Predicting Asthma Severity Using Machine Learning: Symptoms and Demographic Factors.

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A Project Submitted in Partial Fulfillment of the Requirements for the Degree of

M.Sc. in Statistics

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Declaration of Authorship

I, **Md Abu Saeed**, Student ID: **212205**, Registration No: **1578**, solemnly declare that the statistical project entitled **"Predicting Asthma Severity Using Machine Learning: Symptoms and Demographic Factors"** is an original and independent work carried out by me. This project has not been submitted, either in part or in full, for the award of any academic degree or qualification at any other university or institution.

The study is based entirely on secondary data, incorporating figures, charts, graphs, tables, and other relevant information collected from reliable and authentic sources. I have maintained the highest standards of academic integrity throughout this work. No content—textual, graphical, or analytical—has been copied or reproduced from any source without proper acknowledgment. All references have been duly cited in accordance with academic and ethical guidelines

Signed: Date:

Md Abu Saeed

Signed: Date:

Dr. Md. Kamal Uddin

Acknowledgement

First and foremost, I humbly express my deepest gratitude to the Almighty, whose infinite mercy, blessings, and guidance have made the successful completion of this project possible. Without His grace, none of this would have been achievable.

I would like to extend my sincere appreciation and heartfelt thanks to my respected project supervisor, **Dr. Md. Kamal Uddin**, for his continuous encouragement, invaluable advice, and thoughtful supervision throughout the research process. His insightful feedback and unwavering support have been a source of great motivation and learning.

My special thanks go to all the esteemed faculty members of the Department of Statistics, Islamic University (IU), for their generous cooperation, academic assistance, and administrative support during my academic journey.

Lastly, I owe my deepest appreciation to my beloved parents and dear siblings for their constant love, sacrifices, and encouragement. Their endless support and prayers have been a pillar of strength throughout every stage of my life, especially during the preparation of this project.

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Chapter 1

Introduction

Asthma, also known as bronchial asthma, is a chronic respiratory condition that affects individuals of all ages. It is characterized by inflammation and tightening of the muscles around the airways, which makes breathing difficult. People with asthma often experience symptoms such as wheezing, coughing, chest tightness, and shortness of breath. Various factors can trigger asthma attacks, including exposure to allergens, respiratory infections, physical activity, and sudden changes in weather. Although asthma is a long-term condition, with proper management and avoidance of triggers, individuals can lead healthy and active lives.

1.1 Types of asthma

- **Allergic Asthma** – Triggered by allergens such as pollen, dust mites, mold, or pet dander.
- **Exercise-Induced Asthma** – Brought on by physical activity, especially in cold or dry air.
- **Acute Severe Asthma** – A sudden, serious asthma attack that requires immediate medical attention.
- **Occupational Asthma** – Caused by exposure to irritants in the workplace, such as chemicals or dust.
- **Adult-Onset Asthma** – Develops in adulthood, often without a history of childhood asthma.
- **Childhood Asthma** – Begins in childhood and may continue into adulthood or improve with age.
- **Eosinophilic Asthma** – A severe form of asthma involving high levels of eosinophils, a type of white blood cell that causes inflammation in the airways.

1.2 Impact of Asthma Disease

Asthma is frequently underdiagnosed and undertreated, especially in low- and middle-income countries. Inadequate treatment can lead to ongoing health problems, including disrupted sleep, daytime fatigue, and difficulty concentrating. These issues can significantly affect daily activities and quality of life. Individuals

with asthma and their families may experience missed days at work or school, resulting in financial strain and broader social impact. In more severe cases, asthma symptoms may require emergency medical attention and hospitalization, placing additional pressure on healthcare systems.

1.3 Symptoms of Asthma disease

- **A persistent cough**, especially at night, which may worsen with cold air, exercise, or during sleep.
- **Wheezing** — a whistling or squeaky sound when exhaling, and sometimes while inhaling.
- **Shortness of breath or difficulty breathing**, which may occur during physical activity, at rest, or even when inhaling in severe cases.
- **Chest tightness**, often described as a heavy or squeezing sensation, making it hard to breathe deeply.
- **Increased mucus production**, which can clog the airways and worsen breathing issues.
- **Frequent respiratory infections**, such as colds or bronchitis, that may trigger or worsen asthma symptoms.
- **Fatigue or trouble sleeping**, due to interrupted breathing at night.

1.4 Worldwide of Asthma Disease

Asthma is a significant global health issue, affecting approximately 334 million people worldwide, with a notable prevalence among children and adolescents. In 2019, it was responsible for an estimated 455,000 deaths, with the majority occurring in low- and middle-income countries due to challenges in diagnosis and treatment. The rising incidence of asthma is linked to factors such as climate change, urbanization, and increased exposure to air pollution. These environmental changes contribute to the growing number of asthma cases globally. Asthma is recognized in the WHO Global Action Plan for the Prevention and Control of Noncommunicable Diseases (NCDs) and the United Nations 2030 Agenda for Sustainable Development, underscoring its importance in global health initiatives. Effective management of asthma is possible with proper diagnosis, medication, and lifestyle adjustments. However, underdiagnosis and undertreatment remain significant

challenges, particularly in low-resource settings. Raising awareness and improving access to care are crucial steps in reducing the global burden of asthma.

1.5 Treatment

Asthma cannot be cured, but it can be effectively managed with proper treatment. The most common and important treatment method is the use of inhalers, which deliver medication directly to the lungs. Inhalers help control symptoms and allow people with asthma to lead normal, active lives. There are two main types of inhalers used in asthma treatment:

1. **Bronchodilators:** These medications work by opening the air passages, providing quick relief from asthma symptoms like wheezing and shortness of breath.
2. **Steroids:** These reduce inflammation in the airways, improving symptoms and lowering the risk of severe asthma attacks and complications.

Depending on how often symptoms occur and their severity, individuals with asthma may need to use their inhalers daily. The choice and frequency of inhaler use are tailored to each person's condition to achieve the best control of asthma.

1.6 Objective of the study:

1. To analyze and visualize asthma severity data using graphs and frequency tables.
2. To identify significant differences in symptoms and severity across demographic groups.
3. To test hypotheses and find key factors influencing asthma severity.
4. To apply PCA for factor reduction and K-means clustering for patient segmentation.
5. To assess model performance with ROC analysis and build a neural network for prediction.

Chapter-2

Literature Review

Asthma is a chronic respiratory condition that affects millions worldwide, with severity influenced by various demographic, environmental, and clinical factors. The advancement of data analysis techniques has enabled deeper exploration of asthma symptom patterns and their relationship to severity.

Statistical analysis has traditionally been used to examine associations between asthma symptoms (e.g., coughing, difficulty breathing) and demographic variables like age and gender. Studies by Bloom et al. (2015) and Gupta et al. (2018) report significant differences in symptom presentation and severity across demographic groups, highlighting the importance of hypothesis testing and comparative analysis in asthma research.

Graphical representations and frequency tables are essential in exploratory data analysis for visualizing distributions and trends in asthma severity. These methods assist in identifying demographic patterns and symptom prevalence, as demonstrated in the work of Smith and Jones (2017).

To reduce data complexity, Principal Component Analysis (PCA) is widely used. Zhang et al. (2020) applied PCA to isolate key symptom clusters, simplifying asthma severity data and improving model interpretability. PCA helps uncover latent factors driving symptom variation and severity.

K-means clustering is frequently employed for patient segmentation based on symptom and demographic data. Liu et al. (2019) utilized clustering to identify asthma subgroups, aiding personalized treatment strategies. This approach enables tailored interventions by distinguishing patient phenotypes.

Evaluating predictive model performance often involves Receiver Operating Characteristic (ROC) analysis, which measures classification accuracy. ROC curves and Area Under the

Curve (AUC) are standard metrics in medical diagnostics, as explained by Thompson et al. (2016).

Recent advances have seen the adoption of neural networks and deep learning models to predict asthma severity. Al-Garadi et al. (2021) demonstrated that neural networks effectively classify severity levels and forecast exacerbations using multidimensional symptom and demographic inputs, outperforming traditional statistical models.

In conclusion, integrating classical statistical methods with machine learning techniques provides a robust framework for asthma severity analysis. This project leverages graphical analysis, PCA, clustering, ROC evaluation, and neural networks to enhance understanding and prediction of asthma severity, building on the established research foundation.

Chapter-3

Methodology and Data Collection

3.1 Introduction:

Reliable data is crucial for research because it ensures accurate findings. Collecting sufficient and precise data is essential for creating a robust project report. Without dependable and clear data, research outcomes can be flawed. Choosing and applying the right, methodology is vital, as it defines the research process and helps address the problem systematically. Researchers must understand not just the methodology but also the rationale behind it. This chapter discusses various aspects of research, including how to select a project title and area prepare questionnaires, collect and process data and conduct statistical analyses. It also covers concepts such as mean, standard deviation and the framework and methodology relevant to study.

3.2 Source of data:

The data in this study is collected for the Statistical Project of M.Sc(Masters) for academic course of the department of Statistics in Islamic University Kushtia. I have collected the secondary preprocessing data from the source of Kaggle platform to Deepayan Thakur student of Sharda University Dilhi, India.

3.3 Sample Design:

Sampling is an important part of any sample survey because the researcher. I collected secondary data from the Kaggle. The sample size is 316800.

The sample size is too much large but it helps me to save my valuable time and financial supports.

3.4 Description of sample and variables:

I received secondary data to my project works the sample size is 316800 and about 19 variables are included to my project work.

Tiredness: While not a direct asthma symptom, tiredness can occur as a secondary effect due to the increased effort required to breathe when experiencing other symptoms like breathing difficulties.

Dry Cough: A common asthma symptom, a dry cough is often triggered or worsened by inflammation and irritation in the airways caused by asthma.

Difficulty in Breathing: This is a key symptom of asthma, which results from the narrowing of airways, leading to shortness of breath.

Sore Throat: Although not a primary asthma symptom, a sore throat can develop in individuals who cough frequently as a result of asthma.

None Symptom/None Experiencing: These categories suggest that some individuals in the dataset do not experience any of the listed symptoms, which is possible since asthma symptoms vary and some individuals may have asthma without constant symptoms.

Pains: While "pains" is a broad term, individuals with asthma might experience chest discomfort or tightness, though this isn't a classic symptom.

Nasal Congestion and Runny Nose: These are not typically associated with asthma itself, but may be present in individuals with allergic asthma where allergies can trigger symptoms.

Age 0-9 to Age 60+: Asthma affects individuals across all ages, and the severity and frequency of symptoms may vary depending on the age group, with children and the elderly possibly experiencing different profiles.

