of health functioning and quality-of-life outcomes and risk factors.

Transitional care services (TCS) are services provided to all members transferring from one institutional care setting or level of care to another institution or lower level of care (including home settings).

Wellness and prevention programs are programs that aim to prevent disease, disability, and other conditions; prolong life; promote physical and mental health and efficiency; and improve overall quality of life and well-being.

B. Glossary of Technical Terms Used

Area Under the Curve (AUC) A performance metric used to evaluate how well a model distinguishes between members who will and won't experience an outcome. AUC measures the trade-off between sensitivity (recall) and specificity (true negative rate) across thresholds. Higher values indicate better discrimination. AUC ranges from 0.5 (random) to 1.0 (perfect).

Buffer window A time gap added between the end of the predictor period and the start of the outcome observation window to avoid overlap between inputs and labels. This helps prevent label leakage and ensures that predictions are based only on past information.

Calibration A measure of how well predicted probabilities align with actual outcomes. A calibrated model assigns higher risk scores to members who are more likely to experience an outcome. This matters when risk scores are interpreted directly (e.g., used for prioritization or thresholding).

Dask A Python computing library used to process large-scale healthcare data during RSST model development. It enables distributed, memory-efficient operations across multiple processors or machines.

Distributed computing A computing setup where processing is split across multiple machines or processors. This approach was used during RSST model development to handle large Medi-Cal datasets efficiently.

Early stopping / pruning A technique used during model training or optimization to stop processing when performance no longer improves. In RSST, pruning was used in tuning to reduce unnecessary computation.

Feature A variable used by a model to predict outcomes. RSST features include demographics, claims-based indicators, encounter data, pharmacy use, and social service history.

Feature importance A metric that indicates how much each feature contributes to a model's predictions. Feature importance helps users interpret which factors the model relies on most.

Gradient boosting A machine learning method that builds a predictive model in stages, with each stage correcting errors from the previous one. RSST used gradient boosting frameworks such as XGBoost and LightGBM.

Hyperparameter tuning The process of selecting model settings—such as learning rate or tree depth—to improve performance. RSST used automated hyperparameter tuning with Optuna to find the best configurations.

Label leakage When a feature inadvertently contains information about the label (outcome), which can distort model training and performance. RSST used buffer windows and feature checks to prevent this.

LightGBM A gradient boosting model optimized for speed and scalability. LightGBM was one of the modeling methods used in RSST to predict future outcomes from complex Medi-Cal data.

Number Needed to Treat (NNT) A measure of how many members must be flagged as high risk to prevent one adverse event. A lower NNT means more efficient targeting. For example, an NNT of 5 means 5 members need to be assessed to prevent one event.

Optuna A software library used to automate model tuning by searching for the best hyperparameters. RSST used Optuna to efficiently improve performance during model training.

Outcomes The specific adverse events or service gaps the RSST models are trained to predict. Examples include hospitalization, overdose, or failure to refill a medication. Each outcome is binary and tied to a defined time window. Outcomes in the RSST make up the overall subdomain composite that models aim to predict.

Precision The proportion of members flagged as high risk who actually experience the predicted outcome. Higher precision means fewer false positives. Precision helps assess how efficiently the model targets people who benefit from intervention.

Predictors Also known as features. The variables used to generate risk scores. In RSST, predictors come from administrative data sources including claims, pharmacy, encounters, and social service interactions.

Probabilistic predictions Numeric predictions ranging from 0 to 1 that represent the estimated likelihood of an outcome occurring.

Recall Also known as sensitivity. The percentage of members who experienced an outcome and were correctly flagged as high risk. Higher recall means the model is better at capturing true cases. For example, a recall of 0.65 means 65% of true outcomes were identified.

Regularized Logistic Regression A simple, interpretable modeling method that includes penalty terms to reduce overfitting.

Risk score A numeric value representing a member's predicted probability of experiencing a composite of the outcomes of interest in the next 12 months. Risk scores range from 0 (lowest risk) to 1 (highest risk) and are used to assign members to tiers.

SHAP (SHapley Additive exPlanations) A method for interpreting model predictions by calculating how much each feature contributed to a given prediction. RSST used SHAP values to improve model transparency and explainability.

Specificity The percentage of members who did not experience the outcome and were correctly not flagged as high risk.

Supervised learning A machine learning approach where models are trained on input data paired with known outcomes.

Test set A dataset used to evaluate model performance after training and tuning are complete.

Validation set A portion of data used during model development to evaluate different model parameters and select the best learner for a subdomain model. Validation helps ensure that models generalize well to unseen data.

XGBoost A popular machine learning framework used for gradient boosting. It was one of the primary model types used in RSST to generate predictions for several subdomains.

C. Additional Model Detail

1) Tables

Table A.1. Adult Composite and Outcome Prevalence[10]

Outcome	Shorthand	Prevalence	Denominator	Prevalence Rate	Strata-Specific Prevalence Rate
Adult physical health adverse events	Adult_adverse_ph_composite	703337	8875329	8%	-
All cause ip admit	o1	717488	8875329	8%	-
All cause ed visit	o2	532217	8875329	6%	-
Mortality	o5	89048	8875329	1%	-
New morbidity/cci	o9	81854	8875329	1%	-
Adult behavioral health adverse events	Adult_adverse_bh_composite	98127	8875329	1%	-
Psych admit	o3	51918	8875329	1%	-
Psych ed	o4	109876	8875329	1%	-
Intentional self-harm	o6	11990	8875329	<1%	-
Drug overdose	o7	26038	8875329	<1%	-
Injection related adverse event	o8	31006	8875329	<1%	-
All cause ed visits (3+) and short-doyle (1+)	o83	78718	8875329	1%	-
Adult behavioral underutilization	Adult_under_bh_composite	618277	861901	72%	7%
Pcp visits with bh/sud diagnosis	o12	207604	861901	24%	2%
Ambulatory mh/sud visits	o13	452473	861901	52%	5%
Antidep med mgmt	o19	141461	861901	16%	2%
Antipsych for schiz	o20	43112	861901	5%	<1%
Opioid for oud	o21	13294	861901	2%	<1%

[10] Outcome prevalence is calculated at the composite and individual outcome levels using the full eligible population (denominator) and the January 2023 index date from the test set. Underutilization models applied additional inclusion criteria that excluded some members within their respective strata. As a result, denominators for underutilization models are smaller than those used in adverse event models. For underutilization models, prevalence rates for individual outcomes share the same denominator as the composite. This reflects inclusion criteria applied at the composite level rather than for each outcome individually.

