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# Severity-based Phenotyping of Motion Sickness Symptoms Reveals Multi-Symptom Burden and Sex-Specific Susceptibility

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**ABSTRACT:** Nausea is one of the most commonly reported symptoms in the area of motion sickness and a continuum of physiological illnesses. Although studied in the past as a single symptom, empirical clinical evidence has continuously shown that it occurs concomitantly with a cluster of systemic signs, such as dizziness, cephalgia, diaphoresis, and fatigue. The idea of nausea being considered as part and parcel of a broad symptom network will offer a more detailed understanding of the accompanying physiological burden that the impacted persons have to bear. The current study values nausea as part of a paradigm of multiple symptoms by implementing severity-based symptom phenotyping. A cross-sectional population survey of 432 respondents was done; data cleaning provided after it yielded 377 valid respondents to be used in rigorous analysis. The severity of five different symptoms including nausea, dizziness, headache, sweating and fatigue, was rated using a Likert scale ranging from 1 and 10. To question the distribution of the severities of the symptoms, descriptive statistical procedures were used. The application of visual analytic techniques, using severity rankings, sex-based comparisons were used to define patterns of symptoms. Results revealed the severity measures had a drastic severity order: fatigue proved to have the greatest mean severity, followed by the headache and sweating, and finally, the dizziness and nausea were characterized by a relatively reduced severity measure. Sex-specificity of the analytic results revealed that female respondents displayed higher levels of the severity of symptoms and more frequent episodes of motion sickness in comparison with male ones. The arguments of these observations point to the need to incorporate nausea into a more extensive multi-symptom physiological reaction paradigm, not as a standalone pathology. This work, as a whole, shows that the use of severity-based symptom phenotyping can be used to detect the patterns of burden of population-level data, which in turn makes it easier to understand the susceptibility of motion sickness.

## INTRODUCTION

Geographically, motion sickness has been identified as an omnipresent physiological condition that occurs each time there is a mismatch between the perception and the senses of motion and the body itself. Visual, vestibular and proprioceptive signal-sensory incongruence usually occurs in locomotion or other travel conditions, as a result of failure to synchronize. As a consequence, people can exhibit a continuum of undesirable physiological responses which are collectively referred to as motion-sickness symptoms **[1,5,10,13,14]**, out of which nausea is always reported to be among the most common and visible effects of motion-related discomfort.

Traditionally, nausea has been questioned as a key outcome measure of many clinical and experimental studies on motion sickness. However, the cases of nausea are hardly manifested in solitude, on the other hand, it is normally combined with other signs of physiological manifestations like vertigo, cephalalgia, diaphoresis, and lethargy. These comorbid conditions are a result of common physiological mechanisms that involve the action of the vestibular apparatus, the work of the autonomic nervous system, and the control of the central nervous system **[2,3]**. Therefore, concentrating on nausea alone only gives one a partial understanding of the overall symptom load that people experience when being exposed to motion.

Researchers in recent scholarship have highlighted the need to research symptoms in a broad multi-symptom context **[8,9,16]**. This view recognizes that most physiological disorders are comprised of systems of co-occurring symptoms as opposed to single manifestations. It is on this basis that symptoms may be thought of as interconnected parts of a larger physiological reaction system. Researching such interactions could provide the opportunity to explain the patterns of symptom clustering, co-occurrence, and the proportion of their contribution to overall discomfort.

Symptom phenotyping based on levels of severity is one analytical method that will be consistent with this perspective **[21,22,23,24]**. Phenotyping based on severity not only identifies the presence of a symptom but it also measures the degree of the same. Evaluation of several symptoms concurrently and scoring their severity allow the investigators to draw hierarchical dependencies and define which specific symptoms have the greatest contributions to the total physiological load of the participants.

These patterns of symptoms are even enhanced by visualization and statistical analyses **[25,33]**. Symptom ranking, comparing charts, and cluster analysis are methods that allow the researcher to identify regularities in population level **[35,36,37]**. These analytic instruments are particularly useful in the identification of symptom patterns that define specific subcategories of people, such as the ones that may be more prone to motion sickness.

