

Don't Divert Your Attention:

An Analysis of the Effects of Ambulance Diversions in San Francisco on Patient Transportation Time and Mortality Rate

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Executive Summary

When hospital emergency departments become overcrowded, most hospitals in the United States can divert incoming ambulances, putting individuals who need care at risk because it delays time in treatment. This is called going on bypass, and it is a significant issue in the United States, particularly in urban areas. To understand how bypass rates impact urban environments, we analyzed hospital bypass rates and their impact on mortality rates within the county of San Francisco. Using sources from the California Health and Human Services Agency (CHSS), the US Department of Homeland Security (DHS), and the US Census Bureau (USCB), we were able to locate EMS centers, hospitals, population distributions, and census block group distributions in San Francisco county. In addition, we were able to retrieve hospital-specific data regarding types of care and diversions in order to extrapolate bypass rates for all hospitals that accept ambulances. Our models focus on finding the total time it would take for an ambulance to leave the EMS center it is dispatched from, provide initial treatment onsite, and then travel to a hospital. For simplicity, we refer to this as SATT, the Scene And Transportation Time.

First, we created a function that would estimate the SATT based upon an input location. Then, this model was expanded to find the city's average SATT, the SATT of each census block group, and the growth in SATTs until 2050. These models indicated that from 2015 to 2050, the average SATT grew from 36.99 minutes to 37.90 minutes, with a 38.47% increase in ambulance users due to population growth. Then, we created an optimization program that would find the ideal locations of adding one to three new hospitals by minimizing the city's average SATT. If the city government wanted to construct a single new hospital, the ideal location would be within the census group block centered at longitude -122.4402826 and latitude 37.71858529. These models above were extended to compare the impacts of building a hospital at our ideal location with San Francisco's Helen Diller expansion, which is the planned expansion of UCSF Medical Center, to be completed in 2030. Finally, we created a mortality model that linked SATT to ambulance patient mortality rate. This model identified large inequities in mortality rate across census block groups of San Francisco, indicating that mortality rate is much higher for ambulance patients on the southern and western edges of the city than for those located more centrally, with these regions having up to 203.30% higher mortality rates than other city regions.

With our model predicting increases in ambulance diversion times over the next few decades, there is an inevitable risk of increased loss of human life. Furthermore, with bypass rates being widely variable across the city of San Francisco, mortality rates for ambulance patients can range anywhere from 4.85% to 12.11%, with higher mortality rates in the southern and western areas of the city. These regions have higher proportions of Hispanic and Asian populations and regions that have lower diversion times having larger white populations, revealing clear inequities in access to emergency care based on race within the city. From 2015-2050, there is a 42.18% increase in the expected number of deaths for ambulance patients.

We discuss means of minimizing risk by implementing future facilities. We find that our proposed hospital reduces SATTs 5.78% more than the planned Helen Diller expansion to the UCSF Medical Center would. It additionally would reduce diversion hours by 62.99% and therefore mortality rates by 4.98% when compared to the expansion.

We recommend that the San Francisco government and private health insurers incentivize UCSF to build their hospital in our recommended location. They will benefit because of decreased mortality rates and overall severity, resulting in lower costs for them and, consequently, cheaper premiums for consumers.

In addition, we propose a number of behavior changes that can be implemented by members of the San Francisco community in order to reduce risk to patients as well. To free up more hospital space, we suggest means of reducing numbers of patients admitted to hospitals in the first place. Decriminalization of drug usage is shown to reduce the likelihood of overdoses, which we recommend San Francisco implements to reduce overdose-related ambulance patients. Further, increasing government funding for heart disease prevention is recommended in order to reduce the number of heart disease ambulance calls, as heart disease is currently the leading cause of death in the US.

Introduction and Background

Background

In 1986, Congress passed the Emergency Treatment and Labor Act, guaranteeing US residents the right to limited emergency medical and childbirth services.^[19] However, there is a risk that hospitals are not able to meet demand, putting at risk the health and life of individuals seeking service during times of high demand. While hospitals cannot refuse service to patients who walk in the door, hospitals can divert ambulances to other facilities to ease overcrowding. The severity of these risks is wide-ranging, from delays to treat a sickness that can just as easily be treated at home, to severe and potentially life-threatening refusals, either because of a rushed and inaccurate assessment or because of capacity constraints. The frequency of these risks varies significantly by hospital, ranging from no hours per year to up to 21% of the time. We will explore severity and frequency in much more detail in the model.

How do we identify times of limited hospital capacity? Ambulance diversion times measure when a hospital has officially declared that incoming ambulances should be diverted to other facilities due to capacity problems (with some exceptions). The consequences of diversions are substantial and wide-reaching. They have been categorized into four risks:

1. unacceptably prolonged SATT intervals;
2. prolonged out-of-hospital care when definitive hospital-based resources are needed, especially for unstable or critically ill patients;
3. inappropriate attempts by field personnel to predict the specific diagnostic and therapeutic resources needed by individual patients; and
4. delays in, or lack of, ambulance availability to the community because of diversion of units to distant hospitals.^[15]

The consequences of diversion times can apply to any resident of the United States, as health emergencies that result in being transported by ambulances are, by their very nature, unexpected and unpredictable. Even for those fortunate enough never to need to be transported by ambulance, the consequences are felt through friends and family members, making the impact of diversions something that can affect an entire community.

Inequities

In short, San Francisco, like many other urban centers in America, is plagued by the current and historical consequences of racial housing policies and practices. We consider the population distributions in the city by race and how that compares to the risks related to ambulance diversions.

Size

In this paper, we narrow our focus to a single city: San Francisco, addressing an at-risk population as all residents of San Francisco county. This population is estimated by the Census Bureau to include 881,549 individuals in 2019.^[38] Of the hospitals in the county, 58% go on bypass status at least once per year. For all emergency departments across the United States, this number was about 45% in 2003.^[9]

Scope

There are multiple ways to mitigate the risk of hospital diversions. First, as some local and state governments have proposed, they can remove the ability of hospitals to divert ambulances at all.^[3] While patients have to spend less time in transport, this does not solve the issue of overcrowding during peak times.^[26] It is well established that ambulance diversion rates are related to negative health consequences, but the focus of this paper is on minimizing diversion hours through future hospital constructions, not banning ambulance diversions.

Second, efforts can be made within the hospital to treat patients faster, allot more beds to the emergency services, and otherwise improve the efficiency of the hospitals themselves. This is beyond the scope of our study; we assume hospitals make their best efforts to treat the patients that reach them quickly and correctly.

Third, we can redistribute resources. This can be done in three different ways: redistributing EMS locations, redistributing medical resources, and redistributing hospital locations. EMS locations—where ambulances are dispatched from—can be assumed to be fixed because the EMS buildings cannot be moved. In San Francisco county, there are 45 EMS centers, which are over three times the number of hospitals in San Francisco county. The EMS centers are distributed across the city with an attempt to ensure the response time for at least 90% of ambulances is less than 10 minutes for all citizens.^{[4][21]} While constructing a new EMS center is a possible route to explore, an additional EMS center would impact a very minor portion of the population when compared to hospital changes since the EMS centers divide the city into 45 regions.

Moving medical resources such as beds, doctors, nurses, etc. is not an optimal solution because hospitals should be staffed fully if they are experiencing medical diversions. That is, we assume hospitals use all the resources they have room for.

The third option is to modify hospital locations. That comes either by expanding current hospitals by building annexes or by investing in the construction of new hospitals. Since the University of California San Francisco (UCSF) is planning an expansion, the Helen Diller Medical Facility, to begin in 2023, our risk mitigation strategy will focus on this development since it is directly actionable and relevant.^[16] However, we propose that there may be a more optimal location within the city that has a larger impact on diversion times and mortality rates.

COVID-19

COVID-19 has completely upended the healthcare industry. That includes diversions. However, our analysis is limited to before the pandemic began for two reasons. First, there is limited data, which we will discuss in further detail in the next section. Second, diversion hours in the year 2020 have been significantly increased.^[41]

We assume that, by 2025, since the vaccine will have been widely distributed, the ambulance bypass rates will return to pre-COVID-19 levels. Even if it takes longer than 2025 to eliminate the backlog of elective surgeries and other procedures due to COVID-19, these reschedulings will have a minimal impact on emergency departments.^[24] Our models also assume there is not another global pandemic in the next thirty years, but if there is, our prediction would serve as a lower bound. Even if we had the data for 2020, including it would skew our analysis and predictions. Later, we will still discuss our model and findings within the context of the COVID-19 pandemic.

Problem Statement

Ambulance diversions provide significant health risks to individuals by delaying treatment and preventing optimal access to quality care. Everyone who could be transported via ambulance is at risk, which includes the entire US population. We restrict the focus of our analysis to San Francisco county. In order to mitigate the risks of ambulance diversions and decrease hospital overcrowding, San Francisco should incentivize the construction of a new hospital and encourage relevant public policy.

Data Methodology

To frame our paper, we have 2 major focuses. The first focus is **frequency**, which is represented by 2 things. Bypass rates are one measure of frequency. They correlate to the number of ambulance people who can get into crowded hospitals. When bypass rates are too high, we see more people not getting the required care they need. The overall goal for the city is to decrease this frequency as much as possible to ensure all patients get care quickly. Frequency is also used to describe the frequency or concentration of areas with high SATT values, which correlates to more high risk areas. Our second focus is our **severity**, which is modeled by SATT and mortality rate. We are able to find an average SATT and mortality rate for every census block in San Francisco and find which areas of the city are more at risk and see how our proposed changes would impact that. We used the following data sources to quantify our frequency and severity, define historical trends, extrapolate predictions on future trends, and explore the potential outcomes.

Bypass Rates and Hospital Utilization

In general, data about ambulance diversions is limited. No federal agency tracks nationwide bypass rates, even at an annual level. However, the state government of California does make some information publicly available.

The Annual Utilization Report of Hospitals Database provided the number of hours over which ambulances were diverted from hospitals. This data provided diversion hours by month per hospital from 2013 to 2017 in the state of California. Unfortunately, 2018 through 2020 are not yet available, preventing us from considering COVID-19 in the scope we hoped. However, a five year period is useful for modeling change over time, especially as the data tracks hours by facility. It is useful for **defining historical trends**, identifying their **frequency**, and **projecting future trends**. We chose not to include a temporal analysis by facility because, though five points is reasonable when working with sample means, five points is less reliable for single facilities. This dataset also included the coordinates of each facility in latitude and longitude.

In order to make this data usable, we extracted the hospitals in San Francisco county and removed data on any hospitals which did not accept patients coming on ambulances—specifically the Jewish Home, a psychiatric hospital. Further, we found that some hospitals in our initial dataset—specifically the Kaiser Foundation Hospital, the San Francisco General Hospital, and the UCSF Medical Center—were listed more than once for distinct departments of the hospitals. In order to consolidate this data, we added the numbers of diversion hours and admitted patients for the duplicate hospitals and used the summed data to calculate new ratios and probabilities.

The data is made accessible by the California Health and Human Services Agency, an agency of the California state government whose primary purposes include promoting research, supporting the authority and efficacy of the data.

Mortality Rates

In order to determine the effect of ambulance diversions on the mortality rate of residents of San Francisco we utilized data sources analyzing the effect of ambulance scene and transportation time on patient mortality. These allow use to define the **severity** of potential health impacts. An observational study on the relationship between distance to hospital and patient mortality in emergencies found that for patients in severe condition, a 10-kilometer increase in straight-line distance was associated with a 1% increase in patient mortality rate.^{[27][28]}

A second study on emergency medical service response time and mortality in an urban setting contained data on the number of mortalities for different ranges of SATTs.^[6] As it is from the *Prehospital Emergency Care*, a peer-reviewed journal, this can be considered a credible scholarly work. We were able to make this data usable by converting each raw numerical datapoint to mortality rates for each time interval.

