Crystal Hollis

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Racial Disparities in Reproductive Healthcare: An Intersectional Data-Driven Approach

ABSTRACT

Equitable sexual and reproductive healthcare is not just ethical—it is essential for public health and societal progress. The World Health Organization (WHO) defines reproductive healthcare as encompassing services addressing sexual health, reproductive cancers, sexually transmitted infections (including HIV), infertility, intimate partner violence, sexual violence, contraception, family planning, safe abortion, maternal and perinatal health, menopause, comprehensive sexuality education, and female genital mutilation.[1] Addressing all of these facets are critical to women's overall health and autonomy as individuals. Protecting reproductive healthcare as a fundamental human right ensures the dignity, equality, and autonomy of all individuals. It addresses systemic barriers that perpetuate inequities and enables healthier outcomes for women, families, and communities. Women of color, LGBTQ+ individuals, and other marginalized groups face disproportionately poor reproductive health outcomes due to structural racism, implicit bias, and chronic underfunding of public health systems. Addressing these disparities through intersectional, ethical, and data-driven approaches is essential to achieving equity. This approach was explored by employing methodologies to analyze maternal health trends. Machine learning models and exploratory data analysis (EDA) were leveraged to detect and predict patterns of maternal mortality in the United States. Group-level analyses confirmed the disproportionate burden of maternal mortality on marginalized populations. The combination of historical context, literature review, and data analysis validated the necessity of equity-driven, data-informed public health interventions to ensure comprehensive reproductive healthcare for all individuals. Only by addressing these disparities can we advance public health goals, improve women's health, and reduce preventable deaths.

INTRODUCTION

Sexual and reproductive healthcare is a fundamental human right, essential for achieving equity and improving public health outcomes. It empowers individuals to make informed decisions about their body, health, and future. Many national and international organizations recognize its critical role in building healthier communities. WHO includes reproductive healthcare within the framework of universal health coverage, advocating for equitable access to quality services without discrimination.[1] The United Nations links women's sexual and reproductive health to multiple human rights, including the right to life, health, education, privacy, and freedom from torture and discrimination.[2] The American Public Health Association advocates public health issues like abortion access, contraception, sexuality education, and equitable policies.[3] These perspectives reinforce the universal importance of reproductive healthcare and the urgent need to ensure equitable access for all.

However, despite these global benchmarks, the United States lags significantly behind high-income nations in ensuring equitable access to reproductive healthcare. Approximately 700 women die annually from pregnancy-related complications,[4] and Black women experience maternal mortality rates 3.5 times higher than non-Hispanic white women.[5] Other facets of sexual and reproduction health pose significant public health challenges. Over 2.4 million STIs were reported in 2023.[6] Nearly half of all women and two in five men reported experiencing intimate partner violence at some point in their lifetimes.[7] These inequities, alongside gaps in access to fertility services and postpartum care, disproportionately affect Black, Indigenous, and People of Color (BIPOC), low-income populations, and LGBTQ+ communities.

This paper explores how systemic inequities in race, gender, and socioeconomic status shape disparities in reproductive healthcare, and demonstrates how machine learning and data-driven analysis can effectively address these disparities. Protecting and expanding reproductive healthcare as a human right is imperative—not only to eliminate disparities and reduce preventable deaths but also to ensure healthier outcomes for individuals and families across all demographics.

LITERATURE REVIEW

Historical Context

Racial and gender-based healthcare inequities in the United States stem from a history of systemic racism and discrimination. Legacies of slavery, segregation, and biased medical practices have created barriers to equitable care for marginalized communities. This history has shaped mistrust in medical institutions, particularly among Black Americans, while also influencing persistent disparities in maternal mortality, reproductive healthcare access, and pain management. These systemic inequities remain deeply embedded within healthcare systems, exacerbating poor outcomes for marginalized groups.[8]

Current Research

Systemic Barriers to Reproductive Health Equity

Reproductive health outcomes in the United States are profoundly influenced by systemic barriers, including racial and ethnic disparities, implicit biases in healthcare decision-making, and broader social and structural inequities. These interconnected challenges create significant obstacles to equitable care for marginalized populations.

