The Relationship between Asthma Patient Portal Messaging and Air Quality

By

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INTRODUCTION

Asthma is a chronic medical condition that manifests as inflammation in the pulmonary airways and can lead to exacerbations characterized by symptoms like chest tightness, shortness of breath, and disrupted oxygen-carbon dioxide exchange[1]. The CDC reports a prevalence of 19.2 million U.S. adults with asthma in 2018, accounting for 107,000 hospitalizations and 938,000 emergency visits per year[2]. Air pollution is a common and potentially modifiable trigger of asthma exacerbations[3]. Self-management is a hallmark of asthma treatment and includes symptom tracking, trigger awareness, medications, and health-seeking when the risk of exacerbation increases[4]. In this section, I will explain important concepts related to my research. These concepts include the connection between asthma and air pollution, Social Determinants of Health (SDOH), Health-Seeking Behavior (HSB), and Patient Portal messages.

Air Pollution and Asthma

Air pollution is the contamination of air by chemical and physical pollutants, and is a common irritant trigger of asthma exacerbations. The main source of its production is the combustion of fossil fuels by factories and vehicles. The relationship between asthma and air pollution is well-established in scientific literature[5–12]. For example, a study in Central Europe demonstrated that adolescents residing in areas with high vehicle traffic intensity had an elevated risk of developing asthma[6]. Furthermore, the presence of pollution from pesticides in agricultural areas has been associated with increased asthma symptoms in children[7]. Industrialized areas in Durban, South Africa observed an increase in exacerbations of asthma because of pollutants like Particulate Matter 10 (PM_{10}), Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), and Nitrogen Pentoxide (NO_5)[8]. A separate study performed in Detroit, Michigan showed that elevated pollutant concentrations of Particulate Matter 2.5 ($PM_{2.5}$) and Ozone (O_3) led to increased exacerbations in asthmatic children[9]. This effect was observed even when the pollutant levels were approaching the air quality standards set by the United States Environmental Protection Agency (EPA)[9]. Furthermore, a large study of children enrolled in Medicaid across the United States also demonstrated an association between elevated PM levels and a higher prevalence of asthma[10]. Similar associations between air pollutants and asthma have been observed among asthma populations in Brazil[11] and Canada[12]. Overall, pollution, whether from traffic, pesticides, or industrialization, harms individuals' health and puts them at risk for asthma.

SDOH and Asthma

Social determinants of health (SDOH) impact the health of individuals and contribute to health disparities[13–19]. According to the US Department of Health and Human Services, SDOH can be classified into 5 general categories: economic stability, education access and quality, health care access and quality, neighborhood and environment, and lastly, social and community context[13]. An example of disparities related to 'neighborhood and environment' is the observation that people residing in areas with high concentrations of pollutants experience more asthma symptoms. Numerous studies have examined the association between SDOH categories and the symptoms of asthma. One study determined that neighborhoods in New York City with relatively higher asthma prevalence had bigger concentrations of air pollution[14]. The same study also observed that 'economic stability' is related to asthma prevalence, as neighborhoods with lower-income populations had a higher prevalence of asthma[14]. Additionally, Humphrey et. al. observed decreased lung function among lower-income communities in the Denver-Metro and Front Range region of Colorado[15]. Another study concluded that the high socioeconomic status (SES) population's respiratory health is less affected by ozone compared to low SES populations[16]. In addition, economically disadvantaged children with asthma have a higher risk of visiting the emergency department[17]. These observations have increased awareness of the interplay between SES, air pollution, and asthma as neighborhoods inhabited by low-income populations are more likely to experience poor air quality. O'Lenick et al. found that among children with asthma, the per-unit odds ratio indicated a stronger influence of air quality on emergency department visits among low SES populations, while it was lower among high SES populations[18]. Another study found that demographic and geographic data was associated with a higher risk of possible undiagnosed asthma among middle school students in Oakland, California[19]. Here we can see a health disparity influenced by SES between those living in areas with poor air quality and those without.

Health Seeking Behavior and Asthma

HSB is the act of reaching out to a care provider to improve one's health condition[20]. HSB traditionally has been evaluated through qualitative approaches such as interviews and/or surveys completed in person or through phone calls[20–22]. Although survey-based approaches can provide valuable insight into patients' understanding of their health conditions, these approaches may be subject to sources of bias and generally only measure a patient's HSB knowledge and intent rather than their actions[23]. Patient actions may be recorded with electronic health record (EHR) based patient portals with secure messaging. As a result, patient portals offer an alternative avenue for studying health-seeking behaviors.

Patient Portal and Asthma

An EHR-based patient portal is a secure online service that provides patients access to their medical records and allows them to communicate with a health provider[24]. It is a way for the patient to engage with their health by not only viewing and understanding data about their illness but also by creating a conversation. It can tell us about a patient's health-seeking behavior[25]. We can understand the health-seeking behavior of a patient by examining the frequency of messaging data in the patient portal. Although several prior studies have examined patient portal messaging in patients with asthma the effects of poor air quality on patients' health-seeking behaviors via patient portal messaging behavior is not well characterized[25,26].

