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Special Section:
The COVID-19 pandemic: linking health, society and environment

Key Points:

- Most survey respondents (74%) were concerned about air quality
- Age, education, and ethnicity were factors that affected peoples' concerns about air quality
- Respiratory conditions, living near industrial areas, and financial status impacted perceptions

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:
Y. Elshorbany,
elshorbany@usf.edu

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Author Contributions:
Conceptualization: Robin Rives, Yasin Elshorbany
Data curation: Yasin Elshorbany
Formal analysis: Robin Rives, Yasin Elshorbany
Funding acquisition: Yasin Elshorbany
Investigation: Robin Rives, Yasin Elshorbany, Sydney Kaylor

The Relationship Between Air Quality, Health Outcomes, and Socioeconomic Impacts of the COVID-19 Pandemic in the US

Robin Rives[1], Yasin Elshorbany[1], and Sydney Kaylor[1]

[1]School of Geosciences, College of Arts and Sciences, University of South Florida, St. Petersburg, FL, USA

Abstract COVID-19 lockdowns caused significant improvements in air quality in US states where traffic emissions are the main pollution source. In this study, we investigate the socioeconomic impacts of the COVID-19-related lockdowns in states which experienced the greatest changes in air quality, especially among different demographic populations and those with contraindications to health. We administered a 47-question survey and collected 1,000 valid responses in these cities. Our results show that 74% of respondents within our survey sample had some level of concern regarding air quality. In agreement with previous literature, perceptions of air quality were not significantly correlated with measured air quality criteria but rather seemed to be influenced by other factors. Respondents in Los Angeles were the most concerned about air quality followed by Miami, San Francisco, and New York City. However, those from Chicago and Tampa Bay expressed the least amount of concern about air quality. Age, education, and ethnicity were all factors affecting peoples' concerns about air quality. Respiratory conditions, living in proximity to industrial areas, and financial impacts from the COVID-19 lockdowns influenced concerns about air quality. About 40% of the survey sample reported greater concern for air quality during the pandemic, while approximately 50% stated that the lockdown didn't affect their perception. Furthermore, respondents seemed concerned about air quality in general, not a specific pollutant, and are willing to adopt additional measures and more stringent policies to improve air quality in all investigated cities.

Plain Language Summary COVID-19 lockdowns caused significant improvements in air quality in US states where traffic emissions are the main pollution source. In this study, we investigated the socioeconomic impacts of the COVID-19-related lockdowns in states which experienced the greatest changes in air quality, especially among different demographic populations and those with contraindications to health. We administered a 47-question survey and collected 1,000 valid responses in these cities. Our results show that 74% of respondents within our survey sample had some level of concern regarding air quality. In agreement with previous literature, perceptions of air quality were not significantly correlated with measured air quality criteria but rather seemed to be influenced by other factors. Respondents in Los Angeles were the most concerned about air quality followed by Miami, San Francisco, and New York City. Those from Chicago and Tampa Bay expressed the least amount of concerns. Age, education, and ethnicity were all factors affecting peoples' concerns about air quality. Respiratory conditions, living in proximity to industrial areas, and financial impacts from the COVID-19 lockdowns influenced concerns about air quality. Respondents seemed concerned about air quality in general, not a specific pollutant, and are willing to adopt additional measures to improve air quality.

1. Introduction

The COVID-19 pandemic has impacted the entire world. Caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), COVID-19 was declared a pandemic by the World Health Organization (WHO) on 11 March 2020, resulting in a series of lockdowns across the globe (Onyeaka et al., 2021). The pandemic was declared a national emergency in the United States on 13 March 2020, (AJMC, 2021). California became the first state to issue a statewide stay-at-home order on 19 March 2020, with all other states following suit (AJMC, 2021). Lockdown periods varied among the states in length and stringency, continuing in some areas for several months. The geographical extent of the effects of the COVID-19 pandemic in relation to air quality has been global (Lou et al., 2022). Undoubtedly, the COVID-19 pandemic lockdown periods had profound impacts on daily life in the United States. For instance, the COVID-19 pandemic lockdown resulted in a decrease in traffic volume and its associated emissions, thereby affecting air quality in several places (Elshorbany et al., 2021; Lian et al., 2020). According to a previous study (Elshorbany et al., 2021), a significant improvement in air quality was determined in areas where traffic-related emissions were the primary source of air pollution, with improved visibility linked

Methodology: Robin Rives, Yasin Elshorbany, Sydney Kaylor
Project Administration: Yasin Elshorbany
Resources: Yasin Elshorbany, Sydney Kaylor
Software: Robin Rives, Yasin Elshorbany
Supervision: Yasin Elshorbany
Validation: Robin Rives, Yasin Elshorbany
Visualization: Robin Rives, Yasin Elshorbany
Writing – original draft: Robin Rives, Yasin Elshorbany, Sydney Kaylor
Writing – review & editing: Robin Rives, Yasin Elshorbany

to reduced emissions from industrial facilities, transportation, power generation, and other economic activities (Ching & Kajino, 2020; Lian et al., 2020). These results were supported by satellite imagery and ground-based measurements of $PM_{2.5}$ and pollutants criteria around the globe (Ching & Kajino, 2020; Dantas et al., 2020; Mahato et al., 2020).

Air pollution has been linked with a variety of health conditions including autoimmune diseases (Gawda et al., 2017; Ritz, 2010), cardiovascular disease (Pope III et al., 2004), pulmonary conditions such as lung cancer and asthma (Chen & Goldberg, 2009; Ghorani-Azam et al., 2016), neurocognitive disorders such as Parkinson's disease and developmental conditions such as autism (Ghorani-Azam et al., 2016), among others. A link has been found between the death rate of COVID-19 and air pollution, with higher death rates in cities with more pollution (Ching & Kajino, 2020; Isphording & Pestel, 2021). This may be attributed in part to the negative health impacts which occur from exposure to air pollutants. Worldwide, air quality monitoring programs exist to document air quality, logging vast amounts of data on concentrations of specific pollutants such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), particulate matter (PM), and carbon monoxide (CO) (Bishoi et al., 2009). However, this data is not in a context that is intuitive for the community at large to access and understand, which led to the creation of the Air Quality Index (AQI) or the Air Pollution Index (API) (Bishoi et al., 2009; Ott & Thorn, 1976; Shenfeld, 1970). The AQI can be defined as a number system utilized for reporting air quality considering specifically its effects on human health (Bishoi et al., 2009; Murena, 2004; Ott & Thorn, 1976). The AQI is calculated by combining pollutant concentrations using a mathematical expression to derive a single number for an air quality value (Bishoi et al., 2009). Knowledge of AQI was one of several variables utilized in this study to determine air quality awareness.

Several studies have drawn connections between socioeconomic status and inequality in exposure to air quality. Generally, those with lower socioeconomic status (SES) face a higher risk of exposure to air pollution (Bell et al., 2005). Most North American studies have shown that low SES communities experience higher concentrations of criteria air pollutants such as NO_x, SO_2, CO, PM, and ground-level ozone (O_3) (Hajat et al., 2015; US EPA, 2014). This may result from heightened exposure to air pollution through factors such as increased proximity to roadways or indoor air pollution from industrial processes such as the burning of biomass, among other health factors (Bell et al., 2005). Additionally, African Americans, Hispanic Americans, and lower-income groups are more likely to be exposed to pollutants than white Americans, especially those in the middle and upper-income brackets. This is because racial and ethnic minorities, and lower-income individuals, are more likely to live in urban areas and industrial areas where pollution is concentrated (Johnson Gaither et al., 2019; Johnston et al., 2020). This phenomenon is not unique to the United States. A study conducted by the WHO European Region found from previous ecological studies that higher deprivation indices and lower economic position are often linked with higher levels of pollutants including PM and nitrogen oxides (Fairbun et al., 2019).

