ELECTRIC AVENUES:
Optimizing EV Charging Infrastructure for Equitable Adoption in San Mateo

Skyline College

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INTRODUCTION

California's 2035 mandate for zero-emission vehicles necessitates proactive planning for robust charging infrastructure. This research focuses on strategically deploying EV charging stations in San Mateo to enhance accessibility and drive EV adoption. We address variations in EV ownership across zip codes and examine the impact of socioeconomic factors, like median income, on hybrid/electric vehicle adoption rates.

RESEARCH QUESTION

How can we strategically deploy EV charging stations in San Mateo to enhance accessibility and adoption, considering variations in EV ownership across zip codes? Additionally, how do socio-economic factors, like median income, influence hybrid/electric vehicle adoption rates in these areas?

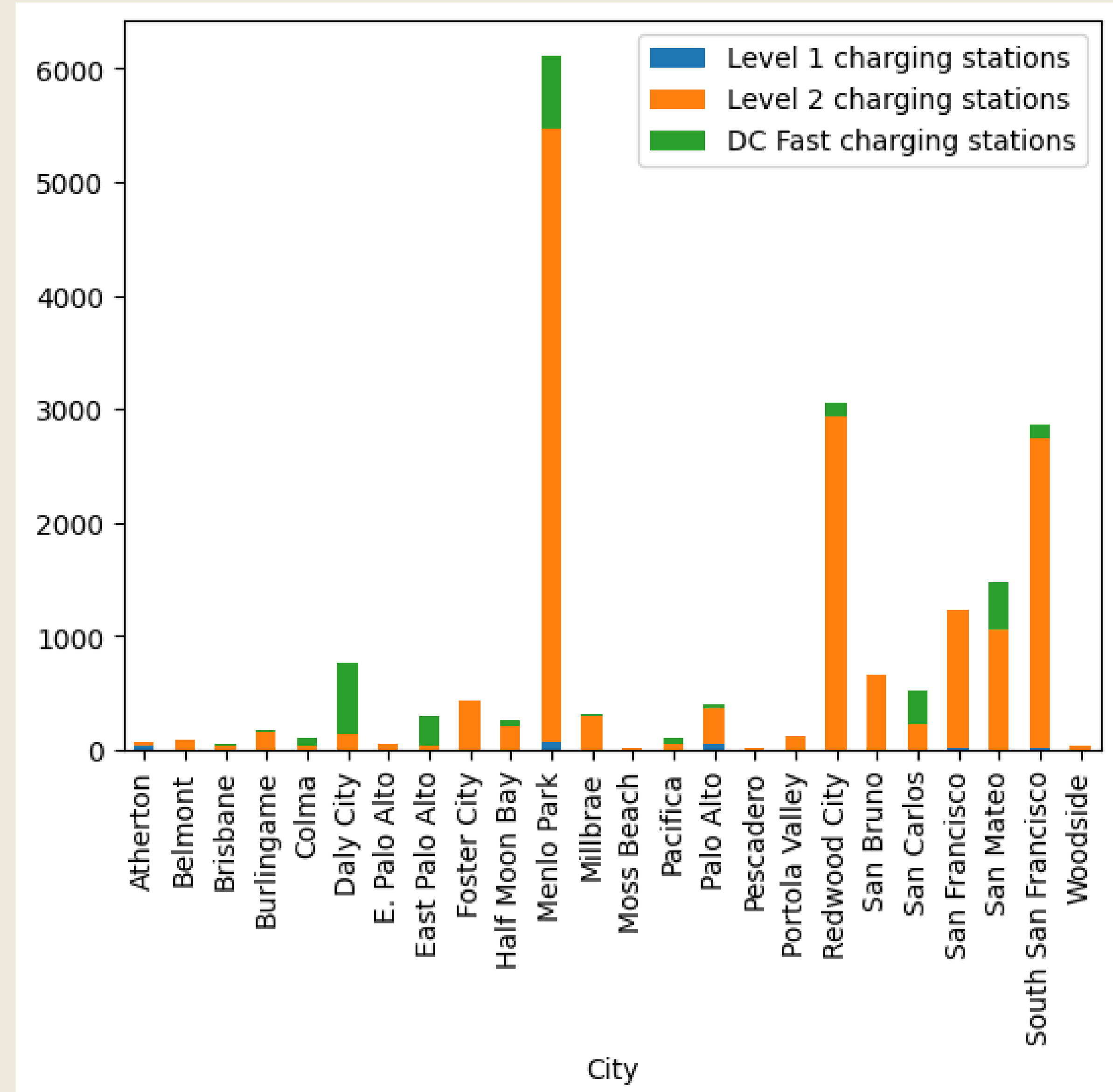
HYPOTHESIS

The hypothesis suggests there is a **correlation** between income levels and consumption of hybrid and electric vehicles (HEVs). Additionally, installing **HEV charging stations** in areas of San Mateo with low HEV ownership but high potential for adoption is expected to facilitate a smoother transition to electric cars for more individuals.

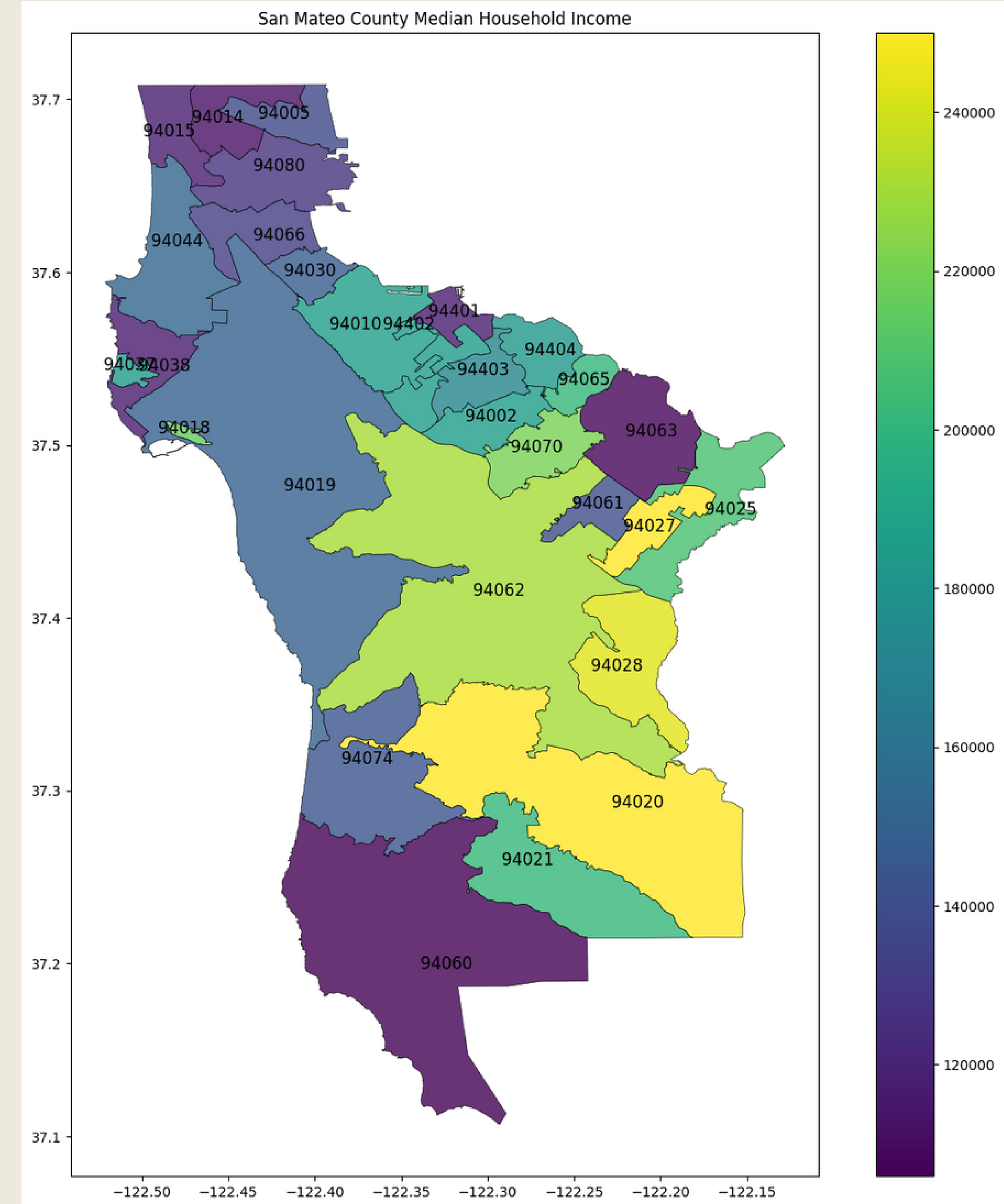
METHODOLOGY

1. The data analysis methodology involved collecting government open-source datasets on various parameters, including different vehicle type counts, charger amounts, population counts, and income conditions by zip code for the entire state of California.
2. The dataset was narrowed to focus specifically on San Mateo County for localized research. The dataset was then cleaned to extract relevant information such as the count of rechargeable vehicles, chargers, population, and middle-income counts by zip code.