Summary

Patient portals provide individuals with asthma the capability to send secure messages to healthcare providers when they are exposed to poor air quality, representing a mode of health-seeking behavior. However, patient portal use for health-seeking behavior may vary in diverse populations and differences in social determinants of health may negatively impact health-seeking behavior within specific populations. For example, if economic status is low, then patients may avoid seeking care that is costly. The impact may be greater when technology is involved since not everyone has access to or understands how to use the technology.

We are not aware of prior research evaluating the health-seeking behavior of individuals with asthma through using patient portal secure messaging when exposed to air pollution[26]. To measure health-seeking behavior, we analyzed the frequency of messages sent through the patient portal. **In this study, we examined the effect of air pollution on an asthmatic population's patient portal messaging. This includes evaluating disparities in health-seeking behaviors among adult asthmatic outpatients using a well-adopted patient portal during spikes in ambient environmental air pollution.**

Study Aims

- Specific Aim 1: Test the association between air quality and patient portal messaging behavior in an asthmatic population.
- Specific Aim 2: Test the association between air quality and patient portal messaging behavior stratified by metropolitan and non-metropolitan areas.
- Specific Aim 3: Examine the message content from unhealthy days to determine what patients communicate with their care provider.

CHAPTER 1 – The Relationship Between Asthma Patient Portal Messaging and Air Quality

Abstract

Objective: Air pollution is a common irritant trigger for asthma exacerbations. Self-management is pivotal in asthma treatment and encompasses symptom tracking, trigger awareness, medication adherence, and seeking healthcare when exacerbation risks rise. Broadly, health-seeking behaviors denote efforts to access health-related knowledge and resources to enhance health status. This retrospective study assessed the connection between health-seeking behavior and air quality, employing the frequency of patient portal messages sent from patients to physicians to gauge health-seeking behavior. Furthermore, we examined the patient message content during periods of elevated air pollution exposure.

Materials and Methods: Subjects included all adult asthmatic patients who visited a Vanderbilt University Medical Center (VUMC) clinic after January 1, 2018. VUMC is a quaternary academic medical center in Nashville, Tennessee. Patient messages were extracted from My Health at Vanderbilt, VUMC's patient portal, spanning January 1, 2018, to July 1, 2022. From VUMC's electronic health records (EHR), we gathered demographic and medical data. The Environmental Protection Agency (EPA) provided us with Air Quality Index (AQI) data, which we aggregated based on county and date. We used Spearman's correlation test to determine the relationship strength between aggregated message counts and air quality across three time spans: daily, weekly, and monthly. Finally, we categorized message content and performed a narrative review of messages sent specifically concerning respiratory symptoms and conditions.

Results: Spearman's correlation coefficient between messages and AQI ranged from 0.32 to 0.41 for monthly data analyses, indicating moderate correlation. For daily and weekly data analyses,

correlation coefficients were between 0.13 and 0.17, signifying weak correlation. All these tests yielded statistical significance ($p < 0.05$). Messages relating to respiratory symptoms or conditions constituted 7% of total messages, and environmental complaints were identified.

Conclusion: Our findings reflect a relationship between asthma patient portal messaging and air quality, which was stronger in the monthly data analysis. In addition, we found that patients commonly communicated about environmental factors that contribute to air pollution.

Background and Significance

Asthma is a chronic lung disease that causes inflammation and swelling in the airways leading to the obstruction of airflow. Common symptoms of asthma include shortness of breath, coughing, wheezing, and chest tightness[1]. In 2022, the National Center of Health Statistics reported a diagnosis of asthma in 1 out of 12 people in the US, making it one of the most common diseases in the US[27]. Furthermore, the outcomes of the 2021 survey reveal that nearly half of individuals with asthma encountered asthma exacerbations during that particular year[27]. Currently, there is no cure for asthma, and treatment is focused on the avoidance of asthma triggers and the use of medications to control symptoms[27]. Knowing how to effectively manage their condition when exposed to allergens is crucial for individuals with asthma[1].

Air pollution is contamination in the air caused by physical and chemical pollutants, and is a common environmental trigger of asthma exacerbations. Human-made processes including vehicle emissions, home heating, chemical manufacturing, or livestock care, along with natural processes including wildfires, decay of organic matter, and volcanism all contribute to air pollution[28]. Some geographical areas are prone to higher air pollution[28]. For example, California has recently experienced several large wildfires related to prolonged drought conditions. In contrast, other areas may have high air pollution because of traffic or other man-made sources, particularly in large metropolitan areas[28]. The following pollutants are known to harm those with asthma: Carbon Monoxide (CO), Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Ozone (O_3), Particulate Matter 5 (PM5), and Particulate Matter 10 (PM10)[28]. Environmental organizations monitor these pollutants to determine the air quality index (AQI), a numerical system developed by the US Environmental Protection Agency (EPA) to uniformly quantify and report the health effects of air quality conditions[29].