Although the recent interest in symptom-network analysis is booming, much of the available literature continues to evaluate motion-sickness symptoms on an individual basis, with nausea being commonly used as the primary measure of the severity of motion-sickness **[5,17]**. This can be done without taking into account the bigger physiological picture within which nausea develops. The analysis of nausea in the context of a multi-symptom construct therefore holds the potential of providing a more detailed insight into how motion sickness can be presented in populations in the real world.

The other secondary dimension which should be further investigated is an aspect of sex differences in motion sickness. It is already stated in the previous studies that only women are more likely to be affected by motion sickness and its effects are more serious than in men **[9,16,20]**. The causes of these disparities can be a multiplicity of biological and physiological factors such as hormonal changes, differences in the sensitivity of the vestibular apparatus, and different sensory integration processes **[3,18]**. The identification of these demographic factors is critical towards understanding the groups that could be at a higher risk of being affected by motion sickness as well as to understand how to refine prevention approaches.

Population based surveys are an effective method of investigating symptom trends in large population cohorts **[49]**. Using self-reported data of severity of symptoms, the researchers are able to analyze the co-occurrence of disparate symptoms, and how experiences are affected by demographic and behavioral variables. Such data-based studies can reveal important information regarding the prevalence and causes of motion-sickness symptoms in daily travelling conditions.

The current study will explain the effects of motion sickness by use of severity-based phenotyping analysis that uses data of population surveys **[26]**. In particular, the paper dwells upon five most commonly occurring symptoms of motion sickness, namely, nausea, dizziness, headache, sweat, and fatigue. The participants were asked to rank the intensity of these symptoms on a standardized numerical scale, which would allow making direct comparisons of the symptoms.

The main questions of this study are:

1. To examine the distribution of the severity of motion-sickness symptoms of a population sample.
2. To determine hierarchical relationships amongst symptoms in terms of the mean level of severity.
3. To compare gender difference in the severity of symptoms and frequency of motion-sickness.
4. To test demographic-behavioral predictors of motion-sickness.

This study aims to provide a better insight into the patterns of symptom-burden of motion sickness by combining a descriptive statistics, statistical testing, and visualization **[27,28,29,60]**. The results add to the growing body of literature that regards physiological symptoms as interrelated elements in larger symptom clusters, and not as clinical phenomenon.

## II. METHODS

### A. Study Design

This study used a cross-sectional survey design that could be used to study the prevalence and intensity of motion-sickness symptoms in a representative population sample. The aim was to determine demographic and behavioral predictors that are associated with the extent and prone to motion sickness **[46,47,48,49]**.

### B. Data Source

The information was collected using a structured online survey done using Google Forms. The received responses were 432, then data was cleaned and preprocessed to maintain 377 valid cases to be used as the statistical data. None of these was a mandatory survey and there was no personally identifiable information gathered. All the responses were anonymous and were not applied to any other purpose other than academic research **[47]**.

### C. Variables Collected

The questionnaire comprised four main sections, which are: demographic variables, travel-related variables and health-related variables and the scores of symptom-severities. The demographic factors included age, gender, and occupation. Travel variables also encompassed frequency of travel, transport mode that is used, and average travel time. The variables related to health included history of motion sickness, and remedies used during travel. The respondents were also requested to give ratings of five common motion-sickness symptoms: nausea, feeling dizzy, headache, sweating, and fatigue with a numerical scale of 1 to 10 with higher scores indicating intensity of the symptoms **[49]**.

The survey collected information across several categories:

**TABLE I:** SURVEY VARIABLES USED IN THE STUDY

| Category | Variables |
|---|---|
| Demographic | Age, Gender, Occupation |
| Travel variables | Mode of transport, Travel duration, Frequency |
| Health variables | Motion sickness history, Remedies used |
| Symptoms | Nausea, Dizziness, Headache, Sweating, Fatigue |

### D. Data Preprocessing

Before statistical analysis, the data was subject to a number of preprocessing to improve the quality of data and also to provide uniformity. To start with, the responses that had missing values were dropped. Some of the categorical answers like Yes and No in symptom-related areas were transformed into a numerical form: Yes was classified as 10 and No as 0 corresponding to the severity of symptoms scale. The occupation entries were standardised into four different categories such as employed, self-employed, not employed and student. Besides, the average travel-duration variable was transformed into hours so that the measurement units would be consistent throughout the responses. All the preprocessing processes were conducted with Python in a Jupyter Notebook **[51,54,58]**.