Outcome	Shorthand	Prevalence	Denominator	Prevalence Rate	Strata-Specific Prevalence Rate
Adult physical health underutilization	Adult_under_ph_composite	2713059	4290776	63%	31%
Pcp visit	o10	772829	4290776	18%	9%
No claims	o99	746422	4290776	17%	8%
Dental care	o11	345051	4290776	8%	4%
Chlamydia screen	o15	594083	4290776	14%	7%
Pharm for htn	o18_a	326312	4290776	8%	4%
Pharm for dm	o18_b	227529	4290776	5%	3%
Asthma med ratio	o41	123667	4290776	3%	1%
Adult social risk adverse events	Adult_social_ae_composite	227505	8875329	3%	-
Housing insecurity	o22	227505	8875329	3%	-

Table A.2. Pediatric Composite and Outcome Prevalence[11]

Outcome	Shorthand	Prevalence	Denominator	Prevalence Rate	Strata-Specific Prevalence Rate
Pediatric physical health adverse events	Pediatric_adverse_ph_composite	284,785	4,549,042	6%	-
All cause ip admit	o1	141,464	4,549,042	3%	-
All cause ed visit	o2	147,980	4,549,042	3%	-
Diagnosis of common chronic illness	o26	28,143	4,549,042	1%	-
Morbidity	o30	18,457	4,549,042	<1%	-
Pediatric behavioral health adverse events	Pediatric_adverse_bh_composite	281,656	4,549,042	6%	-
New diagnosis of mental illness	o27	227,941	4,549,042	5%	-
New diagnosis of developmental delay	o28	13,294	4,549,042	<1%	-
New diagnosis of SUD	o29	24,956	4,549,042	1%	-
Psych admit	o3	13,019	4,549,042	<1%	-
Psych ed	o4	44,542	4,549,042	1%	-
Intentional self-harm	o6	4,537	4,549,042	<1%	-
Drug overdose	o7	2,141	4,549,042	<1%	-

[11] See Table C.1 – Adult Composite and Outcome Prevalence footnote

Outcome	Shorthand	Prevalence	Denominator	Prevalence Rate	Strata-Specific Prevalence Rate
Pediatric behavioral underutilization	Pediatric_under_bh_composite	233,355	299,096	78%	5%
Pcp visits with bh/sud diagnosis	o12	59,690	299,096	20%	1%
Ambulatory mh/sud visits	o13	211,182	299,096	71%	5%
Metabolic Screenings	o39	7,574	299,096	3%	<1%
Follow-up after admission or ED visit for mental illness/SUD	o42	7,851	299,096	3%	<1%
ADHD follow-up care	o43	1,196	299,096	<1%	<1%
Pediatric physical health underutilization	Pediatric_under_ph_composite	914,777	1,559,019	59%	20%
Chlamydia screen	o15	226,628	1,559,019	15%	5%
Well child visits (first 30 months)	o31	126,884	1,559,019	8%	3%
Well child and adolescent visits	o32	352,677	1,559,019	23%	8%
Topical fluoride and/or Dental care	o33	151,667	1,559,019	10%	3%
Immunization status	o36	62,626	1,559,019	4%	1%
Asthma medication indicator	o41	74,408	1,559,019	5%	2%
Pediatric social risk adverse events	Pediatric_social_ae_composite	27,081	4,549,042	1%	-
Housing instability	o22	27,081	4,549,042	1%	-

Table A.2A. Birthing Composite and Outcome Prevalence[12]

Outcome	Prevalence	Denominator (Total Episode-Months in Cohort)	Prevalence Rate
Birthing Post-Pregnancy Behavioral Health Adverse Events	**55,480**	**2,071,461**	**2.7%**
Drug overdose	2,511	2,071,461	0.1%
Intentional self harm	2,741	2,071,461	0.1%
Injection drug related adverse event	3,088	2,071,461	0.1%
Maltreatment/abuse	5,920	2,071,461	0.3%
Psychiatric admission	5,824	2,071,461	0.3%

[12] See Table C.1 – Adult Composite and Outcome Prevalence footnote

Outcome	Prevalence	Denominator (Total Episode-Months in Cohort)	Prevalence Rate
Psychiatric ED visit	47,846	2,071,461	2.3%
Birthing Post-Pregnancy Physical Health Adverse Events	**170,178**	**1,640,968**	**10.4%**
Post-pregnancy hypertensive disorders	116,034	1,640,968	7.1%
Post-pregnancy hemorrhage	20,547	1,640,968	1.3%
Thromboembolism (DVT/PE)	5,599	1,640,968	0.3%
Maternal mortality	609	1,640,968	0.0%
Infant mortality	1,194	1,640,968	0.1%
Infant NICU	37,749	1,640,968	2.3%
Birthing Pregnancy Adverse Events	**577,130**	**1,854,155**	**31.1%**
Drug overdose	201	1,854,155	0.0%
Intentional self-harm	341	1,854,155	0.0%
Injection drug related adverse event	1,200	1,854,155	0.1%
Maltreatment and abuse	2,212	1,854,155	0.1%
Psychiatric ED visit	15,780	1,854,155	0.9%
All cause inpatient admissions	243,400	1,854,155	13.1%
Thromboembolism	4,201	1,854,155	0.2%
Maternal Mortality	43	1,854,155	0.0%
Gestational diabetes requiring insulin	40,050	1,854,155	2.2%
Placental abruption	23,665	1,854,155	1.3%
Severe fetal outcome	14,405	1,854,155	0.8%
Severe maternal morbidity composite	27,241	1,854,155	1.5%
Unplanned c-section	114,271	1,854,155	6.2%
Neonatal NICU	203,191	1,854,155	11.0%
Neonatal mortality	735	1,854,155	0.0%
Neonatal abstinence syndrome	3,317	1,854,155	0.2%
Early preterm and/or very low birthweight	52,241	1,854,155	2.8%