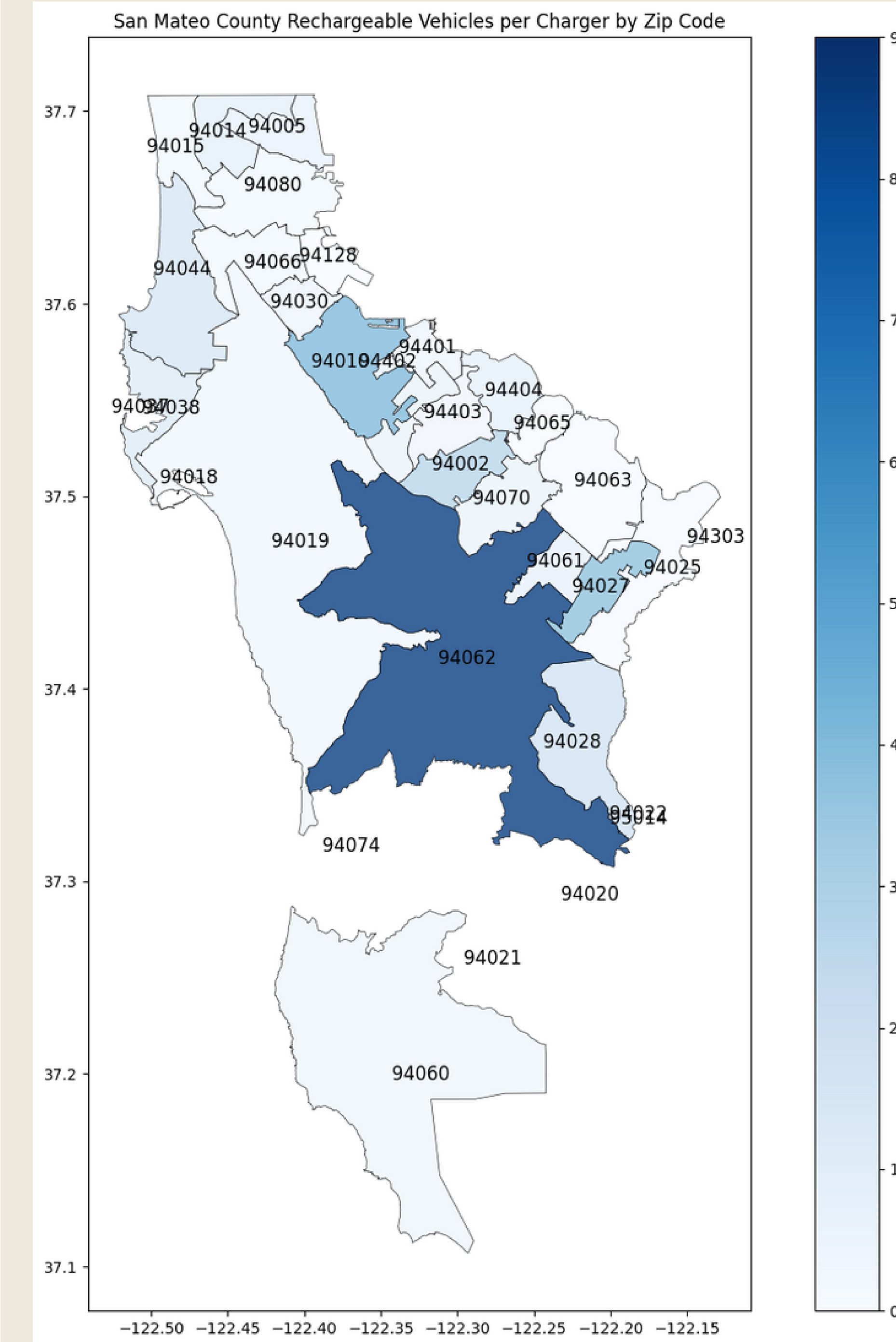
- Calculated the ratio of rechargeable vehicle amounts to the population for each zip code to determine the distribution of rechargeable vehicles and the ratio of rechargeable vehicle amounts to the chargers by zip code to determine the accessibility of public chargers in San Mateo County.
- Performed linear regression analysis on the relationship between rechargeable vehicle counts and middle-income levels for each zip code to explore any potential correlations.
- Graphed the histogram concerning the different types of charging stations for each city.



San Mateo County Charger by City



San Mateo County Medium Household Income

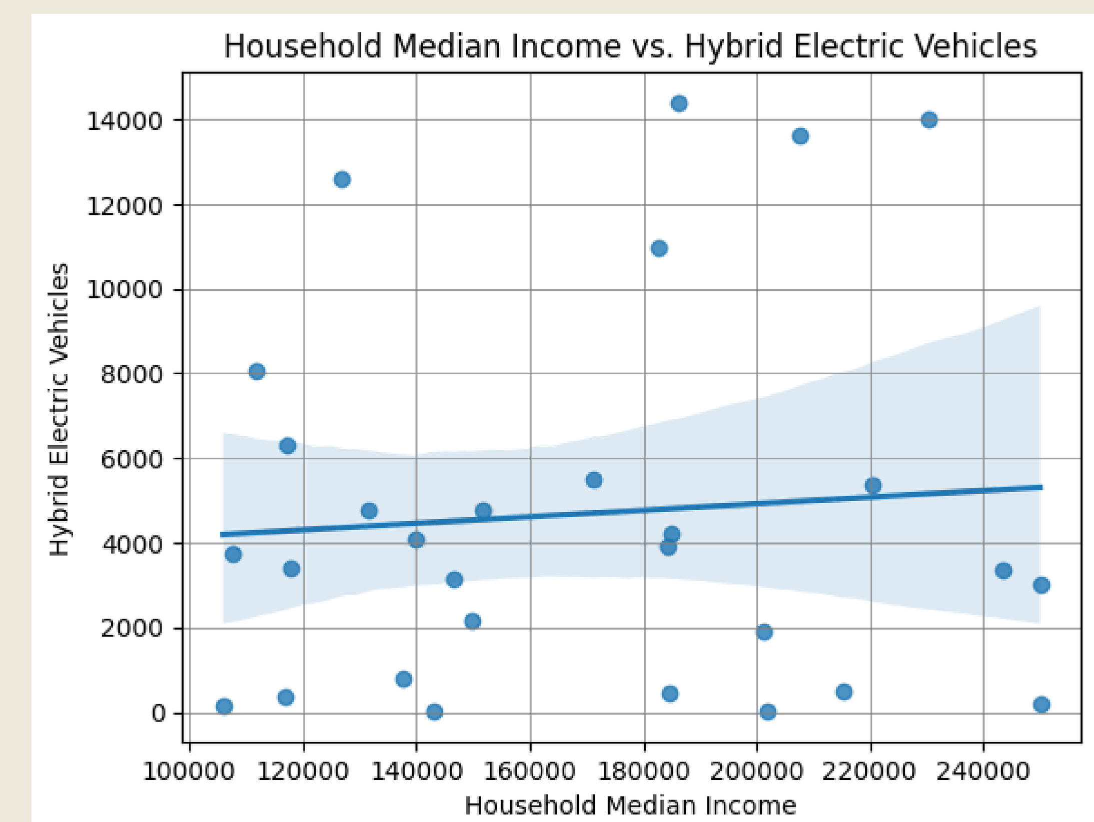


San Mateo County Rechargeable Vehicles per Charger by Zip Code

RESULTS/FINDINGS

The median income versus HEV (Hybrid Electric Vehicles) consumption has a **positive, weak linear correlation**. R^2= 0.347 suggests that median income partially influences the purchase of HEVs but is not the sole reason for their purchase.

