Approval

The dissertation titled "INVESTIGATING MODE CHOICE BEHAVIOR DURING MEDICAL EMERGENCY IN BANGLADESH" submitted by Aftab Ibn Nazim has been accepted as partial fulfilment of the requirement for the degree, Bachelor of Science in Civil Engineering.

Supervisor

Dr. Moinul Hossain
Professor
Department of Civil and Environmental Engineering (CEE)
Islamic University of Technology (IUT)
Board Bazar, Gazipur, Bangladesh

Declaration

It is hereby declared that this thesis report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

Author

AFTAB IBN NAZIM

Aftab Ibn Nazim

Student ID: 170051031

INVESTIGATING MODE CHOICE BEHAVIOR DURING MEDICAL EMERGENCY IN BANGLADESH

BY

AFTAB IBN NAZIM

170051031

A Thesis Submitted in Partial Fulfilment of the requirements for the degree of

BACHELOR OF SCIENCE IN CIVIL ENGINEERING

DEPARTMENT OF CIVIL & ENVIRONMENTAL ENGINEERING

ISLAMIC UNIVERSITY OF TECHNOLOGY

MAY 2022

Approval

The dissertation titled "INVESTIGATING MODE CHOICE BEHAVIOR DURING MEDICAL EMERGENCY IN BANGLADESH" submitted by Aftab Ibn Nazim has been accepted as partial fulfilment of the requirement for the degree, Bachelor of Science in Civil Engineering.

Supervisor

____

Dr. Moinul Hossain
Professor
Department of Civil and Environmental Engineering (CEE)
Islamic University of Technology (IUT)
Board Bazar, Gazipur, Bangladesh

Declaration

It is hereby declared that this thesis report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

Author

____

Aftab Ibn Nazim

Student ID: 170051031

Dedication

To my departed father and eldest brother, my loving mother and my two siblings who have always believed in me and to my devoted teachers who have always guided me

Acknowledgement

First of all, All the praises to The Almighty. We will always be grateful to Allah, who is the most kind and merciful.

Without the insightful direction of Dr. Moinul Hossain, Professor, Department of Civil and Environmental Engineering, IUT, it would have been impossible to execute this thesis. Sir, thank you for your priceless advice, unending support, and constant encouragement.

Our deepest gratitude to Dr. Md. Asif Raihan, Assistant Professor, Accident Research Institute (ARI), Bangladesh University of Engineering and Technology (BUET), who is tenaciously kind and patient. Without his astute supervision, it would be impossible to bring the study to fruition.

Also, we are sincerely grateful to Rifat Hossain Bhuiyan, Lecturer, Department of Civil and Environmental Engineering, IUT, who also has assisted us a lot.

Finally, we would like to thank our cherished family members and everyone else who assisted us in completing our research.

Table of Contents

List of Figures

List of Acronyms

MLR Multiple Linear Regression

BBN Bayesian Belief Network

ITS Intelligent Transportation System

CI Conditional Independence

DAG Directed Acyclic Graph

EM Expectation Maximization

NMV Non-Motorized Vehicle

IUT Islamic University of Technology

LOO Leave One Out

GIS Geographic Information System

WHO World Health Organization

List of Tables

Abstract

During a medical emergency, it is necessary to make multiple crucial, time-sensitive judgments. For example: the quickest way to nearby hospital, the safest way so that the patient is less affected by the road conditions. Bangladesh has seen a considerable increase in the number of motorized vehicles as a result of the country's recent economic expansion and the growing popularity of ride-sharing apps. There are currently more options than ever before for modes of transportation, yet during medical emergencies, individuals still choose to use unconventional modes of transportation.

Previous research on Mode choices in Bangladesh during medical emergencies consists of geospatial aspects, situational analysis of rescue services, statistical analysis without socioeconomic and travel characteristics aspects. There is a gap in research regarding the socio demographic factors, the interaction of social and economic factors and how they affect each other. The following study addresses these factors and constructs relationships between them.

In this study, we aimed to determine the factors that influence the method of transportation chosen and ways they relate to one another during a medical emergency situation. A causal relationship has been shown between factors representing socioeconomic and trip aspects that influence mode selection. Using

Bayesian Belief Network, the network was created based on past research findings and extensive knowledge. PC technique based on conditional independence was used to build the Bayesian network. The Bayesian network was utilized to determine the posterior probability for each of the socio economic and trip characteristics variables.

Results showed that if the accident severity is so fatal that there will be long term consequences, only then people prefer ambulances as mode of transport during medical emergencies. People tend to go for normal motorized vehicles when the education level of the one who brought it is Graduate or above and Patient’s Age is within Twenty to Sixty. This is because highly educated people understand that according to the patient’s mid age, a normal motorized vehicle would be the most suitable to seek medical attention within the shortest possible time frame. This study's findings can serve as a resource for policymakers and medical authorities to understand the current situation and improve upon it.

CHAPTER 1

INTRODUCTION

1.1 Background

A medical emergency is an acute injury or sickness that poses an immediate threat to a patient's life or long-term health. Some of these situations, such as cardiovascular (heart), respiratory, and gastrointestinal, may necessitate the intervention of a trained individual, as the victim may be unable to handle them on their own.

Every year, Bangladesh Motor Vehicles Sales recorded 4,900 units in Dec 2019, compared with 4,650 units in the previous year (https://www.ceicdata.com/en/indicator/bangladesh/motor-vehicles-sales). With the ever increase number of sales of Motor vehicles, during a sudden medical emergency people in Bangladesh still prefers unconventional mode of transports.

In 2014, cardiovascular illness, road traffic accidents, other accidents, and suicides accounted for 45.9 percent of all deaths (N = 13707) in Dhaka, according to an analysis by two hospitals. During the observation period in four study hospitals, only 11.3% of 734 emergency patients were transported to the hospital by ambulance, compared to 63.3% by rickshaw/motor-rickshaw and 25.8% by bus/car. 55.6 percent of emergency patients arrived at the hospital 60 minutes or later following the onset of their symptoms. (Hossain, et al. (2022).

For emergency medical situation to be improved and to save maximum number of lives possible, the mode choices are to be addressed. All of the possible mode choices must be assessed and analyzed to understand the user's mindset while choosing a mode.

1.2 Objective of study

Identifying the key factors that affect the choice of mode during emergency

Finding causal relationship between individual factors

To identify the impact of socioeconomic factors

Identifying the impact of trip characteristics, such as- waiting time, trip cost, trip duration etc.

1.3 Scope of Research

This study concerns about finding out the important factors while deciding the mode of transportation on an emergency medical situation. The survey questionnaire was presented to a large number of people having different levels of income, education, age, gender etc., socioeconomic parameters. Also, the socioeconomic condition of the one who brought the patient to hospital has also been addressed. This has not been addressed by the previous literature works so medical authorities, government can get a better idea of the emergency medical situation a lot better through this study.

1.4 Thesis Outline

The thesis consists of six chapters. The following are brief descriptions of the chapters:

Chapter 1: Introduction

This chapter describes the research's context, problem description, intent, and objective.

Chapter 2: Literature Review

This chapter analyzes the key works of literature that aided in determining the optimal research work plan.

Chapter 3: Data & Methodology

This chapter discusses the research's step-by-step methodology and displays how gathered data were analyzed. Also, this chapter highlights approaches for scoping, limiting, and data acquisition.

Chapter 4: Analysis & Results

This chapter addresses the analysis of gathered data and analyzes the conclusions acquired.

Chapter 5: Conclusion & Recommendation

This chapter summarizes the research's key results and discusses ramifications, policy recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter covers the past literature works on mode choice during emergency situation. This also uncovers the gaps of where future research works can be done.

2.2 Previous Studies on Mode Choice during Emergency

Patients or bystanders often face difficulties while choosing mode of transportation, travel route and destination at the time of emergency. (Wu et. al., 2020) Because in an emergency situation, the decision-making process must be fast and as time goes on, the probability of surviving decreases at exponential rate. As not everyone has knowledge to decide exactly when it is vital to go for emergency services and which mode is needed at which emergency medical cases, it gets difficult to take a fast and reliable decision.

In the urban areas, roads are so congested that they hardly provide any space for clearing off the ambulance. (The Daily Star, 2022) This results in complicated situations where patients die in the road. In Dhaka, a densely populated city with poor traffic control, it is uncommon for an ambulance to have a clear path to its destination quickly.

It is generally assumed that access to healthcare is not an issue in densely populated urban areas due to short distances, we prove otherwise by applying improved methods of assessing accessibility to emergency services by the urban poor that take traffic variability into account. (Ahmed, Shakil et. al., 2019) Although densely populated urban areas usually have short distances to cover, not all class of people can afford the accessibility of these emergency services. Also, in these kinds of areas, the infrastructure, traffic variability, traffic management system, lack of ITS exits which worsens the probability of getting access to the healthcare.