Asthma is a self-managed disease meaning that individuals frequently manage their symptoms and treatment in the home environment[4]. Individuals who do not know how to self-manage their asthma suffer from decreased quality of life, increased healthcare use and costs, and increased risk of early death[4]. Individuals who self-manage their asthma exhibit health-seeking behavior (HSB). HSB encompasses the actions individuals take to improve their overall health condition[20–22]. They actively seek medical assistance to alleviate asthma attacks and gain access to necessary medications. HSB is carried out in various ways, including calling a healthcare provider for advice, attending an in-person visit with a clinician, or using an electronic patient portal to message the patient's care provider[20]. Some studies suggest that engaging in health-seeking behavior can improve morbidity and mortality rates for asthma patients[20,21]. The patient portal is an online account that allows a patient to view their medical records and message their providers[25,30]. This enhances patient-clinician communication so that patients can make informed decisions about their health[24,26,30]. Patients may utilize the patient portal for HSB when they are experiencing increased symptoms or conditions that put them at risk for worsened asthma control, such as when levels of environmental air pollutants are higher.

Our current understanding of how asthmatic patients seek healthcare in unfavorable environments is limited. To address this gap, this study investigated the correlation between air quality and patient portal messaging among asthmatic individuals in Tennessee. We analyzed this relationship in both metropolitan and non-metropolitan regions of the state, and examined the content of messages exchanged during days classified as having 'Unhealthy' levels of air pollution. We hypothesized that patient portal messaging would increase during periods of poor environmental air quality.

Materials and Methods

We conducted an observational retrospective cohort study at Vanderbilt University Medical Center (VUMC), a private, nonprofit academic healthcare center located in Nashville, Tennessee. To comprehensively collect and analyze pertinent information, we obtained patient data from medical records, messaging data from patient portal records, and air quality index data from environmental records. The three diverse data sources came from VUMC's Epic Clarity database, the US Environmental Protection Agency, and the Agency for Healthcare Research and Quality (AHRQ).

The Clarity data warehouse is a relational database containing clinical data abstracted and updated daily from VUMC's Epic clinical EHR (Epic Systems, Verona, Wisconsin, USA). Researchers can access Clarity through an approval process sponsored by the Vanderbilt Clinical Informatics Center (VCLIC) that requires a monthly audit of their queries, among other requirements, including achievement of specific Epic certifications, and came about in partnership with VERA (VUMC Reporting and Enterprise Analytics). This warehouse data is HIPAA compliant. From this database, we gathered clinical data, patient addresses, and patient portal message data. The ZIP code from the patient's address was used to identify each patient's county of residence.

The patient portal messages came from Vanderbilt's electronic patient portal application, My Health at Vanderbilt (MHAV). This is an institutionally developed web- and mobile-based patient portal that became accessible to all VUMC patients in 2007 and was migrated to Epic's My Chart infrastructure in November 2017[24]. MHAV is certified for Meaningful Use Stage 1 and Stage 2 as defined by the US Office of the National Coordinator for Health Information Technology[24]. In MHAV, users have the ability to assign patient messages to either the 'Patient Medical Advice Request' or 'User Message' categories, as specified by Epic's classifications.

The EPA offers numerous public resources containing data on the environment, including comprehensive information on air quality[31]. The EPA provides methods to calculate an AQI for each pollutant based on the measured pollutant concentrations, and an overall AQI is assigned based on the highest of the six individual pollutants' AQI values for that day. The AQI score ranges from 0 to 500, and air quality is considered unhealthy for asthma patients when the AQI is over 100. We obtained daily Air Quality Index (AQI) scores at the county level by extracting pre-generated data from the EPA's Air Quality System (AQS), which serves as the official regulatory repository for air quality data[32]. We included data covering the years 2018-2022. This data contained AQI coverage for 23 out of the 95 counties in Tennessee, with a total of 42 monitors.

The AHRQ is a government agency that funds initiatives to enhance the safety and quality of healthcare in the United States[33]. The agency also focuses on developing resources, information, and data to help consumers, healthcare professionals, and policymakers make informed decisions about healthcare[33]. For this study, we used SDOH data provided by the National Center for Health Statistics (NCHS) for the year 2013 to classify individual counties as either Metropolitan or non-Metropolitan counties based on their assigned Rural-Urban Classification Scheme score[34]. Counties with a NCHS Rural-Urban Classification Scheme score of 1-4 were considered metropolitan whereas counties scored 5 and 6 were considered non-metropolitan areas[35].