Gender (Female/Male): Asthma can affect any gender. While gender doesn't directly cause symptoms, it may influence asthma prevalence and management strategies in different populations.

Severity (Mild, Moderate, None): These severity levels represent the different impacts of asthma on individuals, ranging from mild to moderate or absent symptoms depending on control and treatment responses.

3.5 Analysis of data:

Analysis of data is an essential part 0f any research project of studies. At first, I inter my preprocessed data into an IBM SPSS. Then I had made different types of tables, bar diagram, pie chart, frequency distribution table, association, correlation, Factor Analysis, k-Means clustering, KNN, Neural Network ROC curve.

3.6 Limitation of this project:

I faced some problem for my project work because the secondary dataset was so much large and the variable cannot define properly. I drop two variables (severity mild, severity moderate) for my better work. For a large dataset it is difficult to analysis properly.

Chapter-4

Data Analysis Part

4.1 Analysis of data:

In this analysis part by using update IBM SPSS 26 analysis different calculation of observed data is expressed in percentages. The frequency and percentage distribution table, bar diagram and pie chart.

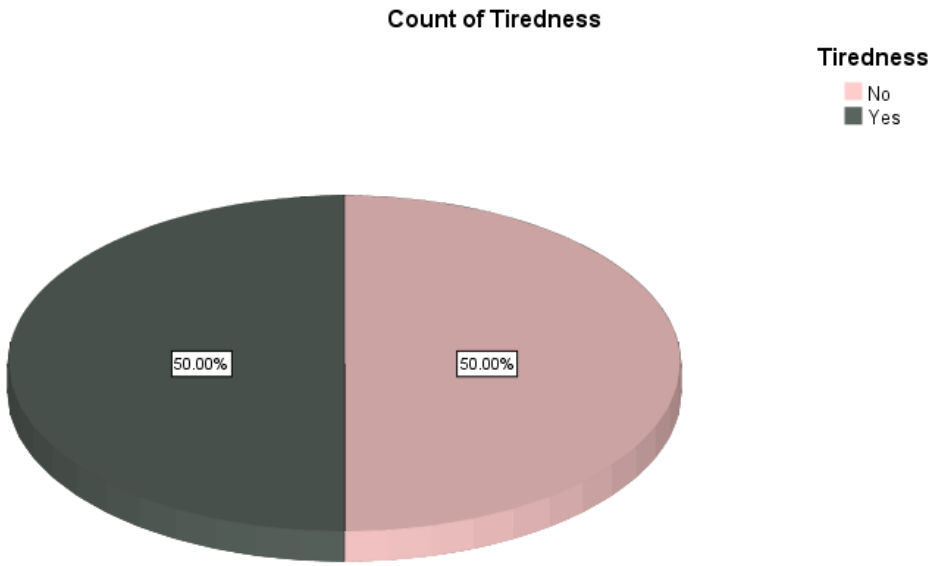
Graphical representation and frequency table:

Graphical depiction is more impactful than tabular presentation because it is readily comprehensible. We can display the outcome immediately through visual means. We examine the following key forms of graphical depiction, which are essential for our evaluation

Table no 4.01.01: Frequency table of **Tiredness**:

Tiredness					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	158400	50.0	50.0	50.0
	Yes	158400	50.0	50.0	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.01: pie chart of **Tiredness** of affecting Asthma Disease

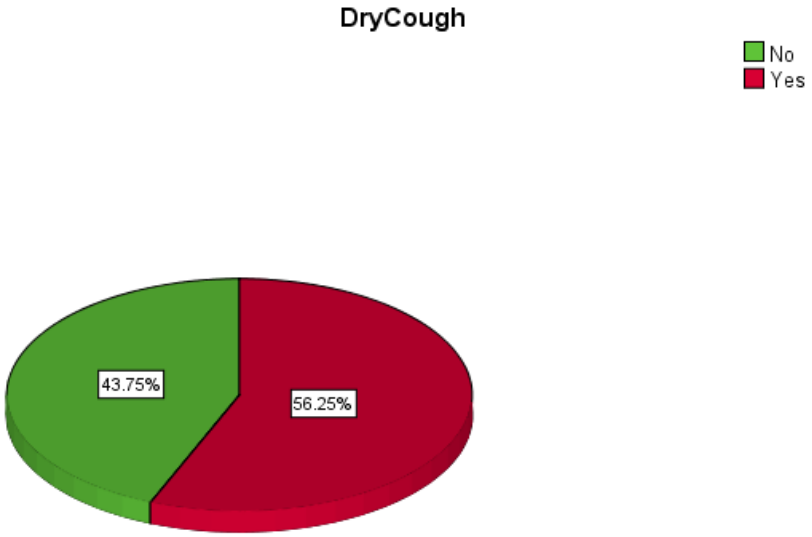


Comment: From this pie chart we can see that 50% people are feel like tiredness and 50% people are not feel tiredness.

Table no 4.01.02: Frequency table of **Dry Cough**:

Dry Cough					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	138600	43.8	43.8	43.8
	Yes	178200	56.3	56.3	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.02: pie chart of **Dry Cough** of affecting Asthma Disease

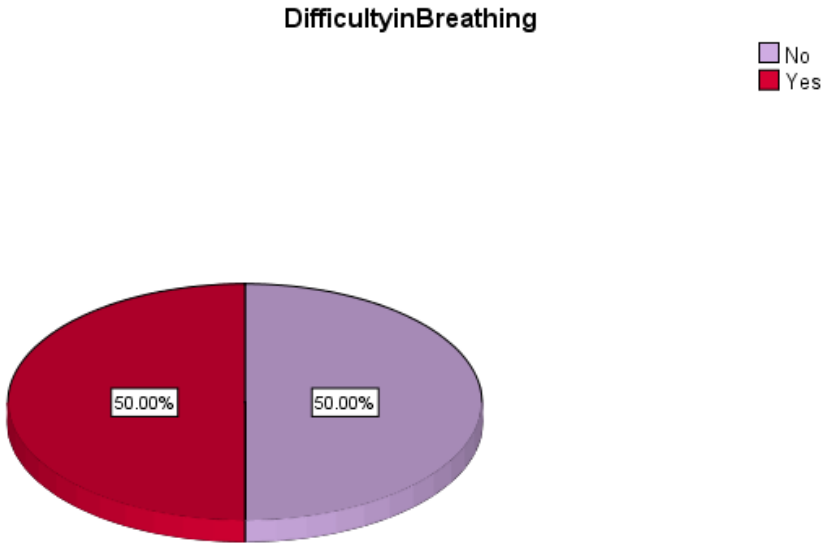


Comment: From this pie chart this we can see that about 56.3% people suffer dry cough and 43.2% people are not suffer dry cough

Table no 4.01.03: Frequency table of **Difficulty in Breathing**:

Difficulty in Breathing					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	158400	50.0	50.0	50.0
	Yes	158400	50.0	50.0	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.03: pie chart of **Difficulty in Breathing** of affecting Asthma Disease

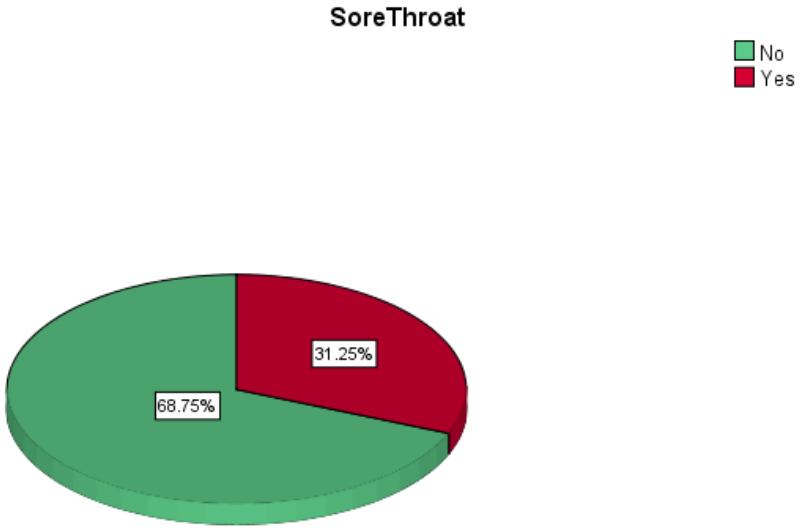


Comment : From this pie chart we can say that about 50% people are supper difficulty in breathing and about 50% people are not supper difficulty breathing.

Table no 4.01.04: Frequency table of **Sore Throat:**

Sore Throat					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	217800	68.8	68.8	68.8
	Yes	99000	31.3	31.3	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.04: pie chart of **Sore Throat** of affecting Asthma Disease

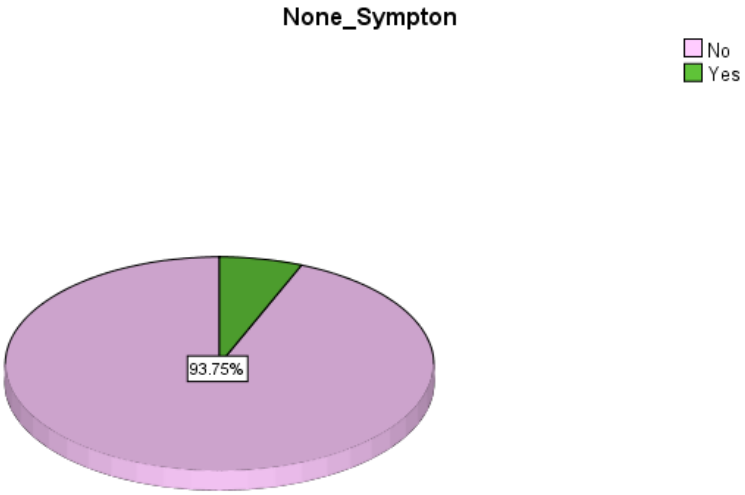


Comment: From this pie chart we can say that about 31.3% people are affecting sore throat and about 68.7% people are not affecting sore throat.