Perceptions research allows scientists to better understand the factors and motivations which affect how the public views topics of interest. This is essential not only to document the level of public understanding of the topic, but also to learn how the public interprets and prioritizes these topics, and why. Understanding these issues helps the scientific community to identify knowledge gaps and societal factors which may be perpetuating these gaps. Several studies have assessed perceptions of air quality using survey research. One such study examined patterns of air quality perceptions in Dallas and Houston, Texas in order to better understand the major factors which shape public perceptions of air quality (Brody et al., 2004). Through examining socioeconomic characteristics, patterns of local risk perception, and the relationship between perceived and measured air quality, it was found that perceptions of air quality were not significantly correlated with measured air quality criteria, but rather seemed to be influenced by location, access to information, and socioeconomic characteristics (Brody et al., 2004). Another study in San Joaquin Valley, California was conducted via the administration of a survey to 744 participants in order to examine public perceptions of air quality (Cisneros et al., 2017). The results of the study revealed that the correlation of those experiencing exposure to high concentrations of $PM_{2.5}$ (particulate matter less than 2.5 microns in size) to those belonging to sensitive health groups, and females perceived the air quality to be poor. Participants also believed that vehicles, factories, and dust were the greatest contributors of air pollution in the area (Cisneros et al., 2017). Knowing this information can help to indicate which demographic groups may not have as much awareness or concern for air quality and whether the public is accurately understanding the source of air pollution in their area.

Several studies relating to public perceptions of air quality in relation to the COVID-19 pandemic have been recently published. Lou et al. (2022) examined perceptions of air quality in 10 countries and found that all survey respondents expressed a perceived improvement in air quality during the COVID-19 pandemic and concluded that this should be a motivation for air pollution mitigation worldwide. Sekar et al. (2020) examined air quality changes due to the COVID-19 lockdown periods in India, and the subsequent perception of air quality by the public. They found that approximately 60% of the respondents perceived an improvement in air quality without the influence of media, which was consistent with actual air quality improvements during this period. Understanding public perception of air quality and sources of air pollution in comparison to scientific measurements, while considering motivating factors such as socioeconomic status, is vital to creating effective and responsible policymaking. Understanding perceptions of air quality is also helpful for the development of risk assessment studies, which aid in developing air pollution risk management and policy and can help to set priorities for air quality improvements (Deguen et al., 2012). Furthering environmental justice is a facet of sustainable development. Environmental justice refers to the principle that all people, regardless of demographic or socioeconomic factors, should fairly share the burdens of environmental hazards and the benefits of environmental amenities (Mitchell et al., 2015). In this study, we determine if and how the 2020 COVID-19 lockdown period may have influenced people's perceptions of air quality in each of our cities of interest relative to socioeconomic levels. The study also contains an environmental justice component, which consisted of determining if socioeconomic factors affect perceptions of air quality and, specifically, assessing whether ethnic minorities or low SES communities have reported heightened exposure to or concern regarding air. We specifically address the following objectives, (a) determine if there are varying perceptions of air quality among different demographic populations, especially considering ethnic minorities, (b) investigate the impacts of health and socioeconomic factors on perceptions of individuals toward air quality in each city, and (c) measure people interest to adopt additional measures to improve air quality.

2. Methods

In this section, we discuss our survey method and the applied statistical approach.

2.1. Survey Setup and Quality Check

Perceptions of air quality and various health, demographic, socioeconomic, and pandemic-related questions were gathered through the administration of a 47-question survey with the help of the Qualtrics survey company. The quota of responses per city was weighted according to population size, with 1,000 total responses. The population size for each city was based on the United States Census American Community Survey data (United States Census Bureau, 2020). The threshold of 1,000 total survey responses was determined to achieve the maximum number of survey responses while maneuvering within cost constraints. Deciding the number of survey responses per city by utilizing population size as the determining factor was the most equitable way to distribute the survey responses. Whereas the majority of the sample was comprised of individual metropolitan cities such as Chicago, New York City, and Los Angeles, the cities within the region of Tampa Bay including Tampa, Clearwater, and St. Petersburg, among other cities, were aggregated since individual population sizes of the cities within Tampa Bay are much smaller than the other cities analyzed in this study. Considering these cities individually would not have allowed for statistically significant sample size in comparison to the other cities evaluated in this study. The distribution of responses per city was as follows: 139 responses from Chicago residents, 160 responses from Tampa Bay residents, 23 responses from Miami residents, 45 responses from San Francisco residents, 203 responses from Los Angeles residents, and 430 responses from New York City residents (Table 1).

The Qualtrics survey data were processed for quality control (QC). Qualtrics survey software provides a tool to eliminate responses that do not meet QC standards (Qualtrics, 2021c). Qualtrics software uses algorithms to prevent fraudulent survey responses, then assigns a QC score to survey responses called Good Completes (GC). A GC score of 1 is considered to be a good-quality response. Any survey response with a GC score greater than 1 is filtered out and replaced with a quality survey response while undergoing the data collection process (Qualtrics, 2021c). Qualtrics replaced flagged survey responses with new responses via a “next in line” approach, through which the survey was reopened and new responses were collected as needed. Additionally, we added

Table 1
Survey Responses per City Weighted According to Population Size

State City	Illinois Chicago	Florida Tampa Bay	Florida Miami	California San Francisco	California Los Angeles	New York New York City	Total
Population size of the cities	2,710,000	3,140,000	454,279	874,961	3,970,000	8,420,000	19,569,240
The ratio of the city's population to the total	0.14	0.16	0.02	0.04	0.2	0.43	1
Number of responses weighted by population size	138	161	23	45	203	430	1,000

Note. The quota of survey responses for each city was rounded to the nearest whole number.

filters with the assistance of Qualtrics to further customize the GC score and those factors which contribute to the overall GC score (Qualtrics, 2021b). Specifically, we created a parameter for responses that set a minimum completion time of 4 min for survey responses. We automatically eliminated any responses with an IP address that differed from any of our specified areas of interest. Users with the same IP address who submitted multiple responses were filtered out to eliminate multiple responses from the same user. We also filtered out incomplete responses and gibberish text entries. Additionally, we individually sorted through the responses to ensure that the responses were consistent with our QC criteria. Poor responses were replaced with quality responses, considering our indicated quotas within each area of interest to reach the 1,000 response mark. We also collected partial responses that met these QC criteria. In total, there were 1,039 collected responses analyzed in this study, 1,000 complete responses, and 39 partial responses. The data were analyzed using statistical analysis involving multinomial logistic regression utilizing SPSS statistical package (IBM Corp, 2020).