We took 17 minutes as the average scene time for an ambulance, a figure which we assume is constant for all patients for the purposes of our model.^[25] This number was found as an average scene time in large urban areas in *BMJ Journals*, an independent, peer-reviewed research journal, supporting the figure's efficacy and reliability. 20 miles per hour was found to be the average ambulance speed through examination of the computers in a number of ambulances^[31]. We took this figure as the average ambulance speed for all patients for the purpose of our model.

Hospital and EMS Center Locations

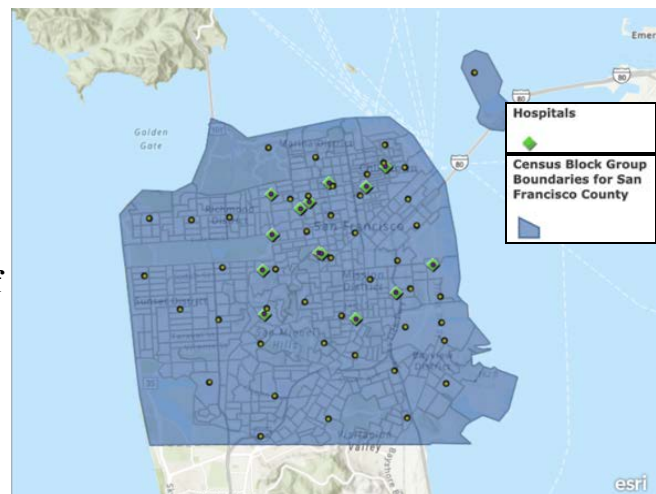
We used data available from the Homeland Infrastructure Foundation Level Database (HIFLD) in order to extract the coordinates (in latitude and longitude) of each Emergency Medical Service (EMS) station, which are responsible for dispatching ambulances. It is useful for calculating SATTs (**severity**), and therefore **frequency** of high severity ambulance diversions.

In order to make this data suitable for our purposes, we extracted only the EMS centers within the San Francisco county area. Once mapped, locations are relatively straightforward to assess for errors in the data.

This data is made accessible by the United States Department of Homeland Security, which is responsible for providing access to statistical reports concerning public security within the United States. The reliability and efficacy of this dataset is supported as it comes from a government agency which is responsible for making this data publicly available.

Populations

We use the Census Bureau's estimates for the population of San Francisco county in 2019, which is the most recently available year.^[38] As the Census Bureau conducts the most comprehensive and detailed reports of the United States population, it is a credible data source. It is useful for calculating **frequency of potential outcomes**. The San Francisco government published a prediction for 2040 as well as historical data, which we used to **predict future trends**.^[35] We also used the



Census Bureau's census block groups, of which there are 579 within San Francisco county, in 2019.^[39] This data is useful for **separating potential outcomes** based on location within the county. While census blocks are the most specific, we abstracted one degree for efficiency in running our calculations and because it is unreasonable to assume such a specific region has enough land available for constructing a hospital. Census block groups have a maximum of 12,169 individuals, with an average of 1,511 individuals per region. The dataset was merged with a shapefile for the geospatial boundaries of the census block groups.^[37] A centroid function was used to find their geographic center, which finds the mean of the longitude and latitude of all points defining the boundaries of the census block groups.^[14]

These regions were each assigned to the nearest hospital by distance to calculate the populations each hospital is responsible for and change over time. We concluded that it would not be reasonable to model the change in population at a census block group level (extrapolating from previous years), because different regions of the city will grow and shrink inconsistently over our thirty-year analysis. This is due to a variety of factors, such as gentrification.

Mathematical Methodology and Analysis

ArcGIS

Because our project is geographically oriented, we used GIS software to map our datasets, visualize our results, and simplify some of the geospatial calculations. We selected ArcGIS online because it is flexible, comes with useful analysis features, and is available for free through a sixty-day free trial made accessible to anyone by the Learn ArcGIS program.^[18]

Assumptions

We address assumptions as they become relevant within the paper, in addition to the following:

- Hospitals with zero diversion hours do not change, even if population increases. This is a reasonable simplification because we simply do not know if a hospital is frequently completely full, or if it is half empty at its most crowded.
- Any changes in immigration and emigration in San Francisco due to COVID-19 stabilizes by 2025. Additionally, the San Francisco local government population prediction for 2040 accounts for COVID-19.
- Each census block group population grows at the same rate as the city; that is, the different regions of the city grow evenly, at least over five year periods.
- With the exception of the planned and proposed increases to the facilities, there are no other increases in medical facility capacities before 2050 in the county.
- Any changes in the capacity of medical facilities due to expansions for COVID-19 patients are removed by 2025. In other words, we assume they are temporary.
- There is never a shortage of ambulances and EMS centers are as efficient as possible so that there is no delay between receiving a call and dispatching an ambulance.
- The number of ambulance users is directly proportional to the population in San Francisco county.
- The number of ambulances summoned to each census block is proportional to the population of that census block.

Models

There are five main sections of our overall model:

- 1) First, we modeled expected SATTs by census block group in San Francisco, accounting for bypass rates in hospitals, which is the likelihood a hospital will divert patients to another hospital.
- 2) Second, we modeled the change in average expected SATTs in 5 year increments from 2015 to 2050, ignoring 2020 due to COVID-19.
- 3) Next, we modeled which locations would be ideal for constructing new hospitals.
- 4) We then compared the impact of adding one new hospital with the current hospital expansion San Francisco plans to begin construction of in 2023.
- 5) The final model then correlated SATTs to mortality rates, exposing the differences in risk of mortality in different regions of the city.

Model 1: Expected SATTs

The first model we created was a JavaScript function that would calculate the expected SATT for a given location, which includes the time the ambulance takes to reach the patient, the on-site ambulance time, and the time it takes the ambulance to transport the patient to the hospital. This function took in four inputs:

- 1) The location of all the hospitals (in longitude and latitude)
- 2) The probability a hospital would be on bypass
- 3) The location of all the EMS centers (in longitude and latitude), and
- 4) The longitude and latitude of a desired location.

The function would iterate through each EMS and hospital to find the closest EMS center and hospital to the desired location. Instead of using straight line Euclidean distance, taxi-cab distance (which is a sum of longitudinal and latitudinal distance) was used to simulate the path of an ambulance along a grid-like city like San Francisco. Converting the longitude and latitudes to pixel points on a screen and then converting pixel distance between points to mile distances, we summed the distance the ambulance travels from the EMS center to the desired location and from the location to the hospital. Dividing the sum by the 20 mph (the average speed of an ambulance), we get the average time when the ambulance is in transit.^{[29][31]} With an average of 17 minutes of on-scene ambulance time, we add 17 minutes to obtain our SATT.^{[25][40]} We get the following formula for the SATT:

$$D_{EMS}(x, y) = \min(|X_{EMS} - x| + |Y_{EMS} - y|) * k$$

$$D_{Hospital}(x, y) = \min(|X_{Hospital} - x| + |Y_{Hospital} - y|) * k$$

$$T = \frac{(D_{EMS} + D_{Hospital})}{20} + 17 \quad \left| \quad k = \text{mile distance:pixel distance} \right.$$

However, to get the overall expected SATT, we must consider the bypass probability, which is the probability of being diverted from a hospital because the hospital is not accepting ambulances due to being on bypass. Using the Annual Utilization Report of Hospitals Database for San Francisco county, we were able to calculate the average annual bypass probability from

2013-2017 by taking the number of hours a hospital is on bypass over the 5 year time period and dividing by the total amount of hours in 5 year. The expected value formula for multiple events is the following, where X represents a possible outcome and P(X) represents the probability of that outcome occurring.

$$E(X) = \sum X * P(X)$$

Applying this to find the SATT, X becomes the distance to a certain hospital and P(X) is the probability of skipping previous hospitals and being admitted into that one. Numbering the hospitals from 1 to 14, with 1 being the closest hospital and 14 being the farthest, the probability of getting into the *n*th hospital would be the probability of not getting into the previous *n-1* hospitals multiplied by the probability that hospital is not on bypass (in other words, accepting ambulances). Therefore, the probability of getting into hospital *n* is:

$$P_n \prod_{z=1}^{n-1} (1 - P_z)$$

The following formula below represents a modified expected value formula that utilizes our inputs:

$$T_{overall} = T_1 * P_1 + T_2 * P_2(1 - P_1) + T_3 P_3(1 - P_1)(1 - P_2) \dots = \sum_{n=1}^{14} \left(T_n P_n \prod_{z=1}^{n-1} (1 - P_z) \right)$$

However, to extend this model, we found the center of each of the 579 block groups and iterated this formula for each one, allowing us to geographically show the differences in SATTs depending on one's location in the city.

To find the average expected SATT, we used a weighted average by summing each block group's product between the block's expected SATT and the group's population and dividing the sum by the total population of the city. The formula for this is the following:

$$T_{average} = \frac{1}{X_{total}} \sum_{B=1}^{579} T_B * X_B$$

where B represents a block group, T_B , represents the average SATT for someone in block B, and X_B represents the population of block B.

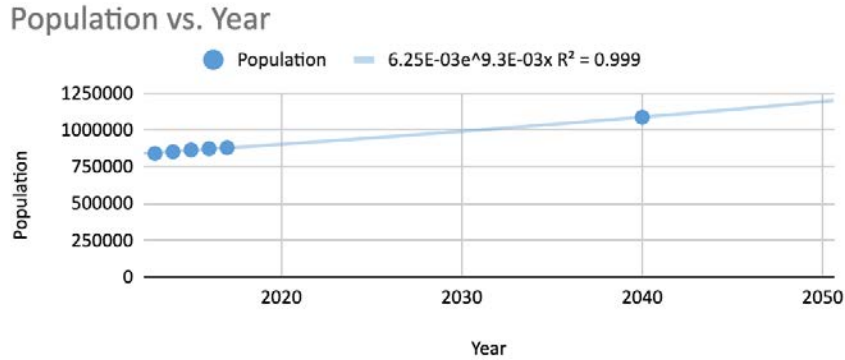
Model 2: Average Expected SATTs from 2015-2050

The first model can be adapted in order to make future predictions. To do so, we must factor in the changes in bypass rates.

As population increases, the number of individuals who are at risk of having a medical emergency increases as well. Assuming this direct relationship between the two, we can assume that will cause more overcrowding in hospitals. With more hospitals overcrowded, there is a higher chance an ambulance will be diverted, causing more diversion hours overall, especially when there are no plans to increase the capacity of hospitals. To account for changes in bypass rates, we will find a formula that correlates the year to a scale factor and modify the JavaScript

program so that for a given year input, the bypass rates could be multiplied by a specific scale factor.

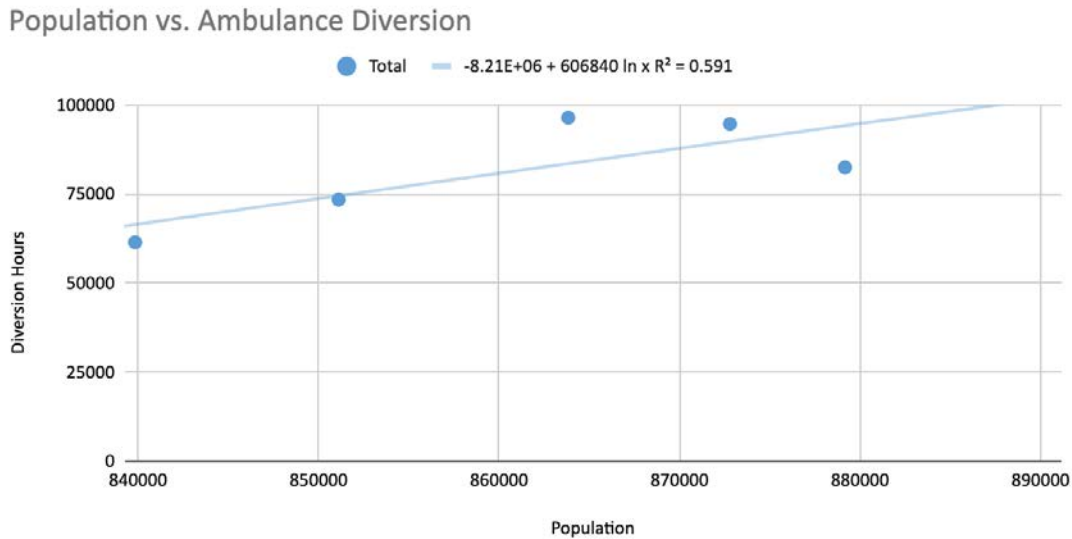
First, we modeled San Francisco’s population by year using historic population data and population prediction data from the San Francisco government. We used data from 2013-2017 instead of using more historical information in order to model current trends in population growth. In addition, we used a population prediction from the San Francisco government as a data point for 2040.