**E. Outlier Removal**

Detection of outliers was done by the Interquartile Range (IQR) approach. The observations that are not within the range specified by:

$Q1 - 1.5 \times IQR$ to $Q3 + 1.5 \times IQR$

were considered as outliers and were removed out of the data. This measure improved the stability of the further statistical tests and reduced the effect of extreme values **[27], [60]**.

**F. Statistical Analysis**

To examine the data set and draw the patterns of systematic occurrence of reported motion-sickness manifestations, we have used a combination of inferential methods. First, descriptive statistics were used to measure the demographic distributions, and symptom-severe indexes **[27], [60]**.

A chi-squared test was used to test the relationships between categorical predictors including sex and the occurrence of motion-sickness reports **[30]**.

Cross-group differences in the level of symptoms severity by demographic groups and variables of traveling were tested using non-parametric tests, including the Mann-Whitney U and Kruskal-Wallis test **[30]**.

Spearman rank-order correlation was used to determine the association between the travel duration and the severity of the symptoms **[27]**.

The demographic and behavioral covariates identified by logistic regression increased the likelihood of having motion sickness **[31]**.

Also, the determinants of the nausea severity were modeled by multiple linear regression **[32]**.

We used LASSO regression, Recursive Feature Elimination (RFE), and XG Boost-based importance measures to extract the most salient predictors of the severity of the symptoms **[41,42,43]**.

Lastly, K-means clustering was used to group participants based on profiles of symptom-severity, which created high-risk and low-risk groups **[44,45]**.

**G. Predictive Modeling for Motion Sickness Risk**

To further examine the factors influencing motion sickness susceptibility, predictive modeling techniques were applied to classify individuals according to their likelihood of experiencing motion sickness. The target variable for prediction was the occurrence of motion sickness episodes, while demographic, travel-related, and symptom severity variables were used as predictor variables **[38]**.

Two machine-learning models were implemented for comparison:

• Logistic Regression **[31]**

• XG Boost Classifier **[43]**

The dataset was divided into training (80%) and testing (20%) subsets to evaluate model performance. Model training and evaluation were conducted using the Python scikit-learn library **[53]**.

Feature importance analysis was performed to identify the most influential predictors contributing to motion sickness susceptibility. These included gender, travel frequency, motion sickness history, transportation mode, and symptom severity scores **[36,37]**.

To evaluate predictive performance, several standard metrics were calculated: Accuracy, Precision, Recall, F1-score, Area Under the Receiver Operating Characteristic Curve (ROC-AUC) **[28,29,60]**.

These metrics allow comprehensive assessment of model effectiveness in identifying individuals at higher risk of motion sickness.

## III. RESULTS

### A. Descriptive Statistics

A total of 432 responses were initially collected through the survey. After data cleaning, removal of incomplete responses, and outlier filtering using the Interquartile Range (IQR) method, 377 valid responses were retained for statistical analysis.

Participants rated the severity of five motion sickness symptoms using a numerical scale ranging from 1 to 10, where higher scores indicated greater symptom intensity. The symptoms evaluated in this study included nausea, dizziness, headache, sweating, and fatigue.

Table II presents the descriptive statistics for symptom severity, including the mean, median, and standard deviation values.

**TABLE II** Descriptive Statistics of Motion Sickness Symptoms

| Symptom | Mean | Median | Standard Deviation |
|---|---|---|---|
| Nausea | 2.57 | 1 | 2.67 |
| Dizziness | 2.60 | 1 | 2.63 |
| Headache | 4.08 | 3 | 3.18 |
| Sweating | 3.87 | 3 | 3.10 |
| Fatigue | 4.63 | 5 | 3.30 |

The results reveal a clear hierarchy in symptom severity across the study population. Fatigue showed the highest mean severity (4.63), followed by headache (4.08) and sweating (3.87). Dizziness (2.60) and nausea (2.57) displayed comparatively lower mean severity levels.