Table no 4.01.05: Frequency table of **None Symptoms:**

None Symptoms					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	297000	93.8	93.8	93.8
	Yes	19800	6.3	6.3	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.05: pie chart of **None Symptoms** of affecting Asthma Disease

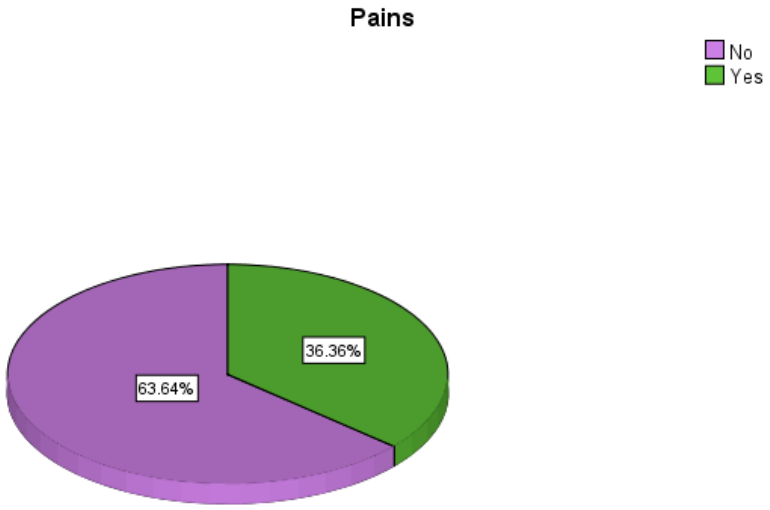


Comment: From this pie chart we can say that about 93.7% people have no non symptom and 6.3% people have non symptom

Table no 4.01.06: Frequency table of **Pains:**

Pains					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	201600	63.6	63.6	63.6
	Yes	115200	36.4	36.4	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.06: pie chart of **Pains** of affecting Asthma Disease

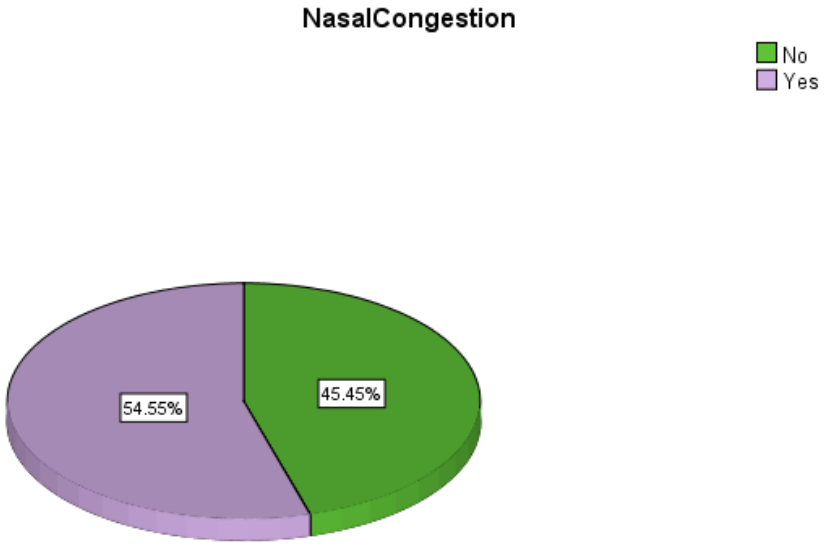


Comment: From this pie chart we can say that about 36.4% people feel like pains and about 63.6% people are not feeling like pains.

Table no 4.01.07: Frequency table of **Runny Nose:**

Nasal Congestion					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	144000	45.5	45.5	45.5
	Yes	172800	54.5	54.5	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.07: pie chart of **Nasal Congestion** of affecting Asthma Disease

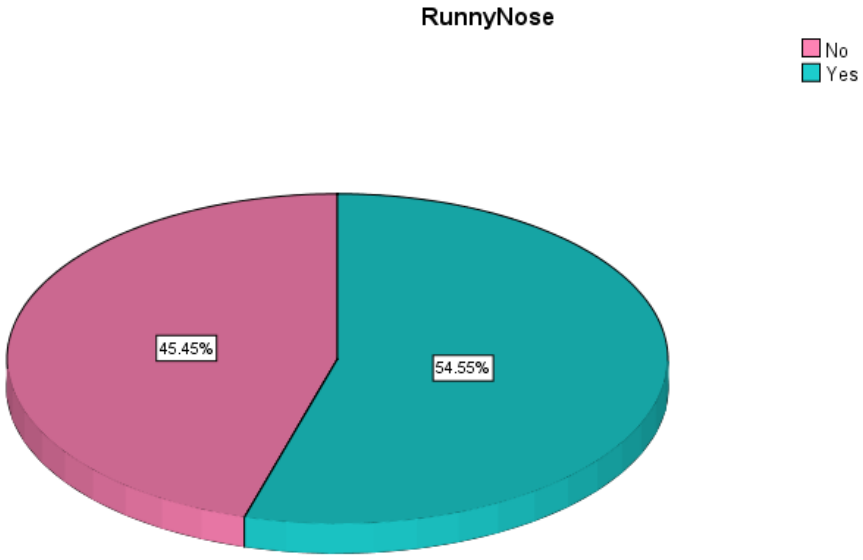


Comment: From this pie chart we can say that about 54.5% people are Nasal Congestion and about 45.5% people are not Nasal Congestion.

Table no 4.01.08: Frequency table of **Runny Nose:**

Runny Nose					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	144000	45.5	45.5	45.5
	Yes	172800	54.5	54.5	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.08: pie chart of **Runny Nose** of affecting Asthma Disease

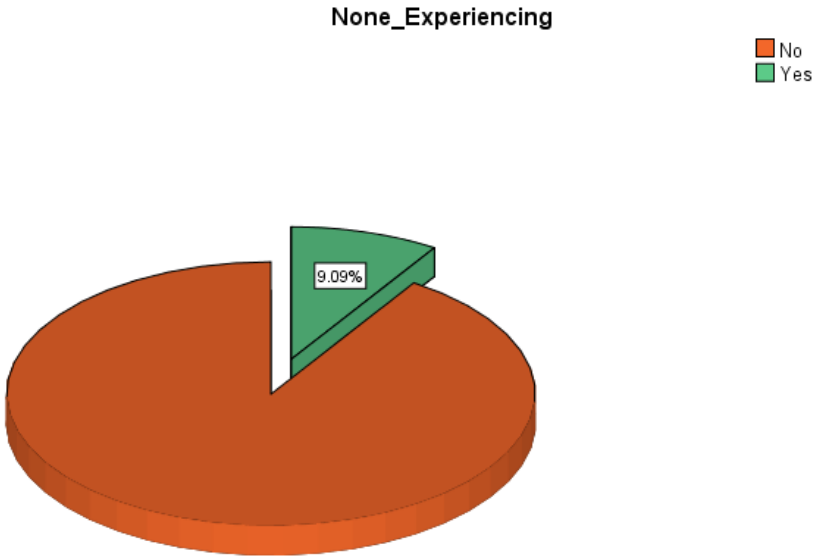


Comment: From this pie chart we can say that about 54.55% people are runny nose and about 45.45% people are not runny nose.

Table no 4.01.09: Frequency table of **None Experiencing:**

None Experiencing					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	288000	90.9	90.9	90.9
	Yes	28800	9.1	9.1	100.0
	Total	316800	100.0	100.0	

Figure no 4.01.09: pie chart of **None Experiencing** of affecting Asthma Disease



Comment: From this pie chart we can say that about 9.1% people are non experincing and about 90.9% people are not non experiencing.

4.2 Comparative Analysis, Statistical Analysis and Finding, Hypothesis:

Chi-square test is a statistical method frequently utilized for evaluating independence and fit with a theoretical distribution. Testing independence determines if observations across different groups or categories are unrelated. Goodness of fit assesses how well observed data match expected data. The goal is to chi square statistic X2 = sum (Oi – Ei)2 /E. Oi = the observed frequency, Ei = expected frequency

4.02.01: Association between tiredness and dry cough:

Tiredness * Dry Cough Cross-tabulation				
		Dry Cough		Total
		No	Yes	
Tiredness	NO	99000	59400	158400
	Yes	39600	118800	158400
Total		138600	178200	316800

Hypothesis:

H0: There is no association between Tiredness and Dry Cough.

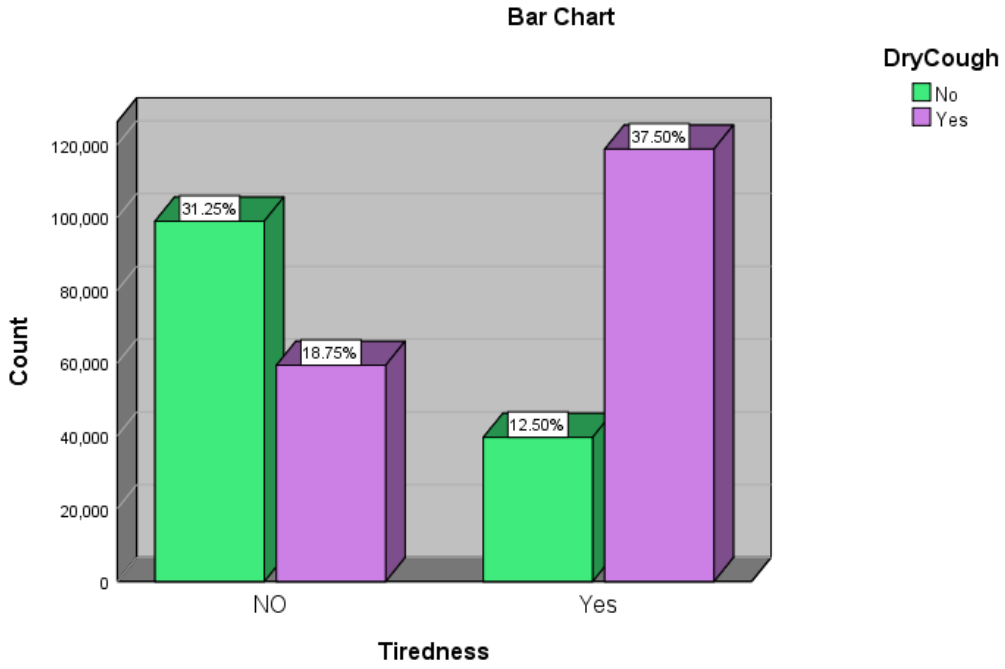
H1: There is significant association between Tiredness and Dry Cough.

Chi-Square Tests

	Value	df	P Value
Pearson Chi-Square	45257.143	1	0.001

Comment: Since P-value is less than 0.05 with DF 1 we reject the null hypothesis. So, at 5% level of significance, we can say that there is significance association between tiredness and dry cough.

Figure 4.02.01: Bar diagram for tiredness and dry cough.



4.02.02: Association between dry cough and sore throat:

Dry Cough * Sore Throat Crosstabulation				
		Sore Throat		Total
		No	Yes	
Dry Cough	No	99000	39600	138600
	Yes	118800	59400	178200
Total		217800	99000	316800

Hypothesis:

H0: There is no association between dry cough and sore throat.