Since an exponential relationship yielded the highest coefficient of determination, we found the following equation between year and population:

$$X = 6.25 * 10^{-3} * e^{9.3 * 10^{-3} * Y} \quad | \quad X = \text{population}, Y = \text{year}$$

With an R² of .999, this is an accurate predictor for population. Then, we modeled a trend between population and diversion hours, which yielded the following graph:

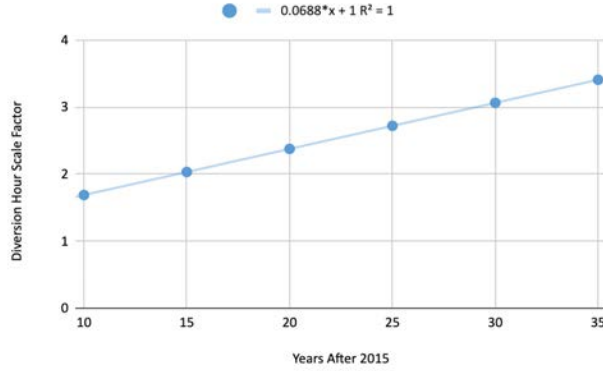


This produced the following logarithmic relationship with an R² of .591:

$$H = -8.21 * 10^6 + 606840 * \ln(X) \quad | \quad H = \text{total diversion hours}, X = \text{total population}$$

Since the variance is greater than 50%, it's a moderately reliable predictor of diversion hours. A logarithmic relationship was chosen because it had the highest R^2 when compared to exponential, linear, and power function. Additionally, there is a limited total amount of time available in a year to be diverted, making this more realistic than alternative functions. The next step was to find a relationship between the year and the percent increase in ambulance diversions. The percent increase was calculated using the data extracted from the formula above.

Predicting the Diversion Hour Scale Factor Increase by Year



This yielded the equation:

$$S(x) = .0688x + 1 \mid S(x) \text{ is the scale factor, } x \text{ is the years after 2015}$$

Given the years after 2015, this equation predicts the scale factor that must be multiplied by the 2015 diversion hours to get the desired year's total diversion hours. Since diversion hours and bypass rates are directly proportional—since an increase in bypass rates directly causes more diversions and thus more diversion hours—we can apply this same scale factor for the bypass rates.

For x years after 2015, the probability of not being able to get into a hospital will increase from $(1 - P_{\text{hospital}})$ to $(1 - P_{\text{hospital}}) \times S(x)$ times the scale factor $S(x)$. The probability of getting into a hospital is 1 minus the probability of not getting into a hospital. Therefore, the probability of getting into a hospital will be:

$$1 - (1 - P_{\text{hospital}}) * S(x) = P * S(x) - S(x) + 1$$

Note that this is an increase from our previous probability of P_{hospital} . Substituting the new probability into the equation established in the previous model, the new formula for expected SATT for x years after 2015 is the following:

$$T_{\text{overall}}(x) = \sum_{n=1}^{14} \left(T_n (P_n * S(x) - S(x) + 1) \prod_{z=1}^{n-1} [(1 - P_z) * S(x)] \right)$$

Using this new equation, we can reuse *Model 1: Expected SATT* to find the city's average expected SATT as well as the block group-specific expected times for any year.

Table 1: Average SATT Compared to Growth in Ambulance Users

	2015	2025	2030	2035	2040	2045	2050

Average SATT	36.9910	37.2356	37.3622	37.4917	37.6239	37.7591	37.8972
Growth in # of ambulance users compared to 2015	+0%	+9.75%	+14.97%	+20.44%	+26.18%	+32.18%	+38.47%

Model 3: Picking Ideal Locations for Future Hospitals

We can expand upon the JavaScript program to test our different hospital locations and identify which location yields the biggest decrease in expected SATT. To simplify the process, we will try to identify in which block the ideal hospital should be located. We will consider the 579 centers of each census block group in San Francisco as potential hospital locations. However, our optimization program will have a runtime of $O(n^3)$, which means that the length of time for the program to run will grow cubically as a function of the number of data points. Therefore, in order to simplify the process, we took a few different steps.

First, we selected only the points with SATTs of the 75th percentile (28.0809 minutes) and above since these regions were in most need of intervention. In addition, as explained in the Risk Analysis, this region is also the most equitable location for a new hospital due to the high concentration of minorities that currently experience disproportionately larger SATTs. This left us with 145 data points. Next, we divided this region into five different sub-regions that each covered the same number of blocks by using a clustering algorithm in ArcGIS.^[14] We found the geographic center of each of the five regions by averaging their coordinates. We applied the methodology from *Model 1* and identified which subregion was ideal. With 29 possible data points in this subregion, we repeated this process once more in order to eliminate more potential hospital locations.

Once we identified an ideal sub-subregion, we ran the six points in that sub-subregion as potential hospital locations and found the new average SATTs for all 579 census block groups as well as the city’s average. The ideal new hospital is the situation where the city minimizes the average commute time. In short, whenever we are comparing points or geographic centers, we are minimizing the average SATT equation from *Model 1*. The breakdown of our process can be shown in the following dataset:

Table 2: Comparing Average SATTs between Centers of Different Regions

	Region #	Longitude	Latitude	Average SATT (minutes)
Broad Region	1	-122.4979525	37.77820656	35.8165
	2	-122.386965	37.72695541	36.0475
	3	-122.4974207	37.74826629	35.4514
	4	-122.4099654	37.71436787	35.5530
	5	-122.4536773	37.71652736	35.1072
Sub region	1	-122.4979525	37.77820656	35.8165
	2	-122.386965	37.72695541	36.0475
	3	-122.4427482	37.71545018	35.0240
Sub Sub Region	1	-122.4372008	37.71874279	35.0046
	2	-122.4479655	37.71423731	35.0887

	3	-122.4336042	37.72199494	35.0956
	4	-122.4390196	37.72107427	35.0331
	5	-122.4402826	37.71858529	34.9898
	6	-122.434032	37.71693873	35.0400

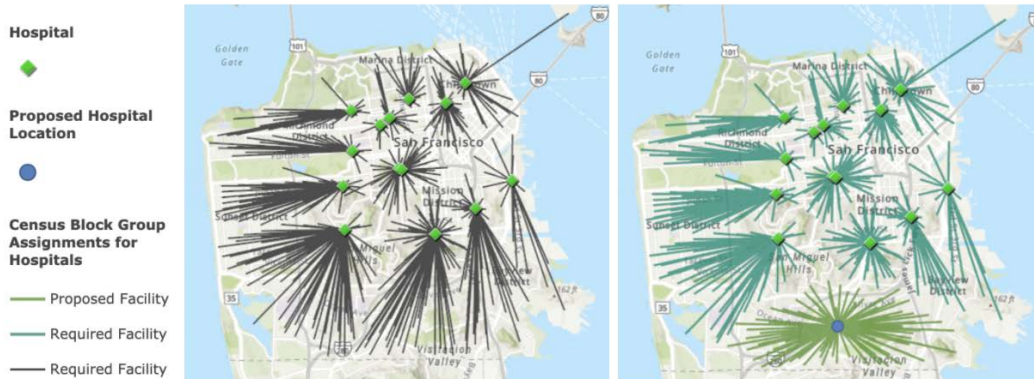
The bolded data points are the locations that minimize estimated SATTs. The ideal location for the next hospital is located at the census block group centered at longitude -122.4402826 and latitude 37.71656529. It's important to keep in mind that the average SATT value was solely used to compare between different potential hospital options. The value itself isn't accurate because we have not accounted for how the addition of a new hospital will impact bypass rates of surrounding hospitals. We will discuss how to find correct SATTs in the following model.

The same process described above can be repeated for adding multiple hospitals. Below is a chart showing the ideal locations for adding 1, 2, and 3 hospitals in San Francisco.

Table 3: Exact Ideal Locations for Additional Hospitals

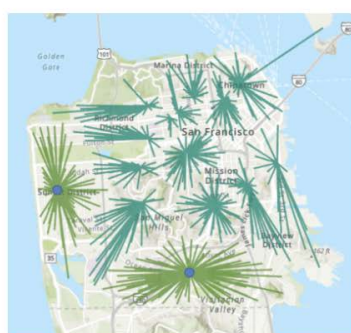
Ideal Locations for Additional Hospitals			
Number of Additional Hospitals	Locations (Longitude, Latitude)		
1	(-122.4402826, 37.71858529)		
2	(-122.4402826, 37.71858529)	(-122.4988206, 37.75419071)	
3	(-122.450142, 37.71950281)	(-122.4036366, 37.72593465)	(-122.4988206, 37.75419071)

The following maps below show the distribution of San Francisco's population among the following four situations: (1) no new hospitals added, (2) one hospital added, (3) two hospitals added, and (4) three hospitals added. As a side note, we will only be considering the implications of adding a single new hospital—the Helen Diller expansion or an alternative—as the budget and planning required for multiple would be unrealistic and outside our scope.

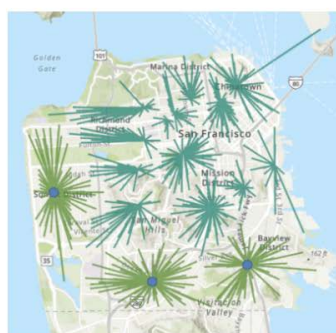


Map 1: Current Facilities

Map 2: One New Hospital



Map 3: Two New Hospitals



Map 4: Three New Hospitals

Model 4: Comparing Ideal Hospital Location to the Helen Diller Expansion

The Diller family has donated over 500 million dollars to construct an addition to the UCSF Medical Center, called the Helen Diller expansion.^[13] Construction is expected to begin in 2023 and finish by 2030. In order to compare this expansion to our proposed hospital, we found the impacts of both constructions.

In order to determine the impact of building our new hospital on the diversion times, we assigned each census block group in San Francisco to the nearest hospital by distance and looked at the change in assigned populations to each hospital as a consequence of adding a new hospital location. We used this percent change to scale the diversion hours (to directly compare to the Helen Diller expansion) and bypass rates (to calculate the impact on citywide expected SATT). Three hospitals had populations impacted by the new hospital: Laguna Hospital, California Pacific Medical Center - St. Luke’s, and San Francisco General. We assumed the new hospital was large enough to handle the population it served without going on bypass, meaning it would have a bypass rate of 0%. This is not uncommon, as six other hospitals in San Francisco county have a 0% bypass rate. Consequently, the total change in diversion hours over the period we studied from 2013-2017 would have been decreased by 6,101.48 hours had the proposed hospital been in operation, which would decrease the total diversion hours over that period by 15.4%. See Table 4.

The Helen Diller Medical Center will increase the UCSF Medical Center’s capacity by 42.11%.^[13] This will decrease the total number of diversion hours at UCSF from 2013-17 substantially (3743.58 hours), but not as much as our new hospital (6,101.48 hours). See Table 5.