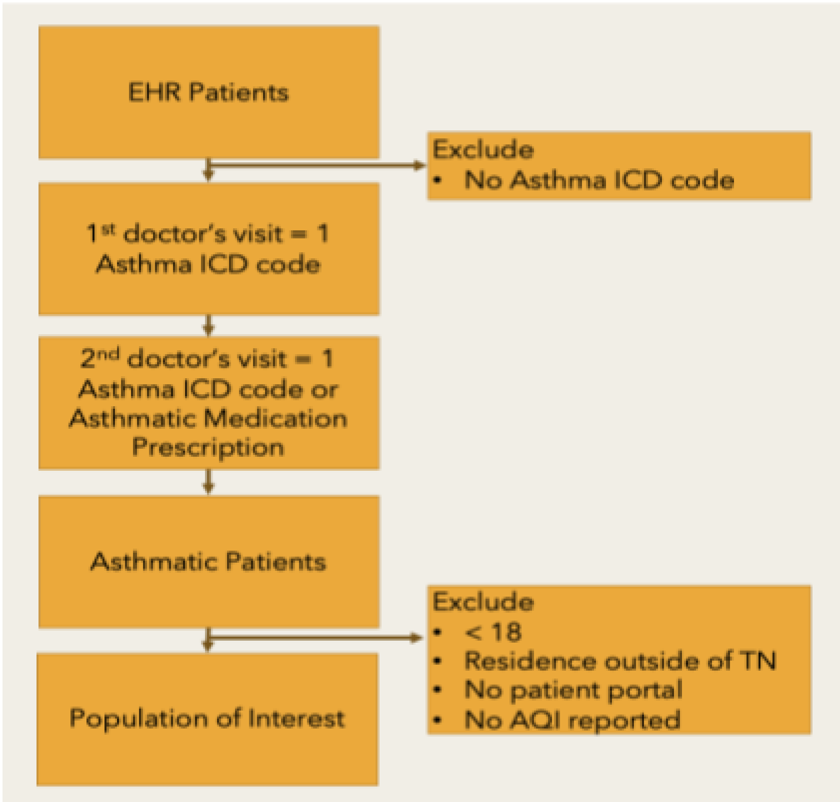
Study Population

We included all adults with asthma who sent at least 1 message through their patient portal between the dates of January 1, 2018, and July 1, 2022. The Vanderbilt University Institutional Review Board approved the study (IRB #220727). We identified asthma patients using a validated EHR asthma phenotype from the University of Chicago (Figure 1)[36]. The EHR asthma phenotype uses a combination of International Classification of Diseases (ICD) codes and medication prescription data. There are 2 ways to meet the EHR asthma phenotype criteria, listed below.

1.) Two separate doctor's visits each with an asthma ICD code present or
2.) An ICD code on the first visit and a prescribed medication on the second visit.

The asthma medications used in the asthma phenotype are listed in Appendix Table 1. We excluded patients who did not live in Tennessee, as well as those residing in Tennessee counties where an AQI score was not reported. Additionally, patients who did not message through their portal account or who were below the age of 18 before January 1, 2018, were also excluded from our analysis.

Figure 1: Schematic of Electronic Health Record Asthma Phenotype



Aim 1: Association between AQI and Patient Portal Messaging

Our first aim was to test the association between air quality and patient portal messaging behavior in our asthma population. Air quality and patient portal messaging were aggregated over three different timeframes; day, weekly, and monthly. Air quality was measured by the maximum AQI score recorded for the 3 timeframes. Patient portal messaging was measured by the sum of messages sent from each patient to their health team via the patient portal over each of the 3 timeframes. We graphed and visually assessed the aggregated air quality and patient portal messaging data separately using scatterplots to assess for visual trends in each source. We tested the correlation between AQI and message count for each of the three aggregated timeframes using Spearman's correlation test. Spearman's is a statistical non-parametric test that measures the association between two variables, with a coefficient range of -1 to 1. By utilizing three different timeframes, we could assess for potential delay in the individual's response to the air quality. We interpreted the Spearman's correlation test based on accepted biostatistical practice, where a coefficient of 1 is considered "Perfect," 0.8-0.99 is "Very Strong," 0.6-0.79 is "Moderate," 0.3-0.59 is "Fair," anything below 0.3 is considered "Poor," and a coefficient of 0 indicates "No correlation"[37].

As a sensitivity analysis, we repeated our Spearman correlation analyses using only messages categorized as "w/ Medical advice request.".

Aim 2: Association between AQI and Portal Messaging Stratified by Metropolitan Status

Residents of non-metropolitan counties may experience more barriers to accessing health care compared to residents of Metropolitan counties[38]. We compared the number of messages sent per individual through a Mann-Whitney U Test. We then repeated our correlation analyses stratified on residents in a Metropolitan versus non-metropolitan county.

Figure 2: County map of Tennessee. The counties circled in red had air quality monitors during the study period.

Aim 3: Narrative Review of Patient Portal Secure Messaging Content

We implemented a narrative research design to investigate the messaging content of asthma patients during days when the air quality was classified as ‘unhealthy’. To be more specific, we extracted message content sent by asthmatic individuals to the health team via MHAV from the Clarity database on days when their county of residence had an AQI score greater than 100.

Messages were classified into one or more of four main categories; Respiratory, Non-Respiratory, Without context, and Non-medical.

1.) Respiratory: any medical topic that is respiratory e.g. "I'm having trouble breathing", "Can you prescribe flonase?".
2.) Non-respiratory: any medical topic that is not related to a respiratory condition.
3.) Without context: related to a medical topic but not enough context to interpret e.g. "I will pick up the prescription tomorrow".
4.) Non-medical: completely non-medical, e.g. greetings, farewell, gratitude.

The classification took two rounds of coding. In the first round, two anthropologists and a biomedical informatics graduate student coded each message into those 4 categories. Any messages where the first-round coders felt they did not have enough medical knowledge to satisfactorily classify the message were reviewed in a second round of coding by two board-certified physicians with experience treating asthma. We allowed for a single message to have multiple classification labels. For example, a patient could include a message about picking up an inhaler but also mention their sprained ankle. After the final categorizations were completed, we summed the messages in each category to have a breakdown of the conversations the individuals were having with their health team. Lastly, we performed a narrative review of the messages in the 'Respiratory' category with the interest of finding messages related to unhealthy air quality.