Notable hotspots include zip codes 94062, 94010, and 94027, encompassing parts of Redwood City and Burlingame. This suggests **a significant gap in public charging availability** in these areas. One possible explanation for the scarcity of chargers in these regions could be attributed to the residential nature of the communities, where individuals primarily charge their vehicles at home rather than relying on public charging stations. However, the presence of high-density residential areas also underscores the need for accessible public charging infrastructure to support EV adoption and mobility.



n = 30

Linear Regression between Rechargeable Vehicle Counts and Median-income Levels

SUGGESTIONS

- Adding chargers to public places like community centers, libraries, and parks for accessibility.
- Incentive for subsidized refurbishments of older EVs
- Implementing more charging stations in places with higher populations, such as Daly City, where there aren't as many EVs at the moment.

CHALLENGES

The County of San Mateo stopped updating Electric Vehicle Charging Stations after the impact of the COVID-19 pandemic started.
We were unable to find the datasets of gasoline prices in the County of San Mateo

DATA SOURCES

- U.S. Census Bureau (2022). Income in the Past 12 Months (in 2022 Inflation-Adjusted Dollars). Retrieved from https://data.census.gov/table/ACSST1Y2022.S1901?q=San%20Mateo%20Income
- Vehicle Fuel Type Count by Zip Code (2022) - dataset - california open data. (n.d.-b). https://data.ca.gov/dataset/vehicle-fuel-type-count-by-zip-code
- San Mateo Electric Vehicle Charging Stations (2019) SMC datahub. County of San Mateo seal. (2019, October 21). https://datahub.smcgov.org/Transportation/San-Mateo-Electric-Vehicle-Charging-Stations/62me-9htk
- Demographics by Zip Code (2022) https://www.california-demographics.com/demographics_reports?source=sample#custom_data_form

Factors Impacting Muni Ridership

Camille Catolos, Zaw San

Question

What factors influenced MUNI ridership from 2015 to 2023?

Background

MUNI or San Francisco Municipal Railway is San Francisco's public transportation system. Muni ridership saw a significant increase since the COVID-19 pandemic in 2023, reaching an average of 433,000 weekday riders, a 25% rise from the previous year. MUNI continues to be a vital part of San Francisco's transportation network and culture, the city's Municipal Transportation Agency (MTA) has developed the Muni Service Equity Strategy to improve transit routes serving low-income, BIPOC, senior, and disabled communities.

Methodology

The City Survey collects residents' feedback on city services. The survey methodology has evolved since the original release in 1996, so analysis and pre-processing required caution. Our analysis focuses on MUNI ratings and transportation behaviors from 2015-2023, using the provided columns. From the 42.7k rows, we utilized **8,703** rows after pre-processing and cleaning.

Key Variables Used: dem_income, dem_age, dem_gender, dem_raceeth, dem_sorient, muni_clean, muni_crowd, muni_nonuser1, muni_nonuser2, muni_nonuser3, muni_rate, muni_c, muni_safe, muni_user_yes, trans_muni_freq

	dem_income	dem_age	dem_gender	dem_mentdis_yes
18	100k to 200k	18-24	Male	NaN
27	NaN	65+	Male	NaN

Clean Data
↓
Analyze 2015-2023 Data Set
↓
Non-Muni Users Anlysis | Muni Users Analysis
↓
Visualization & Reflection

Results

Demographic of Surveyers

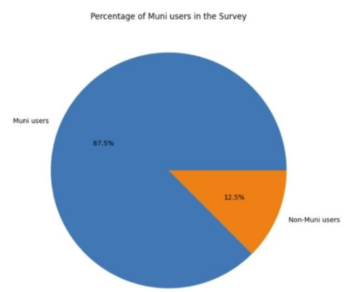


Figure 1: Percentage of Muni Users vs Non-Muni Users

MUNI Ratings In Terms of Amount Ridden

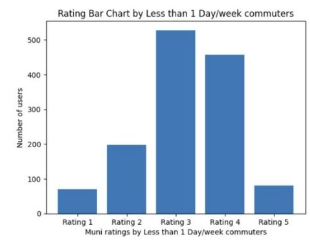


Figure 2: Rating Bar Chart By Less than 1 Day/Week Commuters

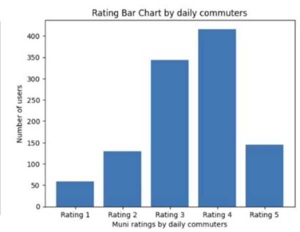


Figure 3: Rating Bar Chart By Daily Commuters

Ridership & Ratings Amongst Riders

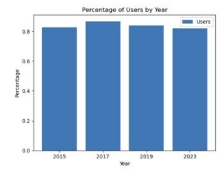


Figure 4: Percentage of Users Per Year

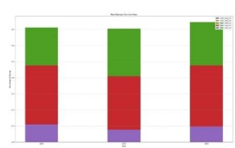


Figure 5: Muni Ratings Over Year

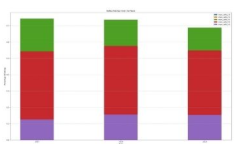


Figure 6: Safety Ratings Per Year

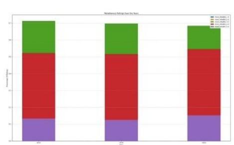


Figure 7: Reliableness Ratings Per Year

Demographics and Relationship to Ridership

Demographic	P-Value
African American	0.987
American Indian or Alaska Native	0.994
Arab/Middle Eastern/North African	0.993
Asian or Pacific Islander or Asian American	0.968
Hispanic, Latino, or Spanish Origin	0.985
Mixed	0.986
White	0.974
Gay, lesbian or same-gender loving	0.983
Questioning	0.987
Straight/Hetero	0.976
Female	0.98
Male	0.978
Straight/Hetero	0.959

Figure 8: P-Values that Show the Relationship Between Demographic and Muni Ratings

Ratings Amongst Non-Muni Users

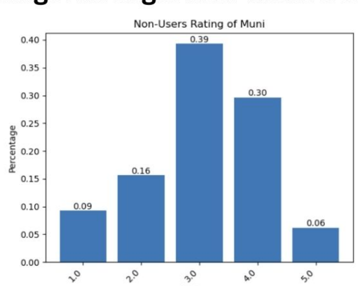


Figure 9: Histogram that represents non-user rating on MUNI

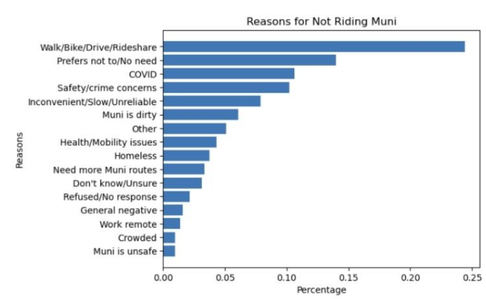


Figure 10: Reasons for Not Riding Muni Histogram

Conclusions

- The majority of surveyors are MUNI users. From 2017 to 2023, there is little fluctuation in MUNI users. The slight decline in usage from 2019 to 2023 may be due to the pandemic.
- Overall, reasons as to why users continue to utilize MUNI are inconclusive due to the lack of changes in ratings.
- The main reason why people do not use MUNi is due to their ability to take other modes of transportation.

Future Work

- Utilize more data sets, such as MUNI Feedback- a dataset that organizes SF311 Cases
- Results may not represent the relationships in data set due to hundreds of rows dropped due to possessing null value, so instead use these data cleaning methods below:

Drop Rows with More than 4 Null Values
↙ Missing Categorical Values → Imputer Methods, K-Means Clustering, PCA
↘ Missing Numerical Values → Median Value

Leasons Learned

- Multiple data sets are often required to fully understand an issue and answer a question
- Pre-processing and data cleaning is a vital step in a data science project. Data, especially collected over a long period is often not fixed, so the data scientist must make decisions on how to organize and clean aspects labels
- Data science is a repetitive process. Insights found throughout the project may spark new ideas, methods, and questions.

Acknowledgments

We would like to thank Tiffany Tra and Carlos De Leon for their mentorship throughout the process. Their guidance and support were invaluable in helping us complete this research project. Thank you Denise Hum and Judy Cameron for their guidance and establishing the partnership between Data Jam and Skyline College.

Socioeconomic Dynamics in San Francisco:

Authors

Tyler Kuwada, Hansen Xiao, Daria Baitazarova, Ashley Gutierrez Carreto

uSOAR Undergraduate Symposium of Academic Research

Skyline College

Abstract

Public safety is paramount in San Francisco to promote thriving communities and attract visitors. However, wealth distribution disparities can significantly influence public safety measures' effectiveness, leading to unequal safety experiences among low-income neighborhoods. Understanding these dynamics is crucial for policymakers to identify and address systemic inequalities, ultimately fostering a safer and more equitable city for all residents and visitors. This research investigates the relationship between wealth distribution and public safety measures in San Francisco, shedding light on the challenges and opportunities for promoting a more inclusive and secure environment.