In Bangladesh, most of the ambulances are mainly just converted from ordinary vehicles. (The Daily Star, 2022) As a result, many modern medical facilities aren't present in these vehicles. Also, if old vehicles are made into ambulances, performance may get severely worse due to bad maintenance, faulty parts, aged vehicle body etc. Then these old vehicles converted into ambulances won't be able to get the patient and drop off the patient at hospital in time.

As the transportation capacity is limited, the resources are scarce and proper management is needed. (Shavarani, S., & Vizvari, B. 2018). The demand is to be addressed properly. Adequate studies, surveys, field site visits are required to assess where the services are required and how the capacity should be distributed upon the whole area which needs to be covered.

The established standards are not met or criteria not fulfilled for the placement of emergency vehicle preemptive scheduling at current intersections. A better comprehension of the travel characteristics of ambulances may aid planners and engineers in identifying intersections that meet the traffic operations and safety objectives for emergency vehicle preemption. (Gkritza, et. Al, 2021)

The correct decision making can make a huge difference in future (Kennedy, et. Al., 1996). People must understand the emergency situation properly and realize the depth of situation. Then they must decide what exactly is needed to be done, why the one chosen should be followed, what are the alternatives, what to avoid, when it should be done, the process to achieve the required goal.

The local emergency response facilities are rarely adequate for majority of places and effective allocation is vital (Repoussis, et. Al., 2016). To minimize the amount of response time and to provide early medical service, its mandatory to allocate all resources such a way that maximum number of patients can be benefitted.

The dynamic and ever - changing nature of the medical emergency demands that prehospital management decisions be made under extreme time constraints (Ofer Amram, et. Al., 2012). As the demand of medical emergency is changing rapidly, the decisions made in the early hours are changing too. This is because of the inclusion of many factors which weren't present before.

The variability of journey time and supply frequency throughout the day's various time periods affects deployment of emergency medical units. (Hao Lei, et. Al., 2009) As the travel time varies throughout the day, the demand also changes. As there are different time schedule for offices, educational institutions, recreational centers, city centers, shopping malls the demand also varies from time to time. It’s important to understand where and when the demand peak arises.

CHAPTER 3

DATA & METHODOLOGY

3.1 Area of Study

The survey data collection area was mainly at Dhaka and also couple of nearby districts.

3.2 Data Collection

The surveyors posed a series of well-planned questions to respondents. Mainly, the questions were asked in Hospitals within the study area. A total of 2352 data were collected and analyzed. 67 Questions were asked to each individual.

Table 1: Statistics of Questionnaire Survey

SI	Variable	Item	Frequency	Percentage
1	Patient – Age	<20	400	17%
		20~60	1505	64%
		>60	447	19%
2	Patient – Income	<=25 thousand BDT	1693	72%
		25~55 thousand BDT	612	26%
		>55 thousand BDT	47	2%

3	Patient – Gender	Male	1247	53%
		Female	1105	47%
		Transgender	0	0%
4	Patient – Education Level	Up to Secondary	635	27%
		Secondary to Graduate	847	36%
		Above Graduate	870	37%
5	Accident Severity	Minor	729	31%
		Severe	165	7%
		Life Threatening	1458	62%
6	Mode Choice	Ambulance	682	29%
		Bus	0	0%
		Non-motorized	141	6%
		Normal Motorized	564	24%
		Special Motorized	917	39%
		Others	47	2%
7	Trip Duration	<20 Minutes	423	18%
		20~40 Minutes	1411	60%
		>40 Minutes	517	22%
8	Transportation Cost	<200 BDT	588	25%
		200~400 BDT	1105	47%
		>400 BDT	659	28%
9	Waiting Time	<20 Minutes	1105	47%

		20 Minutes	635	27%
		>20 Minutes	612	26%
10	Time of Accident	Early to Late Morning	659	28%
		Late Morning to Noon	917	39%
		Noon to Early Morning	776	33%
11	One who brought – Age	<20	188	8%
		20~60	2164	92%
		>60	0	0%
12	One who brought – Gender	Male	1717	73%
		Female	635	27%
		Transgender	0	0%
13	One who brought – Income	<=25 thousand BDT	1200	51%
		25~55 thousand BDT	988	42%
		>55 thousand BDT	165	7%
14	One who brought – Education Level	Up to Secondary	165	7%
		Secondary to Graduate	612	26%
		Above Graduate	1576	67%

The Questionnaire contained patients' personal information (age, gender, income, education level), bystanders' personal information (age, gender, income, education level), trip characteristics (trip duration, waiting time, trip generation time), accident characteristics (severity, time of accident), mode choice variables (mode type, cost of mode), trip experience (trip rating, trip rapidness, trip improvement).

3.3 Work Flow of the Research

At first, out of the 67 variables, 14 variables were chosen for further analysis. For this, Multiple Linear Regression was done in RStudio to determine which variables are significant enough to choose.

Then, to form the network, correlation was done on the same software to determine which network to select.

After that, the Bayesian Network was created to understand the mutual relationship between the selected variables. The conclusion was reached after the analysis.

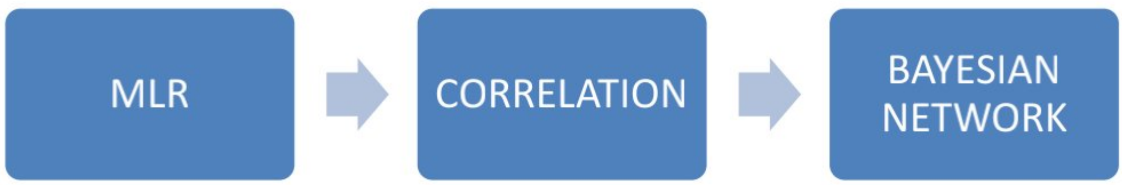

Figure 1: Work Flow of the Research

3.4 Multiple Linear Regression

Regression is a very effective tool to determine the significance of each independent variables of a model. Here, we looked into the P value & adjusted R squared value to determine the significance of each variable and the whole model.

```r
#Brief overview of the whole dataset
head(EMS_Final_Dataset_1_)

#Checking the parameters graphically
pairs(EMS_Final_Dataset_1_[1:14])

#Constructing linear regression model with all possible independent variables
EMS_lm <- lm(formula = `Mode choice` ~ `Patient - Age` + `Patient - Gender` + `Patient - Income` + `Patient - Education Level` + `Accident Severity` + `One who brought - A
summary.default(EMS_lm)
summary(EMS_lm)

#Construction of final linear regression model with the significant independent variables
Final_EMS_lm <- lm(formula = `Mode choice` ~ `Patient - Age` + `Patient - Gender` + `Patient - Income` + `Patient - Education Level` + `Accident Severity` + `One who broug
summary.default(Final_EMS_lm)
summary(Final_EMS_lm)

install.packages("ggpubr")
cor(EMS_Final_Dataset_1_)
```

Figure 2: R Programming Code for MLR & Correlation

```
Residuals:
    Min      1Q  Median      3Q     Max 
-2.5878 -0.9613 -0.0067  0.9122  4.0112 

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)                        6.310021   0.183133  34.456  < 2e-16 ***
`Patient - Age`                   -0.096415   0.018970  -5.082 4.02e-07 ***
`Patient - Gender`                -0.279398   0.057389  -4.869 1.20e-06 ***
`Patient - Income`                -0.046048   0.014579  -3.159 0.001606 ** 
`Patient - Education Level`       -0.077135   0.013936  -5.535 3.46e-08 ***
`Accident Severity`               -0.095032   0.030257  -3.141 0.001706 ** 
`One who brought - Gender`        -0.715172   0.064434 -11.099  < 2e-16 ***
`One who brought - Income`        -0.129340   0.013081  -9.888  < 2e-16 ***
`One who brought - Education level` -0.100241   0.016418  -6.105 1.20e-09 ***
`Trip duration`                    0.121808   0.036241   3.361 0.000789 ***
`Transportation cost (In hundreds)` -0.016586   0.002117  -7.834 7.12e-15 ***
`Waiting time (In 20 minutes)`    -0.049224   0.046352  -1.062 0.288367    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.16 on 2340 degrees of freedom
Multiple R-squared:  0.2246,	Adjusted R-squared:  0.221 
F-statistic: 61.62 on 11 and 2340 DF,  p-value: < 2.2e-16
```

Figure 3: Multiple Linear Regression results

The final equation for the Multiple Linear Regression is:

Patient's Mode Choice = 6.31 – 0.0964(Patient's Age) – 0.2793(Patient's Gender) – 0.046(Patient's Income) – 0.0771(Patient's Education Level) – 0.0950(Accident Severity) – 0.7151(Gender of the one who brought) – 0.1293(Income of the one who brought) – 0.1002(Education level of the one who brought) + 0.1218(Trip duration) – 0.0165(Trip Cost) – 0.0492(Waiting Time)

In the analysis, we inserted every single variable of the whole questionnaire. Then after the initial analysis was done, we only kept the ones with high significant level. In the meantime, it's also important to keep a good adjusted R squared value. In this case, we got an adjusted R squared value of 0.2246 which is moderate for real life dataset like ours.