Table 2
A List of Regressions Showing Dependent and Independent Variables

	Variable	Column
Regression	Dependent[Y]	Independent [X_1, X_2… X_m]
1	Concern Air Quality	Education
		Ethnicity
		Age
		Income
		Income Impacted
2	Concern Air Quality	Location
		Perception Change
		Pollution Type
		Proximity Industrial
3	Familiar AQI	Respiratory
		Respiratory Seasonal
		Respiratory Decrease
		Air Quality in City
4	Air Quality in General	Perception Change
		Air Quality Impressions
		Primary Causes
5	Stricter Air Quality	Actions
		Specific Traffic Regulations
		Petition
		Relocation
		Electric Vehicles

After importing the Qualtrics data into SPSS, categorical variables were given unique names and appropriately labeled as nominal. A nominal variable is one with two or more categories but no specific order to those categories (UCLA, 2021). These variables included Location, Ethnicity, AirQ Impressions, Specific Traffic Regulations, Electric Vehicles, Pollution Type, Perception Change, AirQ in City, Income, Age, and Education, among many other variables (see Table 2). The variables and their corresponding survey questions can be found in Table S1 and Section S1 in the Supporting Information S1, and are publicly available (Date Repository, 2023). All percentages obtained through data analysis and referenced in this paper were rounded to the nearest 10th.

2.2. Regression Analysis

Five multinomial logistic regressions were calculated using SPSS to determine perceptions of air quality as it relates to the COVID-19 pandemic, considering various combinations of variables (see Table 2). The specific variables utilized within each of our regressions are as follows: Regression 1 was run to determine if there are varying perceptions among different demographic populations, or if socioeconomic factors have an impact. The dependent variable used was Concern about Air Quality, and the independent variables were Education, Ethnicity, Age, Income, Income Impacted, and Employment (see Table 2 and Table S2 in Supporting Information S1). Regression 2 was run to determine if proximity to industrial areas in the various cities influenced concern of air quality. The dependent variable was Concern about Air Quality, and the independent variables were Location, Perception Change, Pollution Type, and Proximity Industrial (see Table 2 and Table S3 in Supporting Information S1). Regression 3 was run to determine if health factors impact familiarity with air quality conditions (AQI). The dependent variable for this regression was Familiar with AQI. The independent variables for this regression were Respiratory, Respiratory Seasonal, Respiratory Decrease, and Air Quality in City (see Table 2 and Table S4 in Supporting Information S1).

Regression 4 was run to determine if the COVID-19 pandemic affected respondents' perceptions of air quality. The dependent variable for this regression was Air Quality in General. The independent variables for this regression were Perception Change, Air Quality Impressions, and Primary Causes (see Table 2 and Table S5 in Supporting Information S1). Regression 5 was run to determine if imposing stricter air quality regulations would be supported and which types of regulatory actions were most desirable. The dependent variable for this regression was Stricter Air Quality. The independent variables for this regression were Actions, Specific Traffic Regulations, Petition, Relocation, and Electric Vehicles (see Table 2 and Table S6 in Supporting Information S1).

The equation used for the multinomial logistic regression is as follows (García-Portugués, 2022):

$\Pr[Y_i] = \exp(\beta_1^{(i)}X_1 + \beta_2^{(i)}X_2 + \ldots \beta_m^{(i)}X_m)$, where $\Pr[Y]$ is the probability of the dependent variable, Y as a function of the independent variables, X (see Table 2) and β is their dependency factor.

The probability index, Exp(β), represents the odds ratio, which determines if the odds of the occurrence of one variable over another are increasing or decreasing. Beta ($\beta_{1,2\ldots m}$) is the estimated regression coefficient that has been recalculated to have a mean of 0 and a standard deviation of 1. The use of the β allows for a direct comparison between independent variables to determine which has the most influence on the dependent variable (Monash University, 2021). Referencing the Exp(β) value allows us to extrapolate the result to the general population, thus, showing the odds or probability of someone within a certain city, for example, Los Angeles or San Francisco, being more familiar with the AQI.

2.3. Data Processing

Dummy variables were assigned for all nominal variables. Dummy variables allow nominal variables with multiple categories to be assigned numerical values of a high (1) or a low (0), which allows categories to be converted into a useable form for the regression analysis (Statistics Solutions, 2017). Furthermore, all nominal variables were labeled using the Values Labels function in the statistics software package, SPSS to provide all categorical variables with corresponding numerical codes. Any data that was not automatically coded with both its categorical and corresponding numerical code were manually recorded. After running the first set of regressions, it was apparent that certain variables were experiencing a Hessian Matrix error, which is produced when there is a category of the dependent variable for which at least one predictor is constant (as in, repeated identical answer choices) (IBM, 2012). A solution to this error is excluding some predictor variables or merging categories as needed. Another error we received was that there were cells (i.e., dependent variables levels by subpopulations) with zero frequencies. To address this issue, we examined the Case Processing Summaries provided from running each regression to determine which variables contained categories with marginal percentages of <4%. This influenced which categories were merged and among which variables. Categories within the Income variable were recombined to form 5 larger categories, rather than the initial 8. The categories became the following: <$20,000, $20,000–$40,000, $40,000–$70,000, $70,000–$100,000, and >$100,000.

Within the Income Impacted variable, the categories “Yes, annual” and “Yes, monthly” were recombined into “Yes, income was impacted” to describe those who experienced an impact on their income from the COVID-19 pandemic. Categories within the Employment variable which were combined included Unemployed, job searching, not actively job searching, homemaker, and unable to work into “Unemployed and not working.” Military, self-employed, and employed for wages were combined into “Employed.” Retired, student, and other were combined into Retired and Other. For the Education variable, the categories trade/technical/vocational training, nursery school to 8th grade, no schooling, and some high school no diploma categories were combined into “Any schooling without a High School diploma.” The Masters, Doctorate, and professional degree categories were combined into “Higher Education.”

Due to a very small marginal percentage of Native American respondents across all areas, the categories Native American and Other were combined in order to eliminate the Hessian Matrix error. Within the Gender variable, the non-binary/third gender and prefer not to say categories were recombined into “Nonbinary or unanswered.” Furthermore, dummy variables which consisted of merely null values were deleted from the variables Actions, Pollution, Electric Vehicles, Specific Traffic Regulations, and Language. Recombining the variables, removing the null values, and creating value labels and dummy variables effectively resolved the Hessian Matrix error. Despite recombining categories, some categories among various variables still had a relatively low marginal percentage as seen in the Case Processing Summaries. This is a result of those responses which lie outside of the