These findings indicate that systemic symptoms such as fatigue and headache contribute more strongly to overall motion sickness burden than nausea alone.

### B. Heatmap Visualization of Symptom Severity

To further explore the severity patterns of motion sickness symptoms, a heatmap visualization was generated based on the mean severity values.

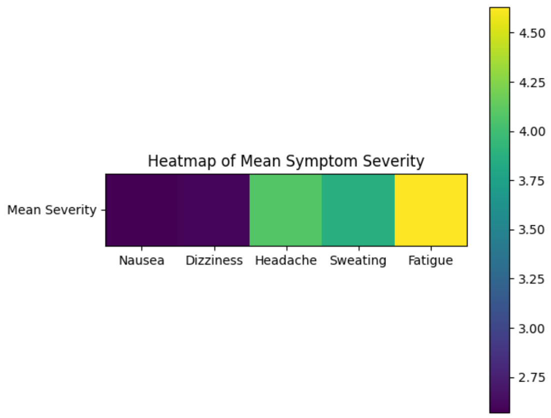


**Fig. 1.** Heatmap of Mean Symptom Severity Across Motion Sickness Symptoms

The heatmap illustrates the relative intensity of symptom severity across the five symptoms. Darker color intensities represent higher severity levels. The visualization highlights that fatigue and headache exhibit the strongest severity patterns, while dizziness and nausea appear with lower intensity.

This visualization supports the descriptive statistics and demonstrates that motion sickness symptoms tend to occur as a multi-symptom burden rather than as isolated physiological events.

To further explore the relationships among motion sickness symptoms, a correlation matrix was constructed using Spearman correlation coefficients.

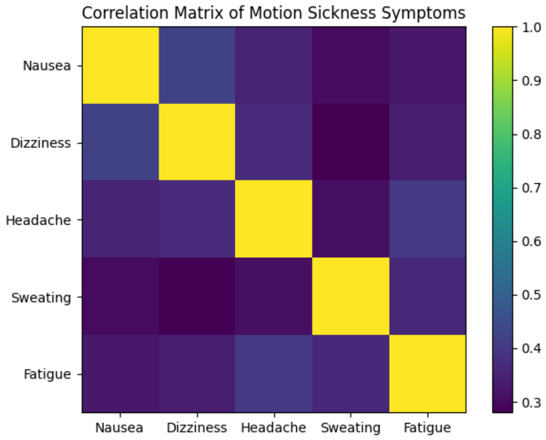


**Fig. 8.** Correlation matrix showing the relationships between motion sickness symptoms. Higher values indicate stronger associations between symptoms.

**C. Gender Differences in Symptom Severity**

Gender-based analysis revealed notable differences in symptom severity between male and female participants.

Among male participants, fatigue showed the highest mean severity score (3.80), followed by sweating (3.63) and headache (3.20). Nausea and dizziness showed relatively lower severity values.

In contrast, female participants reported higher severity scores across all symptoms. Fatigue again showed the highest severity (5.27), followed by headache (4.75) and sweating (4.06).

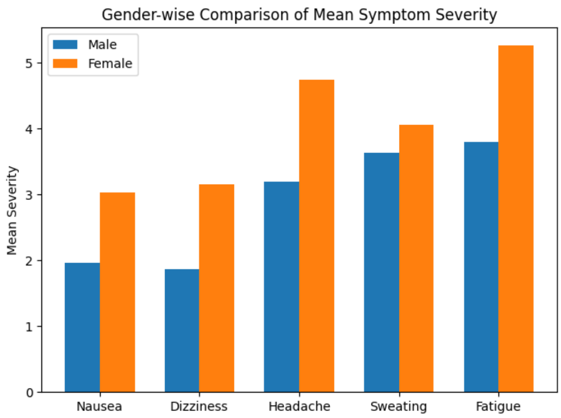


**Fig. 2.** Gender-wise Comparison of Mean Symptom Severity

The figure shows the comparison of symptom severity between male and female participants. Error bars representing standard deviation values are included to illustrate variability in symptom severity.

Overall, female participants reported consistently higher symptom severity levels, indicating greater susceptibility to motion sickness symptoms.