Results

Our study population included 10,699 patients meeting the EHR asthma phenotype. During the study period, there were a total of 445,335 patient portal messages sent. The median [interquartile range] number of messages sent by each patient during the study period was 17 [6-41] (Table 4). Of these messages, 342,803 (~77%) were labeled as 'Patient Medical Advice Request' and the remaining 102,532 (~23%) were categorized as 'User Message'. The AQI data included 40 separate monitoring stations in Tennessee, which covered 21 out of the 23 counties with air quality monitors in the state (Figure 2).

Table 2: Basic Demographic

Characteristics	
Gender – no. (%)	
Female	7650 (71.50%)
Male	3049 (28.50%)
Ethnic Group – no. (%)	
Not Hispanic, Latino/a, or Spanish origin	9523 (89.00%)
Other Hispanic, Latino/a, or Spanish origin	253 (2.36)
Unknown	135 (1.26%)
Decline to Answer	82 (0.77%)
Mexican, Mexican American, or Chicano/a	52 (0.49%)
Puerto Rican	32 (0.30%)
Cuban	6 (0.06%)
Age – median (IQR)	45 (31-59)

Aim 1: Air Pollution and Patient Portal Messaging Trends over Study Period

AQI ranged substantially over the 4.5-year study period, and we observed substantial daily and seasonal variation patterns in the data. There were 31 days (affecting 22 separate calendar weeks, or 18 separate calendar months) that had an AQI score over 100 (Figure 3). In contrast, we observed a somewhat steady increase in patient portal message counts over the study period (Figure 4), with a notable marked increase after March 2020 corresponding to the arrival of the SARS-CoV-2 pandemic in Tennessee. An interesting observation from our analysis is that the message count per day follows two distinct trend lines: the higher trend corresponds to messages sent during weekdays, while the lower trend represents messages sent during weekends.

Figure 3: AQI Values During Study Period. The three scatter plots represent the highest daily, weekly, and monthly AQI values (respectively).

Figure 4: Patient Portal Message Counts During Study Period. The three scatter plots represent the daily, weekly, and monthly totals of patient portal messages sent by the study population (respectively).

Aim 1: Association between AQI and Patient Portal Messaging

We observed weak but statistically significant correlations between patient portal messaging and maximum AQI for the daily and weekly analyses both when analyzing all messages and when analyzing only those messages flagged as being "Medical Advice". Additionally, we observed a fair correlation for monthly analyses of both message groups. By observing the plots from these tests we can see that the confidence intervals (light blue) were at their widest in the regions of high AQI. This is expected due to the lower number of high-AQI events during the study period.

Table 3: Spearman's Correlation Results for Aim 1

Spearman's	**Daily**		**Weekly**		**Monthly**	
All Messages	$r = 0.14$	$p = 6.2\times10^{-9}$*	$r = 0.16$	$p = 0.013$*	$r = 0.40$	$p = .0029$*
Medical Advice Only	$r = 0.14$	$p = 1.1\times10^{-8}$*	$r = 0.15$	$p = 0.019$*	$r = 0.40$	$p = .0028$*

* $p < 0.05$

Figure 5: Message Count vs Maximum AQI. The three scatter plots represent daily, weekly, and monthly analyses (respectively).

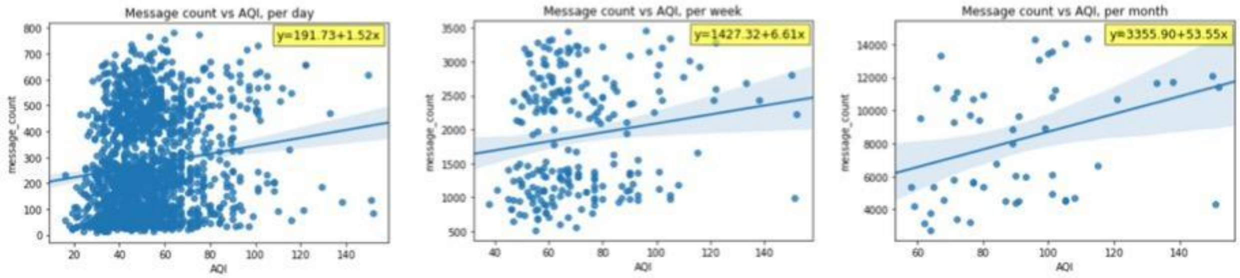
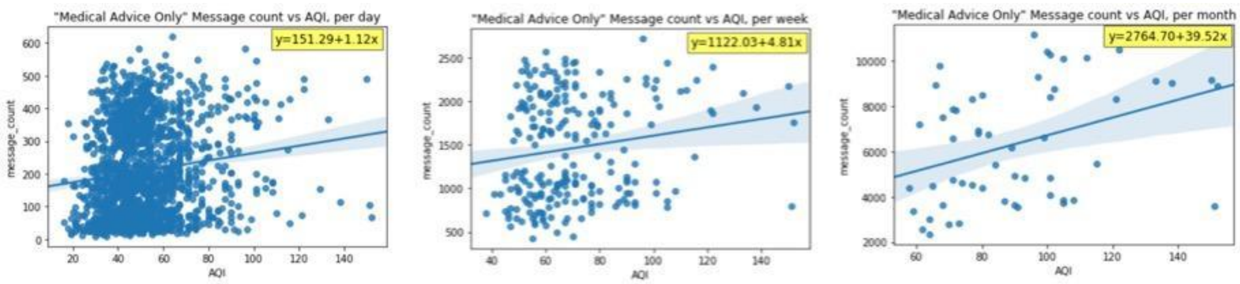


Figure 6: Message Count vs Maximum AQI for ‘Medical Advice Only’ messages. The three scatter plots represent daily, weekly, and monthly analyses (respectively).