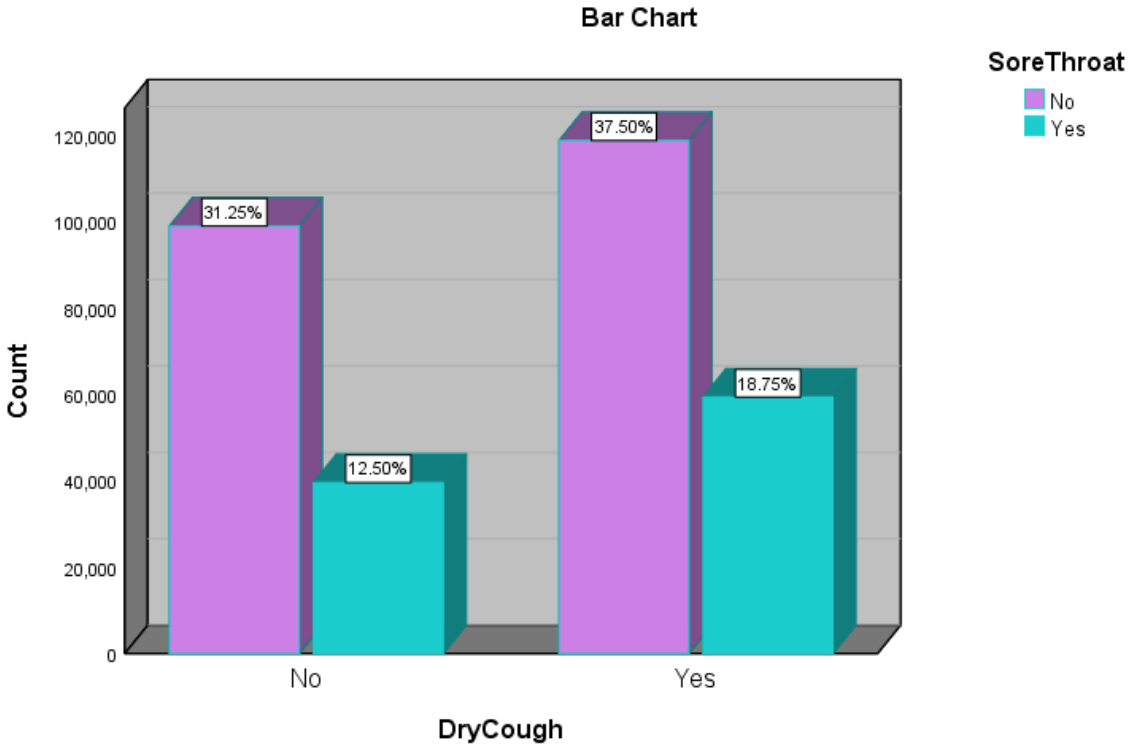
H1: There is significant association between dry cough and sore throat.

Chi-Square Tests

	Value	df	P Value
Pearson Chi-Square	822.857	1	0.001

Comment: since p-value is less than 0.05 with DF 1, we reject the null hypothesis. So, at 5% level of significance, we can say that there is a significant strong association between dry cough and sore throat.

Figure 4.02.02: Bar diagram for dry cough and sore throat.



4.02.03: Association between difficulty in breathing and sore throat

Difficulty in Breathing * Sore Throat Crosstabulation				
		Sore Throat		Total
		No	Yes	
Difficulty in Breathing	No	138600	19800	158400
	Yes	79200	79200	158400
Total		217800	99000	316800

Hypothesis:

H0: There is no association between difficulty in breathing and sore throat.

H1: There is significant association between difficulty in breathing and sore throat.

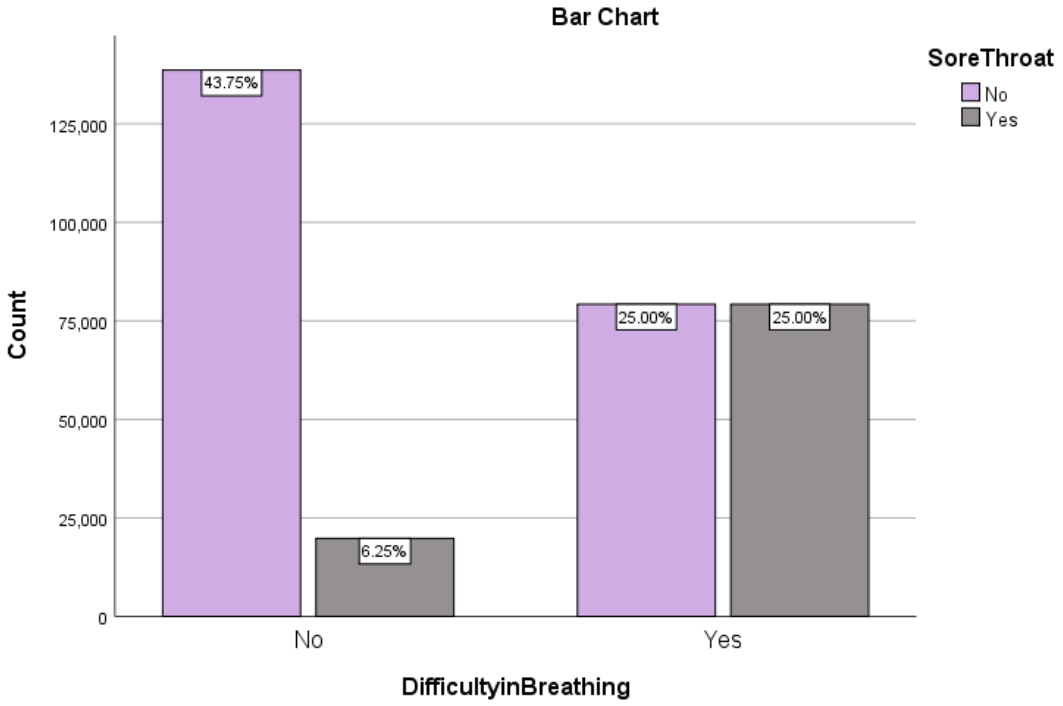
Chi-Square Tests

	Value	df	P Value

Pearson Chi-Square	51840.000[a]	1	0.001

Comment: since p-value is less than 0.05 with DF 1, we reject the null hypothesis. So, at 5% level of significance, we can say that there is a significant strong association between difficulty in breathing and sore throat.

Figure 4.02.03: Bar diagram for difficulty in breathing and sore throat.



4.02.04: Association between nasal congestion and runny nose

Nasal Congestion * Runny Nose Crosstabulation				
		Runny Nose		Total
		No	Yes	
Nasal Congestion	No	86400	57600	144000
	Yes	57600	115200	172800
Total		144000	172800	316800

Hypothesis:

H0: There is no association between nasal congestion and runny nose.

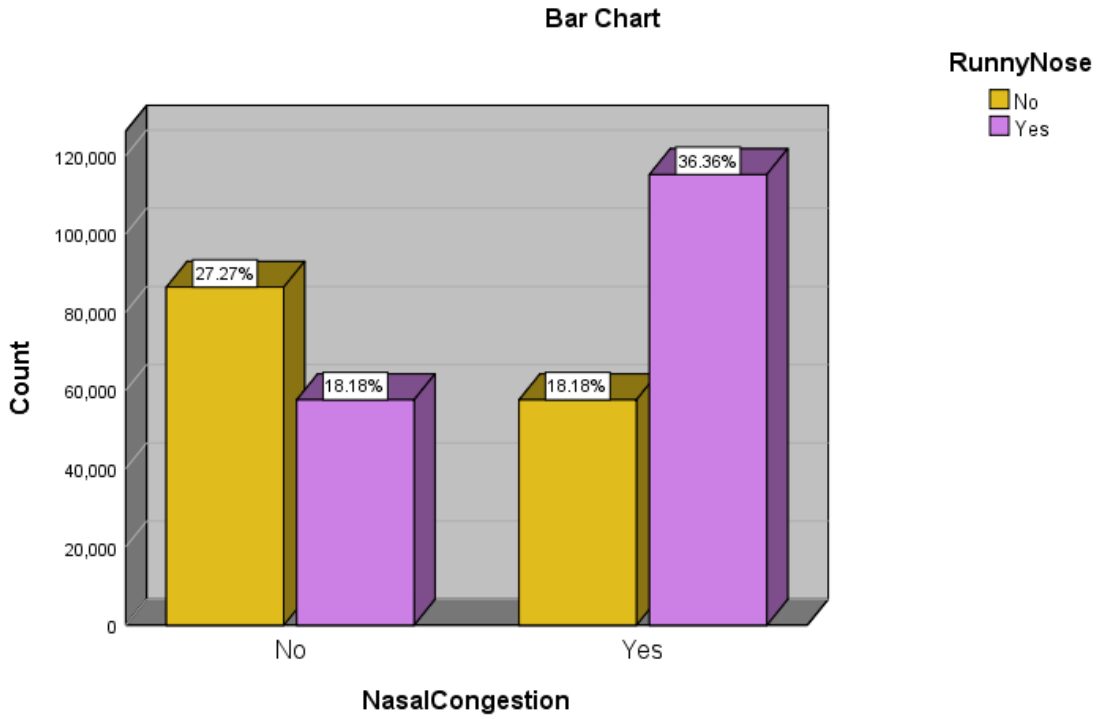
H1: There is significant association between nasal congestion and runny nose.

Chi-Square Tests

	Value	df	P Value
Pearson Chi-Square	22528.000[a]	1	0.001

Comment: since p-value is less than 0.05 with DF 1, we reject the null hypothesis. So, at 5% level of significance, we can say that there is a significant strong association between Nasal Congestion and Runny Nose.

Figure 4.02.04: Bar diagram for nasal congestion and runny nose.



4.02.05: Association between difficulty in breathing and dry cough

Difficulty in Breathing * Dry Cough Cross-tabulation

		Dry Cough		Total
		No	Yes	
Difficulty in Breathing	No	99000	59400	158400
	Yes	39600	118800	158400
Total		138600	178200	316800

Hypothesis:

H0: There is no association between difficulty in breathing and dry cough.

