Developing a Model on Factors Affecting the Mode Choice in EMS

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Approval

The paper titled "Developing a Model on Factors Affecting the Mode Choice in EMS" submitted by Mahibul Taohid Aditya, Tasnim Mahmud, Iffat Jahan Nabila, Md. Zidan Shahriar has been accepted as partial attainment of the requisite for the degree of Bachelor of Science in Civil Engineering.

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Declaration

It is hereby declared that this thesis/project has been performed by us under the supervision of Dr. Moinul Hossain. We have taken appropriate precautions to ensure that the work is original and has not been plagiarized. We can also make sure that the work has not been submitted elsewhere for the award of any Degree or Diploma.

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Dedication

We dedicate this thesis paper to those who have been an unwavering source of inspiration and support throughout our academic journey. Your belief in us and collective efforts have shaped our journey. With deep gratitude, we present this work as a testament to our shared commitment to knowledge and growth.

Acknowledgment

Thanks to Almighty Allah, for Whom we were able to complete our research. Certainly He is the all-knowing and all-powerful, therefore nothing would have been possible without His mercy.

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Finally, we want to thank our beloved family and everyone else who helped us with the study we conducted, whether directly or indirectly.

Preamble

The focus of our study was to find the important aspects responsible for choice of mode of patients and bystanders in case of Emergency Medical Service (EMS). The name of the study is " Developing a Model on Factors Affecting the Mode Choice in EMS". In this study Ambulance, Rental Car, Uber, CNG, Rickshaw, Own Car and others modes were chosen. Different socioeconomic factors, preference and severity of the injury of the patient was recorded. The research's objectives are as stated:

Identifying the factors contributing to mode choice in case of EMS for developing cities. Developing a mode choice model based on EMS. Exploring the possibilities to reduce the Response Time of current EMS from mode choice perspective. Implicating some policies based on which the current situation of the Emergency Medical Service can be improved.

Abstract

Various studies has been conducted on the mode choice model for different kinds of situations such as for work travel mode choice, driver's route choice behaviour, choice of freight transport mode etc for different regions of the world and different unique policies have been recommended (Yamamoto et al., 2002 ; Xie et al., 2003 ; Li et al., 2019) . But till now, no work has been conducted on the mode choice behaviour of the patients and bystanders in case of emergency medical situations and the factors that are responsible behind the choice of those various conventional and unconventional modes. Emergency Medical Situation is a very critical set of circumstances where a minimum room of error can cause huge damage and fatality. This study aims to work on this perspective, where the factors behind the choice of modes will be analyzed, a model i.e., utility function will be developed for each unconventional mode and then possible recommendation will be given on which the unavoidable critical situation can be handled in a compact way. The data for this thesis project was collected from different zones of Bangladesh such as Dhaka, Rajshahi, Bogura, Barishal etc. And the zones were divided into mega-city and sub-urban category. About 1954 data were collected through questionnaire survey where various factors contributed to the decision-making process for the patients and bystanders, including geographical location, severity of the medical condition, availability and accessibility of different transportation options, response time requirements, and resource allocation considerations. C4.5 algorithm was used to find the most responsible factors for the choice of modes. As there are enough data for making a decision tree, the training and testing data-set gave satisfactory observations. Later Multinomial Logit Regression method was used to build up the utility functions of the unconventional modes taking ambulance as the base, where the significant factors were taken (Rob. P-value < 0.05). After the utility functions were generated, based on the factors and modes different interesting findings were allotted. Although the data-set might have been limited and there might be temporal and spatial bias and prejudice, still unique policies have been recommended which can be implied by the government for the betterment of the Emergency Medical Service.