Table A.3. Best Hyperparameters per Model[13]

[13] All hyperparameters are for XGBoost. All XGBoost models were trained using a common set of default parameters unless otherwise specified. These included: objective='binary:logistic', eval_metric='auc', tree_method='hist', device='cuda', sampling_method='gradient_based',

Model	n_estimators	learning_rate	max_depth
Adults Behavioral Health Adverse Events	2833	0.0599	6
Adults Physical Health Adverse Events	1210	0.0359	12
Adults Social Risk Adverse Events†	1868	0.0359	10
Adults Behavioral Underutilization	552	0.0359	16
Adults Physical Health Underutilization	1671	0.0359	10
Peds Behavioral Health Adverse Events	1050	0.0359	12
Peds Physical Health Adverse Events	1671	0.0359	10
Peds Social Risk Adverse Events†	2090	0.0129	10
Peds Behavioral Underutilization	2090	0.0129	10
Peds Physical Health Underutilization	1909	0.0215	12
Birthing Post-Pregnancy Behavioral Health Adverse Events	1285	0.0046	16
Birthing Post-Pregnancy Physical Health Adverse Events	2151	0.0077	10
Birthing Pregnancy Adverse Events	2981	0.0046	16

Table A.4A. Adult Behavioral Health Adverse Events[14]

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9549	0.1733	0.6966	0.9582	108261397	Overall
0.9736	0.1429	0.5316	0.9768	9920799	new_medicaid_enrollee_12_months
0.9481	0.1731	0.7117	0.9515	47948906	sex_m
0.9603	0.1735	0.6815	0.9634	60312491	sex_f
0.9392	0.1747	0.7131	0.9430	74711414	primary_language_eng
0.9891	0.1521	0.4856	0.9908	23857940	primary_language_spa
0.9672	0.1663	0.6460	0.9702	42500094	ethnicity_category_hispanicorlatino
0.9469	0.1760	0.7171	0.9503	65761303	ethnicity_category_nothispanicorlatino
0.9099	0.1702	0.7323	0.9141	446431	race_category_american_indian_or_alaska
0.9911	0.1527	0.5452	0.9922	11256276	race_category_asian
0.9213	0.1829	0.7348	0.9255	8113512	race_category_black_or_african_american
0.9789	0.1700	0.6209	0.9811	1378639	race_category_native_hawaiian_or_other_

---

max_delta_step=1, and a fixed random_state=123 for reproducibility. Learning rate and maximum tree depth were tuned per model.

†These models were not the top performers in terms of AUC but were retained due to their close performance to the best model (LightGBM) and the scalability benefits of XGBoost, which supports multi-GPU training and inference at production scale.

[14] Table A.4A – J -- Subgroup Performance at the Top 5% Threshold per Model

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9650	0.1692	0.6666	0.9679	47710767	race_category_other
0.9444	0.1658	0.6912	0.9482	6204729	race_category_two_or_more_races
0.9514	0.1748	0.6964	0.9549	10472088	race_category_unknown
0.9317	0.1762	0.7255	0.9356	22678955	race_category_white

Table A.4B. Adult Physical Health Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9284	0.5947	0.3669	0.9779	108261397	Overall
0.9354	0.5651	0.3023	0.9826	9920799	new_medicaid_enrollee_12_months
0.9313	0.5942	0.3792	0.978	47948906	sex_m
0.9261	0.5951	0.3578	0.9778	60312491	sex_f
0.9294	0.604	0.3972	0.9768	74711414	primary_language_eng
0.9295	0.5684	0.3086	0.9807	23857940	primary_language_spa
0.9356	0.5757	0.3219	0.982	42500094	ethnicity_category_hispanicorlatino
0.9237	0.6032	0.3902	0.9752	65761303	ethnicity_category_nothispanicorlatino
0.9027	0.5827	0.4249	0.9621	446431	race_category_american_indian_or_alaska
0.9432	0.5844	0.2754	0.9871	11256276	race_category_asian
0.9088	0.6064	0.4302	0.9664	8113512	race_category_black_or_african_american
0.9256	0.589	0.3511	0.9778	1378639	race_category_native_hawaiian_or_other_
0.9332	0.5815	0.3355	0.9808	47710767	race_category_other
0.9347	0.5684	0.3203	0.9815	6204729	race_category_two_or_more_races
0.9277	0.6105	0.3941	0.9768	10472088	race_category_unknown
0.9171	0.6087	0.4187	0.971	22678955	race_category_white

Table A.4C. Adult Social Risk Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9594	0.3430	0.6889	0.9663	108261397	Overall
0.9728	0.3410	0.6113	0.9792	9920799	new_medicaid_enrollee_12_months
0.9437	0.3438	0.7368	0.9509	47948906	sex_m
0.9719	0.3416	0.6170	0.9784	60312491	sex_f
0.9438	0.3422	0.7040	0.9523	74711414	primary_language_eng
0.9930	0.3528	0.4303	0.9959	23857940	primary_language_spa
0.9748	0.3259	0.6219	0.9802	42500094	ethnicity_category_hispanicorlatino