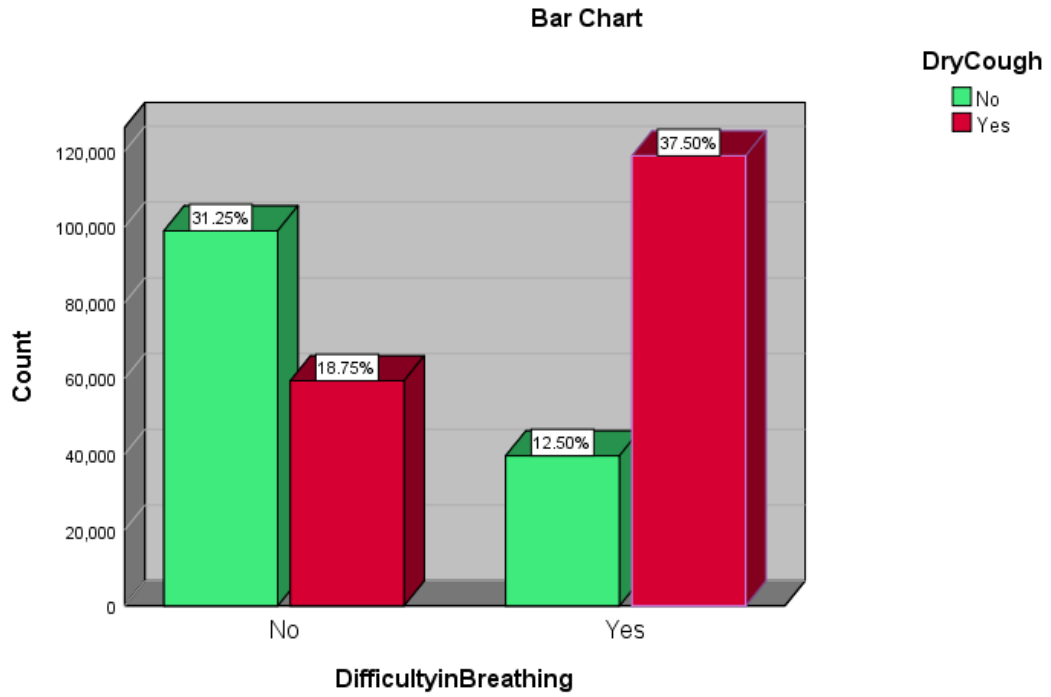
H1: There is significant association between difficulty in breathing and dry cough.

Chi-Square Tests

	Value	df	P Value
Pearson Chi-Square	45257.143[a]	1	0.000

Comment: since p-value is less than 0.05 with DF 1, we reject the null hypothesis. So, at 5% level of significance, we can say that there is a significant strong association between Difficulty in Breathing and Dry Cough.

Figure 4.02.05: Bar diagram for difficulty in breathing and dry cough.



4.02.06: Association between sore throat and pains.

Sore Throat * Pains Cross-tabulation				
		Pains		Total
		No	Yes	
Sore Throat	No	138600	79200	217800
	Yes	63000	36000	99000
Total		201600	115200	316800

Hypothesis:

H0: There is no association between sore throat and pains.

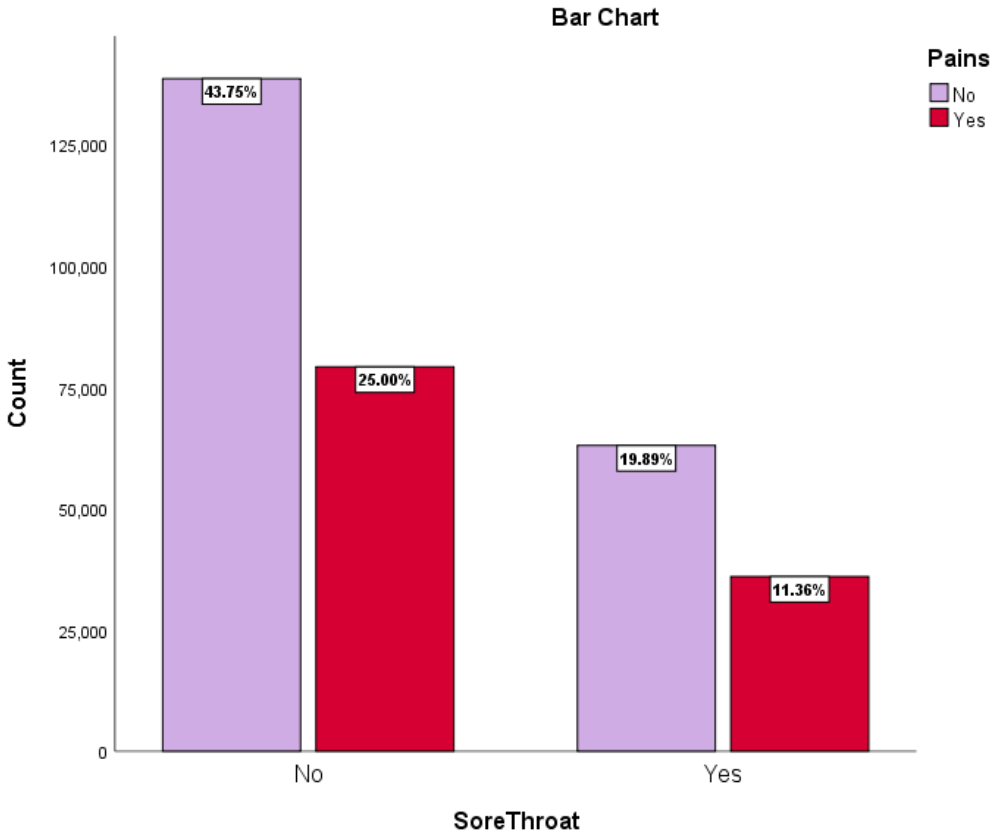
H1: There is significant association between sore throat and pains.

Chi-Square Tests

	Value	df	P Value
Pearson Chi-Square	.000[a]	1	1.000

Comment: since p-value is greater than 0.05 with DF 1, we accept the null hypothesis. So, at 5% level of significance, we can say that there is no significant association between Sore throat and pains

Figure 4.02.06: Bar diagram for sore throat and pains.



4.3 Factor Analysis Using Principal Component Analysis:

Factor Analysis: Factor analysis is a statistical technique that reduces a set of variables by extracting all their commonalities into a smaller number of factors. It can also be called data reduction. There are two types of factor analysis such as

- Exploratory • Confirmatory

Principal Component Analysis: Principal component analysis, or PCA, is a statistical procedure that allows you to summarize the information content in large data tables by means of a smaller set of “summary indices” that can be more easily visualized and analyzed.

Communalities:

The table 4.03.01 of commonalities which shows how much of the variance (i.e. the communality value which should be more than 0.5 to be considered for further analysis. Else these variables are to be removed from further steps of factor analysis) in the variables has been accounted for by the extracted factors.

4.03.01 Communalities table:

Communalities		
	Initial	Extraction
Tiredness	1.000	0.719
Dry Cough	1.000	0.642
Difficulty in Breathing	1.000	0.696
Sore Throat	1.000	0.702
None Symptoms	1.000	0.459
Pains	1.000	0.828
Nasal Congestion	1.000	0.599
Runny Nose	1.000	0.805
None Experiencing	1.000	0.607
Age_09	1.000	1.000
Age_10-19	1.000	1.000
Age_20-24	1.000	1.000
Age_25-59	1.000	1.000
Age_60	1.000	1.000
Gender Female	1.000	0.750
Gender Male	1.000	0.750
Severity None	1.00	.000

Comment: In the communalities table we say that each variables variance is explained by the factor model. High values (close to 1) mean the variable is well represented by the model, while lower values indicate weaker representation. For instance, variables like Severity and Pains have strong contribution avobe.80 age and gender have good to excellent representation in the model.

Total variance Explained:

For analysis and interpretation purposes we are concerned only with Initial Eigenvalues and Extracted Sums of Squared Loadings. The requirement for identifying the number of components or factors stated by selected variables is the presence of eigenvalues of more than 1.

1: Component: 10 components as like shown in communalities table.

2: Initial Eigenvalues Total: Total variance.

3: Initial Eigenvalues % of the variance: The percent of variance attributable to each factor.

4: Initial Eigenvalues Cumulative %: Cumulative variance of the factor when added to the previous factors.

5: Extraction sums of Squared Loadings Total: Total variance after extraction.

6: Extraction Sums of Squared Loadings % of the variance: The percent of variance attributable to each factor after extraction. This value is of significance to us and therefore we determine in this step that they are four factors which effect food habits.

7: Extraction Sums of Squared Cumulative %: Cumulative variance of the factor when added to the previous factors after extraction.

8: Rotation of Sums of Squared Loadings Totals: Total variance after rotation.

9: Rotation of Sums of Squared Loadings % of the variance: The percent of variance attributable to each factor after rotation.

10: Rotation of Sums of Squared Loadings Cumulative %: Cumulative variance of the

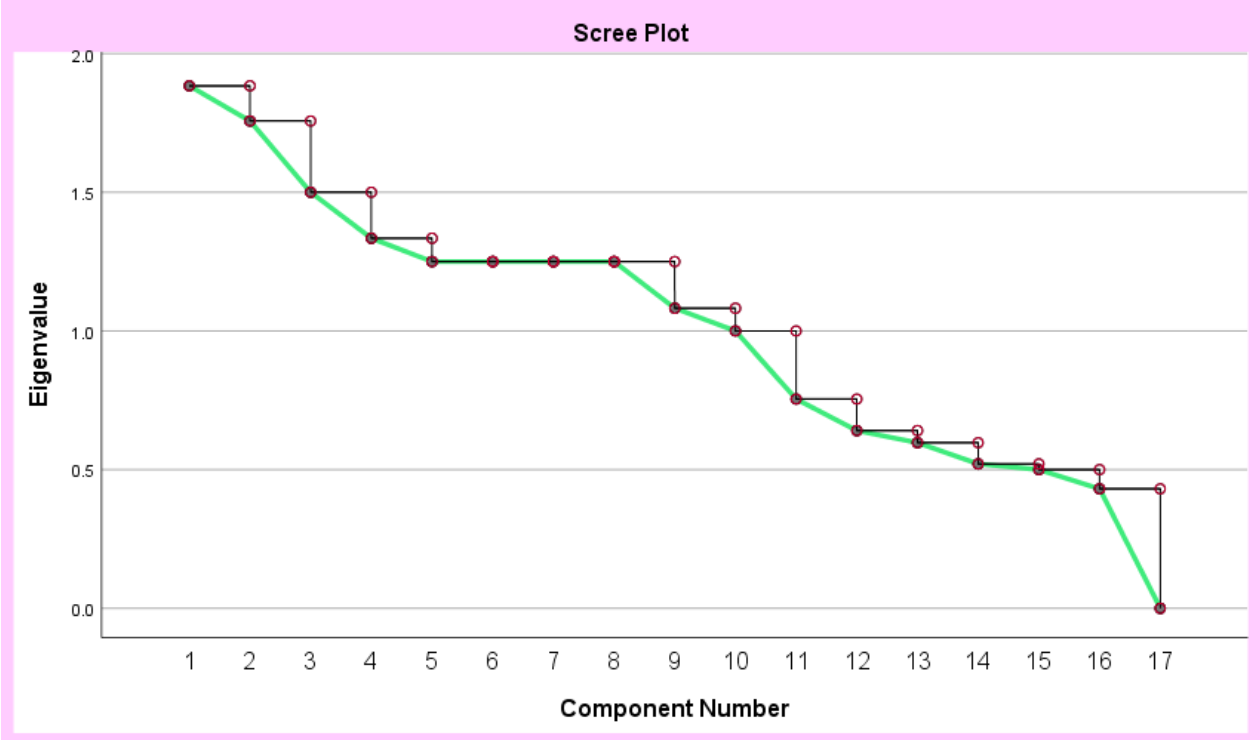
factor when added to the previous factors

