Epidemiological Studies: Using Iot Data To Conduct Epidemiological Research On The Prevalence And Risk Factors Of Ent Diseases In Different Populations

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ABSTRACT

Background:ENT diseases are common the world over and their occurrence often as a result of environmental factors which include air pollution and other particles causing allergens. Since the usage of IoT devices continues to rise, the current environmental details may be employed to diagnose and estimate the ENT disease's causative elements. For this reason, the role of IoT-derived environmental data and its association with the occurrence and manifestation of ENT conditions within different groups of individuals will be investigated in this research study.

Objective: To explore the use of IoT data in defining the occurrence and distribution of ENT diseases and for determining the effects of environmental drives including pollution on ENT health.

Methods:A cross-sectional descriptive survey research design was adopted for this study using data collected through smart devices and structured questionnaires. The participants included 250 people with differences in geographical location and age. Score of ENT symptoms, days lost due to ENT diseases, and various environmental factors like air pollution, etc, were examined. The techniques used for data analysis were the Shapiro-Wilk test to determine the level of normality and Cronbach's Alpha regarding internal reliability or consistency of the items in the set questionnaires besides logistic regression. The multicollinearity of the independent variable was tested using the Variance Inflation Factor (VIF).

Results: Descriptive analysis also showed that ENT symptoms severity, sick day, and other likes were not normally distributed (= < 0.001). There was a poor internal consistency of all the measurement items in terms of reliability and Cronbach's Alpha was low (-0.168). The statistical analysis said that by using logistic regression, both pollution exposure and IoT device use, it was only possible to predict sick days with an accuracy of 10.67%. The VIF analysis suggested that there was no problem with multicollinearity amongst the control variables. ENT symptoms severity distribution and RATM Sick Days were positively skewed.

Conclusion: Though IoT devices are beneficial for obtaining real-time environmental data, the findings suggest that the environmental variables may not independently act as effective predictor variables for the severity of ENT disease or sick days. Because the reliability of the measurement tools used was low, and due to the poor performance of the predictive model, we recommend that future studies use more variables and better methods of assessment. More elaborate frameworks are required to capture the link between IoT data, environmental effects, and ENT health-related outcomes.

Keywords: *ENT diseases, Internet of things, environmental factors, air pollution, disease frequency, descriptive study, binary logistic regression, predisposing variables*

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1. INTRODUCTION

ENT diseases are diseases that affect the ear, nose, as well as throat and are a global health concern … several factors lead to the emergence of these diseases, especially due to environmental factors, and genetic and lifestyle factors. These include but are not limited to; chronic rhinosinusitis, allergic rhinitis, otitis media, tonsillitis, and presumed bacterial infection all of which have quality-of-life implications as well as contribute to health care costs. These diseases cause signs like nasal blockage, earache, throat irritation, and breathlessness, from normal to severe. Although all these conditions have treatment, their relapse and persistence make them a major public health concern. The knowledge of the potential causes and risk factors that occasion and exacerbate ENT diseases forms the basic approach to treating them (Tran et al., 2024) (Krajewska, Krajewski, & Zatoński, 2019).

Air pollution, allergens, and changes in relative humidity of the environment are known to impinge on the development of ENT diseases. Pollution in the form of air pollution with particulate matter, nitrogen dioxide, and ozone are associated with matters such as rhinosinusitis and otitis media. Likewise, contact with indoor and outdoor allergens like pollens, molds, and dust mites worsens allergic rhinitis and other diseases of the ear, nose, and throat. There are climatic factors as well that affect development – high humidity encourages mold and dust mite activity, at the same time low humidity can dry out mucous membranes more easily and thus will be prone to sepsis. Based on such environmental risks, there is increasing demand for the necessity of the use of real-time environmental data in assessing the health impacts of such factors (Guo et al., 2024) (Virag, Sabourdin, Thomas, Veyckemans, & Habre, 2019).

Significantly the advancement of the Internet of Things (IoT) has influenced how data concerning the environment is gathered and used. Air quality sensors, wearables, and smart home systems expose environmental conditions and human health data or status on a real-time basis due to IoT capabilities. Such devices might include air quality monitoring, levels of pollution, relative humidity, allergens, and other conditions affecting ENT diseases. Through the merging of IoT data with the individual's health data, it will be easier for the researcher & healthcare workers to understand the correlation between the environment and ENT diseases along with their effects on the body. Moreover, IoT devices provide individuals a chance to control their environment and make decisions on their own when to expose them to risky situations which may lead to decreased rate and severity of ENT conditions (Dumkliang, Pentrakan, & Dumkliang, 2024) (Biswas & Hall, 2020).