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9494	0.3480	0.7099	0.9572	65761303	ethnicity_category_nothispanicorlatino
0.8744	0.4152	0.8077	0.8814	446431	race_category_american_indian_or_alaska
0.9948	0.3348	0.4635	0.9967	11256276	race_category_asian
0.9149	0.3116	0.6570	0.9277	8113512	race_category_black_or_african_american
0.9845	0.3803	0.5989	0.9889	1378639	race_category_native_hawaiian_or_other_
0.9739	0.2999	0.6146	0.9791	47710767	race_category_other
0.9464	0.3610	0.7163	0.9546	6204729	race_category_two_or_more_races
0.9588	0.3359	0.6580	0.9665	10472088	race_category_unknown
0.9312	0.3791	0.7562	0.9397	22678955	race_category_white

Table A.4D. Adult Behavioral Underutilization

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.3156	0.9612	0.0658	0.9928	11064665	Overall
0.2898	0.9570	0.0617	0.9915	746013	new_medicaid_enrollee_12_months
0.2860	0.9673	0.0790	0.9909	4663338	sex_m
0.3371	0.9542	0.0551	0.9938	6401327	sex_f
0.3119	0.9586	0.0629	0.9926	9379020	primary_language_eng
0.3121	0.9735	0.0889	0.9926	1330548	primary_language_spa
0.2883	0.9611	0.0667	0.9914	3709292	ethnicity_category_hispanicorlatino
0.3293	0.9612	0.0653	0.9934	7355373	ethnicity_category_nothispanicorlatino
0.2564	0.9725	0.0866	0.9894	82388	race_category_american_indian_or_alaska
0.3435	0.9619	0.0471	0.9959	420040	race_category_asian
0.2785	0.9597	0.0787	0.9882	1077127	race_category_black_or_african_american
0.3513	0.9661	0.0739	0.9940	88309	race_category_native_hawaiian_or_other_
0.3010	0.9632	0.0687	0.9922	4314101	race_category_other
0.2939	0.9538	0.0601	0.9913	744561	race_category_two_or_more_races
0.3221	0.9587	0.0675	0.9923	1172935	race_category_unknown
0.3475	0.9608	0.0589	0.9946	3165204	race_category_white

Table A.4E. Adult Physical Health Underutilization

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.4206	0.9406	0.0754	0.9921	52216732	Overall
0.4345	0.9337	0.0442	0.9955	5862856	new_medicaid_enrollee_12_months

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.3896	0.9393	0.0739	0.9909	20421256	sex_m
0.4405	0.9414	0.0764	0.9928	31795476	sex_f
0.4138	0.9422	0.0771	0.9919	37499791	primary_language_eng
0.4267	0.9350	0.0707	0.9922	11708380	primary_language_spa
0.4233	0.9390	0.0659	0.9932	22048178	ethnicity_category_hispanicorlatino
0.4185	0.9415	0.0821	0.9913	30168554	ethnicity_category_nothispanicorlatino
0.3978	0.9506	0.1158	0.9874	237088	race_category_american_indian_or_alaska
0.4202	0.9431	0.0627	0.9939	4069022	race_category_asian
0.4220	0.9410	0.1002	0.9889	4281011	race_category_black_or_african_american
0.4255	0.9440	0.0875	0.9913	589895	race_category_native_hawaiian_or_other_
0.4250	0.9394	0.0676	0.9931	24307995	race_category_other
0.4287	0.9388	0.0687	0.9930	3269442	race_category_two_or_more_races
0.4172	0.9401	0.0795	0.9914	5004166	race_category_unknown
0.4090	0.9419	0.0856	0.9905	10458113	race_category_white

Table A.4F. Pediatric Behavioral Health Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9147	0.2735	0.2183	0.9612	58509970	Overall
0.9563	0.2553	0.1114	0.9879	5608602	new_medicaid_enrollee_12_months
0.914	0.2904	0.2259	0.9617	29959997	sex_m
0.9153	0.2553	0.2097	0.9607	28549973	sex_f
0.9092	0.2744	0.2383	0.956	38558675	primary_language_eng
0.9213	0.2706	0.1753	0.9695	17764789	primary_language_spa
0.916	0.274	0.195	0.9649	32429813	ethnicity_category_hispanicorlatino
0.913	0.2729	0.2481	0.9566	26080157	ethnicity_category_nothispanicorlatino
0.8712	0.2751	0.2659	0.9309	179927	race_category_american_indian_or_alaska
0.9491	0.2733	0.1807	0.9804	3277630	race_category_asian
0.9033	0.2906	0.247	0.9537	3718155	race_category_black_or_african_american
0.9472	0.2819	0.1926	0.9792	518424	race_category_native_hawaiian_or_other_
0.9188	0.2757	0.196	0.9662	32894021	race_category_other
0.9064	0.2673	0.2173	0.9566	3808178	race_category_two_or_more_races
0.9231	0.2713	0.2074	0.9664	6136898	race_category_unknown
0.8851	0.2654	0.2949	0.9333	7976737	race_category_white

Table A.4G. Pediatric Physical Health Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9187	0.3411	0.2613	0.9647	58509970	Overall
0.8583	0.3225	0.3573	0.915	5608602	new_medicaid_enrollee_12_months
0.9173	0.3447	0.2608	0.9644	29959997	sex_m
0.9201	0.3372	0.2618	0.9649	28549973	sex_f
0.9154	0.3343	0.275	0.961	38558675	primary_language_eng
0.9223	0.3592	0.2374	0.9703	17764789	primary_language_spa
0.9145	0.3464	0.2625	0.9631	32429813	ethnicity_category_hispanicorlatino
0.9238	0.3337	0.2595	0.9666	26080157	ethnicity_category_nothispanicorlatino
0.9114	0.3216	0.2679	0.9586	179927	race_category_american_indian_or_alaska
0.9549	0.3362	0.1933	0.9849	3277630	race_category_asian
0.9194	0.339	0.2636	0.9646	3718155	race_category_black_or_african_american
0.9377	0.3476	0.2236	0.9769	518424	race_category_native_hawaiian_or_other_
0.9119	0.3471	0.2671	0.9614	32894021	race_category_other
0.9326	0.3348	0.2137	0.975	3808178	race_category_two_or_more_races
0.9153	0.3358	0.2608	0.9627	6136898	race_category_unknown
0.9263	0.3215	0.2734	0.9654	7976737	race_category_white