The main objective was to determine the variables significance level. In this case, the variables we selected have high significance level.

3.5 Correlation

Correlation was done to understand the relationship between the independent variables.

```
The downloaded binary packages are in
        C:\Users\ASUS\AppData\Local\Temp\Rtmpshncbk\downloaded_packages
> cor(EMS_Final_Dataset_1_)
```

	Patient - Age	Patient - Gender	Patient - Income	Patient - Education Level	Accident Severity	One who brought - Age
Patient - Age	1.00000000	0.063506952	0.01379474	-0.217868453	0.485605159	-0.078969120
Patient - Gender	0.06350695	1.000000000	-0.48166703	-0.100901440	0.023565590	0.058667663
Patient - Income	0.01379474	-0.481667028	1.00000000	0.437644777	-0.036188813	-0.047348769
Patient - Education Level	-0.21786845	-0.100901440	0.43764478	1.000000000	-0.175204768	0.073701997
Accident Severity	0.48560516	0.023565590	-0.03618881	-0.175204768	1.000000000	0.012447019
One who brought - Age	-0.07896912	0.058667663	-0.04734877	0.073701997	0.012447019	1.000000000
One who brought - Gender	-0.05041637	0.139663056	0.03343585	0.110114735	-0.077104172	-0.002362232
One who brought - Income	0.10818518	0.072744169	-0.08031089	-0.007835685	0.126875036	0.179238505
One who brought - Education level	0.11627279	0.170275446	0.03572565	0.292176844	0.005101029	0.010025231
Time of accident	0.06234067	-0.009926077	0.06515363	0.085272969	0.111661240	0.048993267
Trip duration	0.04766656	-0.019657404	-0.05260204	-0.140209369	0.154616890	0.013567125
Mode choice	-0.19124687	-0.150859232	-0.06882460	-0.160808383	-0.167319023	-0.062069777
Transportation cost (In hundreds)	0.21116091	0.066505743	-0.04250219	-0.120752848	0.356799675	0.050896219
Waiting time (In 20 minutes)	0.22770787	-0.066120460	0.04176593	-0.082998752	0.225556587	-0.043093469

	One who brought - Gender	One who brought - Income	One who brought - Education level	Time of accident	Trip duration	Mode choice
Patient - Age	-0.050416366	0.108185183	0.116272786	0.062340667	0.04766656	-0.19124687
Patient - Gender	0.139663056	0.072744169	0.170275446	-0.009926077	-0.01965740	-0.15085923
Patient - Income	0.033435846	-0.080310888	0.035725652	0.065153628	-0.05260204	-0.06882460
Patient - Education Level	0.110114735	-0.007835685	0.292176844	0.085272969	-0.14020937	-0.16080838
Accident Severity	-0.077104172	0.126875036	0.005101029	0.111661240	0.15461689	-0.16731902
One who brought - Age	-0.002362232	0.179238505	0.010025231	0.048993267	0.01356712	-0.06206978
One who brought - Gender	1.000000000	-0.504118065	-0.054684726	-0.036511782	-0.08554487	-0.14008515
One who brought - Income	-0.504118065	1.000000000	0.327682864	0.098663750	0.02621399	-0.18969347
One who brought - Education level	-0.054684726	0.327682864	1.000000000	0.044636819	-0.12669701	-0.26682825
Time of accident	-0.036511782	0.098663750	0.044636819	1.000000000	-0.04853540	-0.06422851
Trip duration	-0.085544873	0.026213990	-0.126697007	-0.048535403	1.00000000	0.03192358
Mode choice	-0.140085145	-0.189693470	-0.266828250	-0.064228515	0.03192358	1.00000000
Transportation cost (In hundreds)	-0.041520249	0.138096027	-0.006972569	-0.015443831	0.41782718	-0.20560625
Waiting time (In 20 minutes)	-0.010173257	-0.090983939	-0.122617478	0.006366299	0.20201194	-0.04194178

	Transportation cost (In hundreds)	Waiting time (In 20 minutes)
Patient - Age	0.211160909	0.227707866
Patient - Gender	0.066505743	-0.066120460
Patient - Income	-0.042502193	0.041765932
Patient - Education Level	-0.120752848	-0.082998752
Accident Severity	0.356799675	0.225556587
One who brought - Age	0.050896219	-0.043093469
One who brought - Gender	-0.041520249	-0.010173257
One who brought - Income	0.138096027	-0.090983939
One who brought - Education level	-0.006972569	-0.122617478
Time of accident	-0.015443831	0.006366299
Trip duration	0.417827178	0.202011935
Mode choice	-0.205606247	-0.041941781
Transportation cost (In hundreds)	1.000000000	0.276016520
Waiting time (In 20 minutes)	0.276016520	1.000000000

Figure 4: Correlation Analysis between the variables

Here we studied all the correlations that exists between the variable and how they interact with the change of each variable.

3.6 Bayesian Network

A Bayesian network is representing of a collection of variables and their relationships graphically. It's a very powerful tool to understand the underlying relationship between these variables visually. An acyclic graph is required to be generated. Because if the graph is cyclic, then the whole process gets into a loop and it doesn't make sense anymore. This Acyclic Graph is known as DAG or Directed Acyclic Graph, Each random variable in a DAG is referred to as a node and is linked by lines called arcs. The nodes on the origin side of an arc are referred to as mother nodes, while the other nodes are referred to as child nodes. The Bayesian framework is founded on the Bayes hypothesis or Bayes rule which is stated below.

$P(A|B)= P(B|A) *P(A)/ P(B)$

Here, P(A) is the chance that A will occur, while P(B) is the likelihood that B will occur. P(A|B) represents the chance of occurrence of A given the occurrence of B, whereas P(B|A) represents the likelihood of B given the occurrence of A. Graphically representing the joint probability distribution, a Bayesian network may be written as a product rule –

$P\ (X1, X2\ldots\ldots Xn) = \Pi P(Xi|pa(Xi))\ ni{=}1$

GeNIe employs the Expectation Maximization (EM) technique to get the joint probability distribution through parameter learning. The EM algorithm is a method for doing maximum likelihood estimation with latent variables present. EM guesses the values of latent variables before optimizing the estimation through a series of iterative adjustments. E-Step (Expectation Step) and M-Step are the two steps that make up the iteration process (Maximization Step). Continuing the iterating until the two levels converge.

3.7 GeNIe Interface

GeNIe refers to Graphical Network Interface. It is widely used to construct graphical decision theoretic models.

The questionnaire data were loaded into GeNIe 3.0.65 Academic Version, and structural learning was performed using the PC method.

At first, the default PC algorithm was implemented. Then from literature review and engineering judgement, the arcs connecting the nodes were reduced significantly to interpret the model better. Finally, this network was formed using 0.05 Significance level.