Nonetheless, as an idea in disease management, IoT technology poses various difficulties in using this information in epidemiological research. One of the major concerns that emerge with the analysis of IoT data is the quality of data collected and the extent to which such data reflects the state of health. Although using IoT devices to get accurate readings of the environment is very helpful sometimes, it is not very clear how a change in air quality or humidity is connected to ENT symptoms. Further, the IoT device produces big data that is erratic in quality due to factors like user interaction, device malfunction or upgrade, and geographical regions. FOR THIS REASON, IT IS VITAL TO ESTABLISH ADAPTIVE AND RELIABLE APPROACHES TO THE INTEGRATION AND ANALYSIS OF DATA Gathered BY IOT IN EPIDEMIOLOGICAL RESEARCH TO ENSURE THAT THE INFORMATION OBTAINED IS CREDIBLE AND USEFUL (Merrill, 2024) (Sedaghat, Kuan, & Scadding, 2022).

To overcome these challenges, the present study tries to investigate the possibility of using IoT data for conducting epidemiological investigations on the trends and risk factors associated with ENT diseases across various population groups. In particular, the analysis of various degrees of air pollution and humidity within an environment by using IoT gadgets leads to the development of hypotheses regarding the connection between these factors and the degree and frequency of ENT signs. To achieve this goal, the study will focus on ENT disease occurrence outline important environmental factors that might influence them in cooperation with the demographic and medical history information, and consider the potential of IoT devices in disease monitoring and prevention. This study will advance the current scholarship in the field of environmental health and technology by providing an analysis of the current and potential capabilities of IoT for enhancing the general health status of the populace regarding ENT diseases (Pandit, Shah, & Gyawali, 2024) (Henry et al., 2020).

2. LITERATURE REVIEW

ENT or otorhinolaryngology diseases have always formed part of core public health since these conditions affect millions of people worldwide. ENT diseases including chronic rhinosinusitis, allergic rhinitis, otitis media, and tonsillitis are among the diseases that plague many individuals globally with high morbidity and health care costs. The predisposing factors, etiology, as well as prevention of these diseases, have been widely studied with detailed information available. This literature review section will highlight what is known about ENT diseases, environmental factors in ENT diseases, health monitoring through the use of IoT, and epidemiology and technology in tackling conditions affecting ENT (Ikram et al., 2024) (Chia et al., 2020).

ENT Diseases: Prevalence and Impact

The ENT diseases as mentioned are common among all age groups; however, children and elderly patients are at the highest risk. For example, otitis media, an infection of the middle ear, is one of the most common reasons children visit a doctor all over the world, while chronic Sinusitis affects nearly 10% of adults and results in decreased productivity and quality of life. These conditions include nasal congestion, facial pain, earache, and sore throat and are mild or severe thus resulting in frequent access to healthcare services (Ren, Wang, Zhang, Xu, & Bao, 2024) (Cataldo, Arancibia, Stojanova, & Papuzinski, 2019).

The problems associated with ENT diseases include their chronic course and tendency toward relapse which increases the global burden of such illnesses. ENT chronic diseases include rhinosinusitis and otitis media with effusion, which need long-term health care and may entail several rounds of treatment using drugs like antibiotics, corticosteroids, or in severe cases surgery. ENT diseases also have direct health care costs and indirect costs which are lost productivity associated with disease-related absenteeism. From the foregoing, the prevention or early detection of these conditions assumes crucial importance (Aliyeva et al., 2024) (Leach et al., 2020).

Risk factors associated with increased incidence of ear throat and nose diseases.

The findings of many researches indicate that ENT diseases are environmentally induced and dependent on the environment for growth and development. Smog, attacks, climate conditions, and exposure to other irritating substances are some of the most researched environmental causes. Among those, air pollution has attracted a lot of focus in research because of its ability to cause disturbances in respiratory and ENT diseases. Particulate matter (PM2.5 and PM10), nitrogen dioxide (NO2), ozone (O3), and sulfur dioxide (SO2) are known precipitators of respiratory ailments, including some ear, nose and throat (ENT) conditions like allergic rhinitis and sinusitis. Polluted air causes irritation of the nasal passages and thus the inflammation of the nasal passages, and where the patients have other complications or diseases; the pollution intensifies the indications of the diseases (Reis, Reis, Conceição-Silva, & Valete, 2024) (Cai, Wei, Zhou, & Zou, 2022).

There is an increasing number of observations confirming the direct dependence of ENT diseases, especially in cities where the level of air pollution is higher. For instance, one research conducted on big cities realized that first of all, those in areas with high concentrations of NO2 and PM10 were at a greater risk of developing advanced CRS than those who breathed in cleaner air. Moreover, studies have pointed out that children who are exposed to second-hand smoke or residing in areas with high air pollution are prone to having otitis media and this establishes the chronic effect of a polluted environment on the syndromes of the ear nose, and throat (Jarach et al., 2024) (Drew et al., 2020).