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List of Acronyms

EMS	Emergency Medical Service
EMT	Emergency Medical Transport
LIC	Low Income Countries
MLE	Maximum Likelihood Estimation
MLR	Multinomial Logistic Regression
TRID	Transport Research International Documentation

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Emergency Medical Services, or EMS is a system that offers emergency medical care. When a serious accident occurs causing injury or illness, the main objective of EMS is to offer the medical emergency of the patient. It is an arrangement of synchronized emergency healthcare & response that involves numerous individuals and groups. (Maine, 2022). The majority of prosperous nations have an implemented EMS system that can be accessed nationwide by dialing only one number (Bhandari et al., 2020). Effective on-scene interventions could save more than half of deaths in developing nations. Organized and safe transportation to a hospital with an emergency care unit could then be followed by a trained examination, stabilization, and diagnosis (International Federation for Emergency Medicine., n.d.).

A major public health issue worldwide is deaths and impairments brought on by inadequate emergency medical rescue services (EMRS). (Cook et al., 2018).Only in 2012, a total of 33,114 patients—1,115 instances involving fatal crashes, 6,772 cases involving catastrophic injuries, and 25,187 cases involving mild injuries—were admitted to various trauma and medical establishments in Karachi. (Tehnicki Vjesnik - Technical Gazette., 2020). At least 190 people were killed, 6,500 were hurt, and 300,000 were left homeless as a result of the Beirut harbor blast on August 4th, 2020, overwhelming the nation's emergency response infrastructure. (Hannoun et al., 2022). These are some of the examples of severe injury cases in the world, where Emergency Medical Service could have played a huge role for minimizing the after-effects of the emergency situations.

Time-sensitive diseases and injuries account for a major share of the disease burden in developing nations. For many health systems in developing nations, providing immediate aid during life-threatening situations is not a top priority (Junaid et al., 2002). One of the most crucial roles of emergency medical services (EMS) is the transfer of individuals in medical emergencies. (Ebrahimian et al., 2014). In New York City, the average daily number of 911 urgent calls reached 6,500 during the COVID-19 epidemic, causing disruptions of up to 4 hours per emergency. (Hannoun et al., 2022). Higher EMS response periods were associated with higher incidence of catastrophic automobile crashes among 2268 US counties, according to a study involving 2214480 ambulances. (Byrne et al., 2019). A study based on the receiving of 911 calls stated that victims with responding time of less than 8 minutes died 7.1% of the time, while 6.4% of victims with a response time of under 7 minutes 59 seconds did so (risk difference of 0.7%; 95% CI: -0.5%, 2.0%). For a period of 8 minutes, the adjusted odds ratio for fatality was 1.19 (95% CI: 0.97, 1.47) (Blanchard et al., 2012).

The transfer of patients solely depends on the modes that carries them. In the context of Bangladesh, where the population exceeds 166 million people and health care resources are often limited, the effect of the choice of modes in EMS becomes even more pronounced. The modes vary depending on whether the service is emergency or not, the condition or impairment of the client, the required distance, and more (East Coast Ambulance., n.d.). Only 49% of Bangladesh's rural roads, according to the World Bank, are deemed to be in good or fair condition, making transportation challenging, particularly in times of emergency. Additionally, according to a survey by the Bangladesh Bureau of Statistics, 24% of rural households had to drive more than 30 minutes to get to the nearest medical facility, showing serious accessibility issues. There is a severe lack of ambulances in Bangladesh, according to official statistics from the government. For instance, there weren't enough ambulances to meet the population's emergency demands in 2019 because there were only 485 ambulances in the entire nation. Due to the lack of resources, it may take longer to reach patients and be more difficult to perform prompt medical interventions (One Ambulance for 300 Patients, 2023).

There are several socioeconomic factors, spatial and temporal data, severity and preference factors on which the choice of mode depends for a patient or a bystander. One must consider a wide range of the most varied factors affecting emergency circumstances when studying the city's traffic status. In the research regarded by Blanchard et al. (2012), patient acuity, age, gender, and the total duration between the scene and the transport were all potential factors. The inclusion requirements were satisfied by 7,760 unit responses, 1,865 of which (24%) were under 8 minutes. Patient age was 56.7 on average (standard deviation was 21.5) (Blanchard et al., 2012). Although no study was conducted based on the choice of modes in case of emergency medical situations, it is important to conduct the study based on different socioeconomic aspects as it can reduce the response and reaction time of patients and ultimately save lives.