Aim 2: Analyses of Metropolitan versus Non-Metropolitan Residents

Among the 21 counties with available AQI data, 16 counties (Williamson, Maury, Davidson, Sumner, Wilson, Montgomery, Hamilton, Madison, Shelby, Knox, Sullivan, Blount, Roane, Loudon, Jefferson, Anderson) were classified as Metropolitan, and 5 counties (Putnam, Lawrence, Sevier, Dyer, Claiborne) were classified as non-metropolitan. Out of the 10,699 asthmatic individuals, 124 lived in non-metropolitan areas and sent 6,651 messages over the study period. This leaves Metropolitan areas with a total of 438,684 messages coming from 10,575 asthmatic individuals. Table 4 displays the basic statistics for messages sent per person residing in Metropolitan vs Non-metropolitan areas. Patients residing in non-metropolitan counties had higher messaging rates compared to patients from metropolitan counties ($p = 0.05$ by Mann-Whitney U test).

Table 4: Basic Statistics for messages sent per person

Population	Number	Median (Interquartile Range)	Overall Range	Mean
Overall	10,699	17 (6-41)	1-2,397	41.60
Metropolitan	10,575	17 (6-40)	1-2,397	41.48
Non-Metropolitan	124	27 (8-27)	1-592	53.64

* $p < 0.05$

Spearman's test yielded weak but statistically significant correlations for daily and weekly analyses of both 'Metropolitan' and 'Non-Metropolitan' patients. In addition, there was a fair correlation for monthly analyses of both strata (Table 5, Figure 7, Figure 8). We can see that the confidence interval (light blue) is at its widest when AQI is high due to the lower number of data points in that region. Also notable from Figure 8, we still observed significant correlations between AQI and patient portal messaging frequency among non-metropolitan counties even though AQI never went over 100 throughout the 4.5 study period.

Table 5: Spearman's correlation results for Aim 2

Spearman's	Day		Week		Month	
Metropolitan	$r = 0.14$	$p = 9.5\times10^{-9}$*	$r = 0.17$	$p = 0.010$*	$r = 0.41$	$p = .0020$*
Non - Metropolitan	$r = 0.13$	$p = 3.4\times10^{-6}$*	$r = 0.14$	$p = 0.021$*	$r = 0.32$	$p = .0018$*

* $p < 0.05$

Figure 7: Message Count vs Maximum AQI for Metropolitan Areas. The three scatter plots represent daily, weekly, and monthly analyses (respectively).

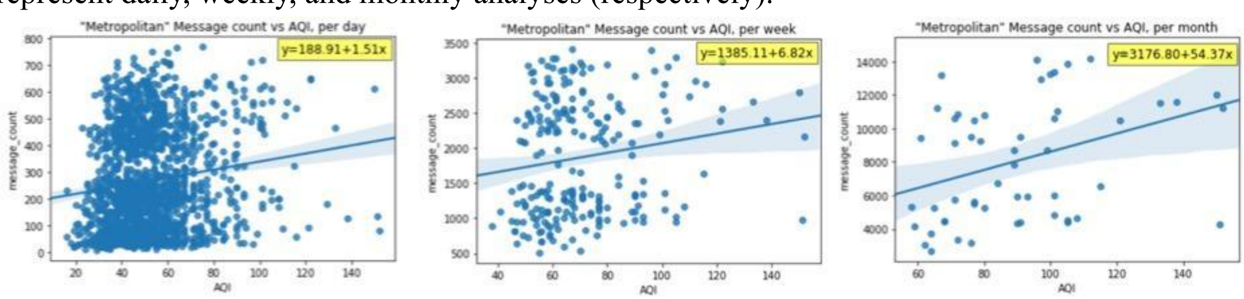
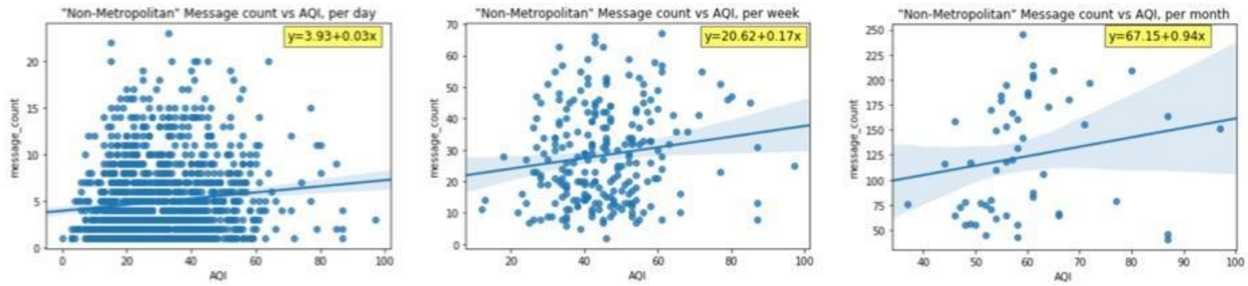


Figure 8: Message Count vs Maximum AQI for Non-Metropolitan Areas. The three scatter plots represent daily, weekly, and monthly analyses (respectively).