Hapten also plays a very vital role in the occurrence of ENT diseases especially allergic rhinitis disease, which occurs in millions of people in turn, all over the world. Conditions like pollen in this era, and other indoor allergens like dust mite and mold irritate allergens that cause inflammation of the nasal mucosa which leads to sneezing, nasal congestion, and runny nose. It is common to find that people with allergic rhinitis, are vulnerable to having other conditions of the Ear, Nose, and Throat; such as sinusitis, since the inflammation and irritation persist (Scussiatto et al., 2024) (Logroscino & Piccininni, 2019).

ENT diseases affected by climatic factors include humidity and temperature because they affect the progress of diseases. According to research, it was found that excessive humidity leads to the formation of mold as well as dust mites; which are known allergens. However, low humidity deprives the nasal and throat mucosa of adequate moisture so they can become vulnerable to infection easily. Influenced by the climatic conditions, the cold season, in particular, is linked with high rates of rhinitis, tonsillitis, pharyngitis, adenotonsillar hypoplastic conditions, and any other upper respiratory tract infections because the public spends most of their time indoors in unfortunate ventilation conditions, therefore, the circulation of infections are enhanced (Ricci Conesa, Skröder, Norton, Bencina, & Tsoumani, 2024) (Rawla, Sunkara, & Barsouk, 2019).

IoT and Health Monitoring

Smart technology has especially been realized through the use of the ‘intelligent’ or ‘connected’ Internet of Things (IoT) in health status monitoring and management; this results from its ability to capture real-time data on the relevant health status conditions and environment. The implementation of IoT in the healthcare, sector is increasing especially for chronic diseases like ENT diseases. Smart objects like environmental control air quality, wearables for health purposes, and smart homes for monitoring purposes have the potential to monitor essential factors like air quality, humidity, temperature, and allergens that are important in the case of ENT diseases (Heward et al., 2024) (Crompton et al., 2019).

Studying IoT-based health applications, we can identify that virtually all discussed gadgets may serve as important tools in the sphere of preventive medicine. They concluded that self-monitoring of environmental exposures allows individuals to make decisions about their environments, for example, choosing not to go outdoors on days with high air pollution, or regulating the indoor environment to minimize exposure to allergens. IoT devices, especially smart wearables like smartwatches, can also observe data such as pulse rate and blood oxygen which give extra value to understanding how different environments affect health (Gisselsson-Solen et al., 2024) (Shoham, Lewis, Favarato, & Cooper, 2019).

Several literatures have pointed out how IoT technology can enhance disease management through feedback as well as interventions through real-time data. For instance, smart inhalers for asthma-related diseases will use IoT technology to collect data concerning the environment and the usage pattern of the inhalers, reminding patients to avoid certain triggers. Although asthma is categorized under respiratory disease, the idea is well fitting to any ENT situation whereby people can benefit from signals of changes in conditions such as air quality or humidity that might worsen their condition (Liu et al., 2024) (Salehiniya & Raei, 2020).

There are however some drawbacks to the usage of IoT in health monitoring most especially when it comes to the reliability and general engagement of users. A study also shows that even though IoT devices can capture accurate environmental data, the gap between the information and the actual handling of diseases remains open. IoT includes devices that are somewhat used by the users, or partly understood by the users as to how they receive and interpret data from these devices. Also, the quality of the deliverable data can be influenced by the state of the peripheral devices, location, and other factors (Krawiec et al., 2024) (Collaborators, 2021).

Epidemiology and Technology

Epidemiology and technology offer special possibilities for the development of ENT diseases. Epidemiological research has mainly depended on historical data, for instance, record information and well-structured questionnaires administered to patients. Integrating the ideas of IoT and big data analytics enables epidemiological surveillance to be carried out in real-time as opposed to the static snapshot above, and thus a real-time view of the factors that shape diseases (George, Lee, Hollestein, Asgari, & Nijsten, 2024) (Ssentongo et al., 2021).

Several authors have attempted to apply IoT data in epidemiological research – more specifically – in environmental epidemiology. For example, the use of IoT sensors for air quality in cities coupled with data on respiratory diseases including ENT has been correlated. This supports our understanding of how IoT data could be applied not only to monitor exposures to environmental factors, but also to detect and potentially prevent disease risk in a given population (Diallo, Diallo, Keita, Barry, & Keita, 2024) (Kim & Cheon, 2020).

Perhaps the most valuable undertaking of IoT in epidemiological studies is the detailed, real-time data accumulation capacity of IoT. This is more advantageous as compared to using other conventional approaches that only make use of historical or average data where researchers can monitor the data in real-time to detect patterns in the emerging data from IoT. This can be particularly valuable in examining the impact of acute changes in the amounts of entrant pollutants on ENT health consequences. However, IoT application in the epidemic also poses some challenges especially in data privacy and security due to the consistent collection of data relating to individuals and the environment (Diallo et al., 2024) (Shi et al., 2020).