Racial and ethnic disparities in reproductive health outcomes remain deeply entrenched. Black women face maternal morbidity and mortality rates significantly higher than those of White women, with a pregnancy-related mortality ratio (PRMR) of 40.8 per 100,000 live births—3.2 times greater than that of White women.[4] Similarly, American Indian and Alaska Native (AI/AN) women experience elevated mortality ratios at 29.7 per 100,000 live births, highlighting the systemic nature of these inequities. [4] These disparities persist across education levels, age groups, and geographic locations, underscoring the structural barriers within the healthcare system. Notably, Black women are disproportionately affected by cardiomyopathy and hypertensive disorders, while AI/AN women are more likely to experience hemorrhage-related complications. [4] Furthermore, the COVID-19 pandemic exacerbated these disparities, with pregnancy-associated deaths rising dramatically among marginalized groups, emphasizing the vulnerabilities they face during public health crises. [9]

Implicit racial biases also contribute to inequities in healthcare delivery and outcomes. Research reveals that 50% of White medical students and residents endorse false beliefs about biological differences between Black and White individuals, leading to underestimation of pain and inadequate treatment recommendations for Black patients. [10] These biases, rooted in historical prejudices, perpetuate systemic inequities in pain management, clinical decision-making, and medical education. Strategies such as cultural humility and structural competency training have been proposed to address these disparities, but further research is needed to establish direct links between implicit biases and specific healthcare outcomes. [11,12]

Social and structural factors further complicate these challenges, particularly for multiracial and Indigenous populations. For instance, multiracial individuals—projected to represent 6% of the U.S. population by 2060—face unique health challenges, including elevated rates of psychological distress and substance use. [8] Similarly, AI/AN women are disproportionately impacted by gestational diabetes mellitus (GDM) and lower breastfeeding rates, despite the protective benefits of breastfeeding.[13] These disparities highlight the intersection of systemic racism, cultural barriers, and inadequate support systems, necessitating targeted interventions to address the unique needs of these populations.

Systemic Barriers to Reproductive Technology

State insurance mandates have improved access to reproductive technologies, increasing live birth rates by 11%, yet significant racial disparities persist. For example, Black recipients of donor oocyte-assisted reproductive technology (ART) achieved a 48.4% live birth rate compared to 69.5% for White recipients, even with policy interventions.[14] Similarly, an analysis of over 1 million autologous IVF cycles found that Black women had 19% lower odds of live births and 25% higher odds of cycle cancellations than White women.[15]

Language barriers further exacerbate inequities in reproductive healthcare. Patients with limited English proficiency (LEP) experienced significantly longer delays in accessing care—4.53 years compared to 2.01 years for English-proficient patients—and had lower cumulative pregnancy rates (15.38% vs. 22.32%).[16] These findings stress the importance of culturally competent care and inclusive policies to eliminate systemic barriers in reproductive health.

Artificial Intelligence in Reproductive Health

The integration of artificial intelligence (AI) into reproductive health presents transformative potential for addressing systemic inequities, as highlighted in two key sources. The World Health Organization's 2024 technical brief outlines AI’s utility in health promotion, diagnostics, and clinical research, emphasizing its ability to expand access to sexual and reproductive health and rights (SRHR) services, particularly in underserved regions.[1] However, challenges such as data privacy concerns, biased algorithms, and the digital divide necessitate comprehensive policies to ensure equitable implementation. [1]

Similarly, the proposal to establish an AI Center of Excellence in the United States underscores AI's potential to address maternal health disparities.[19] This initiative highlights AI's predictive capacity, with models identifying 70% of at-risk pregnancies in the first trimester, and its potential to improve clinical guidelines and reduce disparities. [17]

Nevertheless, limitations such as non-standardized datasets and potential algorithmic biases underscore the importance of ethical frameworks to prevent perpetuation of systemic inequities. [17] Together, these insights demonstrate AI's capacity to revolutionize reproductive healthcare while emphasizing the necessity of ethical oversight and inclusive practices.

Current Policy Efforts

Efforts to address the U.S. maternal health crisis have advanced through initiatives like The White House Blueprint and state-level reports. The 2024 White House report highlights key progress, such as extending postpartum Medicaid coverage to 12 months in 46 states and introducing federal safety standards for obstetric care.[18] In Texas, the 2024 Maternal Mortality and Morbidity Review Committee found that 80% of pregnancy-related deaths were preventable, with leading causes including infections, cardiovascular conditions, and obstetric hemorrhage.[19] Non-Hispanic Black women experienced maternal mortality rates 2.5 times higher than White women, underscoring systemic gaps in healthcare. [19]

Emerging challenges, such as the rollback of abortion protections by Roe v. Wade in 2022, threaten to exacerbate disparities. Healthcare restrictions disproportionately harm marginalized populations, highlighting the urgent need for comprehensive data and equitable policies to address these inequities effectively.