Introduction

To analyze the impact of wealth distribution on various public safety measures in San Francisco. By examining how different income neighborhoods experience disparities in safety, the study aims to identify systemic inequalities and propose targeted interventions to address them. Additionally, the research seeks to raise awareness of wealth inequality's effects on public safety and advocate for social change to create a more equitable and secure city. Through empirical analysis and data-driven insights, this research aims to inform policymakers and community stakeholders about the importance of addressing wealth disparities in ensuring public safety and fostering community well-being.

Methodology

Libraries:

- **geopandas**
- **matplotlib**
- **pandas**
- **numpy**

Variables:

- **Area**
- **Population**
- **Population density**
- **Median household income**
- **Community Resiliency Score**

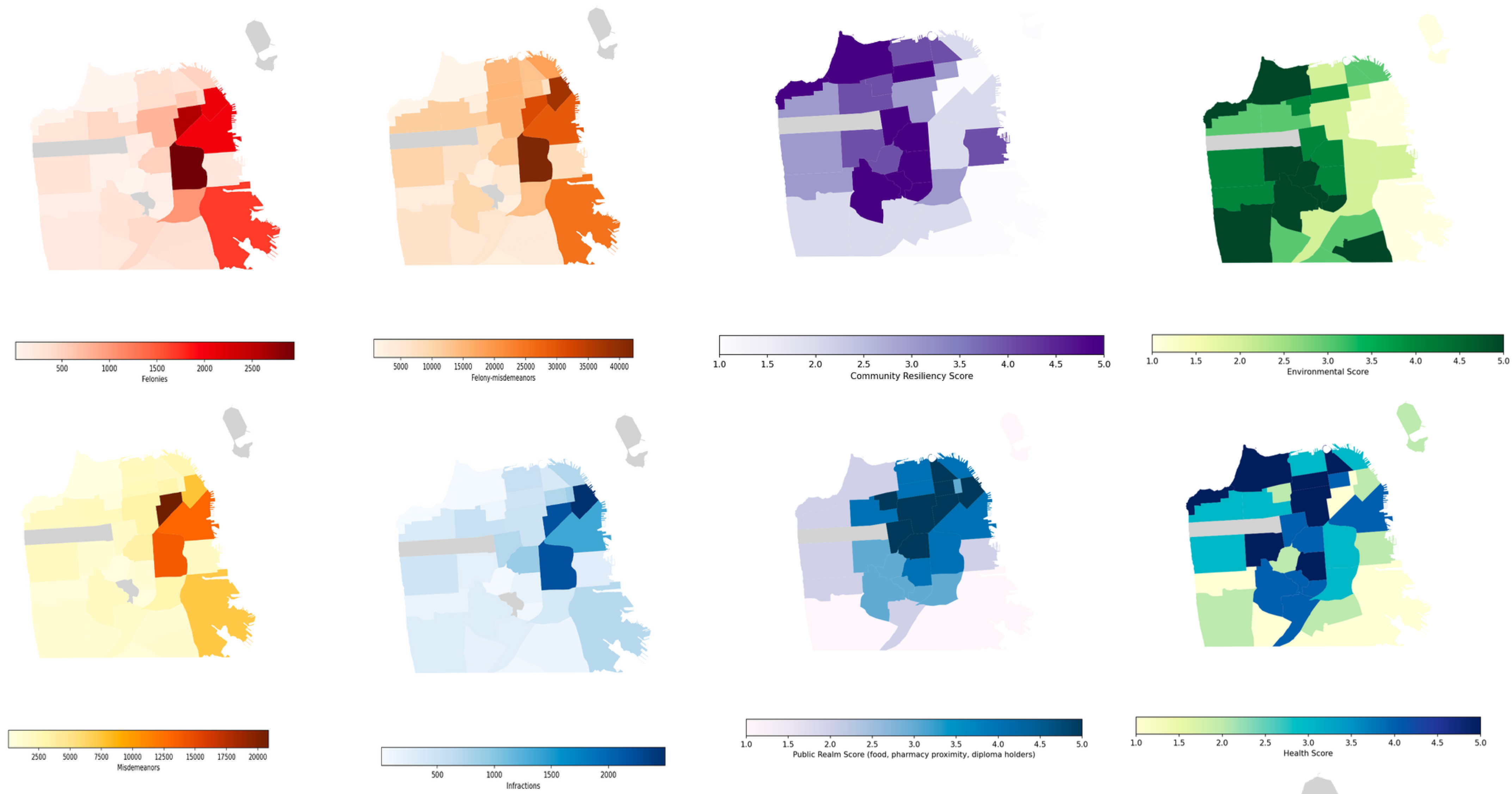
However, we could not find the exact data set of the median income from each of San Francisco's official neighborhoods. Alternatively, we collected data from "San Francisco, California Neighborhood Map - Income, House Prices, Occupations, Boundaries" from City-Data.com. First, we gathered information from 145 San Francisco neighborhoods containing population, population density, median household income, medium rent, and area. We created choropleth maps using geopandas and the scatter line plot using matplotlib.

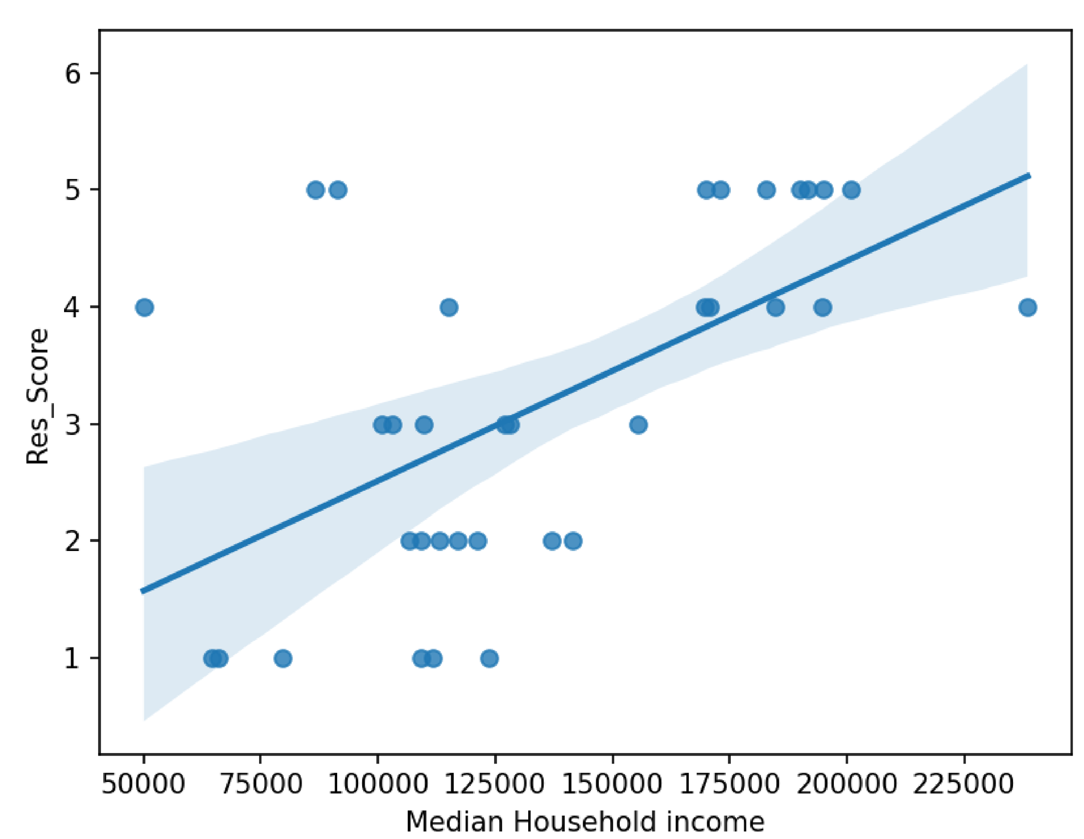
The population undergoes constant fluctuation influenced by birth and death rates, immigration, and emigration. Rent data is subject to variation due to inflationary pressures. While salary data remains continuous, it can fluctuate based on factors such as inflation. Economic impact studies analyze the financial, employment, and household income effects of various activities, such as establishing or expanding businesses, hosting festivals, or constructing regional event centers.