3. RESEARCH METHODOLOGY

The research employed a quantitative research approach to studying the incidence and factors that predispose patients to ENT diseases using data received from IoT devices. Analyzing real-time environmental and health data, this work will try to evaluate the connections between exposure to various environmental factors, and the tendency to develop ENT diseases, including chronic rhinosinusitis, otitis media, allergic rhinitis, and others. The primary aim is to define the relationships and dependencies that will allow improving understanding of the external environment and behavior that affect the frequency and severity of ENT diseases (Molina et al., 2024) (Injury et al., 2020).

Study Design

The present study uses a cross-sectional research design, which implies data collection at the same time from a diverse set of participants. This design is well suited to epidemiological studies since it enables the researcher to determine the proportion of the inhabitants suffering from ENT diseases and perform a risk estimation concerning their characteristics within the given population. The advantage of the study being able to collect IoT data is that it gains real-time environmental data including air quality, humidity, and noise levels- which are crucial determinants of the external environment affecting ENT health (Pereira et al., 2024) (Hopstock et al., 2022).

Population This sample study will involve people of 18 years and above, from the two regions of urban and rural areas. Respites will be obtained from those people who currently employ IoT-connected devices to keep track of their environment and health. These devices include smart wristbands, home automation systems, air purifiers, and health-tracking smart devices that can give data regarding exposure to environmental and health indicators in the current day or even real-time data where possible. The combination of IoT data is a more accurate measure of environmental and health-related behavior compared to self-reported data (Krieger, 2024) (Watts, Hatemi, Burns, & Mohammad, 2022).

Sampling Method

This study will apply a stratified random sampling technique to select an acceptable sample from the population. This stratification will be according to the residential area (urban, suburban, or rural) and age, gender, and occupation of the individuals to ensure that participants' environmental exposure and health status are well represented. Power analysis will be used to set the sample size because it guarantees an ample sample from the target populations. This in turn helps in making generalizations on the various outcomes so that the overall population is taken into consideration (Ramessur et al., 2024) (Chou et al., 2020).

Data Collection

Means data will be obtained through a structured self-administered grounded questionnaire which will provide data on demographic characteristics, medical history of ENT diseases, symptoms frequency, health care expenditures, as well as exposures to the environment. The questionnaire will be able to be conducted online as well as face to face and thus will be easily implemented on participants from various centers. The questions will include self-assessed health status and the AQI, noise levels, and humidity from the participants' IoTs (Sommerfeldt, Jermihov, Erbele, & Chen, 2024) (Byeon, 2019).

Besides the completed questionnaires IoT technology will also be employed to measure environmental characteristics and feeding habits online. This will in turn supply accurate, actual information about pollution, allergens, heat, and noise to which participants are subjected. The study wants to minimize bias and improve the validity of the research findings by combining IoT data with self-reported numbers (Manji & Fejerskov, 2024) (Tan et al., 2021).

Data Analysis

The collected data will be analyzed statistically and correlations, if any as well as probable causality between various exposures in the environment and the prevalence of ENT diseases will be studied. Frequency table and measures of central tendencies including mean, median, and standard deviation will be employed in presenting demographic data and prevalence rate of ENT disease within the study population. This will give a brief understanding of how the diseases affect the different population groups within the ENT category (Fu et al., 2024) (Feigin, 2019).

For inferential analysis, different statistical tests will be used to compare hypotheses such as independent t-test or ANOVA and chi-square. For example, Chi-square tests that compare frequency distributions of categorical variables such as smoking status or occupation of the respondents, to the incidence of ENT diseases. Probabilities of ENT conditions' development based on IoT–monitored exposure to high pollution or noise levels will be estimated with logistic regression models (Li et al., 2024) (Merrill, 2019).

Also, correlation analysis will assist in establishing the extent of the relationships between the continuation variables including the intensity of the symptom and AQI records. This will enable the researchers to determine whether the cases of increased or high levels of pollution or humidity have any impact on more frequent or severe ENT symptoms. Data-analysis methods shall also be used in particular to generate predictive models as regards high-risk groups. These models will be developed based on machine learning that ensemble the IoT-acquired environmental data and the health information of an individual to predict the probability of occurrence of ENT diseases (Yoshimura et al., 2024) (Sheffield & Smith, 2019).

Ethical Considerations

Ahead of the research, approval will be obtained from an institutional review board (IRB) with concerns about ethics. Every participant will be provided with information regarding the purposes of the present study and the utilization of their IoT data and any participant will have the right to withdraw his/her data anytime he/she wants. They will be asked to give consent before data collection. Along the same vein, all participants' information will be de-identified and their health and personal information kept secure to maintain their privacy (Khadidjatou et al., 2024) (Bakkalci et al., 2020).