RESEARCH OBJECTIVE

Addressing sexual and reproductive health disparities through intersectional, ethical, and data-driven approaches is necessary to achieve equity. An exercise to support this thesis was conducted by exploring maternal mortality datasets using machine learning techniques and exploratory data analysis. The objective was to predict maternal mortality rates that can be used to contribute actionable insights and inform policy recommendations.

METHODOLOGY

This project utilized the Provisional Maternal Death Counts and Rates dataset from the National Center for Health Statistics (NCHS), which includes maternal deaths, live births, and mortality rates by jurisdiction, group, and subgroup. Derived from the National Vital Statistics System (NVSS), the dataset reflects maternal mortality rates as of October 16, 2024, calculated for 12-month periods and updated quarterly to incorporate corrections.[20] Death counts between 1 and 9 are suppressed, and rates based on fewer than 20 deaths are flagged as unreliable.[20]

Analysis was conducted using Python in a Jupyter Notebook hosted on the PyCharm Integrated Development Environment (IDE), incorporating data cleaning, exploratory data analysis (EDA), and predictive modeling with AutoGluon. The notebook, available in the Crystal

Hollis Dallas College Portfolio GitHub Repository, contains detailed steps to ensure transparency and reproducibility.[21]

The workflow began with data loading and exploration using pandas to inspect structure, identify missing values, and analyze unique attributes. Sweetviz generated an automated profiling report to summarize the dataset. EDA employed visualization libraries such as matplotlib, seaborn, and plotly to explore trends and relationships.

Feature engineering addressed missing values with feature-engine's MeanMedianImputer and encoded categorical variables like Group and Subgroup using OneHotEncoder. Numeric features were scaled with scikit-learn's MinMaxScaler for standardization. The processed dataset was then saved for modeling.

For predictive modeling, AutoGluon automated model selection, training, and hyperparameter tuning. The dataset was split into training and test sets, and model performance was evaluated using metrics like Root Mean Squared Error (RMSE). Visualizations of predicted outcomes and their distributions highlighted disparities and trends in maternal mortality rates.

RESULTS

This project provides insights into maternal mortality disparities using statistical measures, machine learning techniques, and maternal health data analysis. Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) quantify prediction accuracy, while R^2 and the Pearson Correlation Coefficient measure the model's explanatory power and linear alignment between predicted and actual values. Features like Maternal Deaths and Live Births were critical for prediction, while categorical variables such as age groups were encoded for analysis.

The dataset contained 660 rows and 12 features, with missing values observed in key variables like Maternal Mortality Rate (18%) and Maternal Deaths (11%). Features lacking predictive value, such as Data As Of and Time Period, were dropped, while essential numerical and categorical variables were retained. AutoGluon identified WeightedEnsemble_L2 as the best model, combining predictions from ExtraTreesMSE (84.6%) and NeuralNetTorch (15.4%). The model achieved exceptional performance metrics, including an RMSE of 0.0189 and an R^2 value of 0.989, indicating strong predictive accuracy.

Visualizations as shown in Figure 1 and 2 (Appendix) highlighted systemic trends and disparities. Most predictions clustered between 0.1 and 0.3, with outliers suggesting inequities. An inverse relationship between live births and maternal mortality rates emerged, while deviations pointed to disparities in healthcare quality. Temporal trends revealed a peak in mortality rates in 2021, followed by declines in 2023 and 2024, reflecting COVID-19 pandemic impacts discussed in the literature review . Subgroup analysis underscored age and racial disparities, with significant variability and higher mortality rates among certain groups. The Sweetviz analysis as shown in Figure 3 and 4 (Appendix) confirmed disparities across features like Live Births and Maternal Mortality Rates, with suppressed data underscoring confidentiality challenges. These findings emphasize the need for targeted interventions to address systemic inequities in maternal healthcare.

LIMITATIONS AND FUTURE WORK

While this exercise provides valuable insights into maternal mortality disparities, it is not without limitations. Due to time and resource constraints, the project lacked extensive testing, expert guidance, and peer review, which may affect the strength of the findings. Additionally, the absence of external feedback limits the validation of the methodological framework and results.

To mitigate these limitations, future work will prioritize engaging with domain experts for guidance and review, incorporating feedback from peers and stakeholders to refine the analysis. Rigorous testing across diverse datasets will be conducted to enhance the reliability and applicability of the findings. Furthermore, the inclusion of interdisciplinary collaboration will strengthen the methodological framework and ensure that the research aligns with best practices in sexual and reproductive health data analysis.