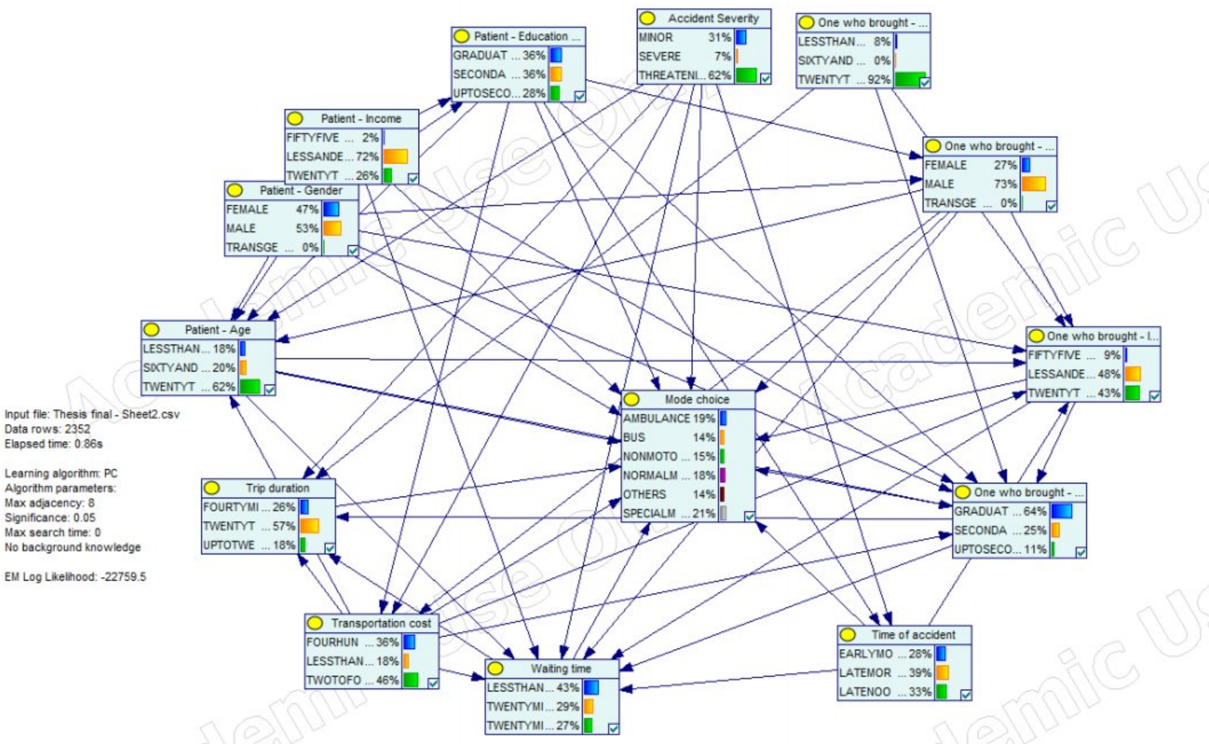

Figure 5: Initial Bayesian Network with PC Algorithm

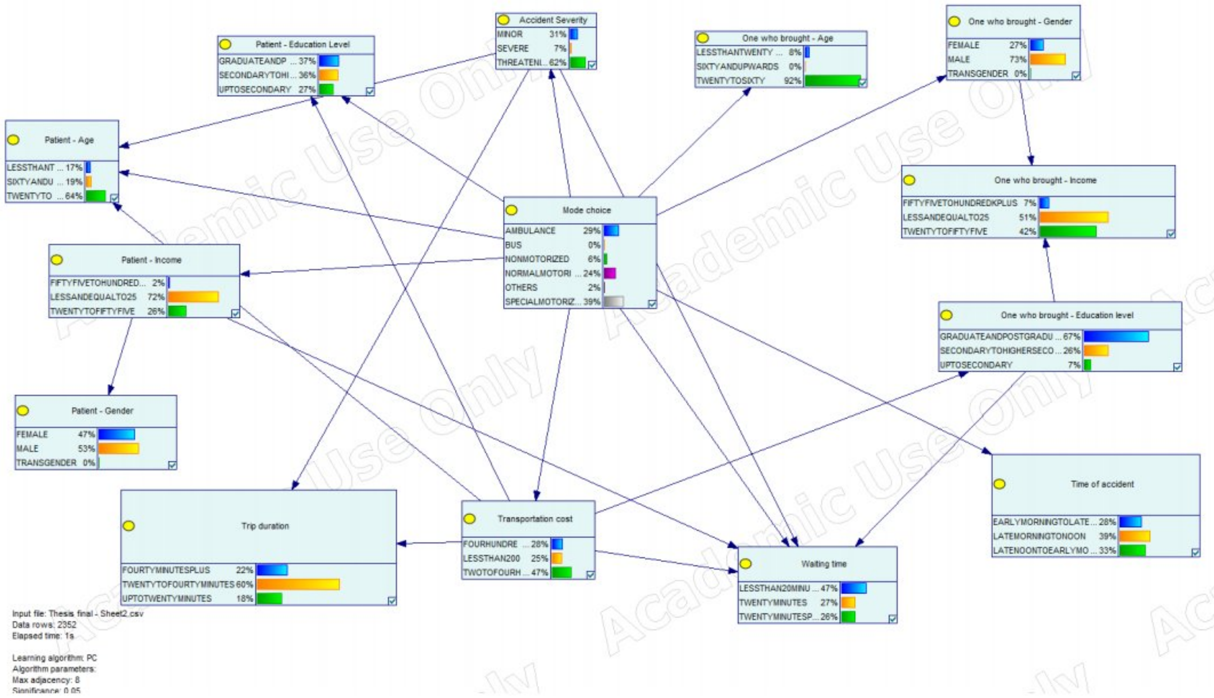

Figure 6: Final Bayesian Network

CHAPTER 4

ANALYSIS & RESULTS

4.1 Introduction

The survey data categorized in such a way that the individual categories don't skew the whole dataset. If there exists such skewness, the results will deviate from the real-life scenario. The arcs and nodes were modified several times. For analysis, sensitivity analysis and tornado diagrams were generated.

4.2 Model Validation

For Model Validation, ROC Curve, Accuracy Check & Confusion matrices were generated. The ROC Curve should stay above 60~70% to indicate a good model. If we observe the ROC Curves for Ambulance, Bus, Non-motorized vehicles, Normal motorized vehicles, Special Motorized vehicles and other vehicles all of them are above 80%. So, the model can be regarded as validated.