Table A.4H. Pediatric Social Risk Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.9523	0.08	0.6998	0.9537	58509970	Overall
0.9324	0.0712	0.707	0.934	5608602	new_medicaid_enrollee_12_months
0.9527	0.0807	0.7022	0.9542	29959997	sex_m
0.9518	0.0792	0.6974	0.9533	28549973	sex_f
0.9311	0.0801	0.7356	0.9327	38558675	primary_language_eng
0.9926	0.0762	0.3306	0.9936	17764789	primary_language_spa
0.9712	0.0754	0.6004	0.9726	32429813	ethnicity_category_hispanicorlatino
0.9288	0.0822	0.7558	0.9302	26080157	ethnicity_category_nothispanicorlatino
0.722	0.1114	0.9103	0.7146	179927	race_category_american_indian_or_alaska
0.9947	0.0914	0.5052	0.9952	3277630	race_category_asian
0.9348	0.0927	0.6654	0.9374	3718155	race_category_black_or_african_american
0.9678	0.0565	0.6185	0.9689	518424	race_category_native_hawaiian_or_other_
0.9795	0.0737	0.5278	0.9808	32894021	race_category_other
0.891	0.0823	0.8053	0.892	3808178	race_category_two_or_more_races
0.918	0.0691	0.7164	0.9197	6136898	race_category_unknown
0.8906	0.0844	0.8162	0.8915	7976737	race_category_white

Table A.4I. Pediatric Behavioral Underutilization

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.2541	0.9692	0.0615	0.9925	3798653	Overall
0.3231	0.9770	0.1830	0.9798	149361	new_medicaid_enrollee_12_months
0.2649	0.9664	0.0587	0.9928	1978536	sex_m
0.2423	0.9720	0.0644	0.9922	1820117	sex_f
0.2616	0.9693	0.0600	0.9931	2657721	primary_language_eng
0.2326	0.9724	0.0635	0.9919	1077401	primary_language_spa
0.2401	0.9714	0.0626	0.9922	2072126	ethnicity_category_hispanicorlatino
0.2709	0.9665	0.0601	0.9929	1726527	ethnicity_category_nothispanicorlatino
0.2485	0.9900	0.1167	0.9934	20030	race_category_american_indian_or_alaska
0.2766	0.9570	0.0684	0.9895	126575	race_category_asian
0.2643	0.9713	0.0668	0.9927	290791	race_category_black_or_african_american
0.2692	0.9609	0.0878	0.9859	19282	race_category_native_hawaiian_or_other_
0.2415	0.9711	0.0633	0.9921	2008188	race_category_other
0.2581	0.9690	0.0644	0.9922	281977	race_category_two_or_more_races
0.2693	0.9672	0.0629	0.9925	326484	race_category_unknown
0.2722	0.9643	0.0487	0.9942	725326	race_category_white

Table A.4J. Pediatric Physical Health Underutilization

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.4662	0.9335	0.0810	0.9921	19527583	Overall
0.4711	0.9591	0.0708	0.9960	4065079	new_medicaid_enrollee_12_months
0.5053	0.9167	0.0507	0.9950	9322099	sex_m
0.4306	0.9398	0.1037	0.9887	10205484	sex_f
0.4520	0.9339	0.0753	0.9924	13784517	primary_language_eng
0.5008	0.9307	0.0875	0.9923	5130519	primary_language_spa
0.4909	0.9240	0.0709	0.9930	9979071	ethnicity_category_hispanicorlatino
0.4405	0.9405	0.0904	0.9910	9548512	ethnicity_category_nothispanicorlatino
0.4443	0.9536	0.0872	0.9935	62934	race_category_american_indian_or_alaska
0.4656	0.9414	0.1328	0.9871	986614	race_category_asian
0.4165	0.9169	0.0585	0.9915	1429960	race_category_black_or_african_american
0.4378	0.9487	0.1071	0.9903	179909	race_category_native_hawaiian_or_other_
0.4884	0.9275	0.0717	0.9932	10404749	race_category_other

Accuracy	Precision	Recall (Sensitivity)	Specificity	Person-months	Subgroup
0.4590	0.9307	0.0791	0.9917	1216306	race_category_two_or_more_races
0.4524	0.9424	0.0790	0.9930	2431728	race_category_unknown
0.4271	0.9421	0.1048	0.9888	2815383	race_category_white

Table A.4K. Birthing Post-Pregnancy Behavioral Health Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Episodes	Subgroup
0.9461	0.2623	0.4361	0.9620	58324	Overall
0.9415	0.2950	0.4198	0.9615	16702	is_preg_detected_at_end
0.9279	0.2367	0.4096	0.9482	6603	age_under_21
0.9562	0.2873	0.4690	0.9691	8746	age_over_35
0.6000	0.4312	0.9431	0.4477	400	housing_instability_12_mont
0.9578	0.2862	0.5033	0.9690	6346	new_medicaid_enrollee_12_
0.9306	0.2612	0.4612	0.9489	42366	primary_language_eng
0.9870	0.2766	0.1781	0.9953	14476	primary_language_spa
0.9637	0.2667	0.3652	0.9773	31696	ethnicity_category_hispanico
0.9256	0.2589	0.4814	0.9437	27421	ethnicity_category_nothispa
0.9070	0.3333	0.3333	0.9500	215	race_category_american_ind
0.9839	0.3636	0.4800	0.9899	2110	race_category_asian
0.8979	0.2404	0.4908	0.9191	4398	race_category_black_or_afri
0.9569	0.3125	0.3846	0.9743	441	race_category_native_hawai
0.9662	0.2734	0.3562	0.9794	30114	race_category_other
0.9380	0.2161	0.3731	0.9563	6424	race_category_two_or_more
0.9481	0.2643	0.4309	0.9638	8387	race_category_unknown
0.8836	0.2759	0.5711	0.9037	7103	race_category_white