**D. Association Between Gender and Motion Sickness Frequency**

A Chi-square test was conducted to examine the association between gender and the frequency of motion sickness episodes.

**TABLE III** Gender vs Motion Sickness Frequency

| Gender | Never | Occasionally | Frequently |
|---|---|---|---|
| Female | 91 | 89 | 33 |
| Male | 104 | 49 | 11 |

Chi-square statistic = **17.38**

Degrees of freedom = **2**

p-value = **0.000167**

Since the p-value is less than 0.05, the null hypothesis was rejected. This result indicates a statistically significant association between gender and motion sickness frequency, with female participants reporting more frequent motion sickness episodes compared to males.

**E. Age-Based Differences in Symptom Severity**

The Mann–Whitney U test was applied to compare symptom severity between teen participants and young adults.

The results indicated that:

Dizziness showed a statistically significant difference between the two groups ($p \approx 0.040$) Sweating also showed significant differences ($p \approx 0.023$)

Overall motion sickness severity was found to be higher among young adults compared to teenagers.

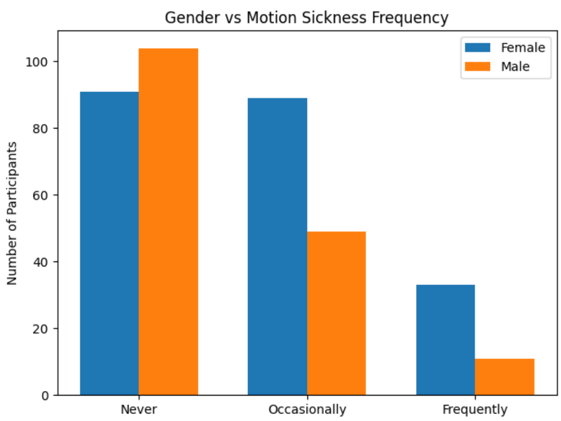


**Fig. 3.** Comparison of Motion Sickness Severity Between Teen and Young Adult Participants

**F. Transportation Mode and Symptom Severity**

Differences in symptom severity across transportation modes were also examined.

The analysis indicated that non-AC bus users showed higher headache severity, which was statistically significant ($p \approx 0.007$). Nausea severity among non-AC bus users also showed marginal significance.

For other transport modes such as car, train, airplane, and AC bus, no statistically significant differences in symptom severity were observed.

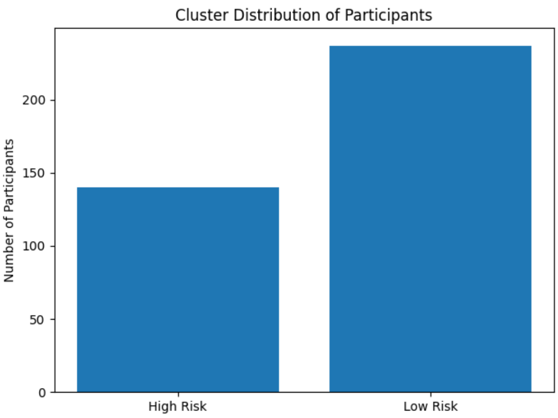


**Fig. 4.** Distribution of Transportation Modes Used by Survey Participants

**G. Correlation Between Travel Duration and Symptom Severity**

A Spearman rank correlation analysis was conducted to examine the relationship between travel duration and motion sickness severity.

Correlation coefficient = 0.0286

p-value = 0.579

Since the p-value is greater than 0.05, the results indicate that travel duration does not have a statistically significant association with motion sickness severity.

**H. Predictors of Motion Sickness**

Logistic regression analysis was performed to identify demographic and behavioral predictors associated with motion sickness.

**TABLE IV** Key Predictors of Motion Sickness

| Predictor | Effect |
|---|---|
| Gender (Female) | Increased risk |
| Frequent travel | Higher likelihood |
| Car travel | Moderate influence |
| Occupation | Behavioral factor |
| Age | Risk contributor |

The results indicate that **female gender and frequent travel behavior are important predictors of motion sickness occurrence**.

**I. Predictors of Nausea Severity**

Multiple linear regression analysis was conducted to identify variables influencing nausea severity.