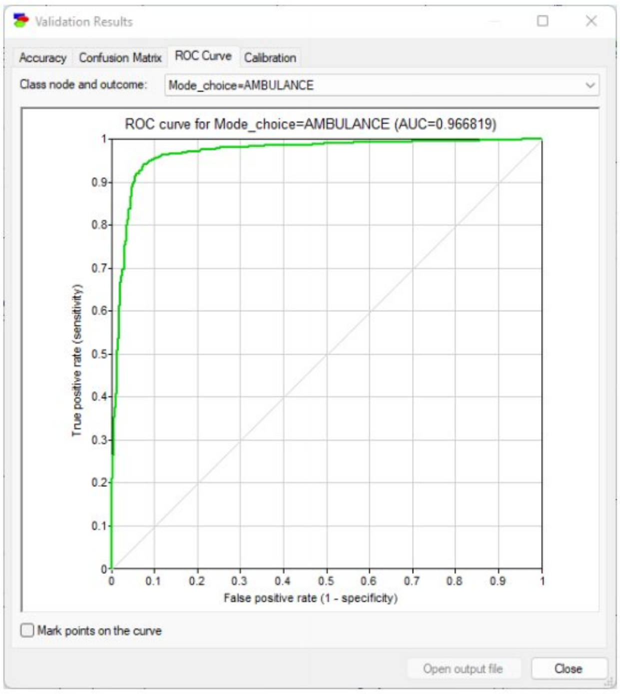

Figure 7: Validation for Ambulance

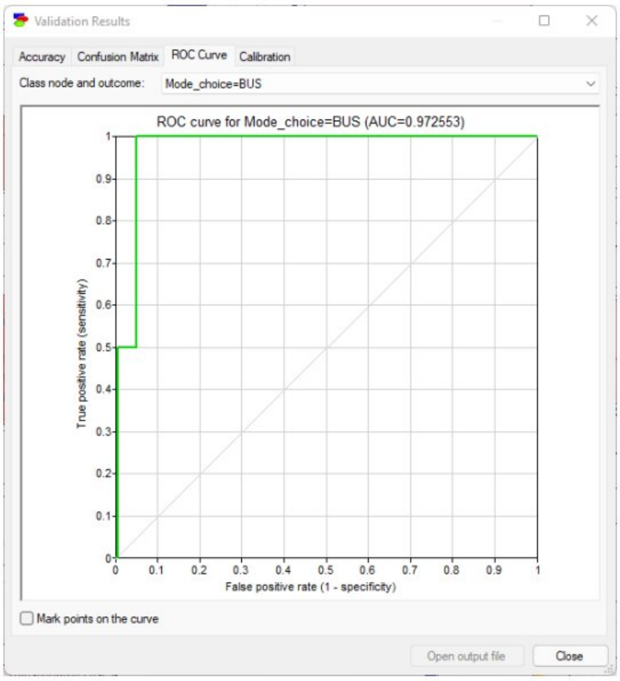

Figure 8: Validation for Bus

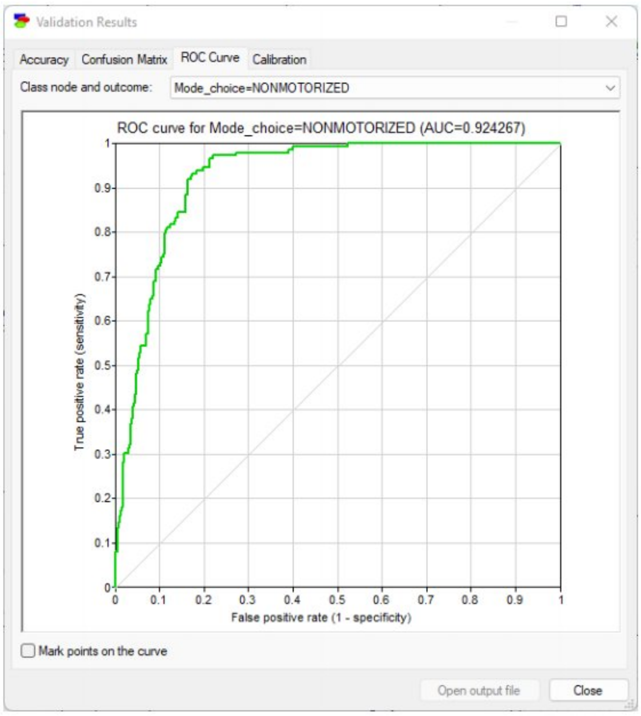

Figure 9: Validation for Non-motorized vehicles

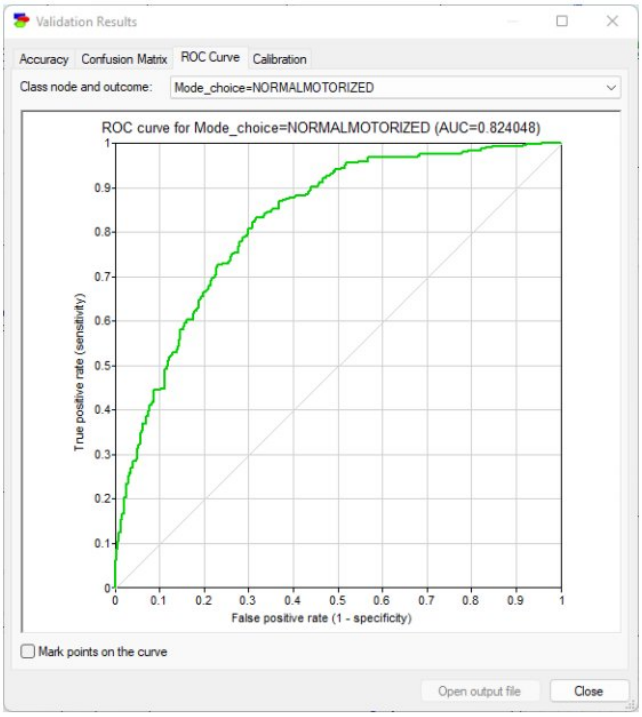

Figure 10: Validation for Normal Motorized Vehicle

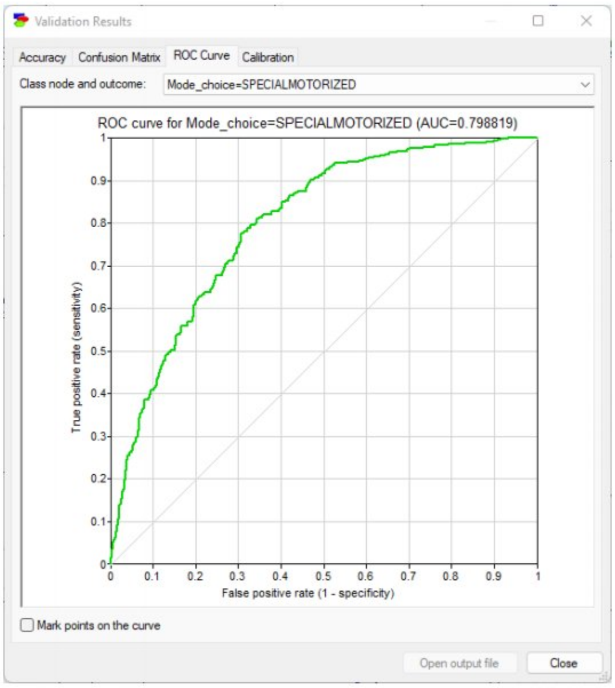

Figure 11: Validation for Special Motorized Vehicle

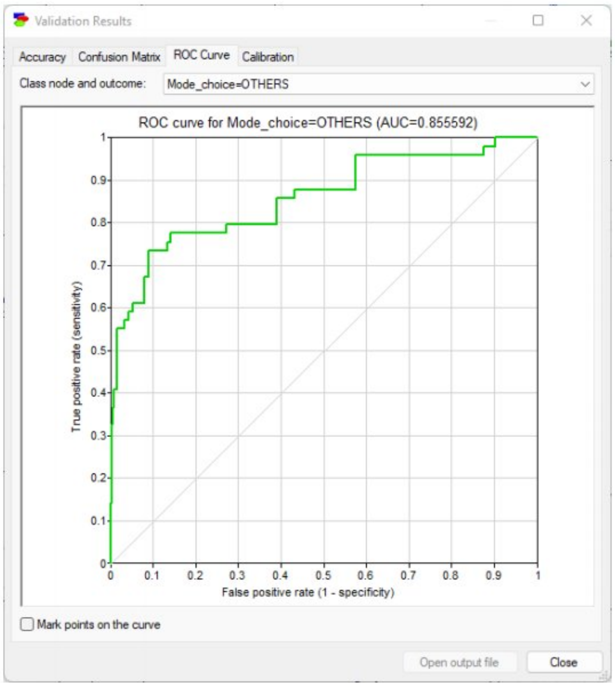

Figure 12: Validation for Other Vehicles

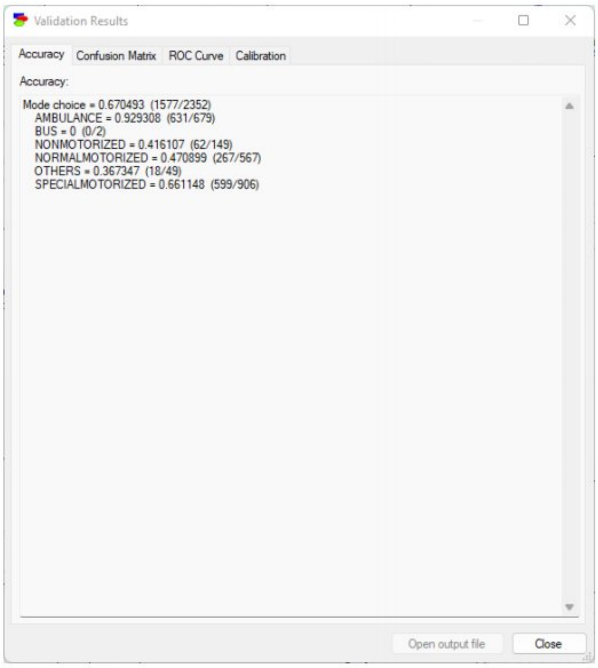

Figure 13: Accuracy Check

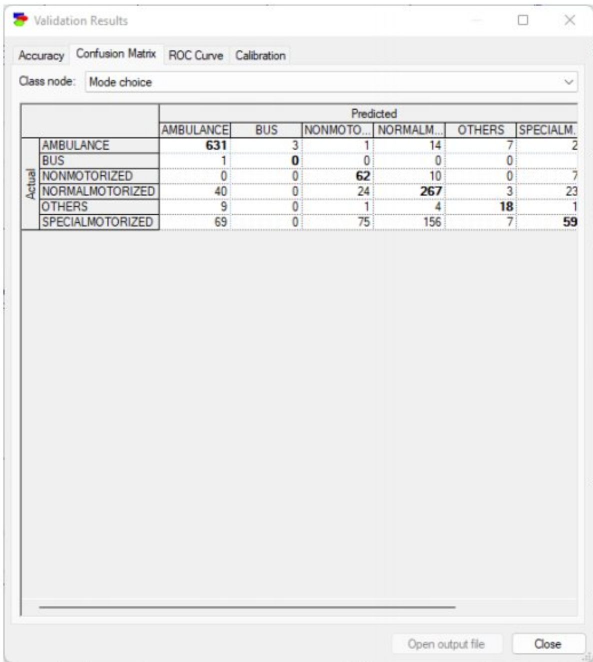

Figure 14: Confusion Matrix

4.3 Model Analysis

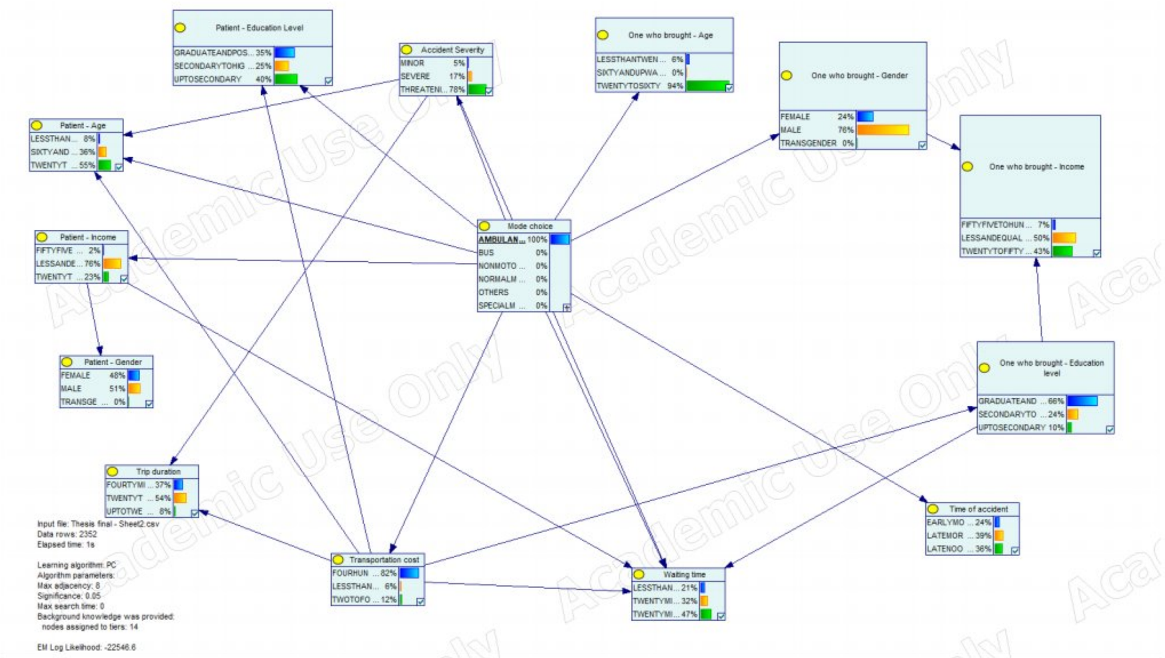

Figure 15: Ambulance preference analysis

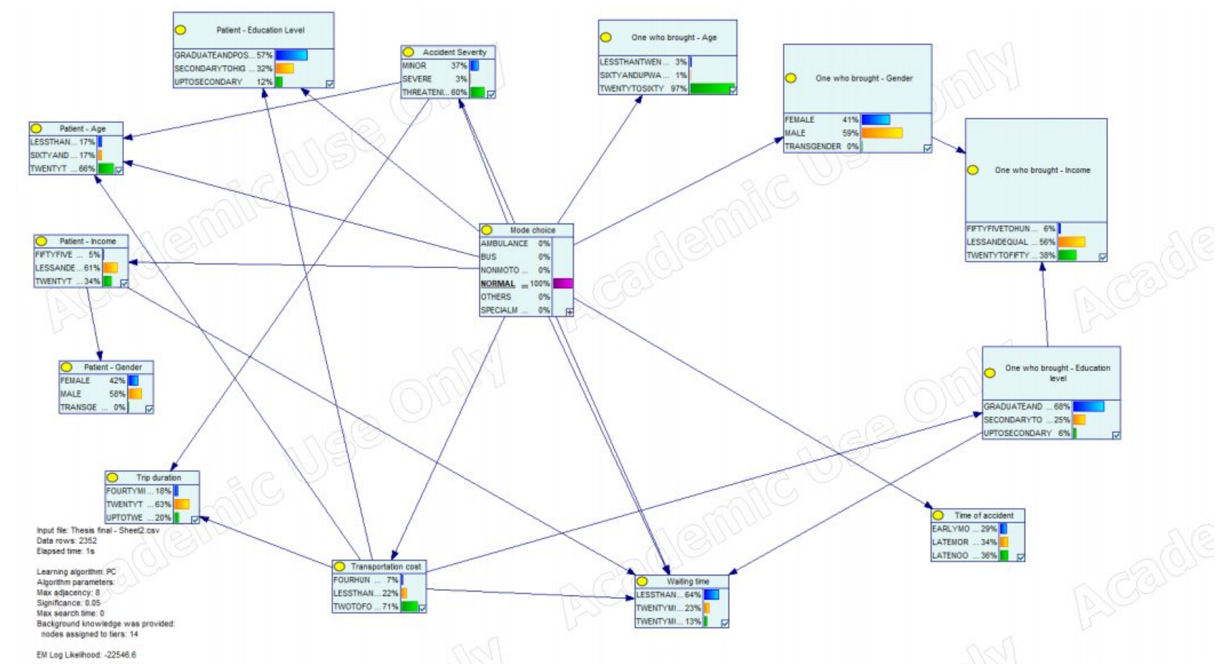

Figure 16: Normal motorized preference analysis

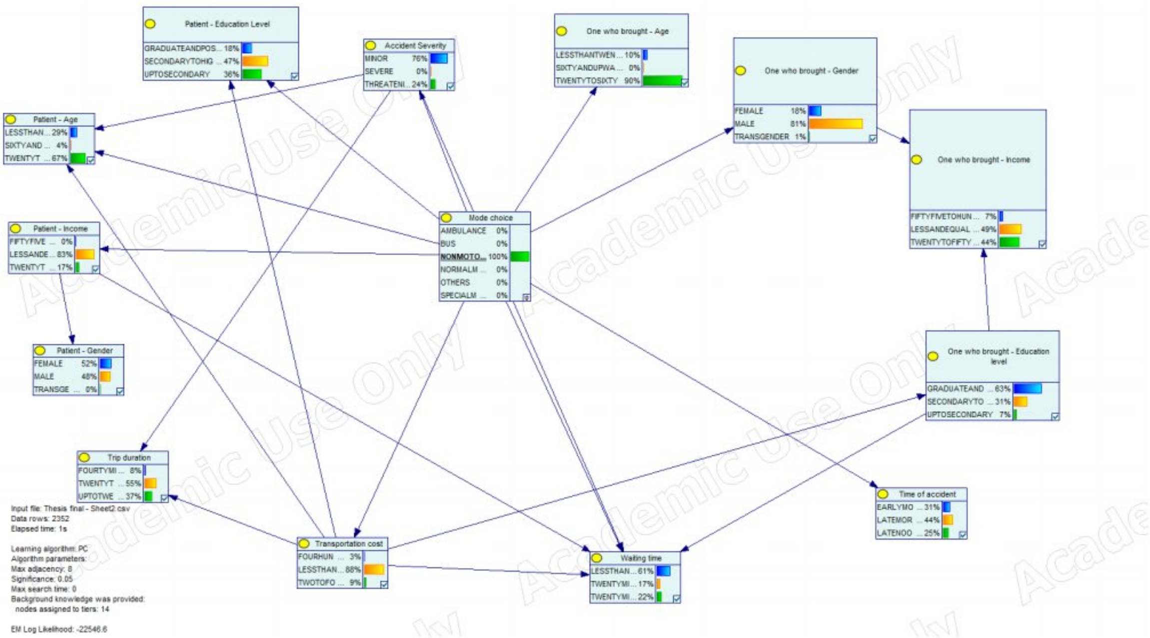

Figure 17: Non-motorized preference analysis

At first, we are analyzing the mode choice preferences.