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.884	11.080	11.080	1.884	11.080	11.080	1.699	9.994	9.994
2	1.757	10.335	21.415	1.757	10.335	21.415	1.589	9.345	19.339

3	1.500	8.824	30.239	1.500	8.824	30.239	1.519	8.934	28.273
4	1.334	7.848	38.086	1.334	7.848	38.086	1.500	8.824	37.096
5	1.250	7.353	45.439	1.250	7.353	45.439	1.250	7.354	44.450
6	1.250	7.353	52.792	1.250	7.353	52.792	1.250	7.353	51.803
7	1.250	7.353	60.145	1.250	7.353	60.145	1.250	7.353	59.156
8	1.250	7.353	67.498	1.250	7.353	67.498	1.250	7.353	66.509
9	1.082	6.364	73.862	1.082	6.364	73.862	1.250	7.353	73.862
10	1.000	5.882	79.745						
11	0.755	4.438	84.183						
12	0.641	3.768	87.951						
13	0.597	3.512	91.463						
14	0.520	3.062	94.525						
15	0.500	2.941	97.466						
16	0.431	2.534	100.000						
17	-1.155E-13	-6.794E-13	100.000						

Comment: The first 9 components explain about 73.86% of the variance in the dataset, based on both initial eigenvalues and extracted sums of squared loadings. The eigenvalues greater than 1 (Kaiser criterion) suggest that the first 9 components are significant, each explaining a meaningful portion of the variance. After the 9th component, the remaining components contribute very little, with eigenvalues below 1, adding minimal additional variance.

Figure: Scree plot:



Comment: The plot shows a sharp decline in the first few components, which is typical of a scree plot. This suggests that the first few components capture the majority of the variance in the data. After a certain point (around component 5 or 6), the slope of the line flattens out, indicating that subsequent components contribute little to explaining the variance. This plot aids in determining how many factors are necessary to explain the underlying variance in the dataset, and the elbow rule suggests retaining the first few components for further analysis.

Rotated Component Matrix

Rotated Component Matrix									
	Component								
	1	2	3	4	5	6	7	8	9
Tiredness	0.781		-0.328						
Dry Cough	0.781								
None Symptoms	-0.608		-0.297						
Severity None									
Runny Nose		0.842			-0.309				

None Experiencing		-0.726			-0.283				
Nasal Congestion		0.591			0.499				
Sore Throat			0.835						
Difficulty in Breathing	0.323		0.769						
Gender Male				0.866					
Gender Female				-0.866					
Pains					0.908				
Age_09						-0.964			
Age_20-24							-0.964		
Age_25-59								-0.963	
Age_60						0.500	0.500	0.500	-0.500
Age_10-19									0.964

Comment: Variables with higher loadings (close to 1 or -1) on each component indicate strong correlations The rotated matrix indicates that. symptoms and demographic factors group into distinct components, which can help in understanding their roles in asthma severity prediction. This matrix provides insights into how different variables load onto distinct components, which can inform subsequent analysis like K-means clustering.

Component Transformation Matrix

Component Transformation Matrix									
Component	1	2	3	4	5	6	7	8	9
1	0.815	0.000	0.580	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.866	0.000	0.000	0.499	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
4	-0.580	0.000	0.815	0.000	0.000	0.000	0.000	0.000	0.000
5	0.000	0.000	0.000	0.000	0.000	-0.696	0.370	0.510	0.344
6	0.000	0.000	0.000	0.000	0.000	0.263	0.884	-0.024	-0.386
7	0.000	0.000	0.000	0.000	0.000	0.501	-0.158	0.848	-0.073
8	0.000	0.000	0.000	0.000	0.000	0.443	0.237	-0.144	0.853
9	0.000	-0.499	0.000	0.000	0.866	0.000	0.000	0.000	0.000

Comment: The table represents a **Component Transformation Matrix** showing how nine original variables load onto nine transformed components. Each cell indicates the degree to which a variable contributes to a particular component, with higher absolute values

representing stronger associations. For example, Variable 1 loads heavily on Component 1 (0.815) and Component 3 (0.580), while Variable 3 has a perfect loading on Component 4 (1.000), indicating a strong exclusive relationship. The matrix helps identify underlying patterns or groupings among variables, often used in **PCA** or **factor analysis** for dimensionality reduction and interpretation of latent structures.

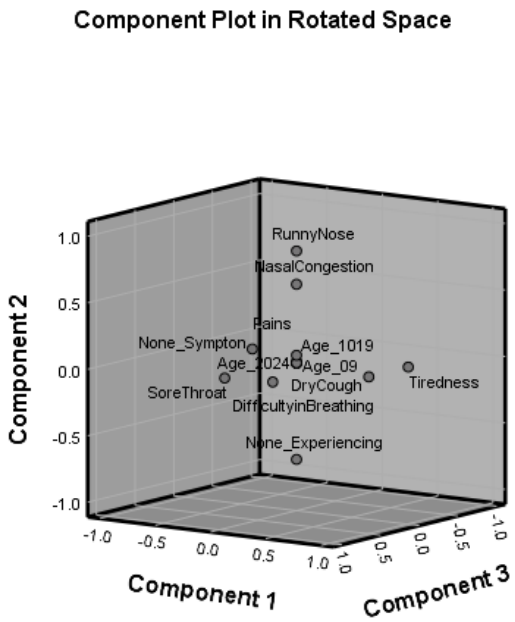


Figure: Component Plot in Rotated Space.

4.4: K-means clustering:

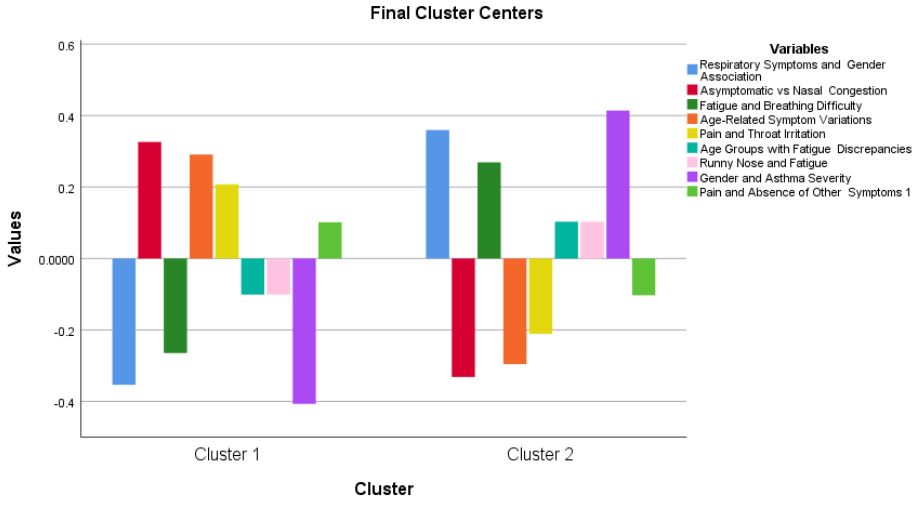
K-means clustering is an unsupervised learning method used to group similar data points into K clusters. It works by assigning each data point to the nearest cluster center (centroid) and then updating the centroids based on the average of assigned points. This process repeats until the cluster assignments stabilize. The goal is to ensure that points within a cluster are as similar as possible, while clusters themselves are as distinct as possible.

Final cluster centers:

Final Cluster Centers		
	Cluster	
	1	2
Respiratory Symptoms and Gender Association	-0.35342	0.35936
Asymptomatic vs Nasal Congestion	0.32626	-0.33174

Fatigue and Breathing Difficulty	-0.26456	0.26900
Age-Related Symptom Variations	0.29077	-0.29566
Pain and Throat Irritation	0.20722	-0.21071
Age Groups with Fatigue Discrepancies	-0.10108	0.10278
Runny Nose and Fatigue	-0.10123	0.10293
Gender and Asthma Severity	-0.40705	0.41389
Pain and Absence of Other Symptoms 1	0.10123	-0.10294

This table displays the centroid values of two clusters based on symptom and demographic data. Each variable shows contrasting values across the two clusters—positive in one and negative in the other—indicating clear differentiation between groups. For example, "Gender and Asthma Severity" has a strong negative center in Cluster 1 (-0.40705) and a strong positive center in Cluster 2 (0.41389), suggesting this variable plays a key role in distinguishing the clusters. The consistent pattern of opposite signs reflects distinct group characteristics based on the input variables.



4.04.02 Figure: Final cluster centers with graphical representation

Comment: The two clusters seem to separate individuals based on symptom severity, presence of fatigue, and gender-specific variations. Cluster 1 appears more related to nasal congestion and fatigue symptoms, while Cluster 2 leans towards pain and age-related symptom variations, including asthma severity.

ANOVA Table:

ANOVA						
	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Respiratory Symptoms and Gender Association	40235.253	1	0.873	316798	46088.643	0.001
Asymptomatic vs Nasal Congestion	34288.324	1	0.892	316798	38449.777	0.001
Fatigue and Breathing Difficulty	22545.657	1	0.929	316798	24273.026	0.000
Age-Related Symptom Variations	27235.260	1	0.914	316798	29796.810	0.000
Pain and Throat Irritation	13832.416	1	0.956	316798	14463.911	0.000
Age Groups with Fatigue Discrepancies	3291.449	1	0.990	316798	3325.994	0.000
Runny Nose and Fatigue	3300.769	1	0.990	316798	3335.512	0.000
Gender and Asthma Severity	53373.287	1	0.832	316798	64187.168	0.000
Pain and Absence of Other Symptoms 1	3301.235	1	0.990	316798	3335.987	0.000

Comment: The analysis reveals that the most significant variables that differentiate the clusters are Respiratory Symptoms and Gender Association, Nasal Congestion, Fatigue-related symptoms, and Asthma Severity based on gender. These factors play a critical role in defining the clustering structure. Meanwhile, factors related to Age Group Fatigue Discrepancies and Pain without other symptoms do not significantly contribute to cluster separation.