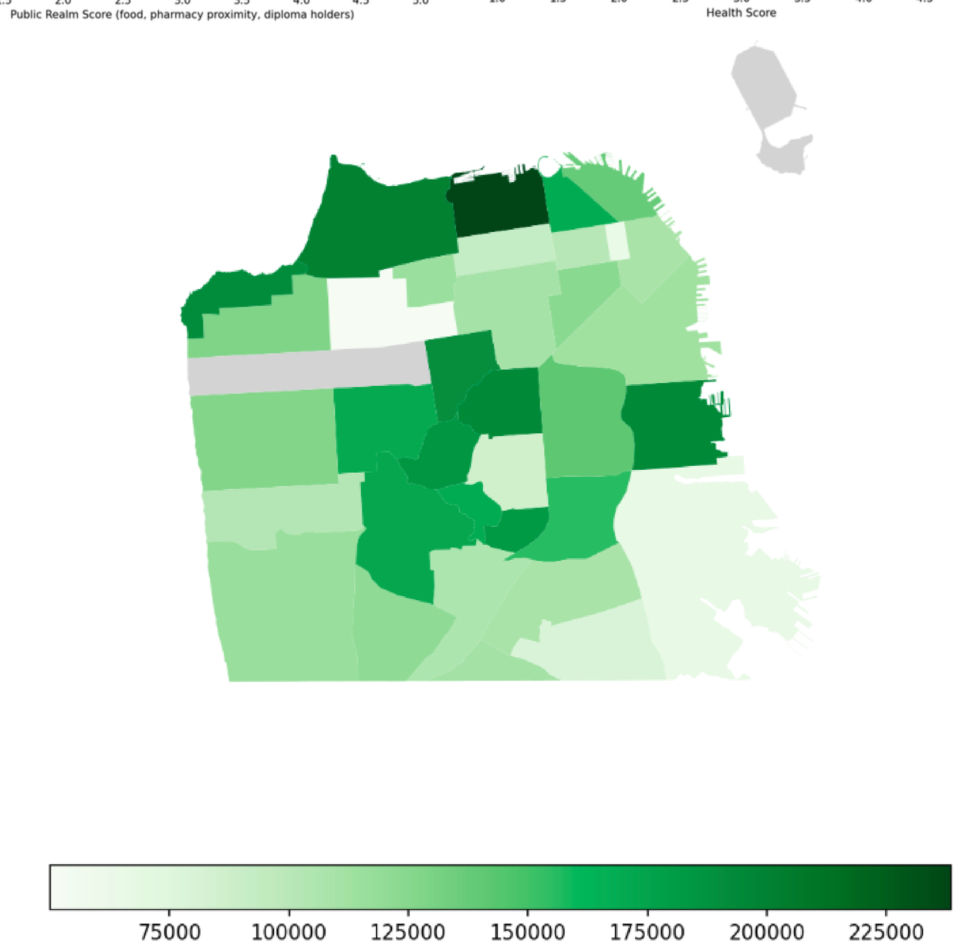
Findings and Analysis

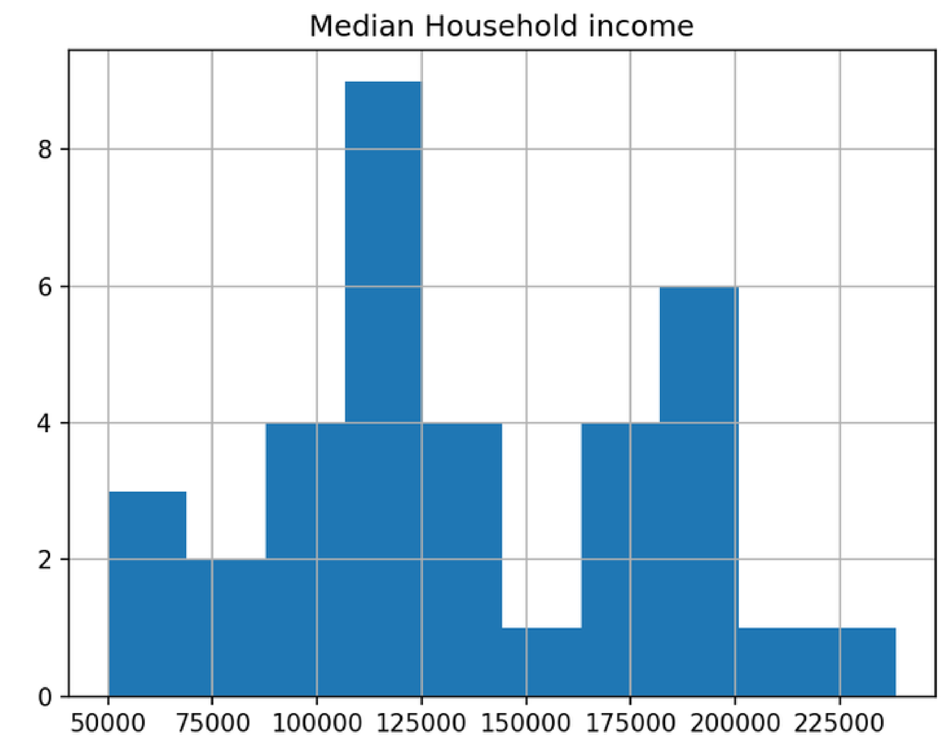
Through our analyses of the effects of income on various public safety factors, we found that income didn't have as much of an impact as we had hypothesized. We had expected that income would have had an inverse relationship with quantity of crimes across neighborhoods (higher income means less crime), however surprisingly this was not the case. When plotting income versus crime frequency (total and individual types), we could not find any correlation, even when compensating for population densities.

However, we did find one meaningful connection between median household income and community resiliency score, suggesting that income does have an effect on public wellness, just not in the area we expected. However this relationship still only had an r^2 score of 0.34, continuing to add on to the suggestion that income is not as important of a factor as expected.









Conclusion

In our analyses and graphing, we did not find any meaningful correlations between our supposed causal variables (income, population, density) and our outcome variables (crime rate, community score). We only had one meaningful correlation, which was between income and total community resiliency score.

This was surprising, as the common conception is that richer people and areas would commit less crime. However it appears that, at least in San Francisco, this is not the case and different factors, such as demographics and other social aspects, appear to matter more. Thus government officials and others seeking to combat the crime problem should look elsewhere than simple income support for a solution.

Other factors that could have influenced our results could have been a lack of proper scale (a city is too small to take income as consideration on societal factors) and impacts of historical events on trends (particularly with COVID, as this is a recent dataset).

In summary, we found that simplistic factors such as income and population are not wholly at fault for the economic and living situation in San Francisco, and that it is a much more complex problem than anticipated.

Addressing Diagnostic Errors in Medical Care: A Focus on Maternal Health Disparities

Donjhai Holland, Sofia Ponder, Essai Taleb

The DataJam, Laney College

1. Introduction

Background: Diagnostic error refers to the failure to establish an accurate and timely explanation of the patient's health problems and communicate that explanation to the patient. Diagnostic errors contribute to 10% of hospital adverse events, frequently involving critical misdiagnoses in three areas: vascular events, infections, and cancers, with a pronounced impact on patients of color. In our study, 'maternal' refers to women during pregnancy and up to a year after childbirth. Focusing on maternal health disparities among Non-Hispanic Black, Non-Hispanic White, and Hispanic mothers throughout the US population, we observe significant disparities. Notably, Non-Hispanic Black women face maternal mortality rates 2-3 times higher than Non-Hispanic White women.

Hypothesis: Our goal is to determine if the leading causes of maternal deaths (LCOD) in these groups correspond to the three leading diagnostic error categories, to identify possible connections and inform targeted strategies for reducing observed disparities.