For ambulance preference, 78% of the people were in life-threatening medical situations. Which means only when the medical situation is very severe, people decide to get an ambulance. We can also see that 36% of the patients are aged 60 or above and 55% of them are within 20 to 60. So, Accident severity and People's Age are the two key factors affecting the mode choice decision.

For Normal motorized preference, 66% of the people are aged between 20 to 60 and 57% of the people are graduate and above in education level. Which means, generally, mid aged highly educated people go for normal motorized vehicles.

Because they realized that normal motorized vehicles would be the most suitable to seek medical attention within the shortest possible time frame for mid aged people.

For Non-motorized preference, 83% of the patients are of secondary level education and 83% of the patients have income less than 20 thousand BDT. Also, trips cost less than 200 BDT 88% of the time. Which refers to the fact that people with low income, low education level prefer non-motorized vehicles.

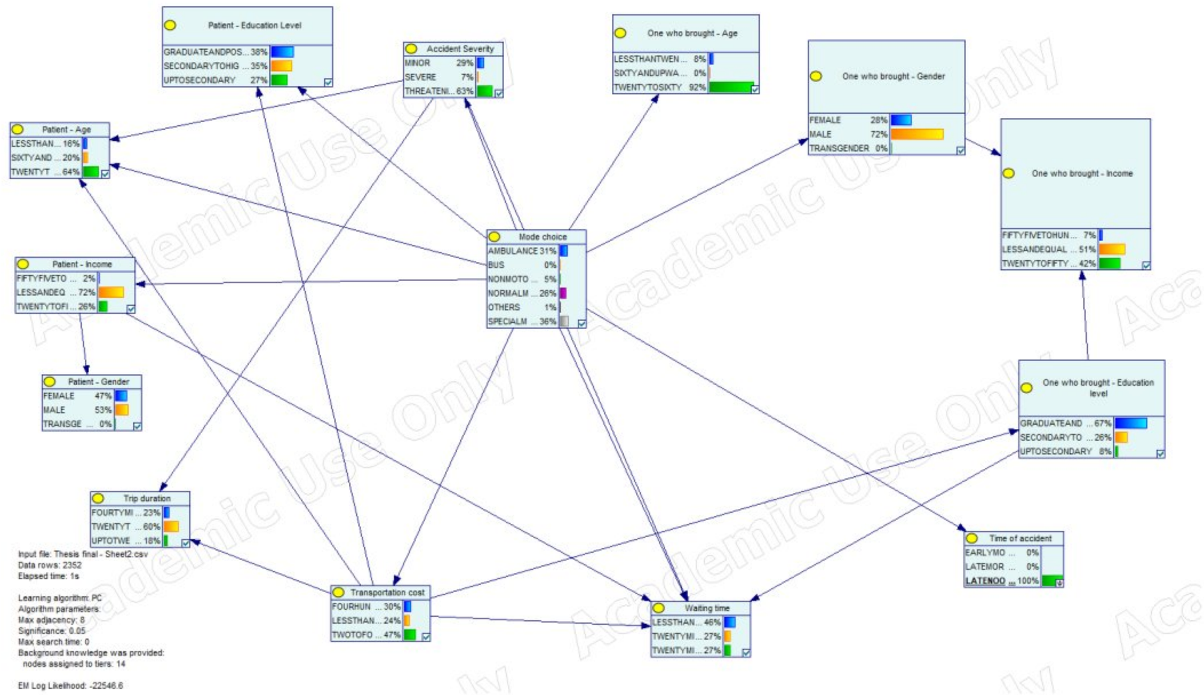

Figure 18: Time of medical emergency analysis

Secondly, we are analyzing Trip Characteristics.