CONCLUSION

In conclusion, addressing racial, gender, and socioeconomic disparities in reproductive healthcare is vital to ensuring equitable public health outcomes. This research highlights the significant role of data-driven approaches, particularly machine learning and exploratory data analysis, in identifying systemic inequities and informing actionable interventions. By uncovering trends and disparities in maternal mortality rates, this study reinforces the need for targeted policy efforts, culturally competent care, and ethical use of artificial intelligence to mitigate barriers and improve access to reproductive health services. While limitations in testing and external validation underscore the need for future refinement, the findings underscore the transformative potential of leveraging data science to advance equity in maternal healthcare. Only through continued research, interdisciplinary collaboration, and equity-focused policies can we reduce preventable deaths, enhance public health, and uphold reproductive healthcare as a fundamental human right.

REFERENCES

1. World Health Organization. The role of artificial intelligence in sexual and reproductive health and rights: technical brief. Geneva: World Health Organization; 2024. ISBN 978-92-4-009070-5. Available from: https://iris.who.int/bitstream/handle/10665/376294/9789240090705-eng.pdf . Accessed January 5, 2025.
2. Office of the United Nations High Commissioner for Human Rights. Sexual and reproductive health and rights. Available from: https://www.ohchr.org/en/women/sexual-and-reproductive-health-and-rights . Accessed January 8, 2025.
3. American Public Health Association. Sexual and reproductive health. Available from: https://www.apha.org/apha-communities/member-sections/sexual-and-reproductive-health . Accessed January 8, 2025.
4. Petersen EE, Davis NL, Goodman D, et al. Racial/Ethnic Disparities in Pregnancy-Related Deaths — United States, 2007–2016. MMWR Morb Mortal Wkly Rep 2019;68:762–765. DOI: http://dx.doi.org/10.15585/mmwr.mm6835a3 . Accessed January 8, 2025.
5. National Institutes of Health. NIH-funded study highlights stark racial disparities in maternal deaths. Available from: https://www.nih.gov/news-events/news-releases/nih-funded-study-highlights-stark-racial-disparities-maternal-deaths . Accessed January 8, 2025.
6. Centers for Disease Control and Prevention. Sexually transmitted infection (STI) statistics. Available from: https://www.cdc.gov/sti-statistics/annual/index.html . Accessed January 8, 2025.

7. Wisniewska MJ. Domestic violence statistics 2024. Break The Cycle. Published October 7, 2024. Available from: https://www.breakthecycle.org/domestic-violence-statistics/ . Accessed January 8, 2025.

8. Grilo SA, Santelli JS, Nathanson CA, Catallozzi M, Abraido-Lanza A, Adelman S, Hernandez D. Social and Structural Influences on Multiracial Identification and Health: A Public Health Mandate to Precisely Measure, Theorize, and Better Understand Multiracial Populations. *J Racial Ethn Health Disparities.* 2023;10:427-445. doi:10.1007/s40615-022-01234-5. Accessed January 5, 2025. Available from: https://link.springer.com/article/10.1007/s40615-022-01234-5 .

9. Margerison CE, Wang X, Goldman-Mellor S, Muzik M, Gemmill A. Changes in racial and ethnic inequities in pregnancy-associated death in the United States during the COVID-19 pandemic. Am J Public Health. 2024;114(7):733–742. doi:10.2105/AJPH.2024.307651. Accessed January 5, 2025. Available from: https://ajph.aphapublications.org/doi/abs/10.2105/AJPH.2024.307651?journalCode=ajph

10. Hoffman KM, Trawalter S, Axt JR, Oliver MN. Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between Blacks and Whites. Proc Natl Acad Sci U S A. 2016;113(16):4296-4301. doi:10.1073/pnas.1516047113. Accessed January 5, 2025. Available from: https://www.pnas.org/doi/full/10.1073/pnas.1516047113 .

11. Marcelin JR, Siraj DS, Victor R, Kotadia S, Maldonado YA. The impact of unconscious bias in healthcare: How to recognize and mitigate it. J Infect Dis. 2019;220(S2):S62-S73. doi:10.1093/infdis/jiz214 . Accessed January 5, 2025. Available from: https://academic.oup.com/jid/article/220/Supplement_2/S62/5552356 .