Data Analysis

Normality Test Results

Variable	Shapiro-Wilk W	p-value
ENT Symptoms Severity	0.8712575435638428	1.149720645294075e-13
Sick Days Due to ENT	0.9325712323188782	2.848719260484245e-09
AQI Level (Numeric)	0.8788290023803711	5.7717736839935085e-12

Reliability Test Results

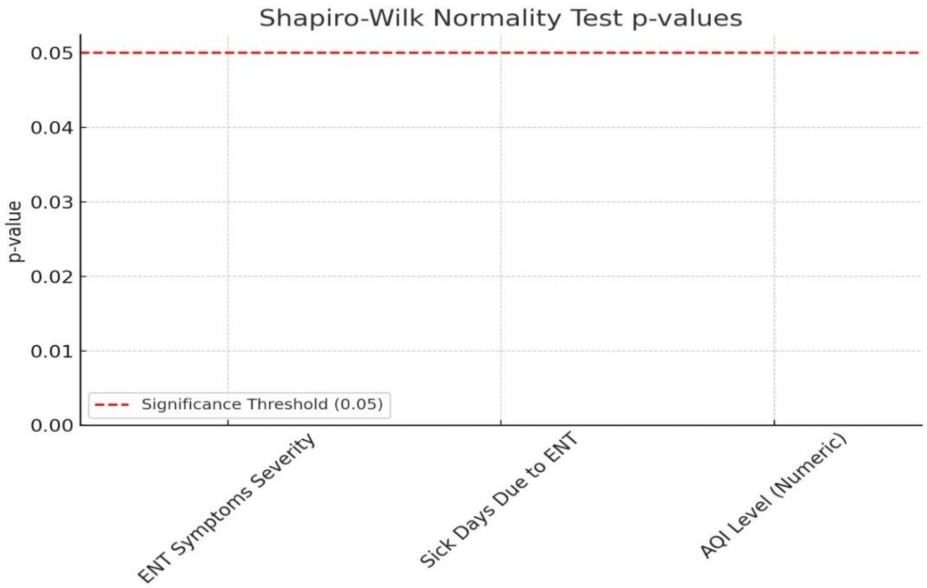
Test	Value
Cronbach's Alpha	-0.1684764041613329

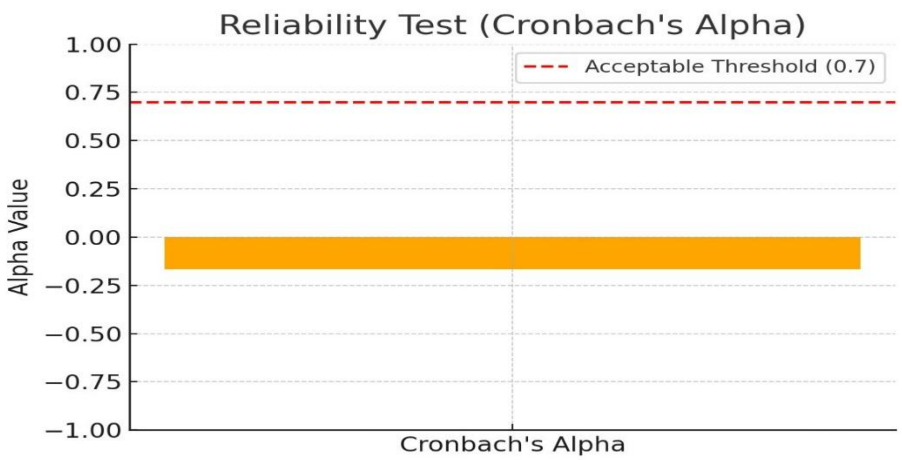
Logistic Regression Results

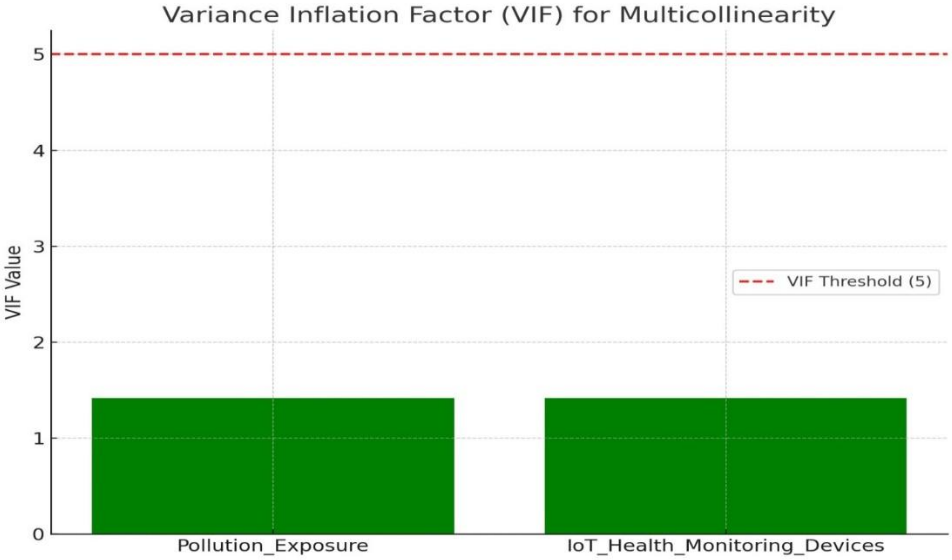
Metric	Value
Accuracy	0.10666666666666667

