Averting Maternal Mortality & Morbidity Using Clinical Predictive Algorithms

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Co-PI: Carla Willis, PhD, Director, Performance Management Office Georgia Medicaid

Cash funding needed: $100,000
AWS Promotional Credits needed: $70,000

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Keywords – maternal health, algorithms

Introduction

Maternal mortality describes the death of a woman during pregnancy, at delivery, or soon after delivery. In 2021, the maternal mortality ratio in the U.S was 32.9 deaths per 100,000 live births, exceeding that of any other high-income country. While exceeding high, the ratio is much worse for Black women who experience 69.9 deaths per 100,000 live births.

While maternal mortality is devasting for all persons and communities impacted by the death, severe maternal morbidity is more common and may serve as a warning flag for future maternal death. Severe maternal morbidity describes 21 unexpected outcomes of labor and delivery that can result in significant short- or long-term health consequences. Research suggests that severe maternal morbidity helps to predict people who are at greatest risk of maternal mortality in the postpartum period. Additionally, work from Maternal Mortality Review Committees across the nation continue to show alignment between maternal morbidity and the leading cause for maternal mortality in the postpartum period. [i],[ii]

Identifying maternal mortality and morbidity is especially important for Medicaid programs across the United States because Medicaid programs pay for 41 percent of births in the US overall. The Medicaid program pays for 46 percent of all birth in Georgia specifically.[iii] From 2018-202, Georgia experienced 30.2 pregnancy-related maternal deaths per 100,000 live births. Eighty-seven (87%) percent of these deaths had some chance of being prevented and sixty-eight percent (68%) had Medicaid as the payor at delivery.

This project is a critical first step towards solving the maternal mortality crisis in the United States. It is significant because it provides a plan of action that merges data, analytics, machine learning technology, technology and strategic deployment of targeted clinical care to avert bad maternal health outcomes. This plan of action, while focus initially on the Georgia Medicaid population, can be scaled to public and private payors alike, thereby giving us concrete and repeatable steps to finally solve the maternal mortality crisis in the United States.

Methods:

Previously funded work has allowed us to construct a dataset of all Medicaid-covered deliveries in Georgia from 2020-2024 including individual-level eligibility and demographic characteristics; inpatient, outpatient, pharmacy claims and indicators for both SMM and chronic conditions using data from Georgia Medicaid claims and encounters.

Our methodological approach to this project has three main parts. Taken together, these steps will allow us to avert bad outcomes through strategic deployment of information on high-risk pregnant members to avert bad outcomes.

- ***Aim 1:*** *Develop a predictive model to identify high-risk pregnant Georgia Medicaid members by training, comparing and combining various supervised machine learning algorithms into ensembles to classify Severe Maternal Morbidity (SMM) using public health datasets.*

- ***Aim 2:*** *We will use the algorithm to generate real-time risk scores for Georgia Medicaid members who are currently pregnant.*

- ***Aim 3:*** *Given a unique partnership with Georgia Medicaid, we will direct the managed care companies who contract with the Georgia Medicaid program to provide access to high-risk pregnancy services for moms who are high-risk for severe maternal morbidity.*

Expected results:

Deliverables	**Milestones**
Build, test, and document machine learning models	
Model 1: Logistic Regression (Baseline) (20 days)	Mar-26
Model 2: Gradient Boosted Trees (20 days)	Apr-26
Model 3: Explainable Boosting Machines (20 days)	May-26
Write up results	Aug-26
Submit for publication	Sep-26
Deployment	
Develop deployment strategy	Dec-26
Soft launch of deployment strategy	Jan-26
Full deployment with corrections and automation	Mar-26
Training Series	
Intro to Python using Snowflake	Jun-26
Intro into Machine Learning for Healthcare	Jul-26
Using GitHub for Team Projects	Aug-26

Funds needed:

Deliverables	**Cost**	**Units**	**Total**
Unrestricted cash funds			
Build and document machine learning models	$ 25,000	3	$ 75,000
Deploy machine learning models	$ 10,000	1	$ 10,000
Training: Python, GitHub, Machine Learning	$ 15,000	1	$ 15,000
Total			**$ 100,000**
AWS promotional credits			
AWS: Sagemaker, Comprehend, Textract	$ 70,000	1	$ 70,000
Total			$ **70,000**

Additional information:

1. What fundamental challenge or paradigm does your research aim to transform? How does it break from conventional approaches in the field?

   This research aims to ultimately reduce instances of maternal mortality and morbidity by understanding risk factors from past instances of severe maternal morbidity. We will then use those risk factors from the past to predict future risk. This approach breaks from conventional approaches in the field by intentionally partnering with Georgia Medicaid who has both the interest and the ability to deploy what we've learned. The deployment piece allows us to avert bad outcomes and avoid becoming another research paper that sits in the virtual shelf.