2. Methodology

Our methodology encompassed two analyses. Firstly, we performed a Linear Regression Analysis with National Center for Health Statistics data on US maternal mortality rates from 2018 to 2021, which focused on Non-Hispanic Black and Non-Hispanic White, and Hispanic mothers, to predict future trends **(Figure 1).**

Secondly, we utilized data from two sources, a Maternal Mortality Review Committee study (LCOD by race/ethnicity in 36 US States, 1018 cases, 2017-2019) and the Pregnancy Mortality Surveillance System data (Maternal mortality rate by race/ethnicity in US population, 2017-2019). We narrowed our focus to 926 cases of Hispanic, Non-Hispanic Black, and Non-Hispanic White groups. We then calculated and adjusted weighted percentages for LCOD to represent the actual US population within each group **(Table 1, Figure 2).**

Figure 1: Maternal Mortality Rate by Ethnicity: Historical Data and Future Predictions

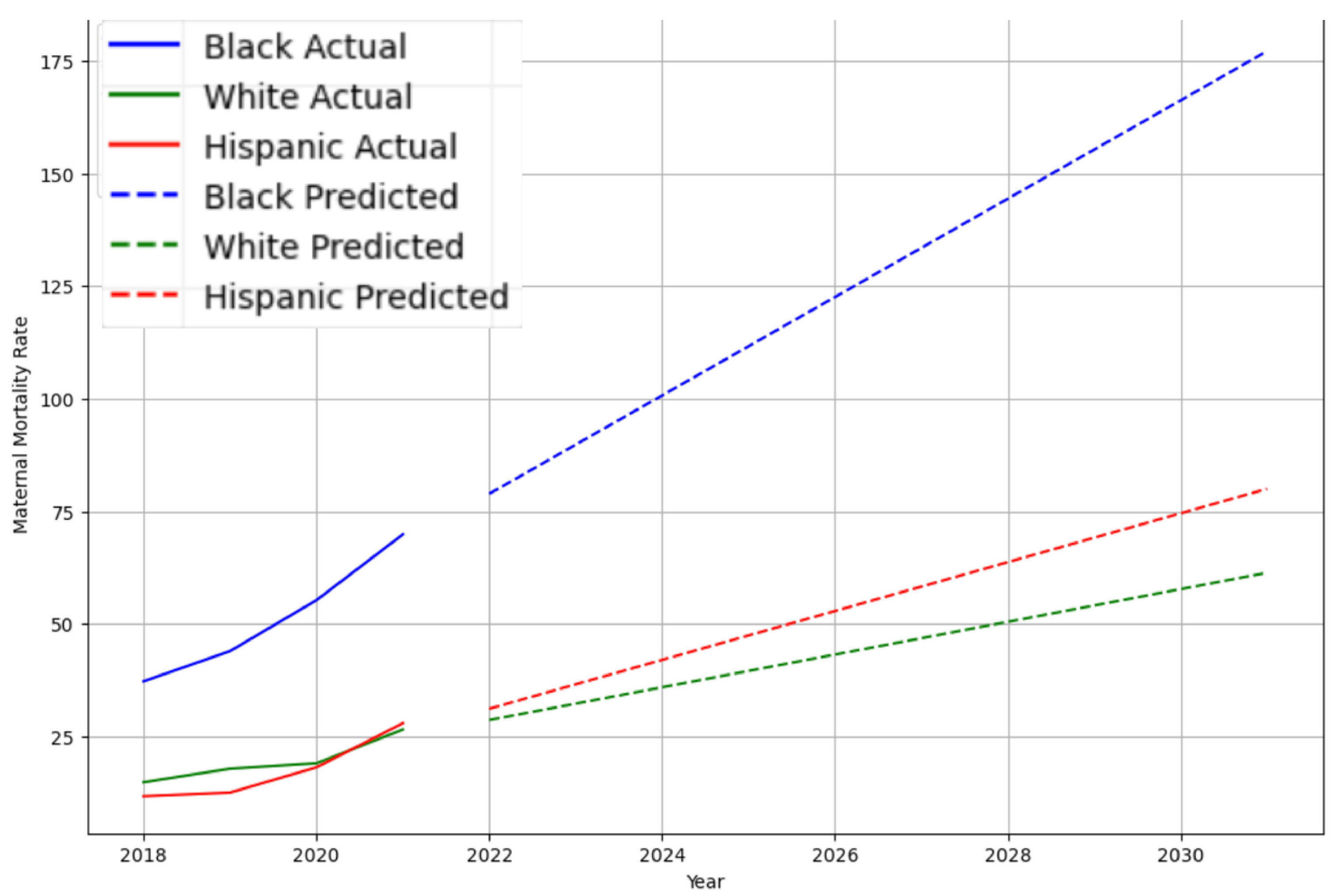
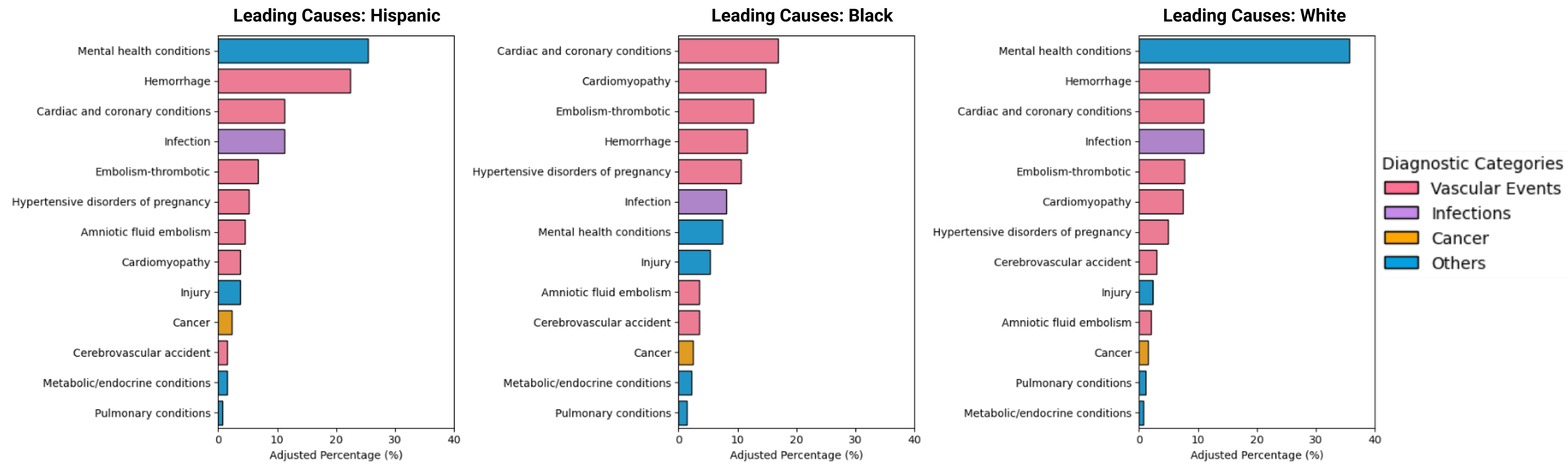


Table 1: Maternal Mortality Rate by Ethnicity: Leading Causes of Death (Weighted)

	Cause of Death	Hispanic % Adjusted	Black % Adjusted	White % Adjusted
0	Mental health conditions	25.373134	7.368421	35.650224
1	Hemorrhage	22.388060	11.578947	11.883408
2	Cardiac and coronary conditions	11.194030	16.842105	10.986547

3. Results

Figure 2: Maternal Mortality Rate by Ethnicity: Leading Causes of Death



4. Research Limitations

1. Access to healthcare data was constrained by privacy regulations.
2. Limited reporting of diagnostic errors due to potential legal ramifications.
3. Restricted data on AI solutions because of the novelty of wearable devices and AI technology.
4. AI Bias:
   a. Lack of inclusivity during pioneering data collection contributes to existing implicit bias in current AI models.
   b. Data analyzed by AI lacks representation from underrepresented populations due to cost, access, and community mistrust, resulting in further bias.

5. Conclusion & Future Work

Conclusion: Our study highlights the possible impact of diagnostic errors on maternal mortality, with over 80% of these deaths identified as preventable. We identified vascular events, infections, cancer, and mental health issues as the leading causes of maternal deaths, corresponding to the primary categories of diagnostic errors in the U.S. healthcare system overall. This alignment suggests an opportunity for intervention. Vascular events include conditions that disrupt normal blood circulation, often leading to severe, life-threatening outcomes. The significance of these findings is amplified by major diagnostic errors that appear in 10% to 20% of autopsies and are implicated in the annual deaths of 40,000 to 80,000 U.S. patients.

Our analysis revealed profound disparities affecting maternal outcomes, particularly for women of color, who are more likely to suffer from misdiagnoses due to factors including explicit and implicit racial biases, missing data, lack of trust, and reduced healthcare access. The introduction of wearable technology could revolutionize the monitoring and early detection of pregnancy and postpartum complications by providing continuous, real-time data on health indicators, crucial for early intervention. Furthermore, improving the inclusivity and accuracy of AI algorithms by integrating comprehensive and representative data, can help mitigate existing biases and enhance diagnostic precision.

By refining diagnostic practices and enhancing data quality and accessibility through advanced technologies like wearable devices, we can begin to reduce maternal mortality rates and narrow the racial disparities in healthcare outcomes. This approach can improve the health and safety of mothers but also sets a precedent for addressing similar disparities across various domains of health.