Now if the medical emergency occurs within late afternoon to early morning, 31% will choose an ambulance,36% will prefer special motorized & 26% will go for normal motorized vehicles. So, 94% of the choices are motorized as during midnight/evening/early morning medical emergencies, people want the lowest possible waiting time to reach the hospital as soon as possible. Surprisingly, even people with low income also prefer motorized vehicles because generally motorized trips are costly which is also evident here with 36% of the trip costing high. But it seems people of all income levels prefer motorized vehicles at these hours because non-motorized vehicles are not fast enough or reliable enough to reach destinations quickly.

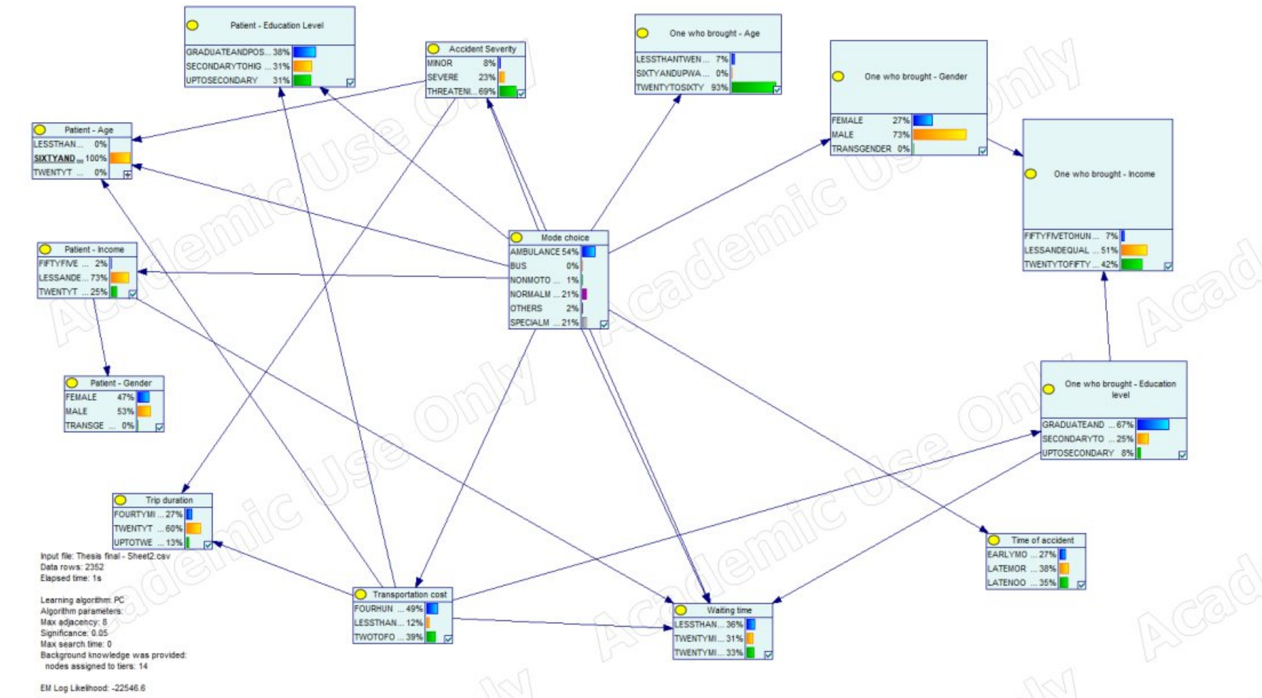

Figure 19: Patient Age analysis

Lastly, we are analyzing Socioeconomic parameters.

If Patient Age is above 60 years, the probability of choosing ambulance jumps from 21% to 54%. Also, For people of such old age, the emergency severity increases to 69%. This is true as people of such old age is very sensitive and suffers way more than normal people. As a result, the mode choice favors ambulance more.

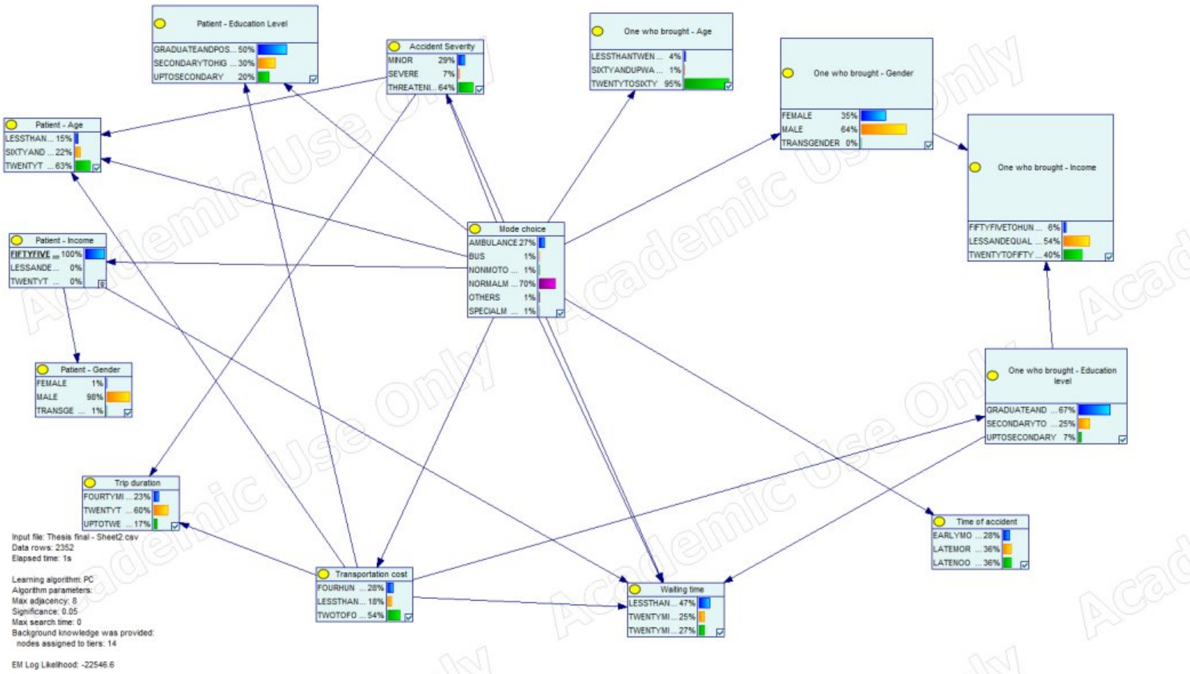

Figure 20: Patient Income Analysis

If Patient Income is above 55 thousand BDT per month, the probability of choosing normal mode jumps to 70% while ambulance is 27%. The waiting time gets really low as high income people prefers fast movement during emergency situation. The trip duration is also within 20 to 60 minutes range. As a result, for socioeconomic aspects, the waiting time and trip duration is affected the most.

4.4 Sensitivity Analysis

Sensitivity analysis is done to graphically interpret whether the variables have strong or weak relationships between them. In GeNIe, the deeper the red color in a variable the stronger the relationship. Here we can see that the majority of the variables have a very deep red color indicating these variables are strongly connected to each other in this network.