1.1 Problem Statement

In developed countries, using an ambulance as Emergency Medical Transport (EMT) is widespread and practical. In contrast, several unusual modes rather than ambulance, are being used in developing and undeveloped countries for Emergency Medical Service (EMS), where the power and potential of these individualistic transports has not been explored yet. The existing system lacks an efficient and well-coordinated approach, resulting in sub-optimal patient outcomes and inadequate utilization of available resources.

In the whole world, let alone Bangladesh, no satisfactory research has been conducted based on the choice of mode for emergency medical service and the factors responsible behind the choice of modes. The current EMS framework in Bangladesh struggles to determine the most appropriate mode of transportation for emergency cases. Ambulances and other modes of transport are not effectively utilized, leading to delays, inefficient resource allocation, and compromised patient care.

The country's inadequate road infrastructure, particularly in rural areas, poses significant barriers to timely and efficient emergency medical transportation. The lack of well-maintained roads and transport systems restricts the availability and accessibility of suitable modes of transport, hindering the delivery of critical medical services.

Bangladesh faces challenges in optimizing its limited resources, including a shortage of well-equipped ambulances, trained medical personnel, and essential medical supplies. The absence of a comprehensive strategy to allocate and deploy these resources efficiently across different modes of transportation hampers the facilities of timely and appropriate emergency care. This is the reason why people tend to move towards the unconventional modes for emergency medical service, which doesn’t fulfill their purpose all the time.

The absence of standardized protocols and guidelines for mode selection in emergency situations contributes to inconsistencies and confusion among emergency respondent. The absence of clear criteria for selecting the most suitable mode based on the extremity and nature of the medical emergency undermines effectiveness of emergency medical services

Although there is a diverse tendency in the advancement of data mining in the area of vehicle crashes, there has not been much investigation into the patterns of different types of crashes.One must consider a wide range of the various aspects causing emergency circumstances when studying the city's transportation status. Available data on infrastructure and accessibility in Bangladesh highlights the existing gaps in case of transportation infrastructure and mode choice of people. Data mining techniques, which enable the multifarious interpretation of information as well as the identification of recurring patterns that aid in decision-making, must be applied to use this data effectively.

1.2 Purpose and Objectives

As no previous research was conducted based on the components affecting the mode choice of patients and bystanders in case of emergency medical service, this study aims to clarify the following points:

Identifying the factors contributing to mode choice in case of EMS for developing cities

- Developing a mode choice model based on EMS
- Exploring the possibilities to reduce Response Time of current EMS from mode choice perspective
- Implicating some policies based on which the current situation of the Emergency Medical Service can be improved.

1.3 Scope of the Study

About 1954 data were collected through questionnaire survey from different zones of Bangladesh, which comprised of mega-city and suburban zones. The severity of the injury of the patient was recorded along with other socioeconomic factors, spatial and temporal data, their preference and most importantly the mode they have chosen for the transfer of patient to the hospital.

1.4 Thesis Outline

The thesis has been conducted under 5 different chapters. They are stated below:

1. Introduction: The chapter contains background & motivation, problem Statement, purpose & objective and scope of the study.

2. Literature Review: The chapter discusses the relevant topics such as EMS system in developing countries, mode choice pattern in EMS, factors affecting the choice of modes etc. backed up by published literature.

3. Study Area, Data and Methodology: This chapter focuses on the scoping, bounding & acquiring methods of the data along with the work flow and selected method for analyzing the obtained data.

4. Analysis and Result: The chapter demonstrates the exploration of the data and interprets the computed results along with the work-flow diagram.

5. Conclusion and Recommendation: This chapter discusses the major findings, inference of policies along with limitation and future scope.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The thesis's literature review chapter focused on various aspects related to Emergency Medical System (EMS) and according mode choice. This chapter begins with the studies concerning the EMS in developing nations. Then examined the pattern of patient mode choice in EMS scenarios. Additionally, it explored the factors that influence mode choice behavior in EMS. Subsequently, it examined major studies carried out in developing nations and made recommendations for future policy based on the results obtained.