12. Schoenthaler A, Williams N. Looking Beneath the Surface: Racial Bias in the Treatment and Management of Pain. *JAMA Netw Open.* 2022;5(6):e2216281. doi:10.1001/jamanetworkopen.2022.16281. Accessed January 5, 2025. Available from: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2793179 .
13. Hebert LE, Nikolaus CJ, Zamora-Kapoor A, Sinclair KA. Gestational diabetes and breastfeeding among women of different races/ethnicities: Evidence from the pregnancy risk assessment monitoring surveys. J Racial Ethn Health Disparities. 2023;10(4):1721-1734. doi:10.1007/s40615-022-01356-w. Accessed January 5, 2025. Available from: https://link.springer.com/article/10.1007/s40615-022-01356-w
14. Liao C, Kotlyar AM, Seifer DB. Effect of state insurance mandates on racial/ethnic disparities in the utilization and outcomes of donor oocyte-assisted reproductive technologies. Fertil Steril. 2023;120(1):111-122. doi:10.1016/j.fertnstert.2023.02.037. Accessed January 5, 2025. Available from: https://www.fertstert.org/article/S0015-0282(23)00170-X/fulltext
15. Correia KFB, Kraschel K, Seifer DB. State insurance mandates for in vitro fertilization are not associated with improving racial and ethnic disparities in utilization and treatment outcomes. Am J Obstet Gynecol. 2023;228(3):313.e1-313.e8. doi:10.1016/j.ajog.2022.10.043. Accessed January 5, 2025. Available from: https://www.ajog.org/article/S0002-9378(22)02158-5/fulltext .
16. Jain M, Peterson A, Nguyen N, Goldsammler M. Reproductive inequity and inferior intrauterine insemination outcomes in patients with limited English proficiency: a retrospective cohort study. *Fertil Steril*. 2023;120(4):844-849.

doi:10.1016/j.fertnstert.2023.05.154. Accessed January 5, 2025. Available from: https://www.fertstert.org/article/S0015-0282%2823%2900525-3/fulltext

17. Sennaar K, Wickerson G. Establishing an AI Center of Excellence to Address Maternal Health Disparities. Federation of American Scientists. Published May 2, 2023. Accessed January 6, 2025. Available from: https://fas.org/document/establishing-ai-center-maternal-health .
18. The White House. The White House Blueprint for Addressing the Maternal Health Crisis: Two Years of Progress. Published July 10, 2024. Accessed January 8, 2025. Available from: https://www.whitehouse.gov/briefing-room/statements-releases/2024/07/10/the-white-house-blueprint-for-addressing-the-maternal-health-crisis-two-years-of-progress/ .
19. Texas Maternal Mortality and Morbidity Review Committee and Department of State Health Services. Texas Maternal Mortality and Morbidity Review Committee and Department of State Health Services Joint Biennial Report 2024. Published September 1, 2024. Accessed January 8, 2025. Available from: https://www.dshs.texas.gov/sites/default/files/legislative/2024-Reports/MMMRC-DSHS-Joint-Biennial-Report-2024.pdf .
20. Centers for Disease Control and Prevention. VSRR Provisional Maternal Death Counts and Rates. Accessed January 5, 2025. Available from: https://data.cdc.gov/NCHS/VSRR-Provisional-Maternal-Death-Counts-and-Rates/e2d5-ggg7/about_data.
21. Hollis CJ. Maternal mortality analysis using Jupyter Notebook. Published January 7, 2025. Accessed January 7, 2025. Available from: https://github.com/crystaljhollis/DallasCollege_Portfolio/tree/main/PHED1304_PersonalCommunityHealth .

APPENDIX

Jupyter Notebook

The Jupyter Notebook used for this analysis includes:

- Data preprocessing steps, including handling missing values.
- Exploratory data analysis with visualizations of subgroup trends.
- Predictive modeling using AutoGluon to estimate maternal mortality rates.

The complete notebook is available on the GitHub Repository (https://github.com/crystaljhollis/DallasCollege_Portfolio/tree/main/PHED1304_PersonalCommunityHealth).