Table 4: Impact of Model-Proposed Hospital on Citywide Diversion Hours 2013-17

Facilities	Assigned Population Before	Assigned Population After	Difference	Ratio	Total Diversion Hours Before	Total Diversion Hours After	Change in Diversion Hours	Bypass Rate Before	Bypass Rate After
Laguna	127,460	84,898	42,562	0.6661	0	0	0	0%	0%
CA Pacific St. Lukes	154,349	70,936	83,413	0.4596	5,771	2,652.2469	3,118.7531	13.18%	6.06%
SF General	81,470	45,860	35,610	0.5629	6,824	3,841.2746	2,982.7254	7.28%	4.10%
Proposed Hospital	0	162,085	162,085		12,595	6,493.5215	6,101.4785	0%	0%

Table 5: Impact of Planned Helen Diller Expansion on Citywide Diversion Hours 2013-17

Facility	Beds Pre-Expansion	Beds Post-Expansion	Difference	Ratio	Pre-Expansion Diversion Hours	Post-Expansion Diversion Hours	Change in Diversion Hours	Pre-Expansion Bypass Rate	Post-Expansion Bypass Rate
UCSF Medical Center	475	675	200	0.5789	8,891	5,147.4211	3,743.5789	20.30%	11.75%

By modifying *Model 2* with the updated bypass rates, we can estimate the SATTs of the two situations. The data below starts at 2030 because that is the year the expansion is planned to be completed. Our proposed hospital would start off being 2.16 minutes better than the expansion in 2030 and increase to 2.36 minutes better in 2050.

Table 6: Proposed Hospital vs. Helen Diller Medical Facility

New Hospital	Average SATT (minutes)				
	2030	2035	2040	2045	2050
Model-Proposed Hospital Location	35.1444	35.2156	35.2873	35.3596	35.4325
Helen Diller Expansion	37.3019	37.4211	37.5432	37.6681	37.7960
Model-Proposed vs Helen Diller Expansion	-2.1575	-2.2055	-2.2558	-2.3085	-2.3635
Percent Difference	-5.78%	-5.89%	-6.01%	-6.13%	-6.25%

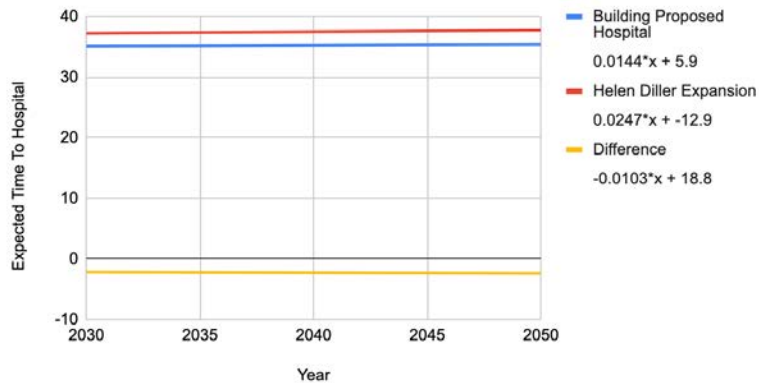
Below are linear models for how each modification will perform over three decades, where T is expected time and Y is the year. The R² value for both is 1.00.

$$T_{proposed} = .0144 * Y + 5.9$$

$$T_{expansion} = .0247 * Y - 12.9$$

$$T_{proposed} - T_{expansion} = -.0103 * Y + 18.8$$

Expected Time To Hospital: Proposed Hospital vs Helen Diller Expansion

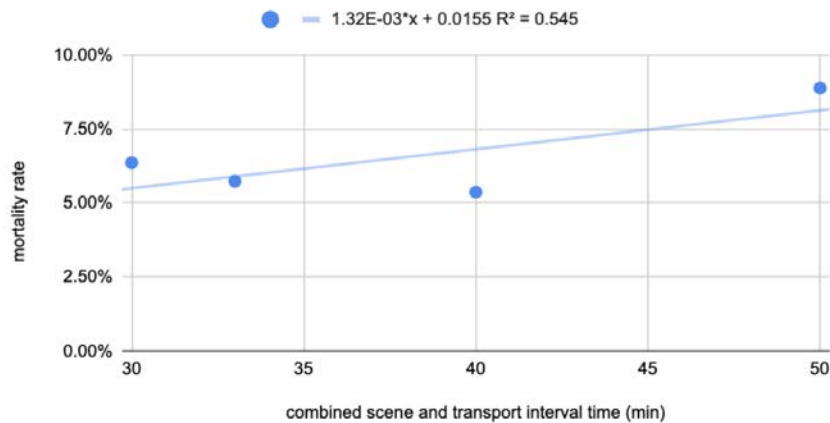


Model 5: Mortality Rate as a Function of SATT

Because we were able to obtain estimations for the average SATT for each census block group of San Francisco—taking into account distance, scene time, and diversions—a mortality rate as a function of SATTs enables us to determine the estimated number of fatalities as a result of ambulance diversions.

Using data from a study on EMS response time and mortality in an urban setting, we converted the data to mortality rates for the given combined SATT ranges to obtain the following distribution. When mortality rates were found for certain SATT intervals, we took the midpoint of these intervals in order to approximate them when determining a regression equation.

Mortality Rate vs. Combined Scene and Transport Interval Time (min)



The variance for a linear regression on this data is moderately high ($R^2 = 0.545$), which justifies the use of the following equation in order to model mortality as a function of SATT:

$$M = 1.32 * 10^{-3} * T + 0.0155 \quad | \quad M = \text{mortality rate (\%)}, T = \text{combined scene and transport time}$$

The use of a linear model is further supported by an observational study relating the distance to hospitals to patient mortality, which determined that a 10-kilometer increase in straight-line distance from a hospital was associated with a 1% increase in patient mortality rate. This study’s focus was limited to patients in severe condition relying on EMS transportation to

hospitals, but its results justify our model’s use of a linear relationship between SATT and mortality rate, because for the purpose of our investigation, we assume an average ambulance speed to be constant at 20 miles per hour for each journey.

Because the total number of ambulance patients who are diverted from hospitals is unknown, it was not possible for us to use this model in order to determine the total number of deaths resulting from ambulance diversions. However, it proves extremely instrumental in demonstrating the disastrous effects of high SATTs as San Francisco’s population experiences growth over the next three decades and is further useful in demonstrating the disastrous effects of inequities in SATTs in different parts of the city.

In *Model 2*, we used a JavaScript program in order to predict the SATT for each census block group for every 5-year increment from 2015 to 2050. Their associated mortality rates can be seen in Table 7.

Table 7: Mortality Rate Growth with No Additional Hospitals

Year	2015	2025	2030	2035	2040	2045	2050
SATT (minutes)	36.99	37.24	37.36	37.49	37.62	37.76	37.89
Mortality Rate	6.43%	6.47%	6.48%	6.50%	6.52%	6.53%	6.55%

Our model predicts a minor change in the average city-wide SATT from 2015 to 2050, of 0.9 minutes, and in turn, a very minor increase in mortality rate (of 0.12%). Though this is reassuring when examining the mortality per capita, it must be noted that San Francisco’s population is expected to experience significant growth in the next 30 years. Because hospital sizes do not grow per capita, mortality rates do not grow proportional with the population. A 42.18% increase in population (and in turn, in EMS patients) will result in significantly more deaths since hospitals with the same capacity as before have to treat more patients and divert ambulances more frequently. Table 8 highlights the severity of ambulance diversions by showing the influence population growth has on the number of deaths if changes are not made to reduce the average SATT.

Table 8: Expected Mortality in Terms of 2015 Population

Year	2015	2025	2030	2035	2040	2045	2050
Equivalent to 2015 population:	1,000	1,097	1,150	1,204	1,262	1,322	1,385
Expected Mortality:	64	71	75	78	82	86	91

This model also makes apparent the inequities throughout the neighborhoods of San Francisco. Using the JavaScript program detailed in *Model 2*, we obtained the SATT and found a minimum of 18.99 minutes, and a maximum of 81.54 minutes. It is clear that there is great discrepancy in SATTs for different census block groups throughout San Francisco. Plugging these values into our mortality model gives a minimum mortality rate of 4.06%, and a maximum of 12.31%. These values are quite alarming: depending on an ambulance patient’s neighborhood

of residence, their chances of mortality could be 91.51% higher than San Francisco’s average—and 203.30% higher than the minimum.

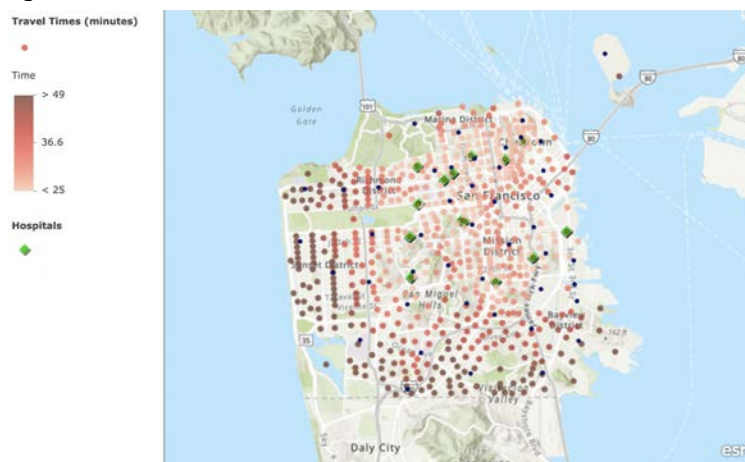
Risk Analysis

Overview

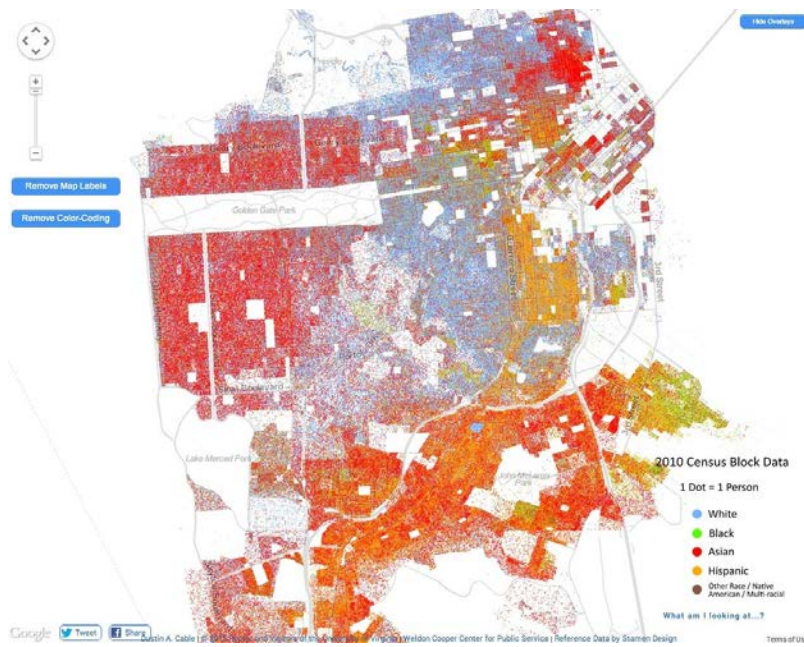
Ambulance diversions resulting from hospitals refusing patients poses a serious risk to patients, and this risk is expected to grow over the next three decades. As frequency—the number of diversion hours—increases, patients suffering from potentially lethal conditions in need of urgent care are at higher serious risk of death if they are not able to receive proper treatment in a reasonable amount of time. We found that the time it takes for a patient to get to a hospital has a substantial effect on the severity of risk—the patients’ mortality rates. Increased SATT as a result of ambulance diversions therefore poses a great risk to the wellbeing of patients. For example, our model predicts that patients with severe conditions who are able to get to a hospital in 25 minutes (including the universal scene time of 17 minutes^[25]) have an expected mortality rate of 4.85%. This figure increases to 7.49% when it takes 45 minutes for a patient to get to a hospital. Though the average SATT for residents of San Francisco is 37 minutes (20 minutes excluding scene time), different parts of the city can range from having an SATT as low as 19 minutes to as high as 81 minutes, dependent on both distance from hospitals and time of possible diversions. This huge disparity in SATTs has a severe impact on the mortality rate of different regions in the city, which ranges from a minimum of 4.85% to a maximum of an alarming 12.11%.