The thesis research commenced with an extensive exploration of scholarly publications and other important sources of information such as- journals, articles, conferences etc. This investigation involved searching for relevant number of outcomes by using specific keywords.

Table 2-1: Number of articles found in online search

Databases	Keywords	Results
Google Scholar	factors affecting emergency medical service	About 2,230,000 results
Google Scholar	modes used for emergency medical service	About 887,000 results
Google Scholar	Mode choice pattern	About 5,710,000 results
Google Scholar	EMS and mode choice modelling	About 31,400 results
Google Scholar	individual choice models for emergency	About 2,720,000 results

Google Scholar	emergency conditions travel pattern	About 804,000 results
Google Scholar	patients’ transportation choice behavior	About 90,300 results
Science Direct	EMS factors in rural and urban areas	2,783 results
Science Direct	factors affecting transportation mode	51,721 results
Science Direct	EMS and mode choice modelling	5,100 results
Science Direct	modes used for emergency medical service	38,564 results
Science Direct	emergency conditions travel pattern	28,152 results
Science Direct	EMS factors in rural and urban areas	84,020 results
TRID	modes used for emergency medical service	6 results
TRID	EMS factors in rural and urban areas	34 results
TRID	factors affecting transportation mode	7 results
TRID	factors affecting transportation mode	587 results
ProQuest	EMS and mode choice modelling	41,627 results
ProQuest	factors affecting transportation mode	419,014 results
ProQuest	individual choice models for emergency	917,850 results
ProQuest	modes used for emergency medical service	529,787 results
ProQuest	Patients’ transportation choice behavior	404,261 results

2.2 EMS System in Developing Countries

Emergency Medical Services (EMS) are an essential component of any healthcare system, providing emergency assistance largely in out-of-hospital situations. (Brice et al., 2022).

According to a study performed by Kirsch et al. (1996), it was found that- in developing countries, injury morbidity and mortality rate is much greater than developed countries. He also found that -more than 85% of all fatalities and 90% of life years with disabilities is lost due to traffic accidents occured in developing nations. In this case, EMS can give medical aid to people who have suffered a sudden sickness or accident. (Moore, 1999b). But Organized EMS systems are generally non-existent in nations with significant economic issues, such as Sub-Saharan Africa or portions of Asia. (Ghaffar et al., 2004).

It has been found that, inadequate transportation hinders the process of emergency medical service (Lungu and others 2001; Samai and Senge 1997). Besides, the interval of response time affects EMS critically (Alanazy et al., 2021).

In general cases, people have an adverse impression about EMS quality. (Tran et al., 2019). Also, inadequate EMS transportation is a major issue for society. (Camasso-Richardson et al., 1997).

2.3 Mode Choice Pattern in EMS

Research has documented that, patients use various types of modes to reach hospital's emergency departments (Brice et al., 2022). In LMICs like Bangladesh, rickshaw, ambulances and auto-rickshaws are used by patients (Boutilier & Chan, 2020).

In accord with Roudsari et al. (2007), in most of the developing countries, no specific method is available to provide emergency medical care primarily, rather patients use modes like public and private vehicles or wheelbarrows or others. Likewise, Shrestha et al. (2018) documented that, patients are transported to hospitals in taxis, bus or other readily available mode of transportation by the relatives that cannot fulfill emergency medical services properly.

From a study conducted by Adamtey et al. (2015) in rural Ghana, found that - less than 10% of victims of traffic accidents were transported to hospitals in ambulances; the majority were transported in taxis or private automobiles. Similarly, a study from Nepal showed that- a significant number of patients did not arrive at the emergency department via ambulance. (Shrestha et al., 2018). Likewise, a study from India found - although not ideal, a taxi is still the most widely used alternative to an ambulance. (Roy et al., 2010).