Table A.4L. Birthing Post-Pregnancy Physical Health Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Episodes	Subgroup
0.8516	0.3456	0.5077	0.8907	48408	Overall
0.9243	0.3668	0.4582	0.9524	16410	is_preg_detected_at_end

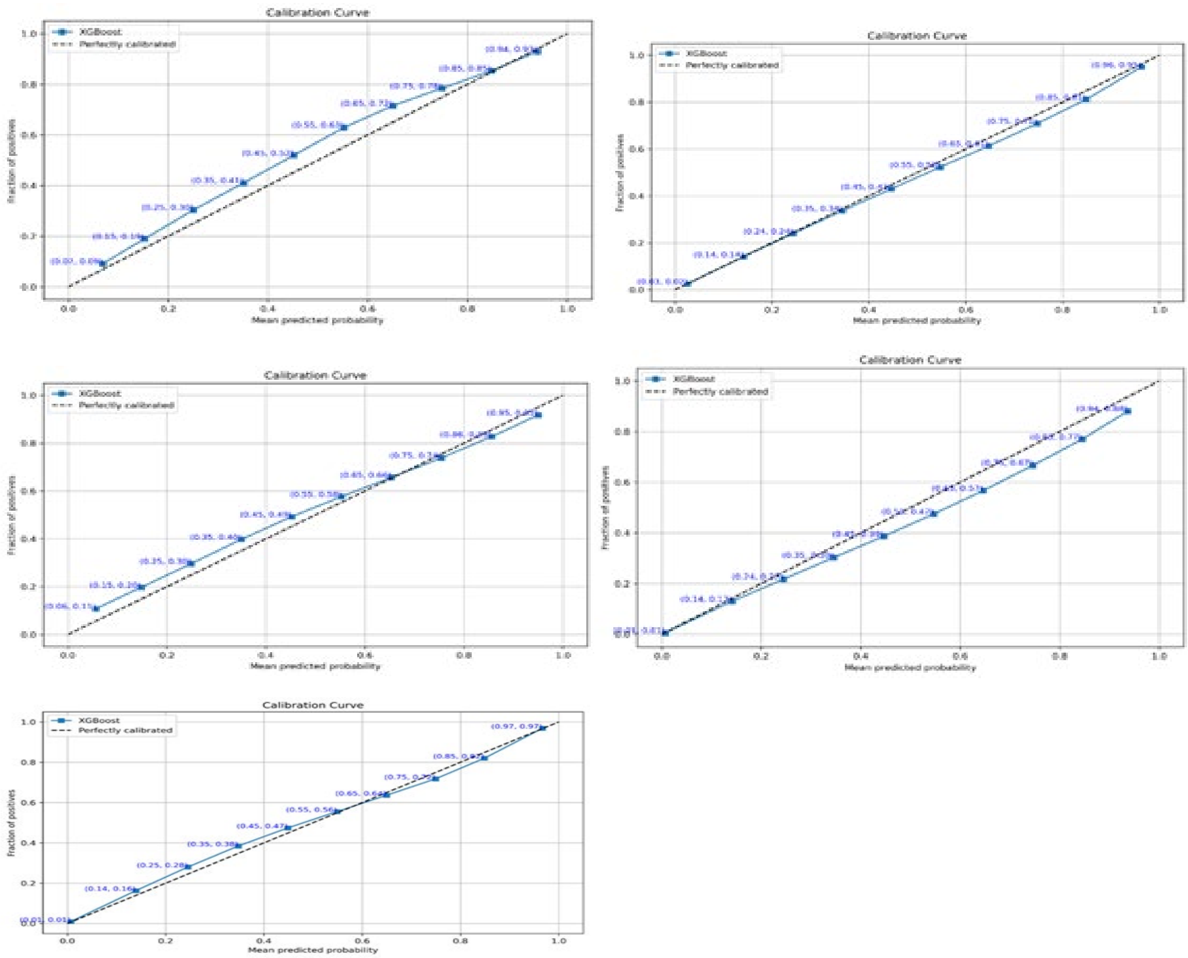
0.9008	0.2842	0.2905	0.9459	5199	age_under_21
0.8065	0.4216	0.6826	0.8291	6921	age_over_35
0.6802	0.4034	0.8571	0.6283	247	housing_instability_12_mont
0.9107	0.3270	0.5213	0.9345	5701	new_medicaid_enrollee_12_
0.8402	0.3408	0.5317	0.8771	35123	primary_language_eng
0.8812	0.3687	0.4376	0.9254	11937	primary_language_spa
0.8555	0.3287	0.4724	0.8966	26032	ethnicity_category_hispanico
0.8473	0.3624	0.5443	0.8840	22999	ethnicity_category_nothispa
0.8603	0.3846	0.5263	0.9000	179	race_category_american_ind
0.8768	0.4688	0.5714	0.9163	1834	race_category_asian
0.8096	0.3882	0.6686	0.8321	3798	race_category_black_or_afri
0.7784	0.2500	0.6053	0.7977	379	race_category_native_hawai
0.8566	0.3309	0.4721	0.8978	24860	race_category_other
0.8548	0.3355	0.5197	0.8904	5282	race_category_two_or_more
0.8613	0.3420	0.4881	0.9007	7028	race_category_unknown
0.8367	0.3387	0.4968	0.8791	5719	race_category_white