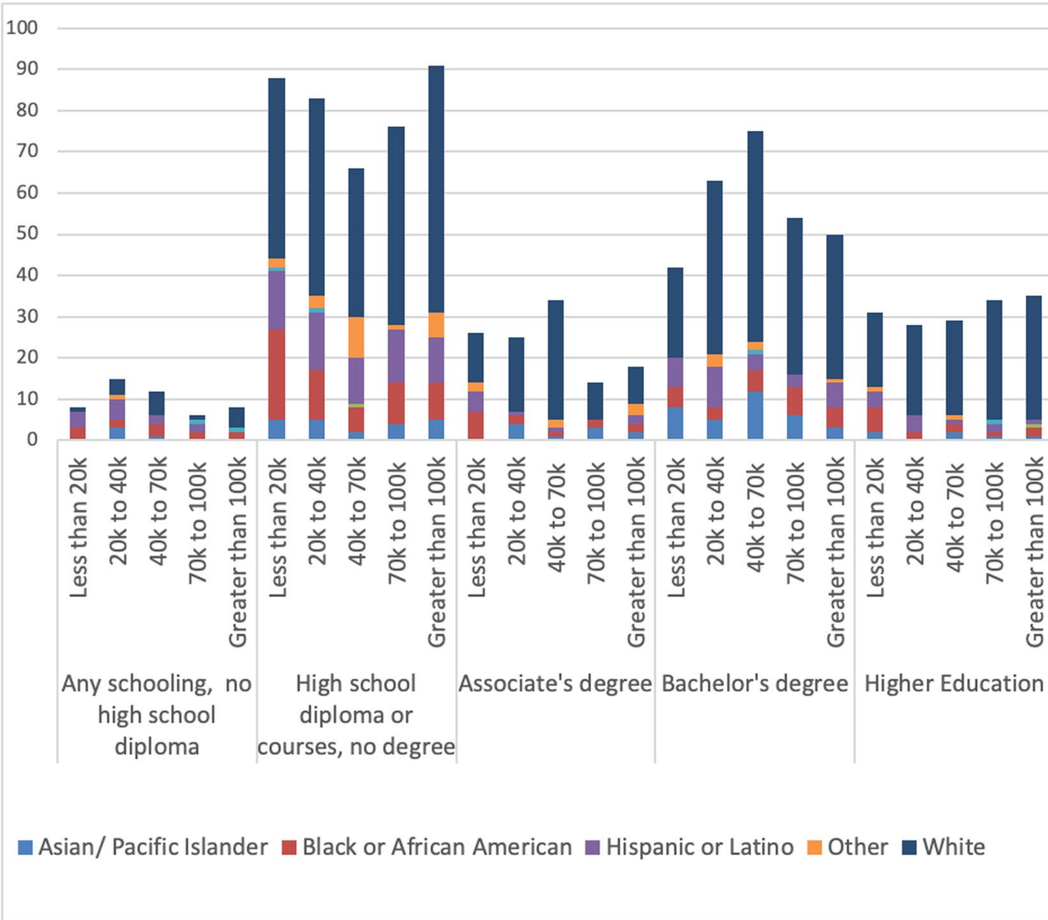

Figure 1. Count of respondents by education, ethnicity, and income.

standard deviation, which cannot be avoided altogether. In addition to the multinomial logistic regressions, the data was further visualized through Pivot Tables in Microsoft Excel and ArcGIS Pro to create a variety of figures.

3. Results

In the following sections, we discuss the respondents' perceptions as a function of the independent variables.

3.1. Concerns to Air Quality

3.1.1. Education, Ethnicity, Location, and Income

Participants' concerns regarding air quality were evaluated using Regression 1 and Regression 2 (see Table 2). From Regression 1, significant variables included Education, Ethnicity, and Income Impacted. The standard confidence level used in this study is 95%. The results revealed that most respondents (74%) are concerned about air quality to some degree. The results also showed that 40% of the respondents possess a high school degree as their highest form of education, followed by those with a Bachelor's degree (15%), and 15% had higher education (PhD, Masters, or professional degree) (see Figure 1). Most of the respondents were White (65%), followed by Hispanic, Latino and Black, and African American with approximately 12% for each. The respondents were nearly equally distributed across all income brackets, with percentages of approximately 20% for each, although most respondents (24%) belonged to the $40,000 to $70,000 range (Figure 1).

The majority of respondents are employed (49%), followed by retired (29%). See Table 1 for more demographic information. Many respondents indicated that their income was not impacted by COVID-19 while 48% of people

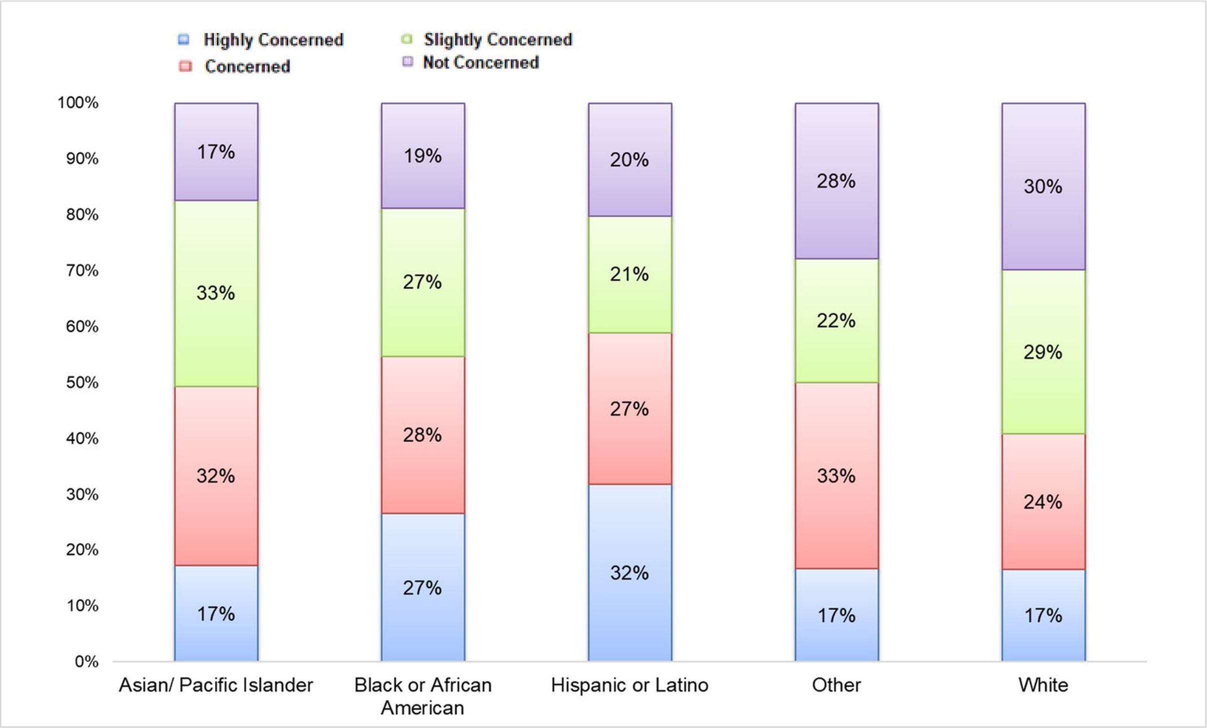

Figure 2. Concern to Air Quality by ethnicity.

did have their income impacted by COVID-19. See Figure 2 for information regarding income impact as it relates to education level of respondents. Additionally, the results of Regression 3 revealed that "the income not impacted" variable was statistically significant across all levels of concern for air quality. This suggests that those who did not experience an impact to income as a result of the COVID-19 pandemic still expressed concern for air quality (Table S2 in Supporting Information S1). Further results from Regression 3 are listed in Section 3.2.

The survey indicated that ethnicity had an impact on the level of concern of air quality among our survey participants. The white respondents constituted the majority of responses in our survey (65%) and also had the highest percentage of respondents (30%) who were "Not Concerned" about air quality. Overall, more respondents (74%) were concerned with air quality (i.e., Highly Concerned, Concerned or Slightly Concerned) than not. While respondents who indicated an ethnicity of Other (an ethnicity other than the listed Asian/Pacific Islander, Black of African American, Hispanic or Latino, or White) made up only 3.5% of our survey sample, they comprised the highest percentage of "Concerned" individuals at 33%. Asian/Pacific Islander respondents made up 7% of our survey sample and 32% reported being "Concerned." Black or African American respondents comprised 12% of our total survey sample but 283% of "Concerned" and 27% of "Highly Concerned" individuals. Finally, Hispanic or Latino respondents comprised 12% of our survey sample but had the most "Highly Concerned" respondents (32%) (See Figure 2).