Distribution and Inequity

Analyzing the SATTs for all hospitals throughout San Francisco makes it apparent which regions are most at risk. Based on our ArcGIS map of SATTs by census block group, the southern and western edges of San Francisco endure much higher SATTs than the central and northeastern parts of the city, placing the residents of these neighborhoods at much greater risk, as can be seen in Map 5.

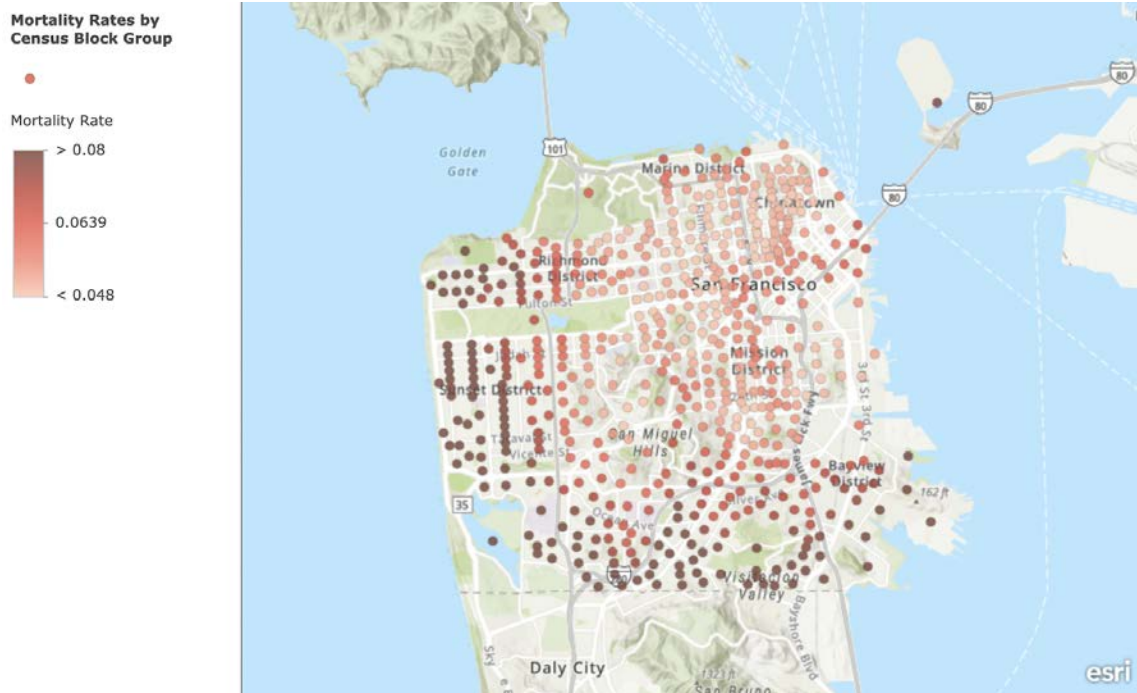


Map 5: SATT (min) by Census Block Group



Map 6: Racial Distribution of San Francisco Residents by Census Block^[10]

Residents on the southern and western edges of the city are at serious risk of not receiving sufficient medical care when relying on ambulances for transportation. With SATTs consistently exceeding 49 minutes, the mortality rate for these residents exceeds 8%. For residents in the center, north, and east sides of the city, who are predominantly white, it rarely exceeds 5%.

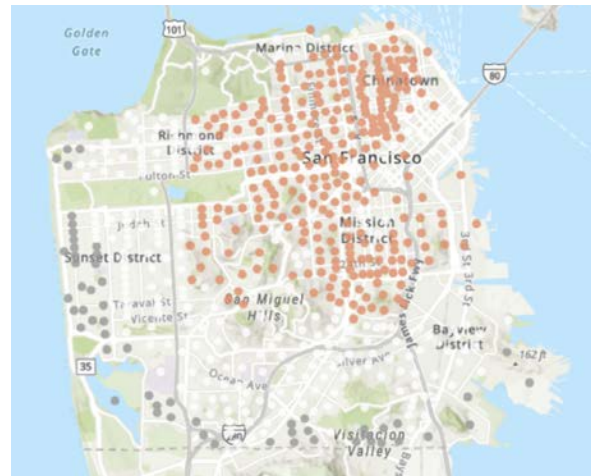


Map 7: Mortality Rate by Census Block Group

Comparing Map 7 with Map 6, which shows the racial makeup of San Francisco,^[10] makes it apparent which populations face the biggest risk: with Hispanic and Asian residents. Ambulance diversions and SATTs pose a much greater risk to these populations than to white populations, which are predominantly located in the central part of the city, where average SATTs (and therefore the mortality rate) are lowest.

Financial Implications in Inequity

The West and South side of San Francisco are disproportionately at risk from high SATTs when compared to other locations in the city. With significantly higher SATTs and mortality rate, these residents are much less likely to receive quality care in time, and it is clear that these regions are more likely to suffer not only health hardships but financial hardships as well. With ambulance costs beginning anywhere from \$743 to \$1,187 and an additional \$18.08 for every mile driven, the west and south side are financially disadvantaged by being farthest from



Map 8: Bottom 50% vs. Top 10% of SATT

the hospital, as shown by longer SATTs from our model.^[30] With ambulances average speed around 20 mph, this means each additional minute is a \$6.03 increase in their cost. This inequity is extremely evident when we compare the 50 percentile of residents with the 10% of residents in San Francisco who have the highest SATTs. The top 10%, which is completely congregated in the West and South side, pays a minimum of \$147.02 more, which can range from a 10.65% to 15.70% increase in ambulance costs when compared to the 50th percentile of residents.

Mortality Rates' Change Over Time

Bypass rates increase with the population as more strain is placed on hospital availability; although SATTs will not increase substantially, the number of expected mortalities is expected to undergo significant increase from 2015 to 2050 due to the expected increase in San Francisco's population.

Based on predictions for the change in the number of diversion hours experienced by each census block group, the percent change in mortality rate is—at first glance—hardly significant. The average SATT experiences a very minor increase, from 36.99 minutes in 2015 to 37.90 minutes in 2050. This results in a small mortality rate change, from 6.43% in 2015 to 6.55% in 2050. The real consequences become apparent when considering the effect population growth has on expected mortality numbers. From 2015 to 2050, San Francisco's population, and consequently the number of ambulance users, is expected to increase 38.47%. Our model predicts a population of 1000 EMS patients would be expected to have 64 mortalities in 2015, as

seen in Table 8. The equivalent population in 2050 is 1,385 EMS patients, where 91 fatalities are expected. Though the change in mortality rate is miniscule, by 2050, the number of EMS patient mortalities is expected to increase by an alarming 42.19%.

Helen Diller Expansion

San Francisco's population growth poses a significant risk to the likelihood that residents will receive adequate emergency medical care without the expansion of hospital capacity. For this reason, expanding hospital capacity is our primary recommendation for mitigating risks to San Francisco's population. We emphasize the importance of decreasing the SATT to hospitals for the southern and western parts of the city, which experience substantially more risk due to San Francisco's current hospital distribution.

Without the planned Helen Diller Medical Center, we predict the average combined SATT across San Francisco will be 37.36 minutes by 2030. If the expansion opens, the average SATT decreases slightly, to 37.30 minutes. The Helen Diller expansion would do little to decrease the SATT and applying the mortality rate model to these times gives an expected mortality rate of 6.47%, as opposed to 6.48% without the expansion. This is an incredibly small change, meaning our model predicts the expansion does little to assuage the risk to San Francisco's population.

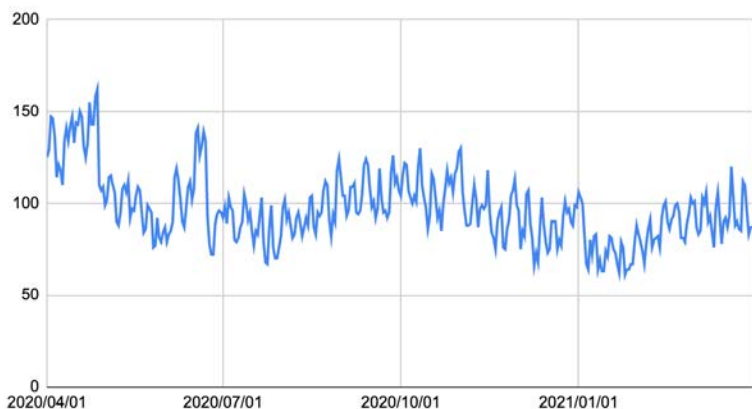
Limitations, Improvements, and Future Research

Our model relies heavily on the consistency of trends. More historical data would improve predictions and allow for facility-by-facility analysis, making the model more sensitive and comprehensive. The model is limited in that it does not account for changes to the capacity and efficiency of the hospitals over time. While this is reasonable for large changes to an individual hospital, we simplify the redistribution of emergency beds, temporary expansions or changes due to COVID-19, and other factors that increase (or decrease) the number of patients a given emergency room can treat. Other improvements include using actual street distances instead of taxicab distance; accounting for severity of the injury for on-scene time calculations, were data to become available; accounting for time between the call and dispatch time; and accounting for ambulance availability and location. These modifications would add depth and precision to our model's frequency analysis. Though unlikely to become available, data on mortality rates as a function of time since dispatch call would significantly improve our model's severity analysis. That issue is perhaps the largest source of inaccuracy in our model.

COVID-19 is one factor we did not include in our model. While our proposed hospital remains in the ideal location long-term, San Francisco's population growth may take longer than expected to recover, decreasing the severity of mortality rates long term. At the same time, the number of hospitalized patients with COVID-19 has significantly increased diversion hours over the past year, increasing the frequency of these risks. The main reasons we did not include COVID-19 in our model was the lack of data of diversion hours during 2020-2021 and the inability to accurately model the impacts of COVID-19 on hospital availability. The following

chart on the left graphs the number of available ICU beds against time using data from the San Francisco government^[E] while the table on the right shows the variance (R^2 value) of the possible ways to model the correlation.

Available ICU beds vs Date



Variance values for graphing free ICU beds	
Type of Graph	Variance
Linear	0.204
Exponential	0.206
Polynomial	0.248
Logarithmic	0.204
Power Series	0.192

With models that would only at best accurately model 24.8% of this relationship, it's clear that COVID-19 is too unpredictable to be accurately compensated for. In addition, with the United States' constant exposure to new strains of the virus, COVID-19 is becoming increasingly unpredictable—even as the new vaccines roll out. Along with the California strain, within the first week of April, San Francisco has already been exposed to a new strain from India that is expected to be more transmissible and less responsive to current vaccines.^[D] Understanding the impacts of COVID-19 and how hospitals are learning to cope will likely have lasting consequences on the future of ambulance diversions and the overcrowding in the emergency department. However, our model is still valid to make recommendations because it represents an accurate lower bound to the changes San Francisco is facing, especially when COVID-19 becomes less of a concern.

Future work should—besides the improvements listed above—consider budgetary constraints and other factors to make specific recommendations around the proposed hospital's location, size, and incentives. While all these changes would vastly improve the accuracy of our model, our model still provides clear evidence of the increasing SATTs, mortalities, and risks associated with ambulance diversions, along with the need for at least one new hospital.

Recommendations

Overview

We offer recommendations in three different categories. First, unfortunately, insurance cannot help hospitals address overcrowding and diversion times. However, insurance still applies to this issue. We recommend local governments and private insurers offer incentives to relocate the planned hospital. Second, we offer a range of strategies to decrease the unnecessary usage of ambulances and hospitals through behavioral changes. Finally, in order to modify outcomes, we

propose an alternative hospital location to the planned Helen Diller expansion, as our model has shown that it is not optimally located within the county to address ambulance diversions.