Visualizations

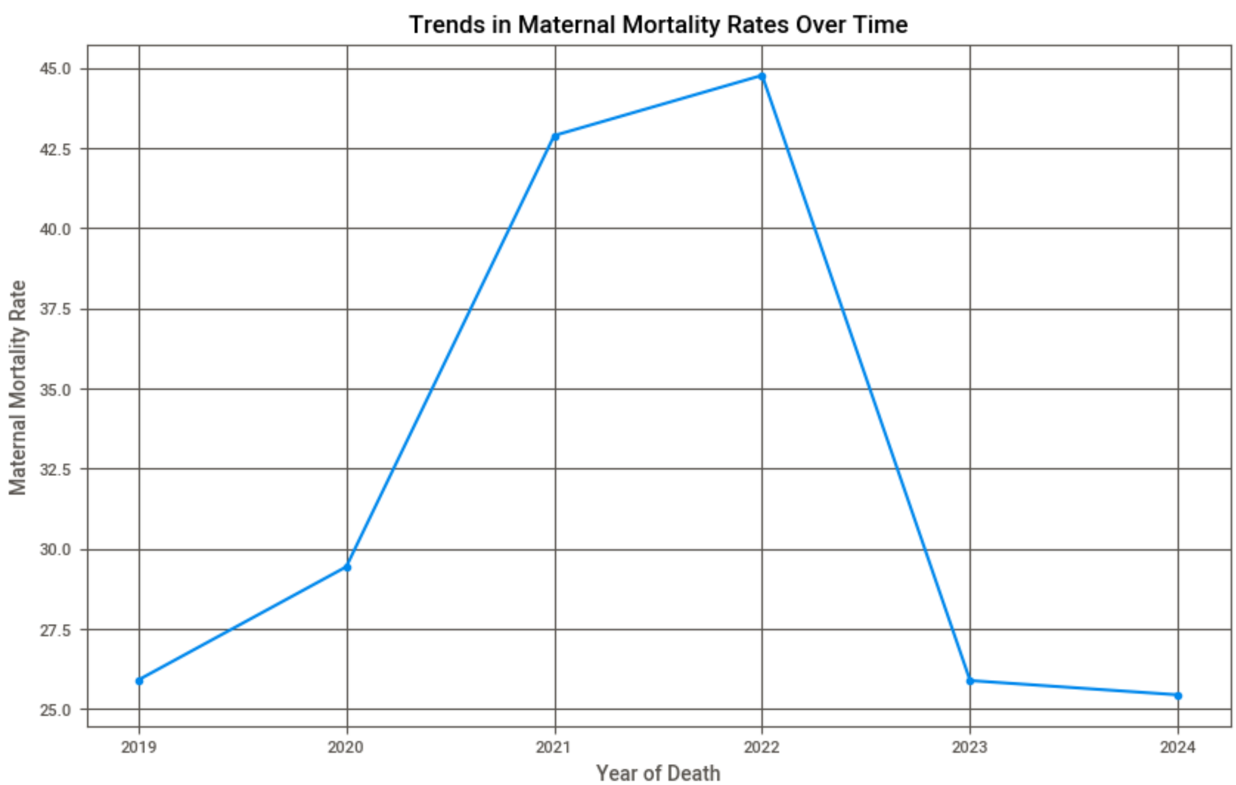

Figure 1 EDA Results

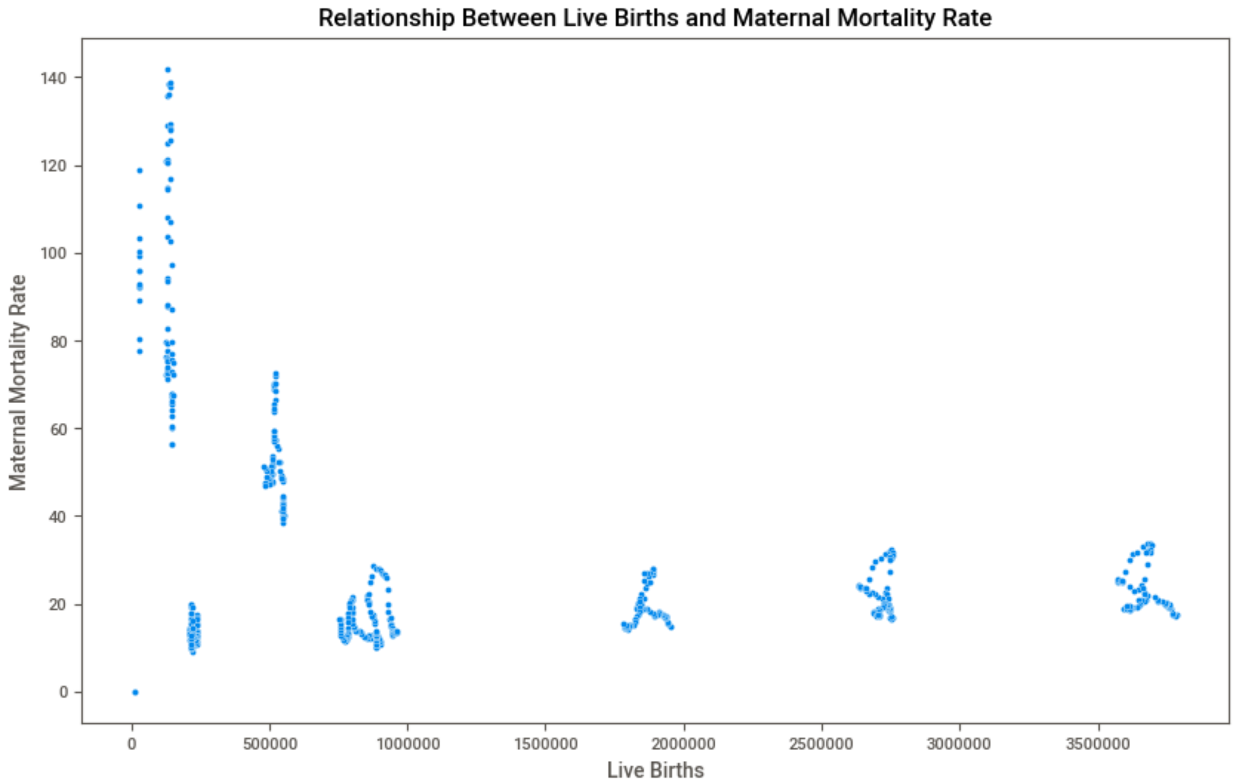