Aim 3: Narrative Review of Patient Portal Message Content during High AQI Periods

We extracted message per day content from patients residing in counties that had days where AQI was over 100. In other words, if Davidson County had a day with an AQI of 102, then we would calculate the number of messages sent for that same day. There was a total of 31 days (1.9%) in the 4.5 years that had at least one county with an AQI over 100 ('unhealthy for sensitive groups') resulting in 2,666 messages coming from 1,358 patients residing in ten counties (10/23, 43% of all monitored) for those days. After a manual review of message content, 189 (7%) messages were labeled as 'Respiratory'. A narrative review of these messages revealed frequent descriptions of symptoms, inquiries for medical and medication advice, and requests for different forms of medical treatment/diagnosis as seen in Table 5. These messages also mentioned environmental factors contributing to air quality such as heat, pollen, mold, and wildfires.

Table 6: Patient Portal Message Content classified as Respiratory.

Topic	Examples
Symptoms	sinus, coughing, wheezing, sneezing, congestion, chest pain, shortness of breath, mucous, drainage
Advice	• Medical: insurance, travel, med cost, follow-up • Medication: mixing info and alternate options
Request	medications, labs, appointments, equipment, specialists
Environment	heat, pollen, mold, wildfire, poor air quality

Discussion

We identified statistically significant relationships between AQI and patient portal message counts among adults with asthma. These associations remained significant when our data was aggregated either on a daily, weekly, or monthly basis. The rho coefficient signaled that AQI and patient portal counts have the strongest relationship when looking at the monthly period. Day and week periods may have low rho correlations due to higher variability in daily messaging counts compared to monthly. This also suggests that a monthly basis is a suitable period to capture relevant portal messages. This is an interesting observation, as a recent meta-analysis suggested the lag time between exposure to poor air quality and asthma exacerbations to be a week at maximum[5]. In theory, it might be that the patients who are sending more messages experience subacutely worse asthma control over weeks/months following poor air quality periods[5]. This information can be used to design proactive systems to improve self-management practices for asthma patients. For example, a text or patient portal messaging system could be employed to alert asthma patients on days when the air quality is unhealthy to prompt increased awareness of environmental conditions or ensure they have adequate supplies of their asthma medications.

We also found that the messaging rates were higher among patients residing in non-metropolitan areas. This suggests that patients residing in non-metropolitan areas are more likely to message through their patient portal compared to those in metropolitan areas. This could reflect less direct access to in-person healthcare compared to metropolitan areas[38]. In addition, even though all non-metropolitan counties included in our study did not experience any days considered unhealthy for sensitive people (AQI over 100), they still had higher overall messaging rates during the study. Asthmatic individuals living in rural areas may be exposed to localized allergens that the monitor does not pick up. This could be through exposure to hay when feeding livestock or mold from a creek.

In the 31 days where AQI was greater than 100, about 7% of all messages submitted through the patient portal by our study population were directly related to respiratory topics. We identified 4 main themes from the messages. Most messages mentioned the symptoms they were experiencing such as coughing, wheezing, and shortness of breath. The second theme involved asking for medical or medication advice such as what medications can be mixed and whether insurance covered their medication. Asthmatic individuals would also message to request appointments, labs, and medications. Finally, asthmatic individuals also messaged their healthcare team concerning their environment. They would prepare themselves with spare medications before traveling to protect themselves from the California wildfires. They would also acknowledge that the heat, pollen, or air quality affected their health and therefore need refills. As a part of future work, we would like to revisit this category and see how much of those were messaging for an acute respiratory problem.

Strengths of our study include a narrative review of the messages sent on days when air quality was poor. In addition to the use of statistical tests for 3 timeframes. This study also has some limitations to consider, such as generalizability. This study focused on asthma patients who received care at our institution and had a home address in a Tennessee county with at least one EPA air quality monitor. However, there are limitations to consider. Firstly, the air quality index was determined solely based on the county of each patient's listed home address, without taking into account other locations such as their workplace or vacation spots. Given the retrospective nature of this study, it is understandable that we lack such information. Nevertheless, patients may spend significant amounts of time in environments not monitored by their assigned air quality monitor, or they may spend a significant amount of time in an environment that did not have any air quality monitor in our dataset. Also, some patients have unstable housing or may have moved during the study period. Additionally, the assignment of Metropolitan status to each county was based on 2013 data. This is the best data available in the SDOH database and we assume that a county has not changed its metropolitan status since then. Furthermore, our primary analyses included all messages sent through the patient portal, and we did not omit messages relating to other non-asthma conditions. This could be overcome in future analysis through the use of Natural Language Processing (NLP). Additionally, all of our correlation analyses used the highest AQI in the state for that day, week, or month. This is a limitation and could be improved on by calculating the average AQI score for the state or by incorporating county-level data using a multilevel modeling framework. Lastly, it is important to acknowledge that patients may have other preferences for seeking healthcare, such as calling or visiting a clinic in person, rather than using the patient portal messaging system alone. In addition, patients may receive care through clinics or hospitals outside of our system, which may affect patient portal messaging behavior as well.