The survey also highlighted the influence of geographic location on perceptions of air quality. Those located within Los Angeles were the most concerned about air quality with 29% of respondents indicating they were "Highly Concerned" and 29% indicating they were "Concerned." San Francisco and Miami were the next most concerned cities, followed by New York City. Respondents from Chicago and Tampa Bay were the least concerned, with 41% of respondents from Tampa Bay and 34% of respondents from Chicago indicating that they were "Not Concerned" about air quality (Figure 4).

Another survey question addressed the importance of air quality (Figure 3). Respondents were asked if their perception of the importance of air quality changed as a result of the COVID-19 pandemic. The majority of respondents in all cities believed air quality to be of the same level of importance despite the COVID-19 pandemic. Most respondents that believed air quality was of greater importance as a result of the COVID-19 pandemic were located in New York and California. Few respondents across all cities believed air quality is less important as a result of the COVID-19 pandemic (Figure 3).

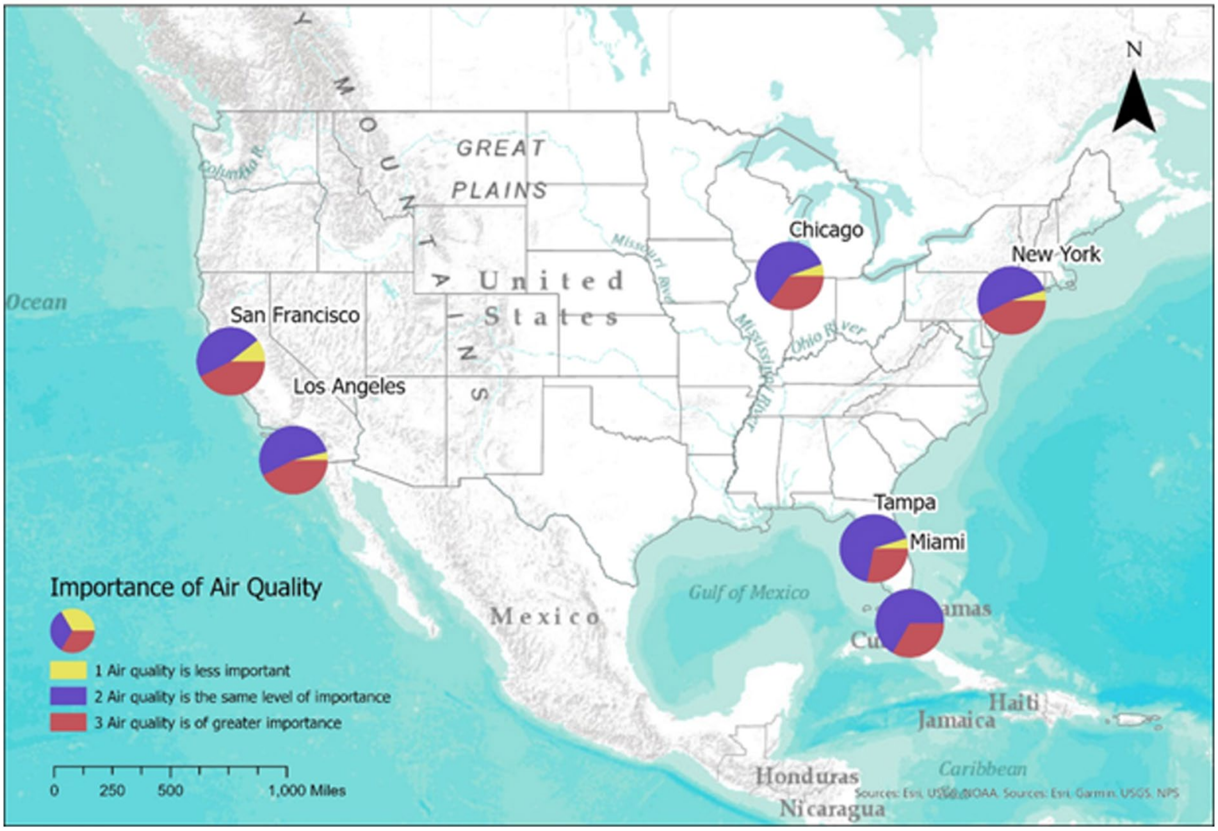

Figure 3. Importance of air quality variable distributed by location.

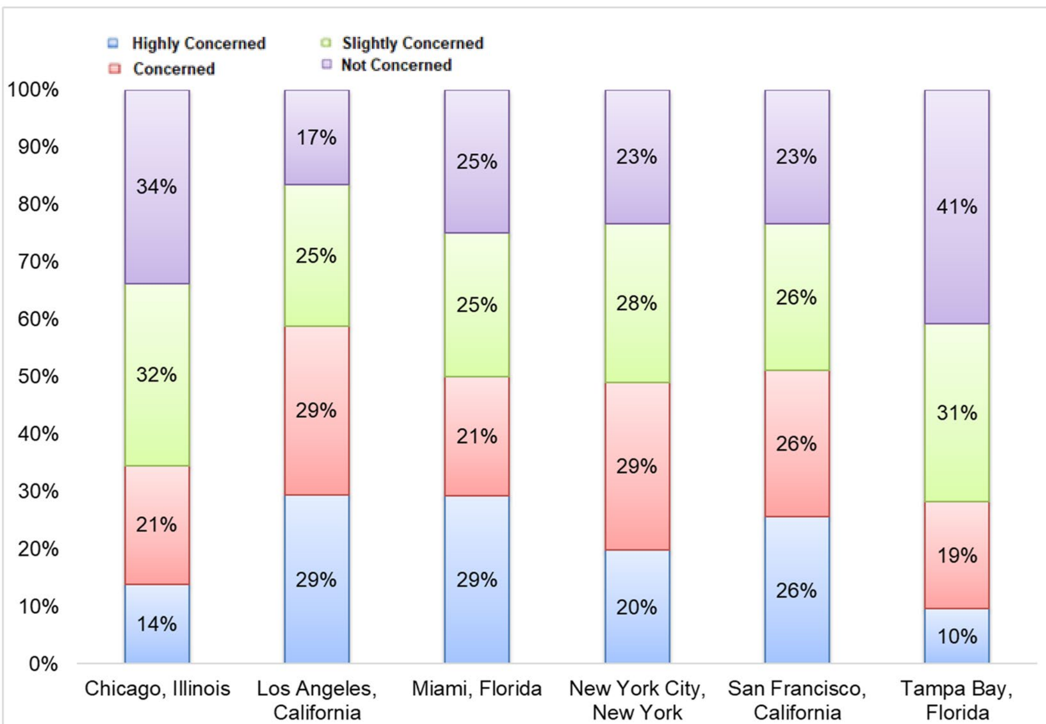

Figure 4. Concern of air quality by location.