Table A.4M. Birthing Pregnancy Adverse Events

Accuracy	Precision	Recall (Sensitivity)	Specificity	Episodes	Subgroup
0.7014	0.5084	0.5024	0.7882	52882	Overall
0.6778	0.4707	0.5168	0.7477	4929	age_under_21
0.7339	0.5448	0.5306	0.8175	7628	age_over_35
0.5948	0.5667	0.7669	0.4265	269	housing_instability_12_mont
0.7473	0.4656	0.4586	0.8368	2810	new_medicaid_enrollee_12_
0.6783	0.4975	0.5430	0.7420	35672	primary_language_eng
0.7533	0.5600	0.4019	0.8832	15449	primary_language_spa
0.7101	0.5224	0.4986	0.8020	30926	ethnicity_category_hispanico
0.6895	0.4922	0.5093	0.7688	22791	ethnicity_category_nothispa
0.6984	0.5532	0.4194	0.8346	189	race_category_american_ind
0.7303	0.5131	0.4204	0.8482	2028	race_category_asian
0.6801	0.4911	0.5775	0.7269	3210	race_category_black_or_afri
0.6579	0.5143	0.4500	0.7703	456	race_category_native_hawai
0.7106	0.5148	0.4904	0.8040	29118	race_category_other
0.6986	0.5250	0.5149	0.7838	5919	race_category_two_or_more
0.7022	0.5130	0.5005	0.7909	6826	race_category_unknown
0.6609	0.4743	0.5459	0.7150	5915	race_category_white

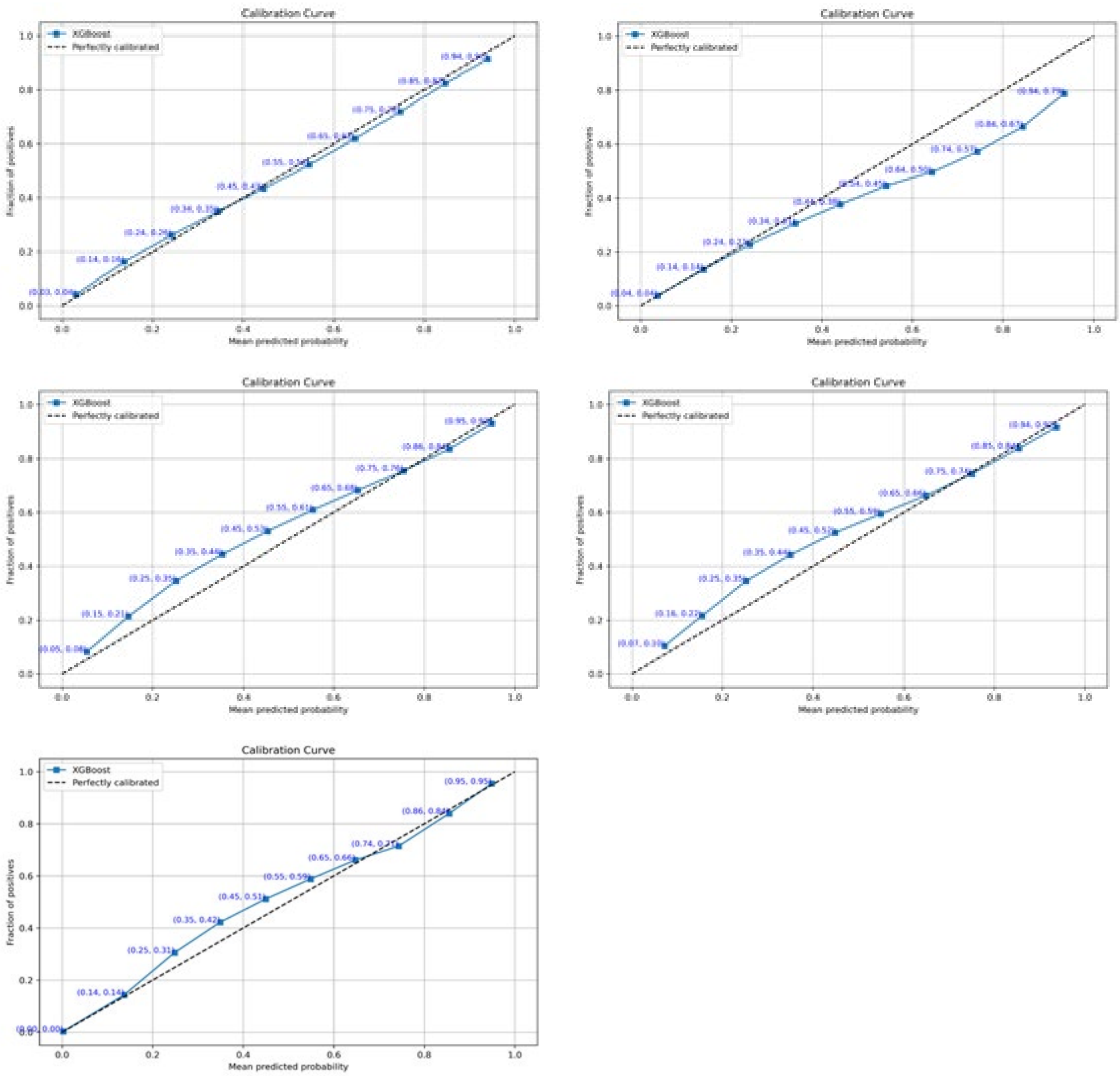
2) Figures

Figure A.1. Grid of Calibration Plots (Adult)[15]



[15] The grid of calibration plots for Adult models is ordered left to right, top to bottom as follows: (1) Behavioral Health Adverse Events, (2) Physical Health Adverse Events, (3) Behavioral Health Underutilization, (4) Physical Health Underutilization, and (5) Social Risk Adverse Events. Each plot compares predicted probabilities to observed event rates across deciles of risk.