Ambulances are not accessible mostly, despite of being the most referred mean of transportation in EMS (Brice et al., 2022). Shrestha et al. (2018) acknowledged that, only a few patients rely on ambulances to undergo emergency services. Also, Wilson et al. (2013) documented that, in most of the LICs only 1% of people can use authorized emergency medical transportation services like ambulances.

Many researchers analyzed the reason behind the absence of ambulance use, which includes the ambulance service being frequently unavailable or delayed in LMICs (Tran et al., 2019), as well as having access to other automobiles and owning a personal vehicle (Shrestha et al., 2018). On the other hand, in many LIC and LMIC, typical modes of transport like motorbikes provide affordable alternatives for the quick movement of patients. (Hofman et al., 2008; Wesson et al., 2015).

2.4 Factors Affecting Mode Choice

A study was conducted by Ebrahimian et al. (2014b) on the factors affecting patient’s decision about transportation in Tehran, Iran. The study found that, patients' financial situation, cultural origins, and level of physical health are some of the variables influencing their mode of transit choice. The existence of pathologic conditions was also considered when deciding on transportation. Furthermore, the unique characteristics of the EMS mission, such as reaction time, the ability to seek guidance, equipment, and particular conditions, influenced their transportation option.

Previous studies have found that individual and family socio-demographic factors are crucial in determining the kind of transportation used. Specific factors that influence travel mode selections include age, socioeconomic status, car ownership, as well as job orientation. (Bhat, 1997; Bhat & Sardesai, 2006). Also, commuters' method of transportation is influenced by a variety of social, economic, cultural, and environmental factors such as trip duration, expenses, delays, the number and ease of transfers, comfort, and others. (Minal and Sekhar, 2014; G et al., 2015)

CHAPTER 3: STUDY AREA, DATA & METHODOLOGY

3.1 Study Area

The study was conducted in Bangladesh. Several Megacities and Townships were part of the study. Districts that were included in the study are Dhaka, Gazipur, Mymensingh, Narayanganj, Narsingdhi, Tangail, Manikganj, Narshingdi, Jhalokathi, Sylhet, Chittagong, Bogura, Barishal. The information was directly collected from the patient or the bystander who has brought the patient to the hospital.