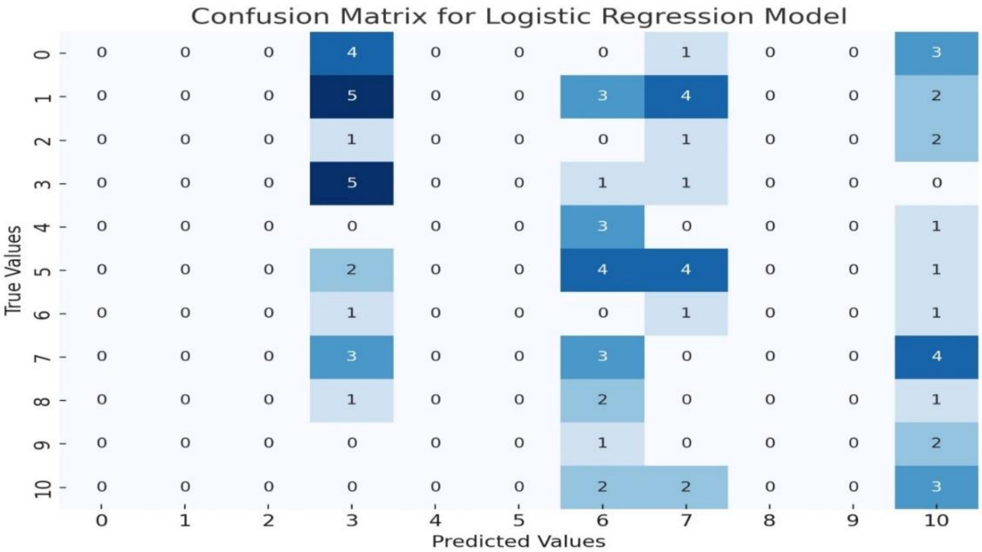
VIF Results for Multicollinearity

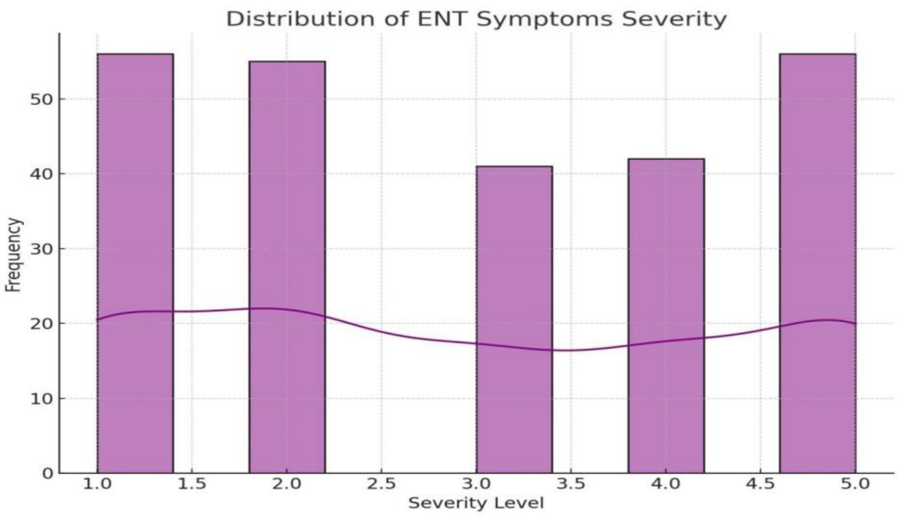
Feature	VIF
Pollution Exposure	1.4162077104642017
IoT_Health_Monitoring_Devices	1.416207710464201