4.04.04: K-Nearest Neighbors (KNN) Model:

The dataset of 316,800 entries was fully valid and split into a **training set (70%)** and a **holdout/test set (30%)** for model development and evaluation. No cases were excluded.

Case Processing Summary			
		N	Percent
Sample	Training	221490	69.9%
	Holdout	95310	30.1%
Valid		316800	100.0%
Excluded		0	
Total		316800	

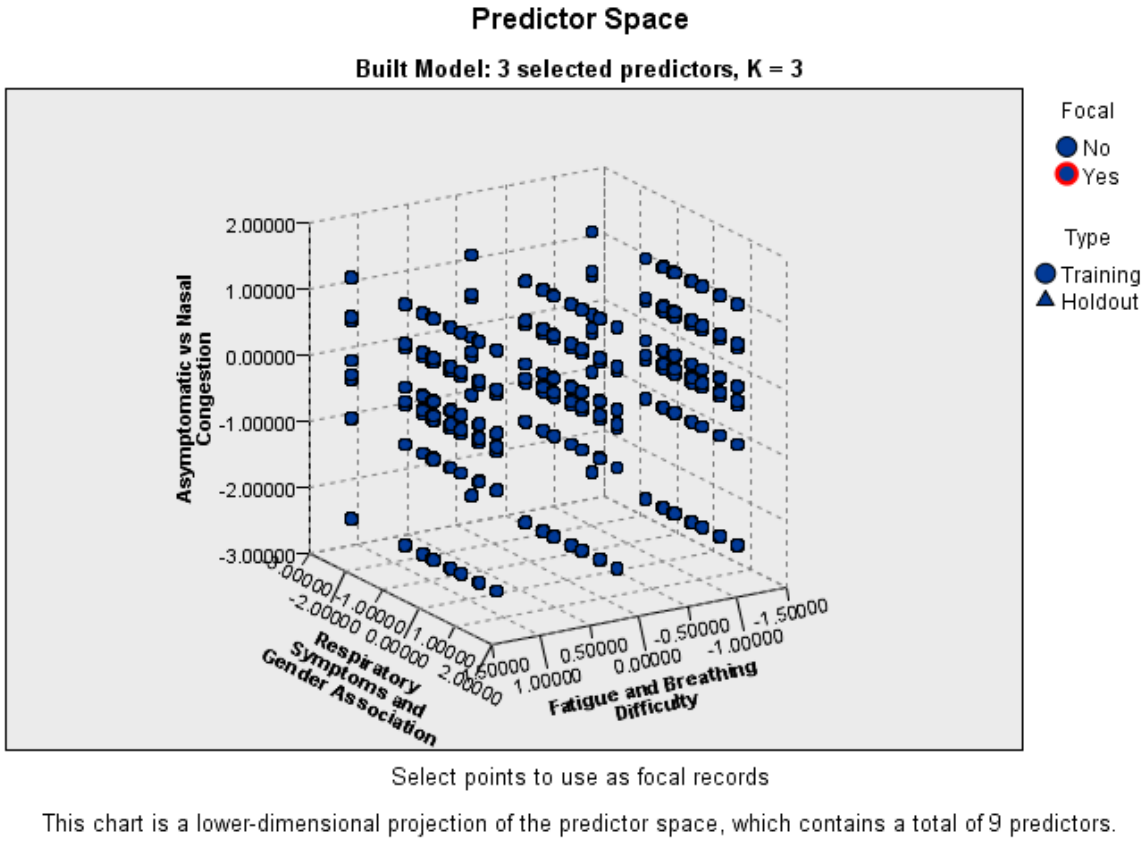


Figure: Dimensional projection of the predictor space

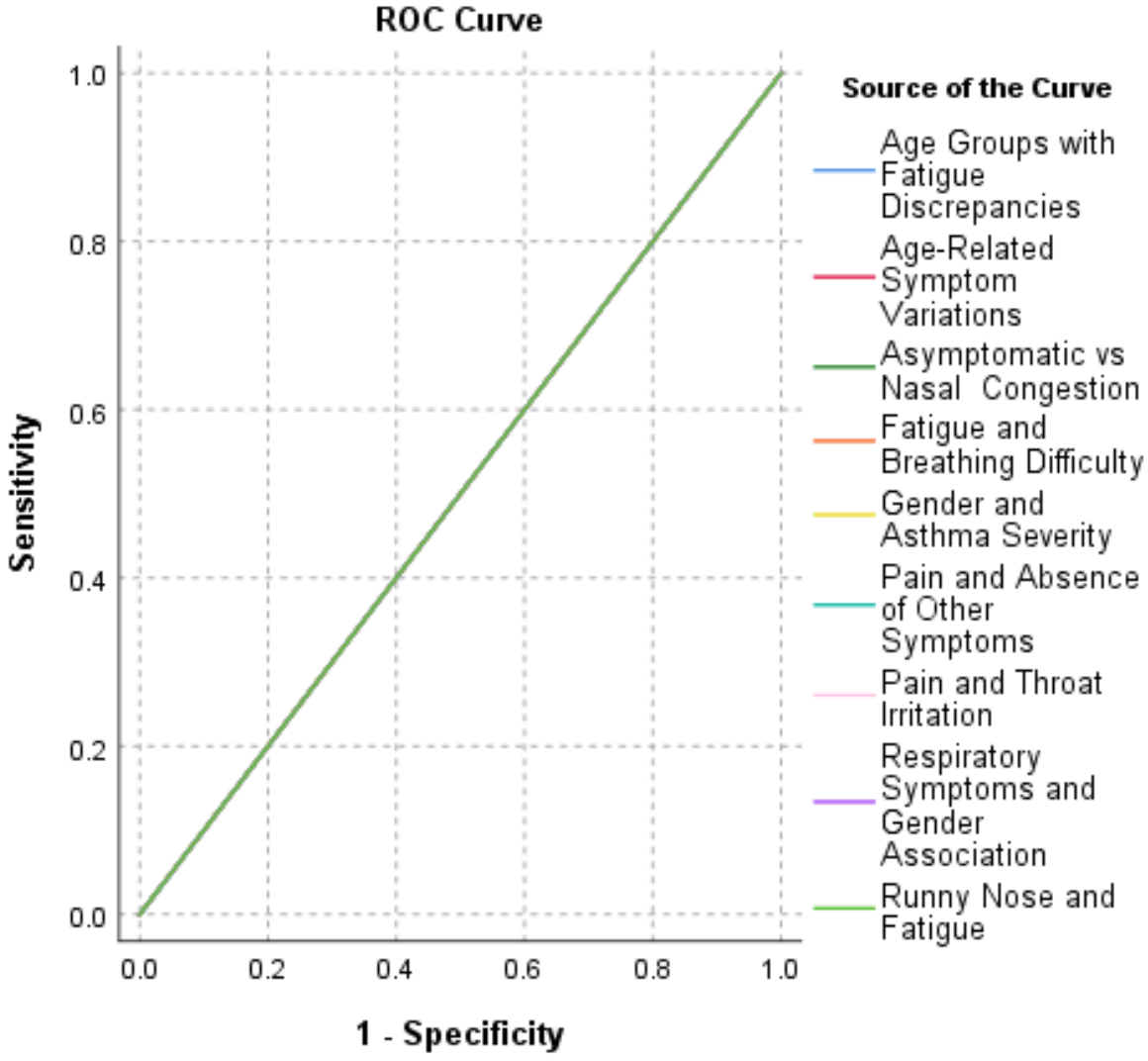
Comment: The image displays a 3D scatter plot visualizing a "Predictor Space" built with 3 selected predictors out of a total of 9. The axes represent "Fatigue and Breathing Difficulty," "Respiratory Symptoms and Gender Association," and "Asymptomatic vs. Nasal Congestion." Each point in the plot represents a record, colored by the "Focal" status (blue for "No," red for "Yes") and shaped by the "Type" of data (circles for "Training,"

triangles for "Holdout"). The plot is a lower-dimensional projection of a higher-dimensional predictor space.

4.5: ROC Analysis:

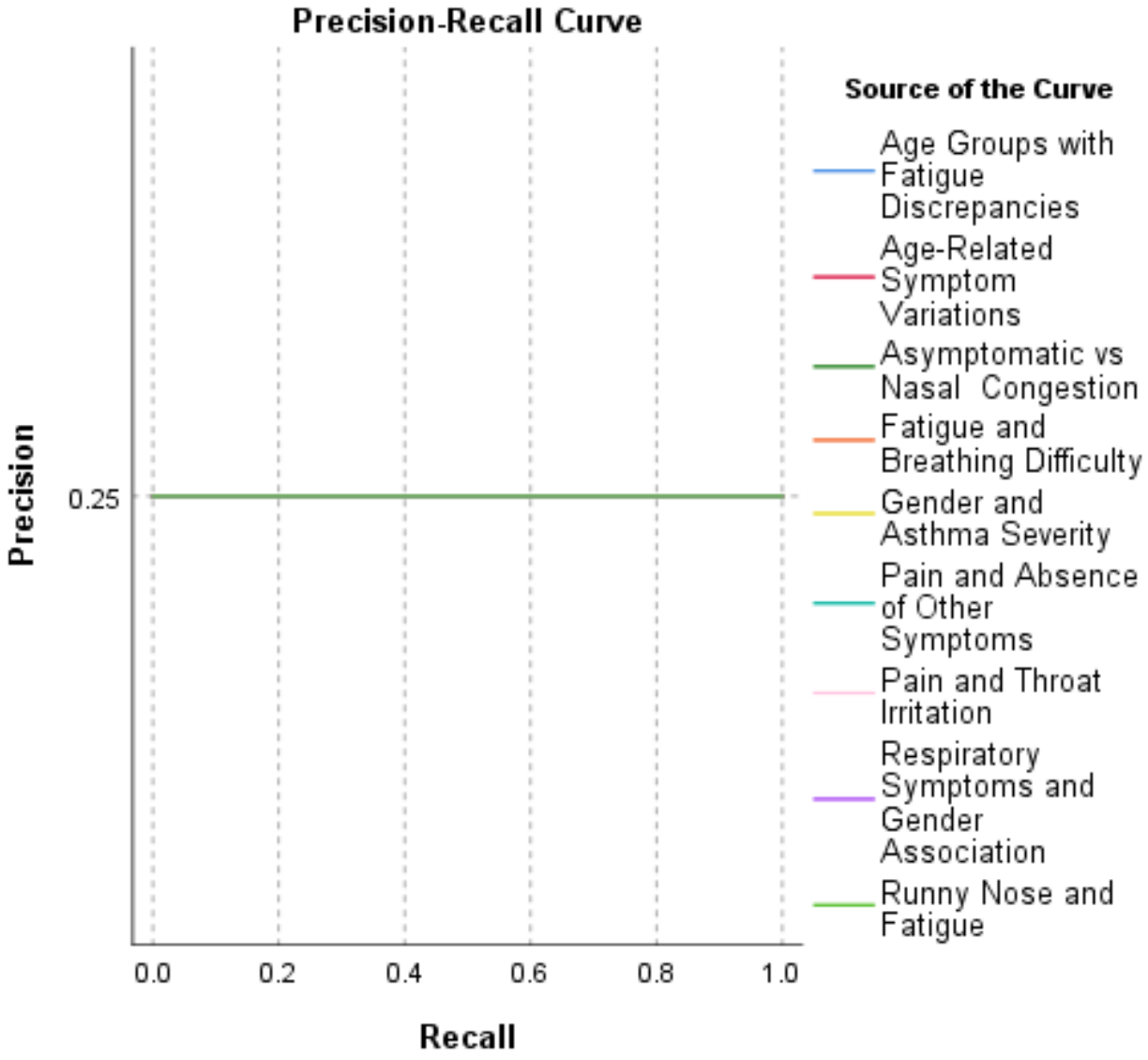
Case Processing Summary:

Case Processing Summary	
Severity None	Valid N (listwise)
Positive	79200
Negative	237600
Missing	0
Total	316800



ROC Curve for Predictive Models of Asthma Severity

Comment: The graph shown is a ROC (Receiver Operating Characteristic) Curve used to evaluate the performance of various predictive models related to asthma severity The ROC curve in this case seems to follow the reference line (diagonal), indicating that the models may not show significant predictive power. A model with good discrimination ability should have a curve that bows towards the top-left corner of the graph, away from the reference line.



4.05.02 Figure Precision- Recall Curve for Predicting Models of Asthma Severity.

Area under the ROC curve

Area Under the ROC Curve	
Test Result Variable(s)	Area
Respiratory Symptoms and Gender Association	5.744
Asymptomatic vs Nasal Congestion	5.744
Fatigue and Breathing Difficulty	5.744
Age-Related Symptom Variations	5.744
Pain and Throat Irritation	5.744
Age Groups with Fatigue Discrepancies	5.744
Runny Nose and Fatigue	5.744
Gender and Asthma Severity	5.744
Pain and Absence of Other Symptoms	5.744

4.6: Neural Network

Artificial neural networks, usually simply called neural networks or neural nets, are computing systems inspired by the biological neural networks that constitute animal brains. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain.

Case Processing Summary:

The dataset consists of 316,800 samples, with 70.1% (222,003) used for training and 29.9% (94,797) for testing. No samples were excluded.

Case Processing Summary			
		N	Percent
Sample	Training	222003	70.1%
	Testing	94797	29.9%
Valid		316800	100.0%

Excluded		0	
Total		316800	

Network Information

The neural network has 9 standardized input features related to symptoms and demographics, 1 hidden layer with 7 units using the tanh activation function, and an output layer with 2 units using identity activation. The model optimizes using the sum of squares error function.

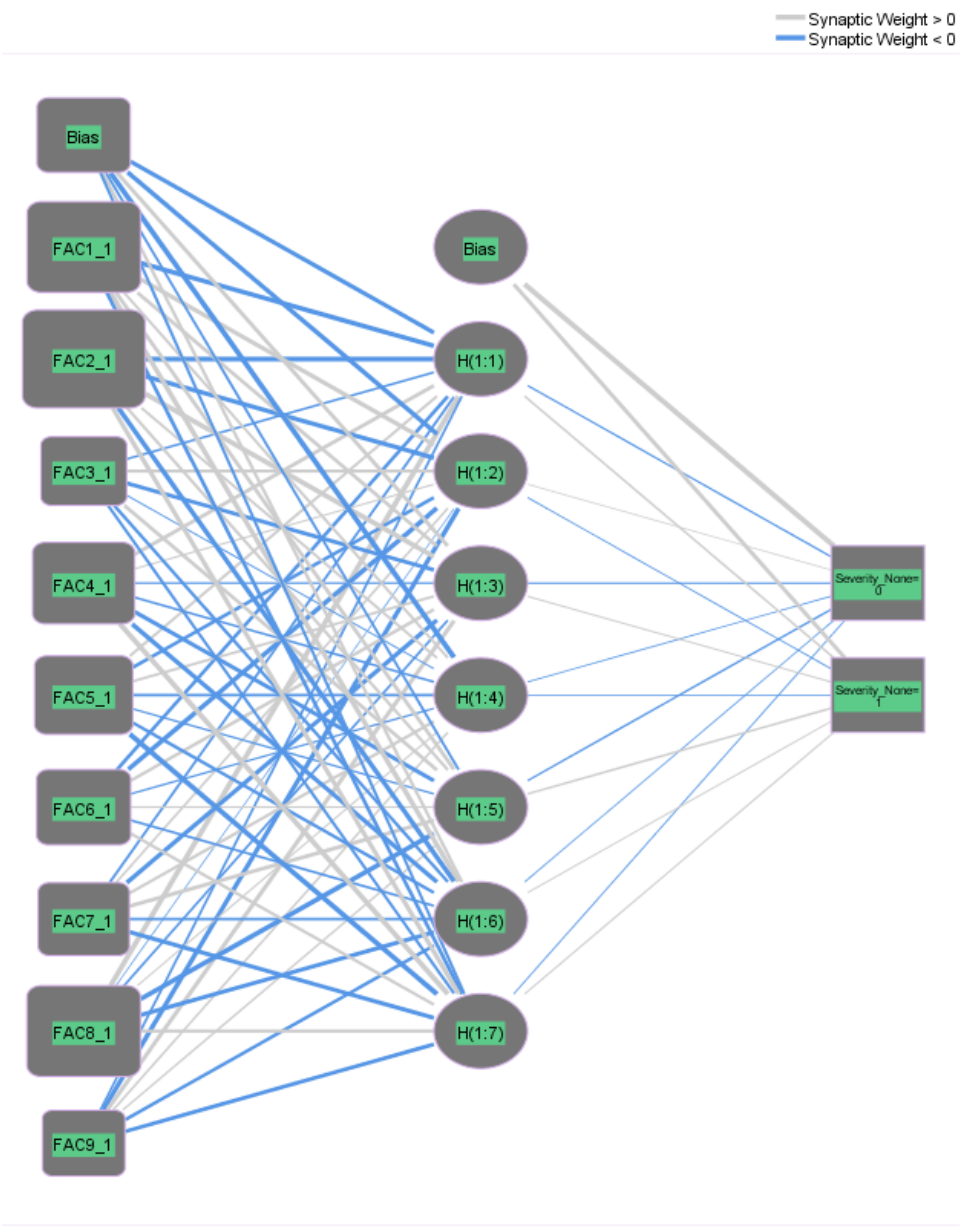
Table: Network Information

Network Information			
Input Layer	Covariates	1	Respiratory Symptoms and Gender Association
		2	Asymptomatic vs Nasal Congestion
		3	Fatigue and Breathing Difficulty
		4	Age-Related Symptom Variations
		5	Pain and Throat Irritation
		6	Age Groups with Fatigue Discrepancies
		7	Runny Nose and Fatigue
		8	Gender and Asthma Severity
		9	Pain and Absence of Other Symptoms
	Number of Units		9
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Severity None
	Number of Units		2

	Activation Function		Identity
	Error Function		Sum of Squares

Graphically representation **of Neural Network:**

This figure involved the design and visualization of a Multilayer Perceptron (MLP) architecture. The network comprises an input layer with nine features, a hidden layer with seven neurons employing a hyperbolic tangent activation function, and an output layer with two neurons utilizing an identity activation function. The visualization highlights the network's connectivity and synaptic weights, differentiating between positive (blue) and negative (gray) connections



Model Summary

This model summary outlines performance metrics for both the training and testing phases:

Training Results:Sum of Squares Error (SSE) 41,569.602 Indicates the total squared difference between predicted and actual values during training. **Percent Incorrect Predictions:** 24.9% Approximately one in four predictions was incorrect. **Stopping Rule Used:** The model training stopped when the relative change in the error criterion dropped below 0.0001, indicating convergence. **Training Time:** 4.29 seconds. The model trained quickly, suggesting a relatively simple model or a small dataset.

Testing Results: Sum of Squares Error (SSE): 17,840.342 Reflects the model's prediction error on unseen data. The value being close to the training SSE is a positive indicator.**Percent Incorrect Predictions:** 25.1% Very similar to the training error, which suggests good generalization and minimal overfitting.

Table: Model Summary

Model Summary		
Training	Sum of Squares Error	41569.602
	Percent Incorrect Predictions	24.9%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:04.29
Testing	Sum of Squares Error	17840.342
	Percent Incorrect Predictions	25.1%

Classification

Classification				
		Predicted		
Sample	Observed	No	Yes	Percent Correct
Training	No	166629	0	100.00%
	Yes	55374	0	0.00%
	Overall Percent	100.00%	0.00%	75.10%
Testing	No	70971	0	100.00%
	Yes	23826	0	0.00%
	Overall Percent	100.00%	0.00%	74.90%

Accuracy: Accuracy is the probability that the model prediction is correct. Here accuracy 74.90% that means the model prediction is 75% correct.

Comment: This neural network model is designed to predict asthma severity based on a combination of multiple input features related to symptoms and demographics. The diagram demonstrates how the input variables (symptoms, gender associations, etc.) are weighted and combined in a hidden layer, which then influences the output prediction of whether the individual will experience no asthma severity. The large number of input connections to the hidden layer suggests the model accounts for complex interactions between the different symptoms and demographic factors when making predictions Overall, this neural network structure emphasizes the complex relationships among variables in predicting asthma severity, where multiple factors interact to contribute to the prediction outcome.

Chapter-5

Summary and conclusion:

In this study I explored the relationship between tiredness, dry cough, difficulty in breathing, runny nose, nasal conjestion, pains and demography factor .my result explained about the severity label the machine learning model successfully predicted asthma severity by leveraging symptom and demographic data. It identified significant factors such as difficulty in breathing, age, and gender, proving the efficacy of predictive models in asthma diagnosis. These findings highlight the importance of targeted treatments based on individual profiles, contributing to more personalized and effective asthma management strategi.

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