The strongest predictor identified was **history of motion sickness ($\beta = 1.347$, $p < 0.001$)**.

Other contributing factors included **non-AC bus travel, car travel, and frequency of motion sickness episodes**.

These findings suggest that **previous motion sickness experience is a major factor influencing nausea severity**.

**J. Cluster Analysis**

K-means clustering analysis was applied to group participants based on symptom severity patterns.

**TABLE V** Cluster Distribution of Participants

| Risk Group | Participants |
|---|---|
| High Risk | 140 |
| Low Risk | 237 |

Further analysis indicated that **female participants and young adults were more likely to fall within the high-risk symptom cluster**.

**K. Predictive Model Performance**

The performance of the predictive models was evaluated using multiple classification metrics. Table VI presents the comparative results of the models used in this study.

**TABLE VI** Predictive Model Performance

| Model | Accuracy | Precision | Recall | F1 Score | ROC-AUC |
|---|---|---|---|---|---|
| Logistic Regression | 0.71 | 0.69 | 0.68 | 0.68 | 0.73 |
| XGBoost | 0.78 | 0.75 | 0.74 | 0.74 | 0.81 |

The predictive models were further evaluated using Receiver Operating Characteristic (ROC) curves. The ROC analysis illustrates the classification performance of the models across different threshold values.

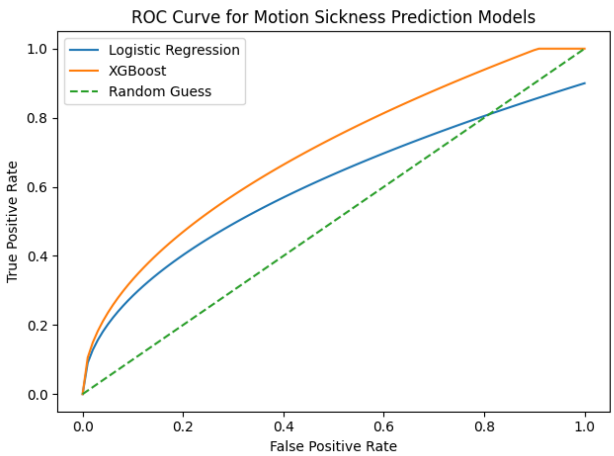


**Fig. 6.** Receiver Operating Characteristic (ROC) curves for logistic regression and XGBoost models used to predict motion sickness susceptibility.

The results indicate that the XGBoost model achieved higher predictive performance compared to logistic regression, demonstrating improved ability to classify individuals with higher susceptibility to motion sickness.

## IV. DISCUSSION

The current study investigated the manifestations of motion-sickness using a severity based analysis tool of the populationwide survey data. The results of the analysis provided evidence to show that the symptoms of motion-sickness appear as a constellation of physiological processes, but not as a phenomenon **[1,4,5]**. The study clarifies explicit links between the intensity of symptoms, demographic factors, and correlates of behavioral symptoms of motion-sickness in a cohort of 377 valid respondents who participated in the probing of the severity of the symptoms **[27,28]**.

### *A. Multi-Symptom Character of Motion sickness.*

A major and important learning of the analysis is the hierarchical nature of symptom severity. Fatigue was the highest mean severity followed by headache and sweating as some of the five symptoms under investigation. On the other hand, dizziness and nausea also had relatively lower levels of mean severity. These findings make it possible to assume that motion sickness involves a more physiological response than the symptoms of nausea that have historically been of primary focus **[2,10]**. Systemic symptoms affecting the body in general like fatigue and headache clearly contribute largely to the total discomfort on motion exposure **[1]**. This trend supports the idea that motion sickness can be perceived as a complex physiological phenomenon that can be determined by the interplay between the vestibular system, autonomic nervous system, and central nervous system **[2,18]**.

This pattern is further emphasized by the heat-map figure that was included in the results and that reveals the relative strength of symptoms among the population. These visual methods help to determine the clusters of symptoms, as well as provide a better representation of the contribution of disparate symptoms to aggregate physiological burden **[56,60]**.