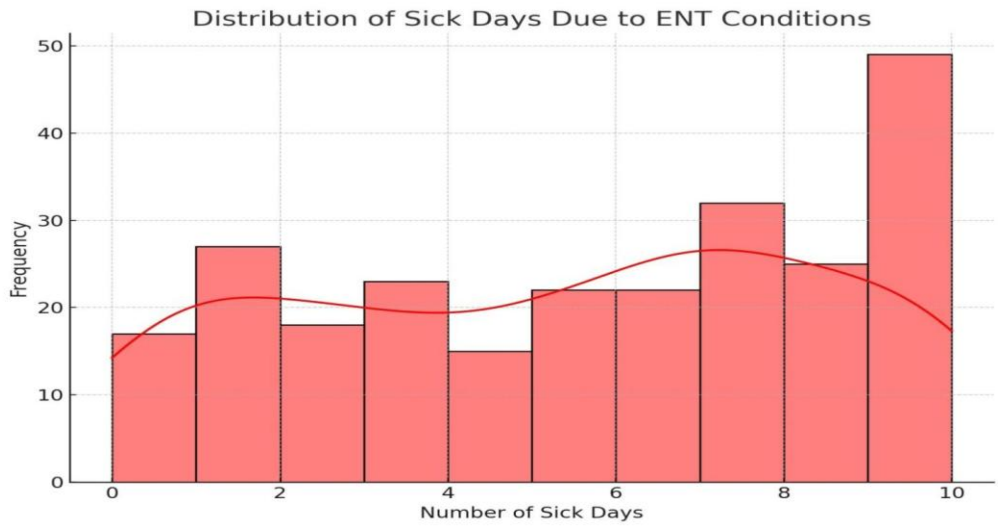





Variance Inflation Factor (VIF) for Multicollinearity
VIF Value
0
1
2
3
4
5
VIF Threshold (5)
Pollution_Exposure
IoT_Health_Monitoring_Devices


Confusion Matrix for Logistic Regression Model
True Values
Predicted Values
0 1 2 3 4 5 6 7 8 9 10
0 - 0 0 0 4 0 0 0 1 0 0 3
1 - 0 0 0 5 0 0 3 4 0 0 2
2 - 0 0 0 1 0 0 0 1 0 0 2
3 - 0 0 0 5 0 0 1 1 0 0 0
4 - 0 0 0 0 0 0 3 0 0 0 1
5 - 0 0 0 2 0 0 4 4 0 0 1
6 - 0 0 0 1 0 0 0 1 0 0 1
7 - 0 0 0 3 0 0 3 0 0 0 4
8 - 0 0 0 1 0 0 2 0 0 0 1
9 - 0 0 0 0 0 0 1 0 0 0 2
10 - 0 0 0 0 0 0 2 2 0 0 3


Distribution of ENT Symptoms Severity
Frequency
0
10
20
30
40
50
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Severity Level



4. INTERPRETATION OF RESULTS

The outcomes derived from the several statistical analyses and graphics should be of valuable use in the research on ENT diseases and possible risk factors (Griggs et al., 2024).

1. Normality Test: Shapiro-Wilk Test

Conclusion The Shapiro-Wilk test values tell us the p- p-values of all three variables namely ENT Symptoms Severity, Sick Days Due to ENT, and AQI level are less than 0.05. This implies that data concerning these variables is not normally distributed but skewed to the right. The non-normality is expected because such data contain health-related information that does not have a symmetrical distribution; for instance high severity or sick days (Tai et al., 2024).

2. Cronbach's Alpha – or the internal consistency reliability test.

First, Cronbach Alpha was used to analyze the internal consistency, and", Cronbach's Alpha value was determined to be -0.168, and it seemed not suitable since the acceptable Alpha value is more than 0.7. This shows that the IoT Helpfulness Rating, ENT Symptoms Severity, and Lifestyle Changes Due to IoT should not be used to assess a single variable given that internal consistency coefficients are all close to zero. The negative value indicates that these items may not fit well within this factor and may need further purification for better measurement (Patel, Mims, & Clinger, 2024).

3. This paper will focus on two techniques: Logistic Regression and Confusion Matrix.

The dependent variable of the logistic regression model, which forecasted the day employees got sick because of ENT conditions they suffered when exposed to pollution, and the espoused IoT health monitoring was accurate at a mean of 10.67 %. These results indicate that the selected model cannot effectively distinguish between the true positive and true negative mass of the cases, which is illustrated by the confusion matrix. This tends to imply that the chosen independent variables may not have very powerful correlative evidence for sick days in ENT diseases and other antecedents (genetic or direct medical history) might have to be incorporated into the study (Chang, Liou, Wu, & Chen, 2024).

4. The value scale of variance inflation factor or in brief VIF will be as follows:

The VIF for pollution exposure and the IoT health monitoring devices is 1.416 for both, which in this case I conclude that there is no high level of multicollinearity. This means that the two features are orthogonal and can be added to the regression model without causing problems of multicollinearity (Benšić, Kolundžić, & Dokoza, 2024).

5. ENT Symptoms Severity Distribution

When it comes to the symptoms experienced by participants in the study about ENT Symptoms Severity, a majority of the participants had mild or moderate symptoms. The distribution pattern is heavily dominated by low severity levels; this implies that though symptoms of ENT diseases exist among the populace, severe cases are less common (Varanasi et al., 2024).