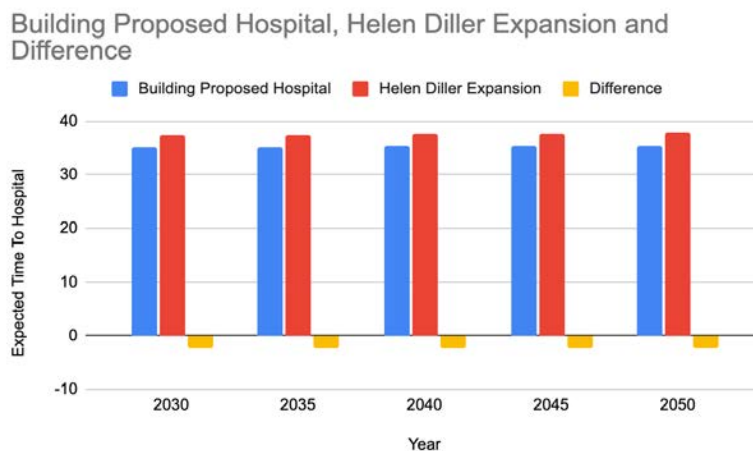
Modifying Outcomes: Future Facilities

The addition to the UCSF Medical Facility will have a significant impact on ambulance diversion times. The development, beginning in 2023 and finishing in 2030, will expand the facility from 475 to 675 beds. It is an appealing choice for two reasons. First, it has the highest bypass rates of all the facilities in the county, making it the best choice to improve bypass rates by expansion of a current facility. Additionally, the facility is aging and in need of improvements to remain up to code. In particular, upgrades must be made by 2030 to meet statewide seismic requirements.^[12]

However, it is not the optimal location when one also considers constructing new locations instead of expanding current facilities. It is also not the most equitable option, as large portions of the southern side of the city—which is primarily Hispanic and Asian—have much higher SATTs in comparison to the north and east sides of the city.

There will still need to be updates to the UCSF Medical Facilities. However, the results of our model suggest that, to have the most significant and lasting impact, (the majority of) the funding should go towards the construction of a hospital in the south side of the city. The UCSF is primarily responsible for choosing a location and providing the funding. Though the new location would be separate from their current campus, it would be in the best interest of the county as a whole for it to be located elsewhere. Additionally, UCSF is a public land-grant university and receives a portion of its funding from the state government.^[8] While our proposed hospital will need to be larger than the expansion currently planned, it could have the impact of decreasing diversion hours by 15.4% across the city in 2015, as compared to 9.4% from the planned expansion. Incentives or subsidies discussed in the insurance section of our recommendations will help offset the cost. Relative to each other, our proposed facility absorbs 62.99% more diversion hours than the planned facility from other hospitals. It is also much better in the long term as the population of San Francisco increases. The proposed hospital will have a yearly increase of .0144 minutes in SATT, which is 40.98% less than the .0247 minute increase from the expansion. This causes an .0103 min yearly increase in the difference between the expected time for these two plans (see Bar Chart 1). Additionally, our proposed hospital is extremely actionable because the planned expansion is still early in the planning stage.

Bar Chart 1



The current hospitals and their allocated census block groups in San Francisco can be seen in Map 1. Our proposed facility would be located as near as possible to (-122.4336042, 37.72199491), which is the center of Census Bureau's GEOID region 060750260012. This is on the corner of Lisbon Street and Persia Avenue, in a residential neighborhood. The most likely opportunities for development are to the west and northwest, along Mission Street. According to the zoning laws in San Francisco, the largest government owned property is a park located at 579 Madrid St, San Francisco, CA 94112. While there may be some trepidation within the community about converting a park into a hospital, there are multiple parks within two census block groups. The largest nearby park is the John McLaren Park, which is 313 acres large and only a 10 minute walk from the block's center.

The modified census block group assignments can be seen in Map 2. Looking to the future, this same model can be used to identify two, three, and or any number additional hospital constructions, as can be seen in Maps 3 and 4.

Using our models, we can compare how the two hospitals impact the city. The proposed hospital would open in 2030 and decrease the expected SATT to 35.14 minutes, while the Helen Diller expansion will only decrease it to 37.30 minutes. Our proposal is 5.78% better, with a difference in 2.16 minutes. As time passes, the expected SATT will increase due to increased populations and increased diversions. However, the yearly increase for our proposed hospital is 40.98% lower than the expansion. This means, over time, the proposed hospital will do increasingly better than the expansion. As shown in Table 6 in the math modeling section, the 5.78% difference in expected SATTs in 2030 will increase to 6.25% by 2050.

This means that with the Helen Diller expansion, San Francisco's average SATT would result in a mortality rate for EMS patients of 6.47% by 2030, whereas building our proposed hospital would result in a mortality rate of 6.19%. This indicates that our proposed hospital does 4.52% better than the planned Helen Diller expansion at minimizing patient mortality in 2030. This figure continues to grow, as by 2050, building the Helen Diller expansion would result in a patient mortality rate of 6.54%, with our proposed hospital resulting in a mortality rate of 6.23%, making it 4.98% better in 2050. The expected increase in mortality rate from 2030 to 2050 is also made much smaller as a result of our proposed hospital than with the Helen Diller expansion, with which the mortality rate is expected to increase 0.07% from 2030 to 2050. This is opposed to our proposed hospital's resulting mortality rate increase of 0.04%. This indicates our proposed hospital is expected to be 75% better at minimizing the growth rate of the mortality rate due to ambulance diversions from 2030 to 2050.

Insurance

It would be in the best interest of insurance companies and the city government to incentivize UCSF to build their hospital in our recommended location, such as by waiving permit and inspection fees. Insurers can contribute by taking part in a type of vertical integration, whereby they become investors in hospitals. In some cases, the hospital will include health plans to take on more risks and become more responsible for the outcomes of their treatment.^{[A][B][C]} The need for capital is one of the most common reasons vertical integrations exist.^[A] These funds from insurers—in combination with the city government—could subsidize the initial construction cost. A hospital in the south side of the city would decrease SATTs and consequently mortality rates, leading to fewer deaths and less complications from medical procedures. In addition, the decreased mortality rate associated with lower SATTs demonstrates that less people from these regions will arrive at the hospital with severe conditions, which will

decrease medical bills. As a result, insurance costs will go down for private insurers, the city municipality, and state government. San Francisco employers covering employees' health insurance, as well as government health insurance options such as Medicare and Medicaid, would also benefit from this decrease due to decreased expenses. Due to the construction of a new hospital, insurance costs would go down throughout the city, leading to lower expenses for residents of San Francisco.

Insurance has a great potential to address the financial implications of ambulance diversions. However, due to the lack of public data regarding the distribution of premiums in San Francisco, our insurance recommendations remain general instead of quantitative.

Behavioral Changes

As explained by our models, the clear growth in population and SATTs will cause a significant increase in not only individuals who will fail to receive timely care, but also a significant increase in yearly mortalities. From 2015 to 2030, there's an average 3.03% growth in ambulance diversions due to population growth, which will cause a 22,380 hour increase in the total yearly diversion hours. With the Helen Diller expansion being completed by 2030, we see yearly diversion hours reach 105,843 hours, with an average 2.85% increase per year. Even if the city chooses our recommendation, we will still see a 2.73% increase in diversion hours per year.

The city should make efforts to offset this increase in diversion hours in order to prevent an increase in their mortality rate. To do so, the city should aim to decrease the expected diversion hours by at least 2.77% every year until 2050 in order to keep the number of actual ambulance diversion hours constant—assuming UCSF continues with the Helen Diller expansion. If they chose our proposed hospital, the city would only have to decrease diversion by 2.65% a year from our predictions. If no new hospitals are built, the city would need to decrease diversions by at least 5% per year. The best way to counteract the yearly growth in ambulance diversions and prevent increased mortalities is to induce behavioral changes in the lifestyles of San Francisco citizens, lessening their need for ambulances.

To decide which behavioral changes would have the most effect on reducing ambulance diversion time, the most common causes of medical emergency calls must be identified. Of the calls with known causes, the top five reasons for medical emergency calls are the following: minor injuries, chest pain/heart disease, accidents, intoxication/poisoning/drug overdose, and breathing difficulties.^[22] While causes of emergencies such as injury or accidents are simply too general to address on a large scale, issues such as heart disease and drug overdose can be mitigated through local or state government action.

With regards to drug addiction, past studies have shown that decriminalization of drug usage has led to increases in the number of people seeking treatment, resulting in a reduction in overdose cases. In Portugal, where in 2001 the consumption of all drugs was decriminalized, the number of people seeking treatment and therapy increased by nearly 60% by 2011.^[5] Furthermore, in France, efforts to fight drug overdose led to the relaxation of laws on prescribing buprenorphine, a narcotic used to treat addiction to opioids, resulting in a dramatic decrease in overdose deaths in the country by 79% over the next four years.^[20] The evidence is clear—the decriminalization of drug consumption and greater accessibility to treatment medication can reduce the number of overdose cases, and could be integral to reducing the number of ambulance calls in San Francisco, if implemented.

California voters have already passed a referendum to pursue the decriminalization of drug consumption. In 2014, proposition 47 was passed, which changed certain low-level crimes,

like drug possession, from potential felonies to misdemeanors.^{[2][11]} Pursuing further drug decriminalization policies like Portugal would be very realistic for San Francisco due to the recent efforts to already pursue such social change. More time and public data are needed to see the impacts of proposition 47 before further policy changes can be recommended, but this is a worthwhile topic for future studies.

For cases relating to chest pain or heart disease, the issue lies primarily with government funding of programs aimed at preventative treatment for heart conditions. Most states in the United States spend an average of 3% of their state healthcare agency budget on heart disease and stroke preventative programs, even though that heart disease is the leading cause of death.^[1] Funding for preventative treatment is especially impactful for preventing heart disease during times of economic downturn and high unemployment. According to a study by the American Heart Journal, even a 1% increase in state government funding for preventative heart disease programs resulted in a notable decrease in cerebrovascular and cardiovascular deaths.^[36] Due to this, governmental policies that promote funding for heart disease preventative care programs could result in a decrease in heart disease ambulance calls, thus helping to mitigate future increases in diversion times.

Though the quantified impact of these changes is extremely challenging to predict and are beyond the scope of this paper, framing these recommendations as possible ways of creating healthier behavioral choices for the people of San Francisco—whether through education and dietary information, through heart disease preventative care, or the increase of drug addiction treatment accessibility—is important for generating initiative around these efforts which have the potential to save lives.

Conclusion

Overall, ambulance bypass rates in San Francisco are shockingly high and only expected to increase as the population of the city grows. With increased ambulance diversions, San Francisco will continue to suffer from increasing numbers of mortalities. Our primary recommendation is to change the location of the planned Helen Diller expansion to the location found by our model, which can be incentivized by the local government and insurance companies. The local government can complement this strategy by promoting behavioral changes that decrease the usage of ambulances. Taking these steps is not only necessary to decrease bypass rates, but also to assuage the mortality rates and inequalities that plague San Francisco.