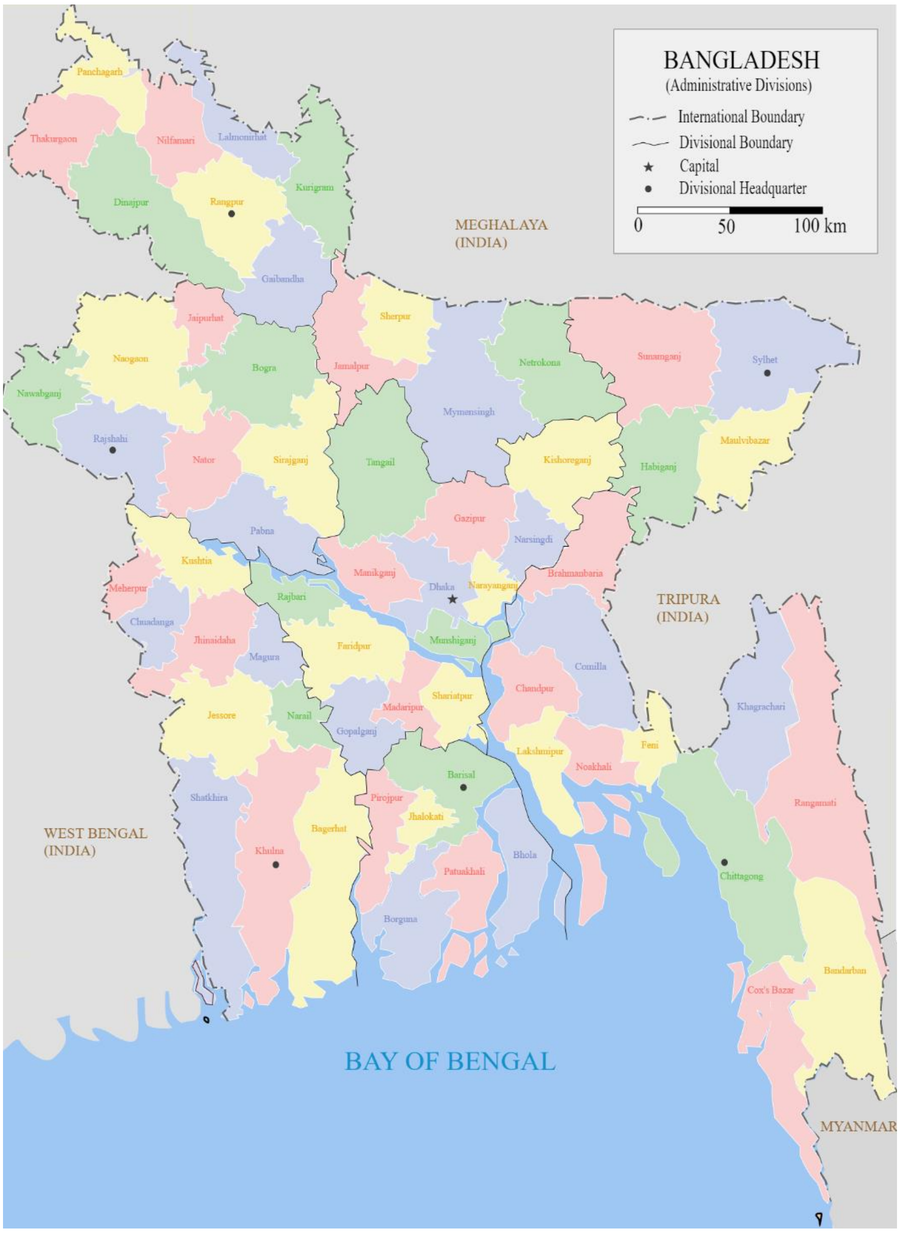

Figure 3-1: Study Area

3.2 Data Collection

A questionnaire survey was developed to retrieve the information from the patient or the bystander. The survey included various socio-economic data (e.g., Age, Income, Profession etc.) about both the patient and the bystander, Different spatial and temporal data (e.g., space and time of emergency, location and distance of hospital. Travel time, waiting time etc.) about the event of emergency, the severity of the patient, the mode they chose and their preference about EMS. A descriptive analysis about the collected data is shown in Table 3-1,

Table 3-1: Socio-economic data

SOCIO-ECONOMIC DATA			
Variable	**Category**	**Frequency**	**Percentage (%)**
Patient Age	18-50	1014	52%
	50+	802	41%
	<18	138	7%
Patient Education	Primary-Secondary	632	32%
	SSC-HSC	466	24%
	Grad/PostGrad	623	32%
	Illiterate	233	12%
Bystander Age	18-50	1854	95%
	50+	97	5%
	<18	3	0%

Bystander Education	Grad/PostGrad	1195	61%
	SSC-HSC	457	23%
	Primary-Secondary	259	13%
	Illiterate	43	2%
Bystander Income	10-35K (Low)	1541	79%
	35-65K (Mid)	386	20%
	65K+ (High)	27	1%
Patient Profession	Employee	819	42%
	Student	295	15%
	Homemaker (Housewife)	642	33%
	Others	198	10%
Bystander Profession	Employee	1356	69%
	Homemaker (Housewife)	289	15%
	Student	256	13%
	Others	53	3%
Car Availability	No	1613	83%
	Yes	341	17%

SPATIAL DATA			
City	Megacity	1524	78%
	Outer-Megacity	45	2%
	Township	385	20%
SEVERITY			
Injury Type	Minor Injury	561	29%
	Life Threatening	559	29%
	Not Life Threatening but will cause long term damage	834	43%
TEMPORAL DATA			
Emergency Time	Morning Peak	747	38%
	Inter Peak	692	35%
	Off Peak	204	10%
	Evening Peak	311	16%

From Table 3-1 we can see that in 95% of the cases the age of the bystander was in between 18-50. Most of the data was collected in Megacities (78%). 69% of the bystanders fall under the category of Low income. It suggests that Bangladesh is a Developing country.