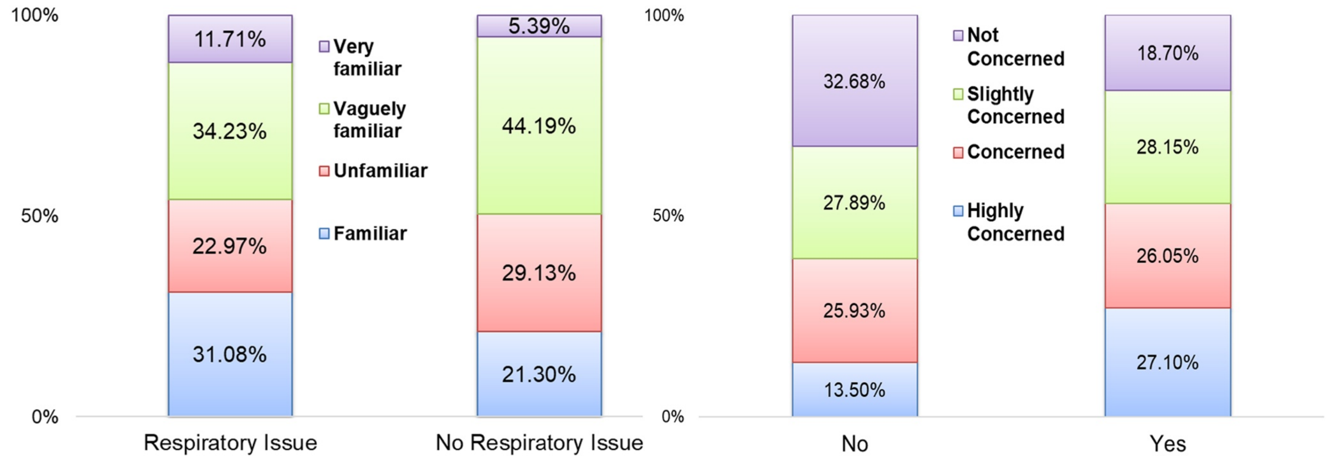

Figure 5. (a) Familiarity with Air Quality Index and respiratory illnesses, (b) *Concern of air quality and proximity to industrial areas*.

3.1.2. Perception Change, Pollution Type, and Proximity to Industrial Locations

Significant variables for Regression 2 included Perception Change, Pollution Type, Proximity Industrial, and Location. The results showed that a majority of people did not experience a change in their perception of air quality as a result of COVID-19 with 56.% reporting air quality as having the same level of importance. However, those who did experience a change in perception of air quality typically reported a heightened level of concern. When asked to select the type of specific pollutants they face in their city, most respondents (33%) indicated several of the listed criteria pollutants. The next highest percentage of respondents (18%) indicated that they were unsure which type of pollution is present in their city. Most respondents who did answer a specific pollutant (17%) listed dust and or PM, in other words, visible pollutants. Most respondents do not live near an industrial area (54%), although 46%, nearly half of the respondents, indicated that they do live within proximity to an industrial area. Regression 2 indicated that Black or African American and Hispanic or Latino respondents were significantly more likely to be highly concerned about air quality, as reported in Table S3 in Supporting Information S1 (see Figure 5b).

3.2. Respiratory Illness and Air Quality Index

Regressions 3 and 4 were used to investigate the relationship between respiratory diseases and familiarity with AQI (regression 3), and Primary Causes, and Air Quality Impressions (Regression 4). Significant variables at 95% confidence from Regression 3 were Respiratory Diseases and Air Quality in City. The results of the survey revealed that 72% of respondents are familiar with AQI to some degree, although the remainder (28%) are unfamiliar with AQI (see Figure 5a). Most respondents (>70%) do not have respiratory issues, both generally and seasonally. Of those with respiratory issues, a majority (62%) do not believe that the COVID-19 lockdown improved their symptoms, although 16% do believe that it did. Most consider the air quality in their city as Average quality (54%). Approximately 25% of respondents consider the air quality in their city to be Very Good and Good; 20.5% believe the air quality in their city to be Very Poor and Poor.

Examining Exp(β) values from this regression, in Los Angeles, California, the odds of being Unfamiliar as opposed to Very Familiar with the AQI, holding age constant, decreases by 0.270 or 73% (Table 3). In other words, those from Los Angeles who took this survey are more likely to be Very Familiar with AQI than Unfamiliar. The same is true of San Francisco, with odds of 0.260 or 74%. In Los Angeles, also the odds of being Vaguely Familiar as opposed to Very Familiar decreased by 0.371 or 63%. From this, we can infer that those respondents from California, and specifically Los Angeles, had a greater understanding of the AQI than those from the other cities in this study.

Significant variables from Regression 4 at 95% confidence included Perception Change, Primary Causes, and Air Quality Impressions. From this regression, most respondents are Equally Concerned about air quality now as they were before the pandemic (66%) and 24% are Even More Concerned. This was true of respondents in all geographies, with 64% of respondents in Chicago, 66% of respondents in Los Angeles, 58% of respondents in Miami, 65% of respondents in New York, and 57% of respondents in San Francisco reporting feeling Equally Concerned

Table 3
Regression 3 Results Comparing Unfamiliar Air Quality Index (AQI) and Vaguely Familiar AQI Significant Variables With the Reference Category Very Familiar AQI

					95% (β)	Confidence interval
Familiar AQI	Location	Std. Error	Sig.	Exp(β)	Lower bound	Upper bound
Unfamiliar	Los Angeles	0.47	0.01	0.27	0.11	0.68
	San Francisco	0.70	0.06	0.26	0.07	1.023
Vaguely Familiar	Los Angeles	0.45	0.03	0.37	0.15	0.90

Note. Odds = Exp(β), Percentage = Exp(β) − 1 *100, Numbers rounded to the nearest 10th. Degrees of Freedom = 1.

about air quality in the present as they were before the pandemic. In Tampa Bay, however, 73% of respondents reported feeling equally concerned about air quality in the present as they were prior to the pandemic. Therefore, across all geographies assessed in this study, the majority of respondents reported feeling equally concerned about air quality in the present time as compared to their feelings toward air quality prior to the pandemic.

When asked to determine the primary causes of air pollution in their area, most people (42%) selected Vehicular Emissions, which was consistent with the results of our previous research, which revealed that vehicular emissions contributed greatly to air pollution in most of our cities of interest (Elshorbany et al., 2021). The next highest source people believed to be a primary cause of air pollution in their area is Industrial Processes, with 28% of people selecting this option. Many respondents (44%) answered that other factors related to the pandemic do not affect their impressions of the importance of air quality. Although, a majority (56%), indicated that their impressions are affected by the pandemic in some way, with 19% of individuals indicating health concerns as the reason (see Figure 6).