Figure 2 EDA Results

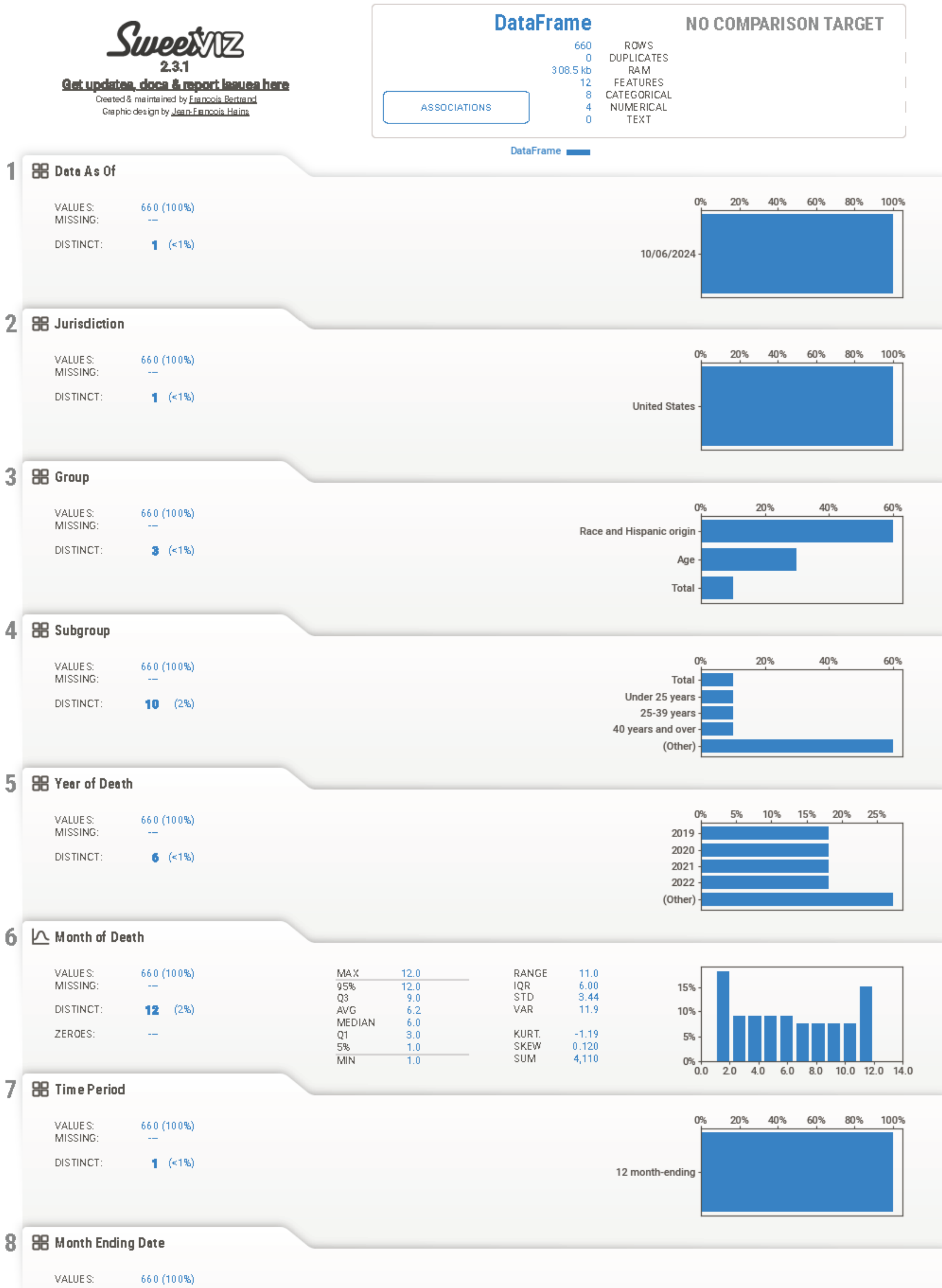

Figure 3 SweetViz