Future work:

- Data collection on diagnostic error by demographics
- Exploration of the correlation between diagnostic errors and maternal mortality rate
- Expanding the application of AI and wearable technologies to find a correlation between device usage and improved maternal vitals and health

Link to References

Social Media & Mental Health

Team & School

Quinn Soon
Laney College Team 2

Research Question

Are mental health condition impacted more by the frequency of social media consumption or the social media platform types?

Keywords

- platform types: visual-based, text-based, hybrid
- mental disorders: ADHD, Anxiety, Depression, Self Esteem

Hypothesis

Social media platform types have a more significant impact on users' mental health than the frequency of social media consumption.

Datasets

We retrieved the dataset from Kaggle, which was originally collected by students from the University of Liberal Arts Bangladesh (ULAB)

- Dataset name: Social Media and Mental Health

This table covers users' demographics, the platform used, frequency of use, relevant scores on questions related to specific mental disorders, and the total score, the accumulated score from each disorder. Users with higher scores have worse mental health conditions.

```
 #   Column
---  ------
 0   Age
 1   Gender
 2   Relationship Status
 3   Occupation Status
 4   Organization
 5   Social Media User or Not
 6   Social Media Platform
 7   Frequency of Use
 8   ADHD Score
 9   Anxiety Score
 10  Depression Score
 11  Self Esteem Score
 12  Total Score
 13  Outcome
 14  Platform Type
```

Fig. 1 The columns in the dataset

Analyses & Results

Our research used Analysis of Variance (ANOVA) and Pearson Correlation to study mental health scores across social media usage patterns. ANOVA checks for score differences among user groups of various platforms or usage frequencies, providing F-value and P-value. A higher F-value indicates significant score variances between groups, meaning the factor (Frequency of Use or Platform Type) impacts mental health more significantly than the other, and a low P-value (below 0.05) confirms that these differences aren't coincidental. Meanwhile, the Pearson Correlation examines the relationship between variables, such as usage frequency and mental health scores, showing if they are correlated. This helps us understand the direct impact of social media on mental health.

The results are:

- ANOVA results for Platform Type:
  - F = 2.7228366952269574
  - P = 0.06592700467807402
- ANOVA results for Frequency of Use:
  - **F = 90.67924321020807**
  - **P = 2.479044478902904e-86**
- Pearson Correlation between Frequency of Use and Total Score:
  - **0.39736870251317785**

The findings from the study indicate that the frequency of social media use has a significant impact on users' mental health, as evidenced by a high F-value (90.68) and an extremely low p-value (<0.001). Users' social media use is strongly associated with mental health scores. With an F-value of 2.72 and a p-value of 0.0659, the type of social media platform does not show a significant effect on mental health scores across different types of platforms.
Furthermore, the Pearson Correlation coefficient of 0.397 between "Frequency of Use" and "Total Score" indicates a moderate positive relationship, suggesting that higher mental health scores are correlated with increased social media use frequency. As a result, usage frequency has a greater impact on mental health than platform type.