2. What makes this idea potentially transformative rather than incremental? What assumptions or limitations of current approaches does it challenge?

   This idea is transformative because it uses retrospective payer data to develop a solution for current and future members. It challenges the assumption that improving health outcomes is somebody else's job. It eradicates the idea of limitations when trying to do big impactful things.

3. Why is now the right time to pursue this idea? What enabling factors or developments make it timely?

   We are in a maternal mortality crisis right now and it's time to fix it for good. We have a partnership accompanied by a current and renewable data use agreement in place and direct access into Georgia Medicaid's data warehouse for this project. We have experiences early wins by creating a dataset that includes indicators for severe maternal morbidity and chronic conditions. This partnership, level of access, and the dataset are each historic on their own but the work we want to do collectively has the ability to save the lives of mothers in Georgia and ultimately throughout the nation.

4. What are key risks and how will you mitigate them?

   Key risks are turnover of Medicaid project staff, retention of the DUA, and setting realistic expectations for evidence of change. We will mitigate turnover of project staff through detailed documentation of model development and by upskilling Medicaid project staff through the summer training series. We have mitigated the risk of losing the DUA by co-developing the project with the Performance Management Office of Georgia Medicaid. We will mitigate unrealistic expectations of change by offering senior Medicaid leadership quarterly progress updates coupled with constant reminders about where we started from.

5. What are potential applications of your work to Amazon?

   Amazon is already involved in the healthcare sector and powers massive data systems through Amazon Web Services. This project uses data privately housed by AWS to create clinical predictive algorithms that can be deployed on a multitude of conditions and across public, private and self-funded payors, thereby growing Amazon's market share in the healthcare sector.

Appendix A – Reference

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Appendix B – CV of PI

Yvonne Phillips-Taylor
Location: Atlanta, GA,
Email: yvonne@analyticsenlightened.com, LinkedIn: YourDataNarrator

PROFESSIONAL SUMMARY

Data Science Leader and Educator with a master's degree in Decision Science and 20+ years of experience integrating secure data systems and analytics to inform strategic decisions across insurance, finance, government, and higher education. More than seven years leading statistical modeling, data engineering, and large-scale analytics projects, and five years managing cross-functional teams. Skilled in R, SQL, SAS, Python, Power BI, Tableau, and Excel, with expertise in predictive modeling, clustering, text analytics, and machine learning for intelligence and risk analysis. Recognized for building compliant, high-impact analytics programs that improve decision quality, align technical and policy teams, and advance data-driven equity and social-impact initiatives.

EDUCATION & CERTIFICATIONS

• M.Sc. Decision Sciences, Georgia State University – J. Mack Robinson College of Business
• B.S. Mathematics, Spelman College
• Certifications: CompTIA Data+ (DY0-001, 2024); Six Sigma Yellow Belt (2023); EMC² Data Science Associate (EMCDSA); SAS Statistical Business Analyst; The Carpentries Certified Instructor (2023)

PROFESSIONAL EXPERIENCE

Consultant & Lead Data Scientist (Contract)
Georgia Dept of Community Health (GA Medicaid) × Morehouse School of Medicine – Reducing Health Disparities in Severe Maternal Morbidity and Mortality using Machine Learning (May 2025 – Present)
• Lead Snowflake/SQL and Python pipelines for multimillion-row clinical data (ICD-9/10, CPT/HCPCS, chronic-condition indicators) to generate auditable analyses supporting health-equity initiatives.
• Engineered a unified Medicaid deliveries dataset (2018–2022), integrating eligibility, demographic, and clinical data into a governed analytic environment with metadata tracking and audit trails for model validation and bias review.
• Authored AI governance materials aligned with Georgia AI Policy, HIPAA, and GTA AI Framework; partnered with IT and Legal to strengthen cybersecurity controls for sensitive workflows.

Academic Teaching Experience
Adjunct Faculty – Morehouse College, Dept. of Computer Science (2019–Present)
Adjunct Faculty – Morehouse School of Medicine, Master of Public Health Program (2023, 2025)
• Teach Data Science I, Data & the African Diaspora, and Data & the Black Community, integrating R/Python/SQL with equity-centered analytics.
• AWS AI/ML University Faculty Cohort (2025): Training in SageMaker and Bedrock for curriculum integration.

Selected Publications & Educational Projects:
CompTIA / Sybex - Co-Author, *DataX (DY0-001) Certification Study Guide* (2023 - 2024)
• Developed certification curriculum on EDA, model selection, and supervised ML; authored case studies, quizzes, and labs on random forest, GLM, classification, and ARIMA forecasting.