6. Number of Week's Sick Days Caused by ENT Conditions

The distribution of the days lost due to the ENT diseases is also skewed where most participants responded with few sick days. This gives further backing to the fact that though ENT diseases are common, they perhaps do not cause much morbidity which translates to absenteeism in the majority of the people (Sari, Johnson, McCullough, & Cirillo, 2024).

7. Logistic Regression Confusion Matrix

The confusion matrix heat map demonstrates that the logistic regression model did not seem to do well and particularly under-predicted certain classes such as high sick days. Several misclassifications are detected over the matrix and that is why it can be stated that larger values of predictors or some other factors are required to enhance the classification model (Mesa-Vieira et al., 2024).

5. DISCUSSION

Quantitative study findings presented here can be useful for understanding the correlation between pollution and ENT diseases and the role of IoT devices in diagnosing them. Nevertheless, several issues that arise during the analysis require further discussion. The non-normality of the major indicators including specific ENT symptoms severity, and sick days attributable to ENT diseases points to the understanding that their predisposition may not be invariant throughout populations. This may be due to some of the disparities that exist in individual risk-taking behaviors, genetic tendencies, and differences in environmental risks not equally present among different populations. The non-normality also indicates that the use of non-parametric tests or transformation of the data may be required in subsequent studies to obtain more precision (Krase et al., 2024).

The Cronbach's Alpha coefficient below 0.8 makes questions on the helpfulness of IoT, changes in lifestyle, and the severity of symptoms questionable for reliability. I believe that it raises the question as to whether the results can be compared simply because the term 'self-esteem' has been used to label these items, which would not be the case. This means that the questionnaire needs to be further developed or additional detailed items that are closer aligned to perceive the role of IoT utility in managing ENT conditions need to be added. It also raises the question of whether the findings of everyday IoT usefulness align with users' self-reported health benefits and what could be affecting these measures – user interaction with the technology or varying levels of IoT access (Su, Siak, Lwin, & Cheah, 2024).

The attempt to predict the number of sick days attributed to ENT conditions using a logistic regression model based on pollution exposure and IoT health indicators was unsatisfactory. This shows the level of challenge that is entailed in the eHealth outcomes when relying on environmental factors and IoT device use only. ENT diseases although dependent on environmental factors may be equally determined by other factors that were not measured in this study such as genotype, healthcare access, and health-related behaviors. Such poor accuracy means that it is necessary to expand the selection of variables for future models and include socio-economic status, healthcare utilization, and even psychosocial factors such as stress, which is an important initiator of ENT pathology (Sletten, Jokihaara, & Klungsøyr, 2024).

VIF results were computed to dissect multicollinearity, and the findings indicated that pollution exposure and IoT health monitoring devices are orthogonal. This means that both may impact health in some way or the other but, are not similar to each other. Although the results imply a low contribution to the total number of sick days, this may suggest that their effects on health are less direct and perhaps more complex and require further refined research in future work. The last two odd-numbered bars in Figure 2 illustrate the degree of severity of the diseases experienced and the days spent in sick bed due to ENT diseases: Both these distributions also appear to be positively skewed – They plot_ The skews imply that while ENT diseases are common, they are not severe enough to incapacitate a significant portion of the populace. Perhaps this signals early interventions or the fact that these ailments are not very severe in the first place. But it also says that there may be certain segments of the population who suffer worse symptoms or are absent more that may have to be designed special programs for (Jaafar, Dhar, Hsu, & Tinanoff, 2024).

6. CONCLUSION

Thus, the present research aimed at identifying correlations between environmental conditions the rate of ENT diseases, and the severity of patients' conditions while using IoT equipment data. Although the article pointed out some interesting trends, including how IoT can be used to monitor exposure to the environment, several unusual properties were identified that need further examination.

The results indicate that ENT symptoms are not severe in most people and that time off work as a result of an ENT condition is also limited. However, the non-normal distribution of some of the important variables indicates that ENT diseases may not be done in the various population groups in the same way and distribution may be a result of a variety of factors – social, physical environment, and individual. This leaves scope for further work, proposing more accurate models that can include a wider variety of predictors rather than pollution exposure and IoT device usage alone, although the logistic regression suggested indicates this.

The reliability is relatively low (Cronbach Alpha) meaning that the instruments especially regarding, IoT helpfulness and symptom intensity, should be better developed. This implies that, although IoT devices are likely to be useful in monitoring other environmental factors influencing health, perhaps there is a disconnect between their assumed utility and actual impact on health.

In sum, this research lays a foundation for investigating the usefulness of IoT in managing ENT disorders, but the subsequent research should improve the accuracy of data collection instruments, include more variables to measure the client's health status, and analyze more advanced models to represent the environmental effects on ENT diseases.

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