3.3. Impacts on Traffic Regulations and Policies

Nominal variables from Regression 5 included Traffic Regulations and Electric Vehicles. Results from this regression showed that a majority of respondents (62%) believe the United States should enforce stricter air quality standards. Although, 20% of respondents were unsure about this. Most people (37%) indicated they take several actions to reduce their carbon footprint. Actions that most participants are willing to take to reduce their carbon footprint include LED light conversions, limiting travel, solar panel installations, trying to conserve

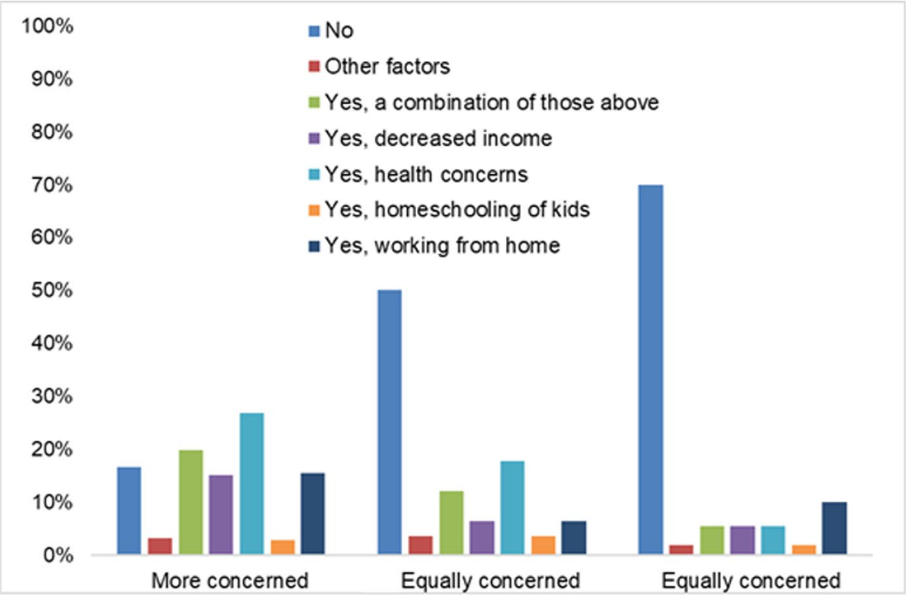

Figure 6. Perception of air quality in general and air quality impressions.

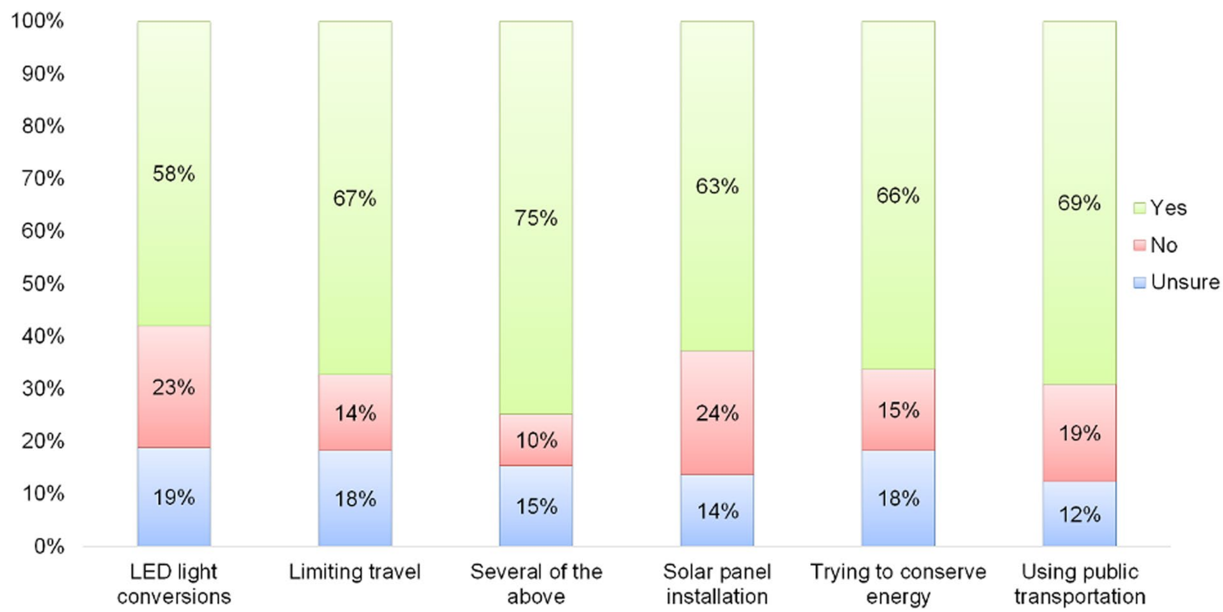

Figure 7. Support for stricter air quality regulations and personal actions participants take to reduce their carbon footprint.

energy, and using public transportation (see Figure 7). In total, 84% of respondents are taking at least some action to reduce their carbon footprint. Most individuals (53%) support air quality regulations to reduce traffic emissions. In all of the cities examined, more respondents reported "Yes" in support of stricter air quality regulations than "No" in opposition, across all income brackets. Many respondents (40%) indicated they support the use of cleaner technology (e.g., electric cars) to improve air quality (knowing reduced traffic emissions in some places improved air quality). In total, 71% of people would support a petition to increase government spending on environmental research to better diagnose other sources of pollution. Most individuals (44%) would not relocate to another area due to air pollution in their current area, although 36% indicated Maybe. When asked which methods people would support to encourage others to use electric vehicles, 35% of people selected all of the above. Although, a significant fraction of respondents (23%) did not support any of the listed measures to encourage the use of electric vehicles. Of all survey participants, 12% indicated they were "Not Concerned" about air quality and not in support of measures to encourage the use of electric vehicles.

4. Discussion

The regression results (Table S2 in Supporting Information S1) based on our survey indicate that Hispanic or Latino respondents followed by Black or African American respondents were the most concerned about air quality. However, it was not evident through the data as to why Hispanic or Latino and Black or African American respondents had heightened concern about air quality. The results from the survey are supported by a previous study by Johnson (2011) examining the effects of differing acculturation and ethnicities on the perception of air quality, which suggested that different races including non-Hispanic White, Hispanic, and non-Hispanic black populations had slightly different perceptions of air quality. Native language/language spoken further seemed to affect perceptions of air quality (Johnson, 2011), that is, the language in which a survey is administered can affect the outcome, as this demonstrates that those from various cultures who speak different languages have differing thoughts and perspectives.

Additionally, numerous air-pollution-specific studies have found that generally nonwhite ethnic groups are more concerned about air pollution (Johnson, 2011; Macias, 2016). The study design can contribute to this phenomenon. A study found that when questions are posed in terms of environmental risks, people of color demonstrate higher levels of environmental concern than white respondents, with especially African American participants generally expressing higher concern for the environment than white participants (Macias, 2016). Furthermore, African Americans, Mexican, and Latin American immigrants all indicated perceiving greater risks from vehicular emissions than native-born white respondents (Macias, 2016). Previous studies found that African

American and Hispanic population subgroups face greater exposure to poor air quality (Mott, 1995). Generally, Hispanic and African American communities have above-average air polluting facilities and a larger amount of nonattainment areas, or areas that do not meet the national standard for air quality as directed by the National Ambient Air Quality Standards specified in the Clean Air Act (Mott, 1995; US EPA, 2014). This furthers our findings from the survey that these ethnicities have been disproportionally impacted, resulting in a negative perception of air quality. Although no conclusive evidence was found among proximity to industrial areas, education, income, and employment variables on perceptions in all cities and specifically Hispanic or Latino and Black or African American respondents, further research is necessary to determine what factors may be further influencing perceptions of air quality. This is especially important in terms of social and environmental justice and addresses the disproportionate ways in which air pollution affects communities of color. A limitation of the study was that the responses received did not exactly reflect each city's unique demographics. Although we aimed for our survey demographics to mirror the demographics of the populations within each of our sample areas, in cities such as Tampa Bay, Chicago, and New York, there were considerably fewer Black or African American survey respondents. Meanwhile, for the City of Miami, we received a higher number of Black or African American survey respondents as compared to the population of Black or African American residents in the city (Table S8 in Supporting Information S1).