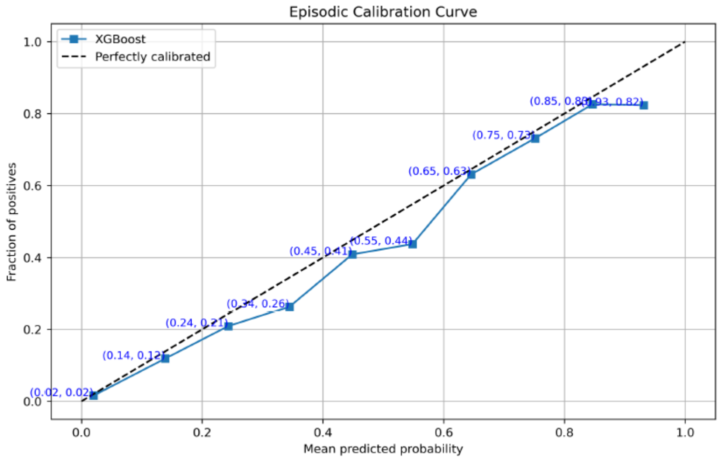
Figure A.2. Grid of Calibration Plots (Pediatric)[16]



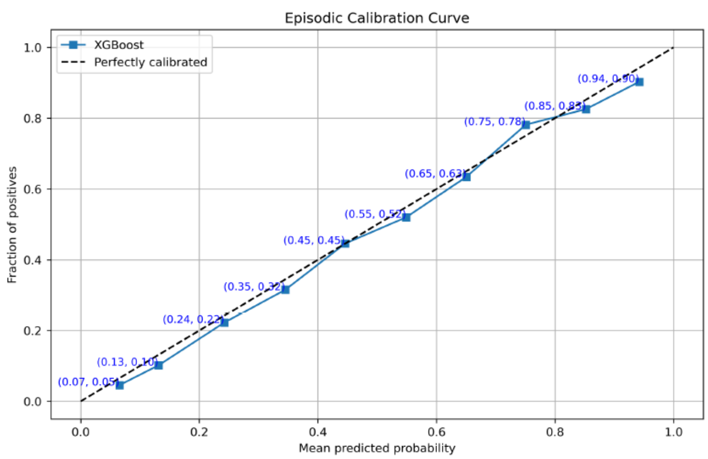
[16] See Figure A.1 – Grid of Calibration Plots (Adults) footnote

Figure A.3. Grid of Calibration Plots (Birthing)

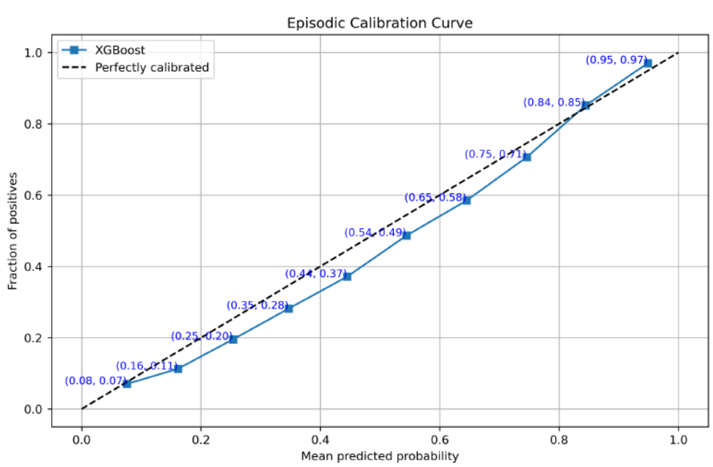
Post-pregnancy Behavioral Health Adverse Events



Post-pregnancy Physical Health Adverse Events



Pregnancy Adverse Events



D. References

References used for performance benchmarks for V1 models:

Gao, J., Reyes, E. M., Scherer, J. A., and Cooper, K. M. 2021. "Predicting Opioid Use Disorder and Associated Risk Factors in a Medicaid Managed Care Population." American Journal of Managed Care 27 (10): e328–e336.

Holcomb, R., Murali, M., Dalton, D., and Shade, L. 2022. "Predicting health-related social needs using machine learning in Medicaid and Medicare populations." Scientific Reports 12: Article 5085.

Lo-Ciganic, W.-H., Huang, J. L., Zhang, H. H., Weiss, J. C., Kwoh, C. K., Donohue, J. M., and Cochran, G. 2021. "Using machine learning to predict risk of opioid overdose among Medicaid beneficiaries in the United States: A cross-sectional study." PLOS ONE 16 (4): e0248360.

Lo-Ciganic, W.-H., Huang, J. L., Zhang, H. H., Weiss, J. C., Donohue, J. M., Kwoh, C. K., and Cochran, G. 2022. "Machine learning prediction of opioid overdose risk among Medicaid beneficiaries in two US states: A retrospective cohort study." The Lancet Regional Health – Americas 9: 100181.

Patel, M., Callison-Burch, C., Stewart, E., Le, Q., and Shah, N. H. 2024. "Predicting all-cause acute care visits among Medicaid beneficiaries using machine learning." Scientific Reports 14: Article 7183.

Pourat, N., Wallace, S. P., Slusser, W., and Kominski, G. F. 2023. "Identifying people experiencing homelessness in Medicaid data: A validation study using California's Whole Person Care program." Health Services Research 58 (1): 21–30.

Rahman, M. M., Yu, S. W. Y., Lightman, M., and Mezuk, B. 2022. "Machine learning to predict suicide-related events among Medicaid beneficiaries with mental illness." Journal of Affective Disorders 304: 27–35.

Yu, J., Brenner, P. R., Kedia, S. K., DeMik, R. J., and Mackey, K. 2022. "Predicting potentially avoidable psychiatric emergency department visits using machine learning: A national study." Psychiatry Research 312: 114558.