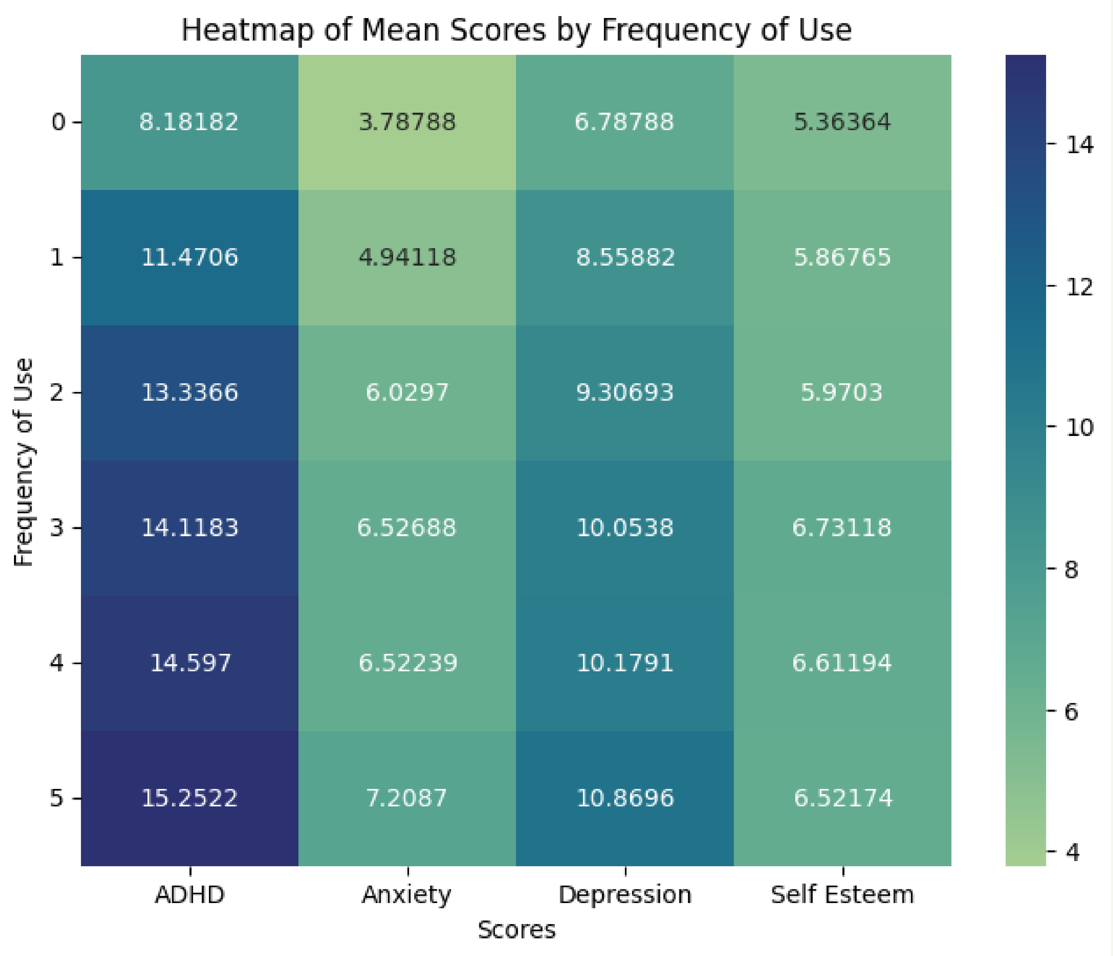


Fig. 2 Heatmap of Mean Scores by Frequency of Use

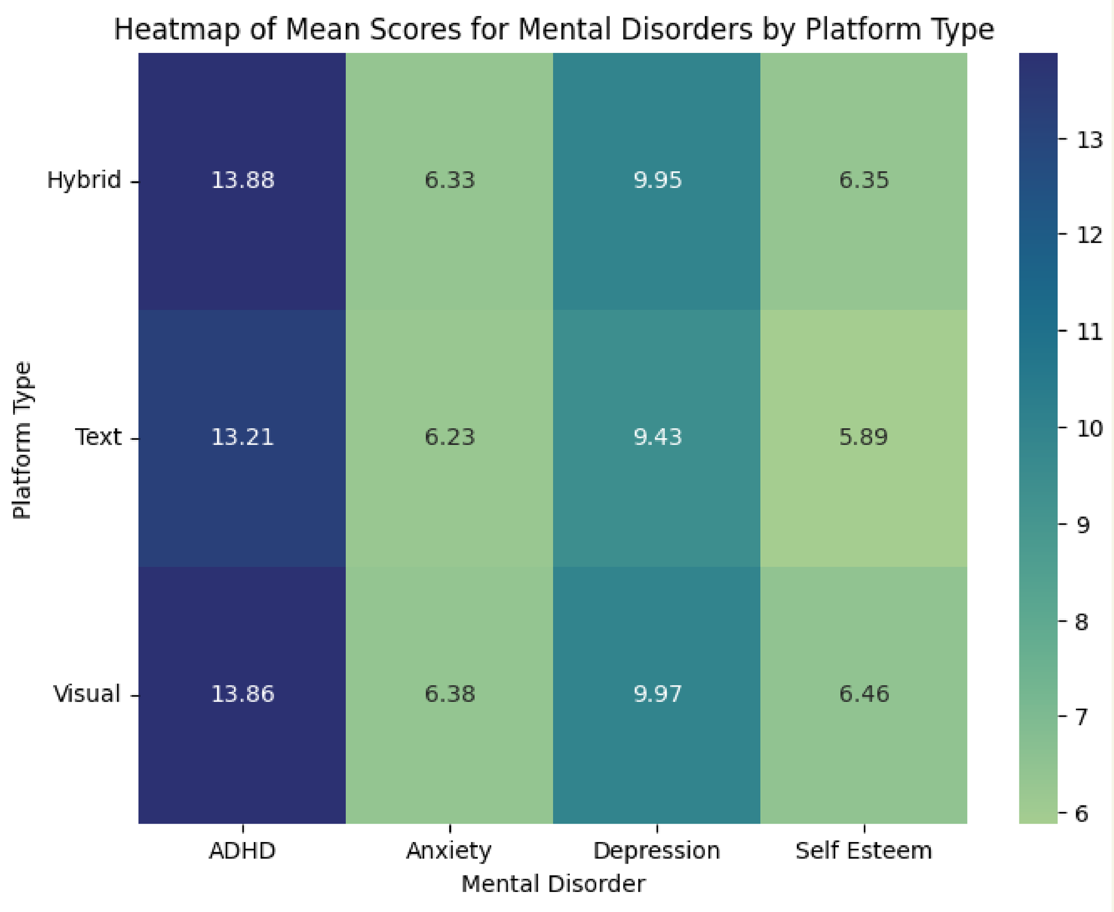


Fig. 3 Heatmap of Mean Scores by Platform Type

Challenges

1. As this topic is relatively new, finding relevant datasets targeting social media and mental health was challenging.
2. Our limited experience posed challenges in organizing and cleaning the dataset for efficient and effective analysis.

Suggestions

According to this research, social media consumption frequency can negatively impact mental health. Therefore, we strongly suggest **reducing your use of social media**, no matter what platform you use. For future research, researchers should investigate the different impacts of social media usage on users, depending on their demographics.

Summary

The heatmaps above showed how average scores for different mental health issues change with how often people use social media and the kind of platforms they use. These average scores, which add up to the total scores, showed that the scores go up more noticeably with increased usage frequency than with the type of platform used. Simply put, how often people use social media has a more substantial negative effect on their mental health than the specific platforms they're on, which was a surprising finding compared to what we initially thought..

“Fleet of the Future” in perspective. EV's vs BART

Paris Middleton-Berry, Siuling Pau-Sanchez, Shotaro J Terasaki

Instructor: Kyla Oh. **Peer Mentor:** Kyaw Swar Ye Myint[1]

Laney College, [1]UC Berkeley

Introductions

Research Question What is the environmental impact comparison between actively using BART and the increased use of electric vehicles in the San Francisco Bay Area? Which transportation option will contribute more to reducing CO2 emissions in the future?

Hypothesis BART's CO2 emissions per passenger are lower than those of electric vehicles making it a greener choice. Despite both using electricity, BART's investment in renewable energy and expansion plans may reduce overall emissions more effectively than EVs, whose production and power generation still significantly contribute to CO2 emissions. BART's approach seems to offers a more sustainable urban transport solution.

Key Words

EVs – Electric Vehicles. Plug-in battery powered commercial cars.

BART – Bay Area Rapid Transit. Main underground public transportation system around the SF Bay Area.

VRM – Vehicle Revenue Mile. Mile traveled with passengers aboard.

GHG – Greenhouse Gases. Sources of global warming.

MTCO2e – Metric Tonnes of CO2 equivalent. Measurement of GHG emissions with the same global warming potential than a ton of carbon dioxide.

Methods

Calculations, Equations

To analyze and compare the CO2 emissions between Electric Vehicles and the Bay Area Rapid Transit, a detailed methodological approach was employed:

Initially, total energy use in Megajoules per vehicle revenue mile for BART and average miles driven along with CO2 emissions per mile for EVs were calculated. This included linear extrapolation to estimate missing data for earlier years based on observed trends (Figure 1).

The total annual energy consumption was then derived by multiplying the number of trips by the average trip length and the estimated energy use. For a more nuanced analysis, the portion of energy derived from non-clean sources was calculated, and a standardized emission factor was applied to estimate greenhouse gas emissions.

These steps facilitated the computation of emissions per thousand vehicle revenue miles, enabling a direct comparison between the two transportation modes (Figure 2). The analysis was further refined by calculating standard deviations and margins of error for the extrapolated BART emissions data, providing a quantitative basis for assessing the environmental impact of both EVs and BART over time, especially in light of BART's efforts to utilize cleaner energy sources and implement more efficient "Fleet of the Future" trains.

Datasets

Year	Total energy use (MJ / VRM)	Total GHG emissions (MT CO2e / thousand VRM)	Yearly Change in Energy Use	Yearly Change in GHG Emissions	Standard deviation of sample of MTCO2e (2015 to 2022)	Margin of Error (MOE) for MTCO2e 95% confidence level	
						MOE 1.514499	
						Lower Bound	Upper Bound
2013	20.358571	1.391429				-0.123070	2.905928
2014	20.774286	1.655714				0.141215	3.170213
2015	21.19	1.92	-1.26	-0.26	0.757249		
2016	19.93	1.66	0.59	-1.44			
2017	20.52	0.22	0.37	0.03			
2018	20.89	0.25	0.29	0.01			
2019	21.18	0.26	2.52	-0.15			
2020	23.70	0.11	-1.96	-0.01			
2021	21.74	0.10	-3.46	-0.03			
2022	18.28	0.07					
		Averages	-0.415714	-0.264286			

Figure 1 – BART Energy Use. Linear Extrapolation

	Electric Vehicles						BART			
Year	Number of registered vehicles (thousands)	Average miles driven in California each year (thousands)	Total VRM	California's average MTCO2e emission per vehicle	MTCO2e per mile	MTCO2e per thousand miles	MTCO2e per thousand miles	Number of trips (millions)	Average trip lenght (miles)	Total VRM
2013	11,542	7994	92,266,748	0.62822618	7.85872E-05	0.078587213	1.39	118,000,000	14.0	1,652,000,000
2014	24,523	8914	218,598,022		7.04763E-05	0.070476350	1.66	117,000,000	14.0	1,638,000,000
2015	38,506	8624	332,075,744		7.28463E-05	0.072846264	1.92	126,000,000	14.4	1,814,400,000
2016	52,788	8687	458,569,356		7.23180E-05	0.072317967	1.66	128,500,000	14.4	1,850,400,000
2017	73,128	8750	639,870,000		7.17973E-05	0.071797278	0.22	124,200,000	14.6	1,813,320,000
2018	101,933	8852	902,310,916		7.09700E-05	0.070969971	0.25	120,600,000	14.8	1,784,880,000
2019	125,770	8649	1,087,784,730		7.26357E-05	0.072635701	0.26	118,100,000	15.0	1,771,500,000
2020	117,361	7590	890,769,990		8.27702E-05	0.082770248	0.11	32,200,000	15.0	483,000,000
2021	132,019	7949	1,049,419,031		7.90321E-05	0.079032102	0.10	24,600,000	15.0	369,000,000
2022	161,729	8061	1,303,697,469		7.79340E-05	0.077934026	0.07	41,100,000	15.0	616,500,000

Figure 2 – Annual MTCO2e emissions from EVs and BART

Results and Discussion

Figure 3 – BART and EV's MCTO2e yearly per thousand miles

Figure 3 is comparing the MTCO2e emissions per thousand miles for Electric Vehicles and BART. It highlights significant differences in environmental impact between these individual transportation and mass transit systems over various years. Initially, EVs exhibit substantially lower emissions per thousand miles across all observed years compared to BART, with EV emissions fluctuating approximately between 0.07 to 0.08 MTCO2e, distinctly lower than BART's earlier emissions, which reached as high as 1.92 MTCO2e.

However, the trend undergoes a notable shift, especially during the period affected by COVID-19, where BART's emissions per thousand miles drastically decrease to levels as low as 0.07 MTCO2e, closely mirroring the emissions from EVs. This significant reduction is attributed to several factors, including operational adjustments, reduced ridership during the pandemic, and notably, BART's introduction of the "Fleet of the Future" trains. These new trains are designed for higher energy efficiency and lower emissions, significantly contributing to the overall reduction in BART's carbon footprint.

In conclusion, while individual EVs currently showcase lower MTCO2e emissions per thousand miles, the advancements in BART's operations, particularly the introduction of the "Fleet of the Future" trains and the shift to cleaner energy sources, demonstrate the potential for mass transit systems to evolve into even more environmentally friendly alternatives. This progression, coupled with the intrinsic efficiency of moving larger numbers of passengers per trip compared to individual EVs, suggests that supporting and utilizing mass transit like BART could emerge as the more sustainable choice for urban transportation in the long term.

Limitations

- Unavailability of open-sourced GHG data.
- Extrapolation of data.
- Impact of COVID-19.
- Emission Factors Variability.