A comparison of the Average Travel Time and Average waiting time is presented in Figure 3-2,

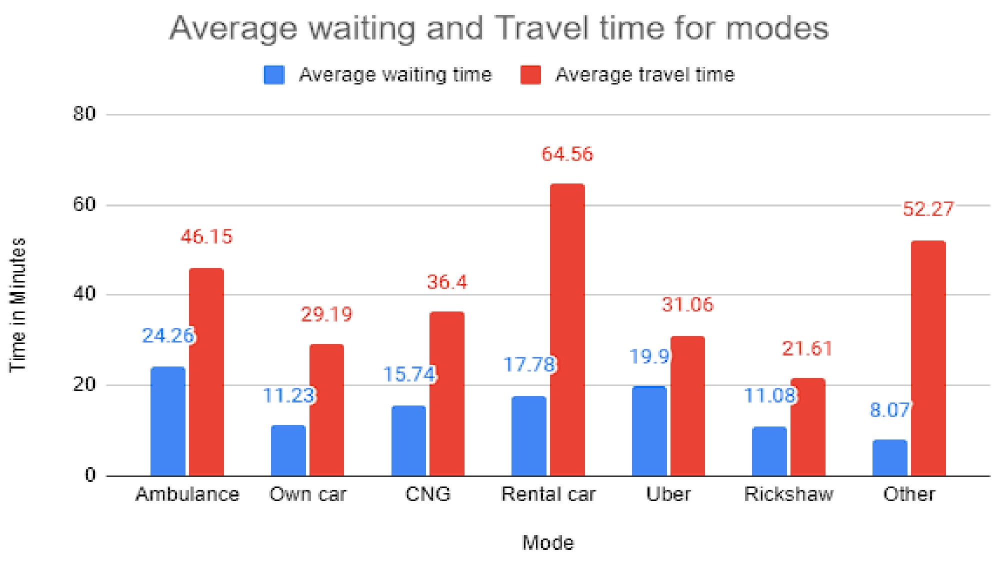

Figure 3-2 Comparison of travel time and waiting time of different modes

It is seen that the Travel Time for Ambulance and Rental Cars are almost the same as they are for the same purpose but the waiting time for ambulance is 24.26 minutes which is the highest among these modes. And the waiting time for rickshaw is 11.98 minutes which is the lowest.

A comparison of Average Cost and Average Cost per Kilometer is shown in Figure 3-3