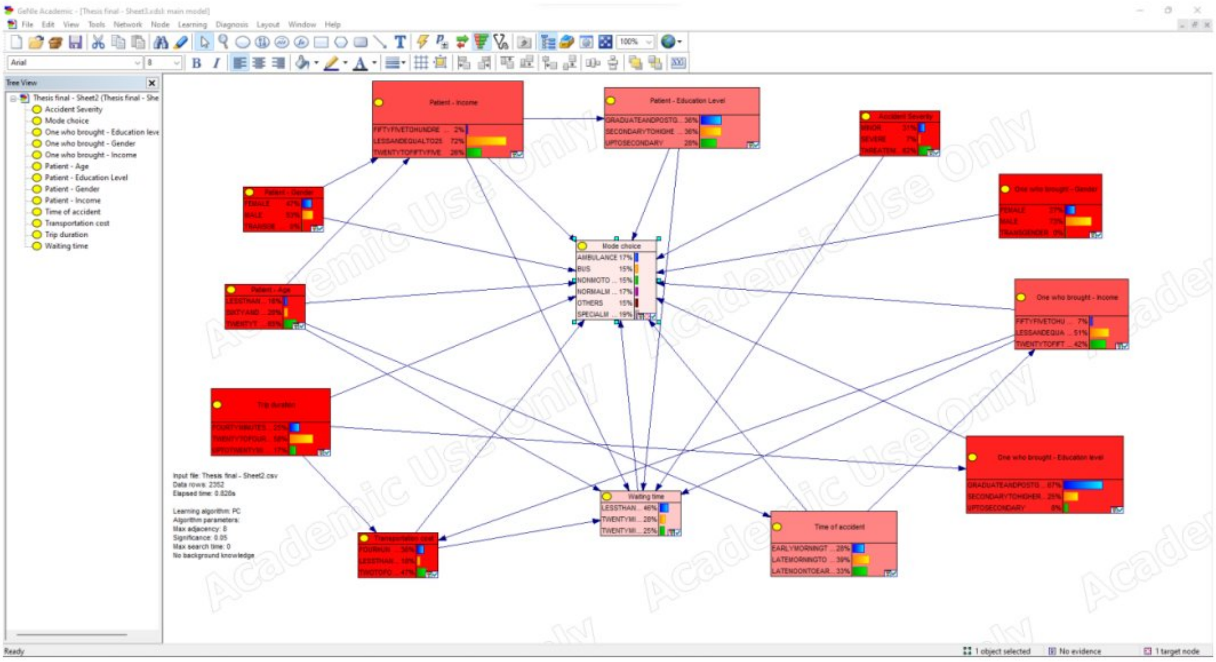

Figure 21: Sensitivity Analysis

CHAPTER 5

CONCLUSION & RECOMMENDATION

5.1 Key findings

After analyzing mode choice preferences, the most crucial variables are Accident Severity, Patient's Age, Patient's Education level.

For Socioeconomic preferences, Patient's age, income, education level are the main factors behind the decision-making process.

For trip characteristics, the crucial variable found here is Trip duration and Trip cost.

Surprisingly, for the one who brought, only the education level of the person seems to be affecting the mode choice decision. This makes sense as during the medical emergency, the patient may not be in the right health condition to take correct decisions instantly.

Also, the income level of the person who brought is also vital factor. This makes sense as the initial cost may be covered by the one who brought. If that person is of high income, shorter trip duration and faster mode choice can be expected.

5.2 Policy Implication & Recommendation

From the key findings, it's evident that Patients socioeconomic variables and trip characteristics are the main factors behind the decision-making process. Also, the income and education level of the one who brought is important.

The modern technologies like helpline, mobile app services need more marketing and exposure. From our study, it showed that majority of people don't even know that these facilities exist in the first place.

There must exist immediate medical service equipment in the ambulances and these should be present in adequate quantity.

Government regulated ambulance service which would be cost effective needs to be present. As a result, people of a large variety of income can have access to them.

Execute proper survey and realize the accident/medical emergency hotspots. Pre locationed ambulance can be a vital solution.

Emergency lanes need to be introduced in the roads which can be beneficial for the quick transportation of the ambulances.

For temporary solution, the drivers on vehicles on the road need to educated in such a way that they clear out lanes for emergency vehicles to move.

5.3 Limitation and Future Scope

Although we have addressed a lot of socio-economic variables, more variables can be included in the future works. For example: the occupation, what's the current dwelling condition of the patient, the access to the modern internet, the access to the modern technologies etc.

In this study, GIS study wasn't done. So, the road condition, nearby important buildings, daily traffic study, location of patient, location of hospital etc. were completely unknown. Future studies can include these and show that there may exist other variables related to GIS which affects the mode choice decision making process.

For selecting the variables, multiple linear regression was the only method considered. The p value and the adjusted R squared value may not always show the whole scenario. More machine learning algorithms could be used to verify the decision.

The survey locations could be changed and include a more detailed data of the rural areas. This can give a better picture of the real-life scenario in rural areas.

REFERENCES

Blank, F. (2021). A spatial queuing model for the location decision of emergency medical vehicles for pandemic outbreaks: the case of Za'atari refugee camp. Journal Of Humanitarian Logistics And Supply Chain Management, 11(2), 296-319. https://doi.org/10.1108/jhlscm-07-2020-0058

El Itani, B., Ben Abdelaziz, F., & Masri, H. (2019). A Bi-objective Covering Location Problem. Management Decision, 57(2), 432-444. https://doi.org/10.1108/md-04-2018-0474

Kar, K., & Khasnabis, S. (2009). Effective Usage of Harmful Events Data in Transportation Safety Management. Transportation Research Record: Journal Of The Transportation Research Board, 2137(1), 3-12. https://doi.org/10.3141/2137-01

Lei, H., Cheu, R., & Aldouri, R. (2009). Optimal Allocation of Emergency Response Service Units to Cover Critical Infrastructures with Time-Dependent Service Demand and Travel Time. Transportation Research Record: Journal Of The Transportation Research Board, 2137(1), 74-84. https://doi.org/10.3141/2137-09

Hutton, J., & Graham, J. (2009). Rural Preparedness for Traffic Control in Agricultural Emergencies. Transportation Research Record: Journal Of The Transportation Research Board, 2137(1), 95-106. https://doi.org/10.3141/2137-11

Repede, J., Jeffries, C., & Hubbard, E. (1993). ALIAS: A Graphical User Interface for an Ambulance Location Model. International Journal Of Operations & Production Management, 13(12), 36-46. https://doi.org/10.1108/01443579310048227

Griffith, J., & Roberts, D. (2020). How we roll: A fire engine to every call? Fire department resource allocation and firefighter support in the United States. International Journal Of Emergency Services, 9(3), 409-419. https://doi.org/10.1108/ijes-12-2019-0066

Repoussis, P., Paraskevopoulos, D., Vazacopoulos, A., & Hupert, N. (2016). Optimizing emergency preparedness and resource utilization in mass-casualty incidents. European Journal Of Operational Research, 255(2), 531-544. https://doi.org/10.1016/j.ejor.2016.05.047

Shavarani, S., & Vizvari, B. (2018). Post-disaster transportation of seriously injured people to hospitals. Journal Of Humanitarian Logistics And Supply Chain Management, 8(2), 227-251. https://doi.org/10.1108/jhlscm-12-2017-0068

Schmid, V. (2012). Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. European Journal Of Operational Research, 219(3), 611-621. https://doi.org/10.1016/j.ejor.2011.10.043

Wankhade, P., & Murphy, P. (2012). Bridging the theory and practice gap in emergency services research: a case for a new journal. International Journal Of Emergency Services, 1(1), 4-9. https://doi.org/10.1108/20470891211239281

Kusumasari, B. (2012). Network organisation in supporting post-disaster management in Indonesia. International Journal Of Emergency Services, 1(1), 71-85. https://doi.org/10.1108/20470891211239326

French, M., Fan, Y., & Stading, G. (2015). An exploratory study of factors influencing emergency response performance. Management Research Review, 38(5), 559-576. https://doi.org/10.1108/mrr-11-2013-0274

Gkritza, K., Collura, J., C. Tignor, S., & Teodorovic, D. (2021). An Analysis of the Characteristics of Emergency Vehicle Operations | Emerald Insight. Emerald.com. Retrieved 8 May 2021, https://www.emerald.com/insight/content/doi/10.1108/9780080467542-025/full/html.

Griffith, J., & Roberts, D. (2020). How we roll: A fire engine to every call? Fire department resource allocation and firefighter support in the United States. International Journal Of Emergency Services, 9(3), 409-419. https://doi.org/10.1108/ijes-12-2019-0066

Repoussis, P., Paraskevopoulos, D., Vazacopoulos, A., & Hupert, N. (2016). Optimizing emergency preparedness and resource utilization in mass-casualty incidents. European Journal Of Operational Research, 255(2), 531-544. https://doi.org/10.1016/j.ejor.2016.05.047

Shavarani, S., & Vizvari, B. (2018). Post-disaster transportation of seriously injured people to hospitals. Journal Of Humanitarian Logistics And Supply Chain Management, 8(2), 227-251. https://doi.org/10.1108/jhlscm-12-2017-0068

Schmid, V. (2012). Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. European Journal Of Operational Research, 219(3), 611-621. https://doi.org/10.1016/j.ejor.2011.10.043

Wankhade, P., & Murphy, P. (2012). Bridging the theory and practice gap in emergency services research: a case for a new journal. International Journal Of Emergency Services, 1(1), 4-9. https://doi.org/10.1108/20470891211239281

Kusumasari, B. (2012). Network organisation in supporting post-disaster management in Indonesia. International Journal Of Emergency Services, 1(1), 71-85. https://doi.org/10.1108/20470891211239326