Dataset Analysis page 1

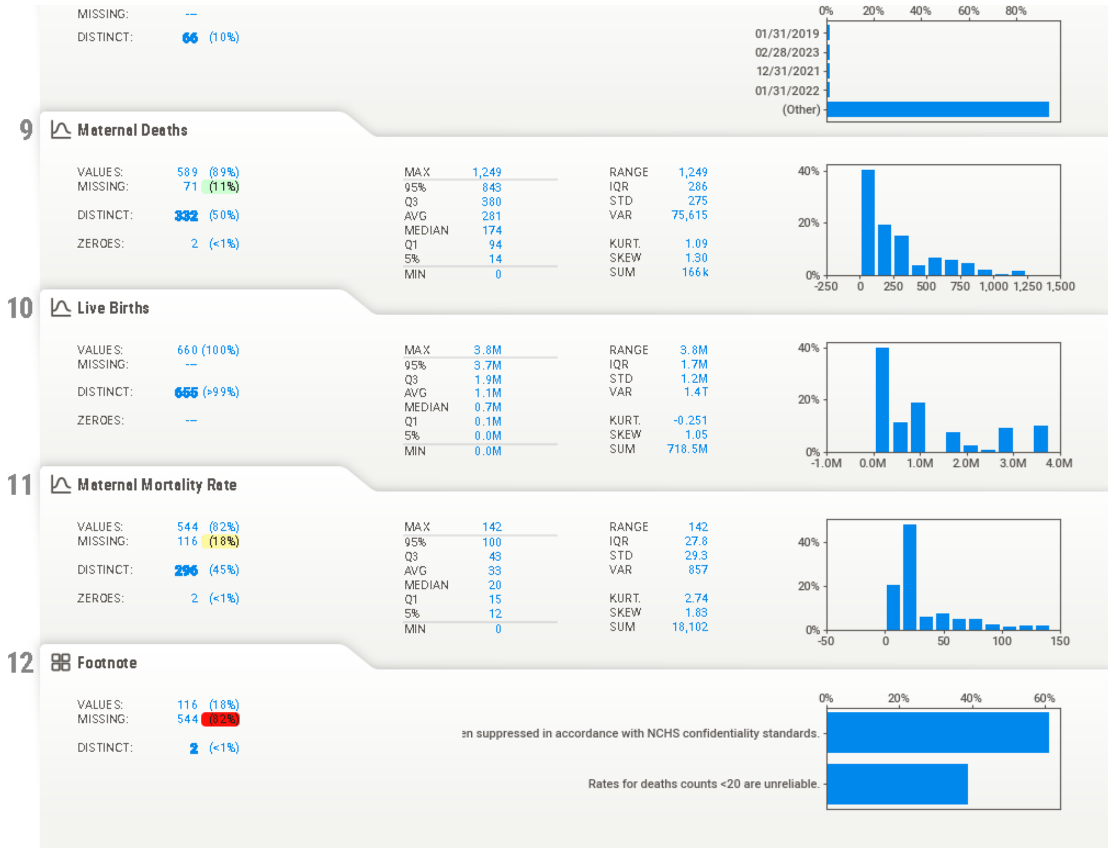

Figure 4 SweetViz Dataset Analysis Page 2