References Cited

1. A Public Health Action Plan to Prevent Heart Disease and Stroke. (2020). U.S. Department of Health and Human Services; Centers for Disease Control and Prevention. https://www.cdc.gov/dhdsp/action_plan/pdfs/action_plan_full.pdf
2. About Proposition 47 | My Prop 47. (2016). My Prop 47. <https://myprop47.org/about/>
3. Ambulance Diversion. (2016). Health Affairs Health Policy Brief. doi: 10.1377/hpb20160602.353150
4. Ambulance Response to Life-Threatening Emergencies | City Performance Scorecards. (2019). Sfgov.org. <https://sfgov.org/scorecards/public-safety/ambulance-response-life-treatening-emergencies>
5. Bajekal, N. (2018). Want to Win the War on Drugs? Portugal Might Have the Answer. <https://time.com/longform/portugal-drug-use-decriminalization/>
6. Blanchard, I. E., Doig, C. J., Hagel, B. E., Anton, A. R., Zygun, D. A., Kortbeek, J. B., ... Innes, G. D. (2012). Emergency Medical Services Response Time and Mortality in an Urban Setting. *Prehospital Emergency Care*, 16(1), 142–151. doi:10.3109/10903127.2011.614046
7. Brey, J. (2019). Investigating the Roots of Exclusion in San Francisco. <https://nextcity.org/daily/entry/investigating-the-roots-of-exclusion-in-san-francisco>
8. Budget. (2020). <https://www.ucsf.edu/about/ucsf-budget>
9. Burt, C. W., McCaig, L. F., & Valverde, R. H. (2006). Analysis of Ambulance Transports and Diversions Among US Emergency Departments. *Annals of Emergency Medicine*, 47(4), 317–326. doi:10.1016/j.annemergmed.2005.12.001
10. Dickey, M. R. (2013). These Maps Reveal The Racial Makeup Of San Francisco And Silicon Valley. <https://www.businessinsider.com/maps-show-racial-divide-in-silicon-valley-2013-9>
11. Drug Decriminalization. (2018). Drug Policy Alliance; [drugpolicy.org](https://drugpolicy.org/issues/drug-decriminalization)
12. Farley, P. (2018). UCSF Receives \$500M Commitment from Helen Diller Foundation to Begin Planning New Hospital. <https://www.ucsf.edu/news/2018/02/409741/ucsf-receives-500m-commitment-helen-diller-foundation-begin-planning-new>
13. Farley, P. (2021). Groundbreaking Community Workforce Agreement for UCSF Parnassus Heights Project is Boon for Local Jobs, Economy. <https://www.ucsf.edu/news/2021/01/419651/groundbreaking-community-workforce-agreement-ucsf-par-nassus-heights-project>

14. Finding Centroids. <https://doc.arcgis.com/en/arcgis-online/analyze/find-centroids.htm>
15. Glushak, C., Delbridge, T. R., & Garrison, H. G. (1997). Ambulance diversion, Prehospital Emergency Care, 1:2, 100-103, DOI: 10.1080/10903129708958797
16. Hilburg, J. (2020). Herzog & de Meuron will design San Francisco's newest hospital. <https://www.archpaper.com/2020/07/herzog-de-meuron-san-francisco-newest-hospital-pa-rmassus-heights/>
17. How insurance companies set health premiums. U.S. Centers for Medicare & Medicaid Services. <https://www.healthcare.gov/how-plans-set-your-premiums/>
18. Learn ArcGIS - Access ArcGIS Software. <https://learn-arcgis-learn.org/hub.arcgis.com/pages/access-arcgis-software>
19. Is Health Care a Right? (2018). Thomson Reuters. <https://healthcare.findlaw.com/patient-rights/is-health-care-a-right.html>
20. Lopez, G. (2019). Cities are considering safe injection sites. A federal judge just said they're legal. <https://www.vox.com/science-and-health/2018/1/25/16928144/safe-injection-sites-heroin-opioid-epidemic>
21. Medearis, A. (2013). The Wild West of Ambulance Charges. <https://priceonomics.com/the-wild-west-of-ambulance-charges/>
22. Møller, T. P., Ersbøll, A. K., Tolstrup, J. S., Østergaard, D., Viereck, S., Overton, J., ... Lippert, F. (2015). Why and when citizens call for emergency help: an observational study of 211,193 medical emergency calls. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, 23(1). doi:10.1186/s13049-015-0169-0
23. Moore, Eli, Montojo N., and Mauri N. (2019). *Roots, Race, and Place: A History of Racially Exclusionary Housing in the San Francisco Bay Area*. Haas Institute for a Fair and Inclusive Society, University of California, Berkeley. haasinstitute.berkeley.edu/rootsraceplace
24. Moskop, J. C., Sklar, D. P., Geiderman, J. M., Schears, R. M., & Bookman, K. J. (2009). Emergency Department Crowding, Part 2—Barriers to Reform and Strategies to Overcome Them. *Annals of Emergency Medicine*, 53(5), 612–617. doi:10.1016/j.annemergmed.2008.09.024
25. Nagata, I., Abe, T., Nakata, Y., & Tamiya, N. (2016). Factors related to prolonged on-scene time during ambulance transportation for critical emergency patients in a big city in Japan: a population-based observational study. *BMJ Open*, 6(1), e009599. doi:10.1136/bmjopen-2015-009599
26. Nakajima, Y., & Vilke, G. M. (2015). Editorial: Ambulance Diversion: the Con Perspective. *The American Journal of Emergency Medicine*, 33(6), 818–819. doi:10.1016/j.ajem.2015.03.005

27. Nicholl, J., West, J., Goodacre, S., & Turner, J. (2007). The relationship between distance to hospital and patient mortality in emergencies: an observational study. *Emergency Medicine Journal*, 24(9), 665–668. doi:10.1136/emj.2007.047654
28. Nicholl, J., West, J., Goodacre, S., & Turner, J. (2007). The relationship between distance to hospital and patient mortality in emergencies: an observational study. *Emergency Medicine Journal*, 24(9), 665–668. doi:10.1136/emj.2007.047654
29. Pinto, L. R., Silva, P. M. S., & Young, T. P. (2015). A generic method to develop simulation models for ambulance systems. *Simulation Modelling Practice and Theory*, 51, 170–183. doi:10.1016/j.simpat.2014.12.001
30. Reid, M. (2019). Ambulance rates going up by 2.3%
<https://www.theridgefieldpress.com/news/people/article/Ambulance-rates-going-up-by-2-3-14005268.php>
31. Rich, C. and Pearson, J. (2017). <https://www.quora.com/profile/Casey-Rich>.
32. San Francisco Metro Area Population 1950-2021. (2021). Macrotrends LLC.
<https://www.macrotrends.net/cities/23130/san-francisco/population>
33. San Francisco. (2018). Data Commons. <https://datacommons.org/place/geoId/0667000>
34. Schopper D., Lormand J.D., Waxweiler R. (eds). (2006). Developing policies to prevent injuries and violence: guidelines for policy-makers and planners. Geneva, World Health Organization.
https://www.who.int/violence_injury_prevention/publications/39919_oms_br_2.pdf
35. The Bay Area in 2040: Chapter 2. (2019). Plan Bay Area.
https://mtc.ca.gov/sites/default/files/2-The_Bay_Area_In_2040.pdf
36. Tomaselli G, et al. (2018). Government continues to have an important role in promoting cardiovascular health. *American Heart Journal*. <https://doi.org/10.1016/j.ahj.2017.11.002>
37. U.S. Census Bureau (2019). Cartographic Boundary Files
<https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html>
38. U.S. Census Bureau (2019). QuickFacts: San Francisco County, California.
<https://www.census.gov/quickfacts/fact/table/sanfranciscocountycalifornia/PST045219>
39. U.S. Census Bureau (2019). Total Population: Block Groups, San Francisco County, California.
<https://data.census.gov/cedsci/table?q=population&g=0500000US06075.150000&tid=ACSDT5Y2019.B01003&moe=false&hidePreview=true>
40. Vincent-Lambert, C., & Mottershaw, T. (2018). Views of emergency care providers about factors that extend on-scene time intervals. *African Journal of Emergency Medicine*, 8(1), 1–5. doi:10.1016/j.afjem.2017.08.003

41. Walker, W. (2020). 'We're At A Breaking Point;' COVID Ambulance Diversions Becoming Common In Santa Clara County.
<https://sanfrancisco.cbslocal.com/2020/12/25/were-at-a-breaking-point-covid-ambulance-diversions-becoming-common-in-santa-clara-county/>
42. Watanabe, B. L., Patterson, G. S., Kempema, J. M., Magallanes, O., & Brown, L. H. (2019). Is Use of Warning Lights and Sirens Associated With Increased Risk of Ambulance Crashes? A Contemporary Analysis Using National EMS Information System (NEMSIS) Data. *Annals of Emergency Medicine*.
 doi:10.1016/j.annemergmed.2018.09.032

Additional References Cited

- A. Robinson, J. C. & Casalino L P. (1996) Vertical integration and organizational networks in health care. *Health Affairs*, 15, no.1:7-22. doi:10.1377/hlthaff.15.1.7
- B. Aguiar-Díaz, I., Ruiz-Mallorquí, M. V., & González López-Valcárcel, B. (2018). Insurance company as dominant shareholder and financial performance in for-profit hospitals. *Spanish Journal of Finance and Accounting*.
<https://doi.org/10.1080/02102412.2018.1527474>
- C. Post, B., Buchmueller, T., & Ryan, A. M. (2017). Vertical Integration of Hospitals and Physicians: Economic Theory and Empirical Evidence on Spending and Quality.
<https://doi.org/10.1177/1077558717727834>
- D. CBS San Francisco. (2021). "India "Double Variant" Strain Of COVID-19 Detected In San Francisco Bay Area." CBS San Francisco.
<https://sanfrancisco.cbslocal.com/2021/04/05/india-double-variant-strain-of-covid-19-detected-in-san-francisco-bay-area/>
- E. *Hospital Capacity*. (2017). Sfgov.org.
<https://data.sfgov.org/stories/s/Hospital-Capacity/qtdt-yqr2/>

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Code Appendix 1

This JavaScript program outputs a CSV file with estimated SATTs from 2015-2050 for each block. The commented lines code represent the visual component of the program that adds unnecessary runtime.

```
var year=2015;

for (var yearCounter = year; yearCounter <= 2050; yearCounter +=5) {

var magnitude=(yearCounter-2015)*0.0688+1;

//createCanvas("map");

//corners of San Fran
//var xcord = [-122.508528, -122.508528, -122.380441, -122.380441];
//var ycord = [37.709096, 37.804294, 37.804294, 37.709096];

//loop variable
var i;

//data for hospitals
var xhos = getColumn("hospitalData", "Longitude");
var yhos = getColumn("hospitalData", "Latitude");
var numHos = xhos.length;
var nombre = getColumn("hospitalData","Name");

var chance = getColumn("hospitalData","Risk");
for(var ii=0; ii<chance.length; ii++){
  chance[ii]=chance[ii]*magnitude;
}

var orderChance=[];

for(var q=0; q<chance.length; q++){
  chance[q]=1-chance[q];
}

//data for ems coordinates
var emsx = getColumn("ems","LONGITUDE");
var emsy = getColumn("ems","LATITUDE");

//distance to x,y from ems/hospital
var disEms;
var minDistance;
var hospitaltime=[];

//closest hospital index
var indexOfMin;

//closest ems index
var indexEms;

//Assumptions
var averageAmbulanceSpeed=20;
var ambulanceTransitionTime=17;

//START OF ACTUAL EXECUTION
setupMap();

//calibrate pixel to miles
var pixelToMile = pixelMile();

//GET COORDINATES
var coordLong = getColumn("coords","LONGITUDE");
```



```

var coordLat = getColumn("coords","LATITUDE");

//var expiTimeData={};
var pop = getColumn("coords","POPULATION");
var popSum=0;
for(var i=0; i<pop.length; i++){
  popSum+=pop[i];
}

//console.log(popSum);
//var expiTimeData={};
var output;

var totalTP=0;

for(var v=0;v<coordLat.length; v++){

  // expiTimeData.Longitude=coordLong[v];
  // expiTimeData.Latitude=coordLat[v];
  // expiTimeData.Population=pop[v];
  repetition(coordLong[v],coordLat[v]);
  // expiTimeData.Time=(output+ambulanceTransitionTime)*pop[v];
  // createRecord("expiTime", expiTimeData);
  totalTP+=(output+ambulanceTransitionTime)*pop[v];
  reset();
}

console.log(totalTP/popSum);

console.log("Done");
}
////////////////////
////////////////////
////////////////////

function reset(){
  //data for hospitals
  xhos = getColumn("hospitalData", "Longitude");
  yhos = getColumn("hospitalData", "Latitude");
  numHos = xhos.length;
  nombre = getColumn("hospitalData","Name");

  chance = getColumn("hospitalData","Risk");
  for(var ii=0; ii<chance.length; ii++){
    chance[ii]=chance[ii]*magnitude;
  }

  for(var q=0; q<chance.length; q++){
    chance[q]=1-chance[q];
  }
  orderChance=[];

  //distance to x,y from ems/hospital
  hospitaltime=[];

  emsx = getColumn("ems","LONGITUDE");
  emsy = getColumn("ems","LATITUDE");

  //START OF ACTUAL EXECUTION
  setupMap();
}

function repetition(x,y){
  for (var p=0;p<numHos;p++){
    everything(x,y);
  }
  //calculate the estimated time
  var expectedTime=0;