Conclusion

Overall, we observed statistically significant correlations between air quality and health-seeking behavior among asthmatic adults receiving care at our center. The strongest correlations were observed when the data was aggregated on a monthly basis suggesting that a monthly basis may be a suitable period to assess the relationship between air pollution and HSB in asthma patients. Metropolitan and non-metropolitan areas had the same result with similar outcomes. Even though non-metropolitan areas did not experience bad air quality, they messaged more compared to patients in metropolitan areas. Our narrative review found that a significant portion of the messages sent during high AQI periods related to respiratory topics, and patients commonly mentioned environmental factors as a contributor to their health-seeking behavior.

SUMMARY

Summary of Results

This study identified a significant positive relationship between air quality and health-seeking behavior as assessed by patient portal messaging for an asthmatic population at VUMC. This relationship was seen when data was aggregated over daily, weekly, and monthly periods. The analyses over monthly aggregation periods resulted in a fair correlation, which was the strongest relationship in this study. This finding does raise the question if a monthly period is a suitable time frame for a person to respond to AQI. In a way, the messages sent can be seen as a reflection of the urgency of the problems people are messaging about, and it also may reflect how asthmatic individuals self-manage their asthma around periods of exposure to worse air quality. We also found that there is a positive statistically significant relationship among patients residing in metropolitan and non-metropolitan areas. Through qualitative analysis, we observed that many of these patients use the patient portal as a tool for health-seeking behavior and are aware that the environment plays a role in their health. This is important because although there is much research on air pollution and asthma, less is known about using the patient portal as a tool for assessing health-seeking behavior.

Limitations

The study focused on asthma patients at Vanderbilt with a home address in a Tennessee county with at least one EPA air quality monitor. This limited the diversity in the population. In addition, the study does not consider the air quality in other locations such as an individual's workplace or vacation spots. The assignment of Metropolitan status to each county was based on 2013 data which could have changed in the past decade. We did not omit messages related to other non-asthma conditions and this can be improved by the use of machine learning methods such as NLP. Also, the correlation analyses used the highest AQI in the state for that day, week, or month, which is a limitation that could be improved by using average AQI scores or incorporating county-level data. Lastly, patients may have other preferences for seeking healthcare and may receive care through clinics or hospitals outside of the system.

Future Directions

This research could be expanded on by validating in additional settings or patient populations, with a focus on assessing the use of patient portal messaging systems among more diverse populations. Potential distinctions could arise from geographic disparities in the distribution of environmental air pollution, or from differences in the racial, ethnic, and socioeconomic backgrounds of individuals affected by asthma. This diversity may give additional evidence that there is an association between air quality and health-seeking behavior. The rigor of this work can also be enhanced by adjusting for other factors such as seasonality, consecutive days of high AQI, patient demographics, and socioeconomic indicators through generalized estimating equations.

Conclusion

There is a substantial amount of evidence to support the relationship between air quality and asthma. However, the health-seeking behavior in asthma patients when exposed to poor air quality has been lacking. Gaining an understanding of how individuals with asthma seek healthcare can assist in their self-management. In this study, we discovered a positive correlation between air quality and health-seeking behavior. Furthermore, we observed that individuals with asthma are conscious of how their environment affects their health and utilize the patient portal as a means to access healthcare.

APPENDIX

<u>Table 1</u>: Asthma medications and RxCUIs used to identify asthma patients in the EHR

Medication Name	RxCUI	Brand Name	RxCUI
Beclomethasone Dipropionate	1348		
Budesonide	19831		
Flunisolide	25120		
Fluticasone Propionate	50121		
Mometasone	108118		
Triamcinolone	10759		
Ciclesonide	274964		
Budesonide-Formoterol	389132		
Fluticasone-Salmeterol	284635		
Mometasone furoate	30145	Dulera	1372704
Fluticasone Furoate + Vilanterol		Breo	1539887
Montelukast	88249		
Zafirlukast	114970		
Zileuton	40575		
Cromolyn Sodium	3538		
Nedocromil	31563		
Omalizumab	302379		
Levalbuterol	237159		
Albuterol Sulfate	142153		
Metaproterenol	7688		
Pirbuterol	33767		
Terbutaline	10368		
Salmeterol	36117		
Formoterol	25255		
Arformoterol	304962		
Indacaterol	1114326		
Aminophylline	689		
Theophylline	10438		
Ipratropium Bromide	203212		
Tiotropium Bromide	393575		
Aclidinium Bromide	1303097		
Umeclidinium Bromide	1487512		
Albuterol + Ipratropium	214199		
Umeclidinium + vilanterol	1487518		

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