Geographically, we found that people in Los Angeles, Miami, and San Francisco were the most concerned about air quality, while those in Chicago and Tampa Bay were the least concerned. This finding is only partially correlated with actual air quality changes which took place during the COVID-19 lockdown period in our areas of interest. During the COVID-19 lockdown period, Chicago experienced a general increase in NO_2 and thus worsening air quality conditions (Elshorbany et al., 2021), yet participants from Chicago expressed less concern about their overall air quality. Within the areas of Miami and Tampa Bay, Florida, and New York City, New York, there was a general decrease in NO_2 during the COVID-19 pandemic lockdown period (Elshorbany et al., 2021), which may contribute to slightly less concern about air quality. While within San Francisco and Los Angeles, California, the levels of NO_2 remained relatively constant (Elshorbany et al., 2021), there was still a higher level of concern for air quality in these areas. Furthermore, survey respondents located within California were more familiar with the AQI than those in the other states we surveyed. This may be explained by the frequent occurrence of wildfires and their impact on air quality in California, especially in the northern portion of the state. One study conducted in California on the perceptions of threat and efficacy as they relate to air quality found that those residing in areas vulnerable to wildfires and smoke tend to utilize the AQI to complement their senses, showing a relationship between natural hazards and perceptions of air quality (Santana et al., 2021). Further research is needed to determine if the frequent occurrence of wildfires has resulted in this greater concern for air quality in California. Likewise, further research is needed to better understand the reason why respondents from Tampa Bay and Chicago expressed lesser concern regarding air quality. Previous studies indicated that perceptions of air quality were not necessarily correlated with measured air quality, but were influenced by factors such as location, access to information, and socioeconomic characteristics (e.g., Brody et al., 2004).

The higher number of responses from Black or African American survey participants in Miami (25%) and New York (17%) seems to have contributed to the higher level of concern for air quality reported in these locations. Likewise, high percentages of Hispanic respondents in Los Angeles (22%), Miami (17%), and New York (13%) may have contributed to the high level of concern for air quality in these cities. The large number of Asian/Pacific Islander respondents in San Francisco (21%) and a moderate amount of Black or African American (9%) and Hispanic (11%) respondents may have contributed to a higher level of concern for air quality. The highest percentages of White respondents were located in Chicago (75%) and Tampa Bay (87%), which may contribute to the lower level of reported concern for air quality in these cities. Therefore, the cities with a higher overall percentage response rate from people of color including Miami, New York, Los Angeles, and San Francisco demonstrated a higher level of concern over those cities with a lower percentage response rate from people of color. This finding is consistent with the literature, as explained in the discussion above. See Table S8 in Supporting Information S1 for further information regarding the distribution of race of respondents in each city surveyed.

Regarding health outcomes, people with respiratory issues were found to be more familiar and concerned with the AQI than healthy individuals. This is consistent with another recent study which found that survey respondents living in a household with someone with a respiratory issue were more likely to perceive worsening pollution

(Reames & Bravo, 2019). Our results suggest that those who experience a higher risk or vulnerability to the effects of air pollution express greater concern for air quality.

Limitations of the study stem from the use of the Qualtrics company platform for survey administration. Through conducting the survey in partnership with Qualtrics, the study population was limited to those within the Qualtrics network, that is, respondents are limited to the Online Panel Distribution network of Qualtrics, through which Qualtrics sources survey participants (Qualtrics, 2021a). The Online Panel distribution function allows the author to target particular groups based on specified demographic and geographic quotas. Qualtrics then sources participants through their online panels to take the survey. We did not have direct control over how the survey was advertised, or which forums or platforms the survey was posted/provided within, thus limiting our control over the sourcing method of study participants. Additionally, this study may be improved by expanding the sample size, such that more responses can be collected for each city. One thousand survey responses were collected across all cities, weighted by the population size of each city. This resulted in some cities having comparably fewer responses than others, which limited the survey population and led to the need to merge categories and remove predictors from regressions which experienced a Hessian Matrix error. Having a larger survey sample size and larger data pool may have helped to reduce the Hessian Matrix error from occurring.

Additionally, the decision to consider the larger Tampa Bay region rather than the individual cities within the region was inconsistent with the remainder of the sample, which consisted of individual, large cities. Agglomerated Tampa-St. Petersburg-Clearwater, known as the Tampa Bay Area, is considered a metropolitan area and frequently clustered for statistical purposes (City Population, 2022). Aggregating the data of the cities within Tampa Bay, rather than considering Tampa Bay's individual constituent cities, provides for a better sample size in relation to the larger cities examined in this study, and thus a more accurate comparison within this study. Additionally, this creates a case study within the paper on regional air quality dynamics. There is also potential to expand this study to encompass larger regions of the other locations reviewed in the study, such as incorporating the larger Miami-Dade County.

Furthermore, this study shows correlations among various factors which may impact perceptions of air quality, though more research needs to be conducted to examine the causality of specific perceptions among different demographics of study participants within our areas of interest. Additional studies may also address how perceptions may vary in the future once temporary air quality improvements as a result of the COVID-19 pandemic have subsided, as old challenges impacting air quality are likely to re-emerge as normal activity resumes (Saladié et al., 2020).

The results of this study are beneficial for both policymakers and community members alike, as it is essential to document and consider the opinions of the public when creating new policy measures. As our survey results indicate, most participants support the adoption of stricter air quality standards and are willing to take personal actions to improve their carbon footprint, which is an indicator of the desire of the public to see improvements in air quality. This research may inform the policy decision-making process to address these concerns regarding air quality moving forward.

5. Conclusion

This study addresses perceptions of air quality in several cities in the United States which experienced changes to air quality as a result of the COVID-19 lockdown period. Individuals of various demographic backgrounds and underrepresented populations participated in a survey to assess perceptions of air quality, and how it relates to various health and socioeconomic factors. Multinomial logistic regression was conducted to evaluate those factors which may have impacted the survey respondents' perceptions of air quality. Overall, it was found that 73.6% of respondents within our survey sample had some level of concern regarding air quality. Hispanic or Latino followed by Black or African American respondents were the most concerned about air quality. Age, education, and ethnicity were all factors that affected concern about air quality to some degree. In agreement with previous literature, perceptions of air quality were not significantly correlated with measured air quality criteria but rather seemed to be influenced by other factors. Location, socioeconomic level, proximity to industrial areas, and respiratory conditions had an apparent impact on perceptions of air quality. Survey respondents from cities in our study area within California expressed a higher concern for air quality and greater awareness of the AQI than those within other cities. Survey respondents within Miami also expressed greater concern, with those from Chicago and Tampa Bay expressing the least amount of concern about air quality. Most survey participants indicated that they would support stricter policy measures governing air quality, such as policy measures to reduce traffic-related emissions and incentives to encourage the use of electric vehicles.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Survey questions, results, and IPSS data are available in Supporting Information S1. IPSS data file is also publicly available at https://doi.org/10.5281/zenodo.7685625.

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