```

```

expectedTime += 1*orderChance[0]*hospitaltime[0];
for(var a=1; a<numHos; a++){
  var probability=1;
  for(var b=0; b<a; b++){
    probability*=(1-orderChance[b]);
  }

  expectedTime +=probability*hospitaltime[a]*orderChance[a];
}
output=expectedTime;
//console.log("EXPECTED TIME: " + expectedTime);
}

function everything(x,y){
  var hdis=closestHospital(x,y);
  var emsdis=closestEms(x,y);
  //console.log("Hospital to x,y: "+ (hdis*pixelToMile)+" - "+*/nombre[indexOfMin]);
  //console.log("Ems to x,y: "+(emsdis*pixelToMile));
  var total=(emsdis*pixelToMile+hdis*pixelToMile);
  //console.log("Total dis: "+total);
  var time=(total/averageAmbulanceSpeed*60);
  //console.log("Time: "+ time);

  appendItem(orderChance,(chance[indexOfMin]));

  appendItem(hospitaltime,(time));

  removeItem(nombre,indexOfMin);
  removeItem(xhos,indexOfMin);
  removeItem(yhos,indexOfMin);
  removeItem(chance,indexOfMin);

  //console.log(hospitaltime);
  //console.log(orderChance);
}

function closestHospital(x,y){
  var xpos = (x+122.508528)*2200+20;
  var ypos = (y-37.804294)*-2500+35;
  //setStrokeColor("red");
  //circle(xpos, ypos, 10);
  //setStrokeColor("black");

  indexOfMin = 0;
  minDistance = Math.abs(xpos-xhos[0])+Math.abs(ypos-yhos[0]);

  for(var j=0; j<xhos.length; j++){
    var taxi = Math.abs(xpos-xhos[j])+Math.abs(ypos-yhos[j]);

    if(taxi<minDistance){
      minDistance=taxi;
      indexOfMin=j;
    }
  }

  //setStrokeColor("green");
  //circle(xhos[indexOfMin], yhos[indexOfMin], 15);

  //console.log(xhos[indexOfMin] +", "+ yhos[indexOfMin]);
  //setStrokeColor("black");

  return minDistance;
}

//pixel to mile scale factor
function pixelMile(){

```

```

var difx=(xhos[2]-xhos[3]);
var dify=(yhos[2]-yhos[3]);
var pixeldis = Math.sqrt(difx*difx+dify+dify);
var actualdis=2.42;

return actualdis/pixeldis;
}

function closestEms(xi,yi){
var xpo = (xi+122.502244)*2500+10;
var ypo = (yi-37.807143)*-2500+50;

indexEms = 0;
disEms = Math.abs(xpo-emsx[0])+Math.abs(ypo-emsy[0]);
//console.log(disEms);

for(var k=0; k<emsx.length; k++){
var tuxi = Math.abs(xpo-emsx[k])+Math.abs(ypo-emsy[k]);

if(tuxi<disEms){
disEms=tuxi;
indexEms=k;
}
}

//setStrokeColor("purple");
//circle(emsx[indexEms], emsy[indexEms], 15);
//setStrokeColor("black");
//console.log(disEms);
return disEms;
}

function setupMap(){
//transform coordinates
for (i=0;i<4;i++){
xcord[i]=(xcord[i]+122.508528)*2200+20;
ycord[i]=(ycord[i]-37.804294)*-2500+35;
}

//create city
//rect(xcord[0], ycord[0], xcord[2]-xcord[1], ycord[1]-ycord[0]);

//model hospitals

for(i=0;i<xhos.length; i++){
xhos[i]=(xhos[i]+122.508528)*2200+20;
yhos[i]=(yhos[i]-37.804294)*-2500+35;

//circle(xhos[i], yhos[i], 4);
}

//model ems centers
for(i=0;i<emsx.length; i++){
emsx[i]=(emsx[i]+122.508528)*2200+20;
emsy[i]=(emsy[i]-37.804294)*-2500+35;

//setStrokeColor("orange");
//circle(emsx[i], emsy[i], 4);
//setStrokeColor("black");
}
}
}

```

Code Appendix 2

This JavaScript program runs through possible hospital locations and outputs the city's average SATT for each situation, which can be minimized to find the ideal location. The commented lines code represent the visual component of the program that adds unnecessary runtime.

```
//createCanvas("map");
var xnew = getColumn("newHospitals", "Long");
var ynew = getColumn("newHospitals", "Lat");

var avgTime=[];

for(var z=0; z<xnew.length; z++){
  //corners of San Fran
  //var xcord = [-122.508528, -122.508528, -122.380441, -122.380441];
  //var ycord = [37.709096, 37.804294, 37.804294, 37.709096];

  //loop variable
  var i;

  //data for hospitals
  var xhos = getColumn("hospitalData", "Longitude");
  var yhos = getColumn("hospitalData", "Latitude");
  appendItem(xhos,xnew[z]);
  appendItem(yhos,ynew[z]);

  var numHos = xhos.length;
  var nombre = getColumn("hospitalData", "Name");
  appendItem(nombre, "New Hospital");

  var chance = getColumn("hospitalData", "Risk");
  appendItem(chance,0);

  var orderChance=[];

  for(var q=0; q<chance.length; q++){
    chance[q]=1-chance[q];
  }

  //data for ems coordinates
  var emsx = getColumn("ems", "LONGITUDE");
  var emsy = getColumn("ems", "LATITUDE");

  //distance to x,y from ems/hospital
  var disEms;
  var minDistance;
  var hospitaltime=[];

  //closest hospital index
  var indexOfMin;

  //closest ems index
  var indexEms;

  //Assumptions
  var averageAmbulanceSpeed=20;
  var ambulanceTransitionTime=17;

  //START OF ACTUAL EXECUTION
  setupMap();

  //calibrate pixel to miles
  var pixelToMile = pixelMile();

  //GET COORDINATES
```

```

var coordLong = getColumn("coords","LONGITUDE");
var coordLat = getColumn("coords","LATITUDE");
var pop = getColumn("coords","POPULATION");
var popSum=0;
for(var i=0; i<pop.length; i++){
  popSum+=pop[i];
}

//console.log(popSum);
//var expiTimeData={};
var output;

var totalTP=0;
for(var v=0;v<coordLat.length; v++){

  // expiTimeData.Longitude=coordLong[v];
  // expiTimeData.Latitude=coordLat[v];
  // expiTimeData.Population=pop[v];
  repetition(coordLong[v],coordLat[v]);
  // expiTimeData.Time=(output+ambulanceTransitionTime)*pop[v];
  // createRecord("expiTime", expiTimeData);
  totalTP+=(output+ambulanceTransitionTime)*pop[v];
  reset();
}
appendItem(avgTime,totalTP/popSum);
console.log(avgTime);

console.log("Done");
}
////////////////////////////////////
////////////////////////////////////
////////////////////////////////////

function reset(){
  //data for hospitals
  xhos = getColumn("hospitalData", "Longitude");
  yhos = getColumn("hospitalData", "Latitude");
  appendItem(xhos,xnew[z]);
  appendItem(yhos,ynew[z]);
  numHos = xhos.length;
  nombre = getColumn("hospitalData", "Name");
  appendItem(nombre,"New Hospital");

  chance = getColumn("hospitalData","Risk");
  appendItem(chance,0);
  for(var q=0; q<chance.length; q++){
    chance[q]=1-chance[q];
  }
  orderChance=[];

  //distance to x,y from ems/hospital
  hospitaltime=[];

  emsx = getColumn("ems","LONGITUDE");
  emsy = getColumn("ems","LATITUDE");

  //START OF ACTUAL EXECUTION
  setupMap();
}

function repetition(x,y){
  for (var p=0;p<numHos;p++){
    everything(x,y);
  }
  //calculate the estimated time
  var expectedTime=0;
  expectedTime += 1*orderChance[0]*hospitaltime[0];
  for(var a=1; a<numHos; a++){

```

```

var probability=1;
for(var b=0; b<a; b++){
  probability*=(1-orderChance[b]);
}

  expectedTime +=probability*hospitaltime[a]*orderChance[a];
}
output=expectedTime;
//console.log("EXPECTED TIME: " + expectedTime);
}

function everything(x,y){
  var hdis=closestHospital(x,y);
  var emsdis=closestEms(x,y);
  //console.log("Hospital to x,y: "+ (hdis*pixelToMile)+" - "+*/nombre[indexOfMin]);
  //console.log("Ems to x,y: "+(emsdis*pixelToMile));
  var total=(emsdis*pixelToMile+hdis*pixelToMile);
  //console.log("Total dis: "+total);
  var time=(total/averageAmbulanceSpeed*60);
  //console.log("Time: "+ time);

  appendItem(orderChance,(chance[indexOfMin]));

  appendItem(hospitaltime,(time));

  removeItem(nombre,indexOfMin);
  removeItem(xhos,indexOfMin);
  removeItem(yhos,indexOfMin);
  removeItem(chance,indexOfMin);

  //console.log(hospitaltime);
  //console.log(orderChance);
}

function closestHospital(x,y){
  var xpos = (x+122.508528)*2200+20;
  var ypos = (y-37.804294)*-2500+35;
  //setStrokeColor("red");
  //circle(xpos, ypos, 10);
  //setStrokeColor("black");

  indexOfMin = 0;
  minDistance = Math.abs(xpos-xhos[0])+Math.abs(ypos-yhos[0]);

  for(var j=0; j<xhos.length; j++){
    var taxi = Math.abs(xpos-xhos[j])+Math.abs(ypos-yhos[j]);

    if(taxi<minDistance){
      minDistance=taxi;
      indexOfMin=j;
    }
  }

  //setStrokeColor("green");
  //circle(xhos[indexOfMin], yhos[indexOfMin], 15);

  //console.log(xhos[indexOfMin] +", "+ yhos[indexOfMin]);
  //setStrokeColor("black");

  return minDistance;
}

//pixel to mile scale factor

function pixelMile(){
  var difx=(xhos[2]-xhos[3]);
  var dify=(yhos[2]-yhos[3]);

```

```

var pixeldis = Math.sqrt(difx*difx+dify+dify);
var actualdis=2.42;

return actualdis/pixeldis;
}

function closestEms(xi,yi){
var xpo = (xi+122.502244)*2500+10;
var ypo = (yi-37.807143)*-2500+50;

indexEms = 0;
disEms = Math.abs(xpo-emsx[0])+Math.abs(ypo-emsy[0]);
//console.log(disEms);

for(var k=0; k<emsx.length; k++){
var tuxi = Math.abs(xpo-emsx[k])+Math.abs(ypo-emsy[k]);

if(tuxi<disEms){
disEms=tuxi;
indexEms=k;
}
}

//setStrokeColor("purple");
//circle(emsx[indexEms], emsy[indexEms], 15);
//setStrokeColor("black");
//console.log(disEms);
return disEms;
}

function setupMap(){

//transform coordinates
for (i=0;i<4;i++){
xcord[i]=(xcord[i]+122.508528)*2200+20;
ycord[i]=(ycord[i]-37.804294)*-2500+35;
}

//create city
//rect(xcord[0], ycord[0], xcord[2]-xcord[1], ycord[1]-ycord[0]);

//model hospitals
for(i=0;i<xhos.length; i++){
xhos[i]=(xhos[i]+122.508528)*2200+20;
yhos[i]=(yhos[i]-37.804294)*-2500+35;

//circle(xhos[i], yhos[i], 4);
}

//model ems centers
for(i=0;i<emsx.length; i++){
emsx[i]=(emsx[i]+122.508528)*2200+20;
emsy[i]=(emsy[i]-37.804294)*-2500+35;

//setStrokeColor("orange");
//circle(emsx[i], emsy[i], 4);
//setStrokeColor("black");
}
}

```