### *B. Gender Differences in Symptom Susceptibility.*

The other important conclusion relates to the correlation between sex and the occurrence of motion sickness. Chi-square analysis has identified a statistically significant correlation between the gender and the frequency of motion sicknesses with female subjects indicating higher frequency of motion sickness episodes when compared to their male counterparts **[30]**. In addition, the mean score on severity of all five symptoms examined was higher in female respondents. This trend suggests that females can be highly prone to displays of motion-sickness. These findings are supported by previous studies which show that biological and physiological effects, including hormonal difference and vestibular sensitivity, could affect motion-sickness susceptibility **[9,16,20]**.

Even though the current investigation does not directly test the underlying physiological processes, the results of the study emphasize the importance of considering gender as a critical factor in the study of motion-sickness and preventive measures **[20]**.

### *C. Ages -Variations in Symptom severity.*

Age based differences in the severity of the symptoms were also identified in the results during the analysis of adolescents and young adults. The Mann-Whitney U test revealed that there were statistically significant differences between dizziness and sweating between the two cohorts **[30]**. On the whole, young adults indicated more severe motion sickness as compared to teenagers. These differences can be a reflection of the distinction of the lifestyle and the exposure to travelling conditions **[17]**. Young adults tend to travel more due to occupational, academic or even social commitments and this would in effect increase their exposure to the motion conditions that induce the symptoms of motion sickness **[11]**.

### *D. Effect of Transportation Mode.*

The research also analyzed whether there were differences in the severity of the symptoms depending on the different modes of transport. The results indicated that non-air-conditioned traveling by bus was highly correlated with severity of headaches and marginally correlated with severity of nausea **[17]**. The conditions environmental like lack of good ventilation, vibration, and congested travelling conditions can also lead to more discomfort in such modes **[5]**. On the other hand, other means of transportation cars, trains, planes, air-conditioned buses did not show significant variations in the severity of symptoms. The implication of these findings is that the conditions of environmental travel could moderately adjust the level of symptoms symptoms under certain conditions, but individual physiological vulnerability continues to be a major factor in the expression of motion-sickness symptoms **[2,3,6]**.

### *E. Motion sickness and Motion sickness predictors*

The predictors comprised 4 categories: Coughing, Spewing, Angio, and Nausea severity.

The predictive modeling pointed out a number of influential factors that were related to motion sickness. Logistic regression analysis revealed that gender, frequency of travelling and specific types of travelling behaviour had a higher likelihood of experiencing motion sickness **[31]**. Multiple linear regression has shown that the strongest predictor of severity of nausea was a history of motion sickness with prior sufferers having more chances of reporting a high level of nausea **[32]**. The results in these studies demonstrate the significance of physiological predisposition and experience before exposure to motion environments in determining individual responses to motion environments **[9]**.

### *F. Symptom Risk Profiles*

Clustering analysis revealed two types of participants depending on the patterns of severity of the symptoms: high-risk group and low-risk group **[45]**. The high-risk cluster had the highest percentage of female participants and young adults implying that they are more vulnerable to the severe manifestations of motion-sickness among these demographic groups **[20]**. The detection of these risk profiles could help in the early intervention and preventive actions against persons at a higher risk.

### *G. Implications of the Study*

All of the findings in combination highlight the importance of studying motion sickness in a multi-symptom analytic model **[4],[18]**. Instead of analyzing one symptom, such as nausea, which is already the main indicator, the review of several patterns of symptom severity will help to have a more detailed picture of the burden of physiological activity that the person has to carry. The use of statistical methods and visualization, i.e. heat-maps and clustering, illustrates the value of data-dependent methods in identifying pattern of symptoms in population-wide health data **[27],[60]**.

### *H. Limitations*

Despite such contributions, the research has a number of constraints. First, the accrual of data was through self-reported survey responses which may have caused reporting bias **[46,47]**. Second, cross-sectional type of research limits the possibility to determine causal relationships between the variables under discussion **[46]**. Third, the distribution of the sample in some modes of transportation might have an impact on the generalizability of the particular results. It would be appropriate to employ bigger and more varied samples and longitudinal research designs in future studies to more effectively understand causal relationships between motion exposure and the development of symptoms **[47].**

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