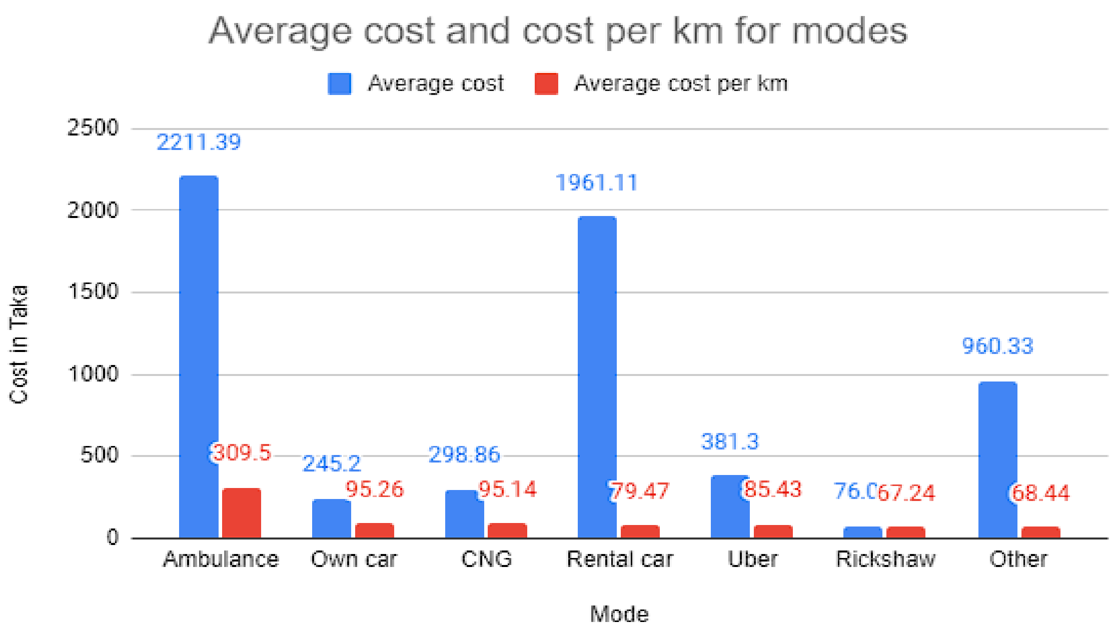

Figure 3-3: Comparison of the cost of the modes

From the figure 3-3 it is visible that the average cost of ambulance and rental cars are much higher than the other modes which is understandable because both of these modes are used for the same purpose in most of the cases, which is for the long-distance trips. But the interesting fact is the average cost per kilometer for ambulance is significantly higher than any other compared modes. Which discourages the patients to use ambulance in case of an emergency.

A graphical representation of people's preference in case of an emergency is shown in Figure 3-4

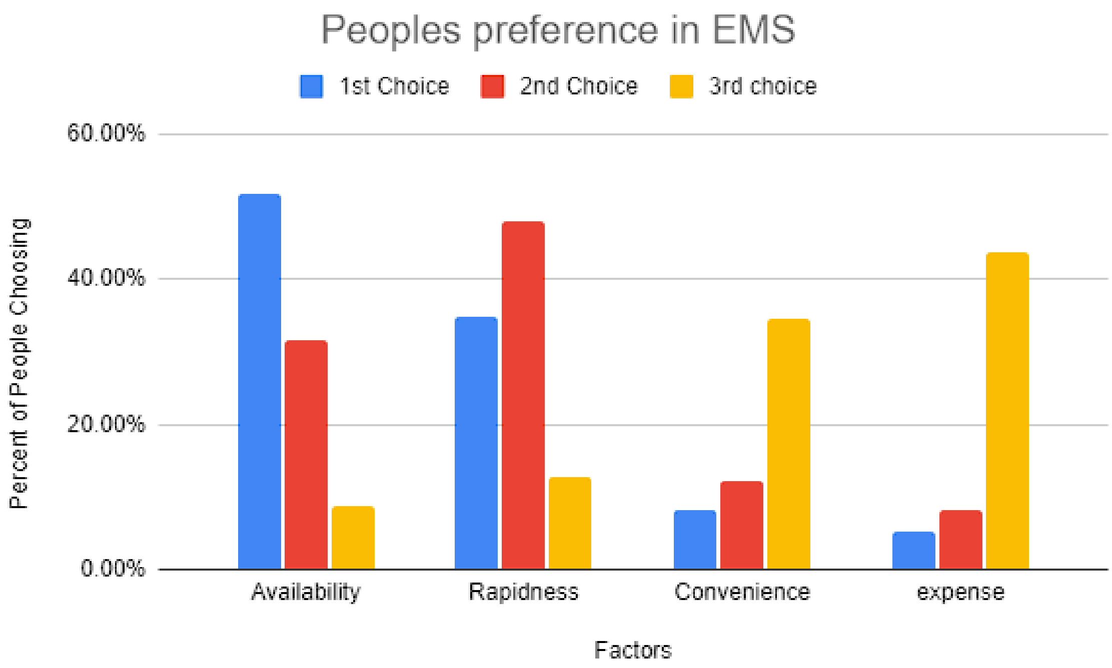

Figure 3-4: People's preference in choosing EMS

According to figure 4 about 52% of the respondents prefer availability of the mode in case of an emergency event. Then around 36% of the respondents prefer Rapidness. But people generally don't care much about the cost in these scenarios.

3.3 Workflow of Research

The workflow diagram of the research-

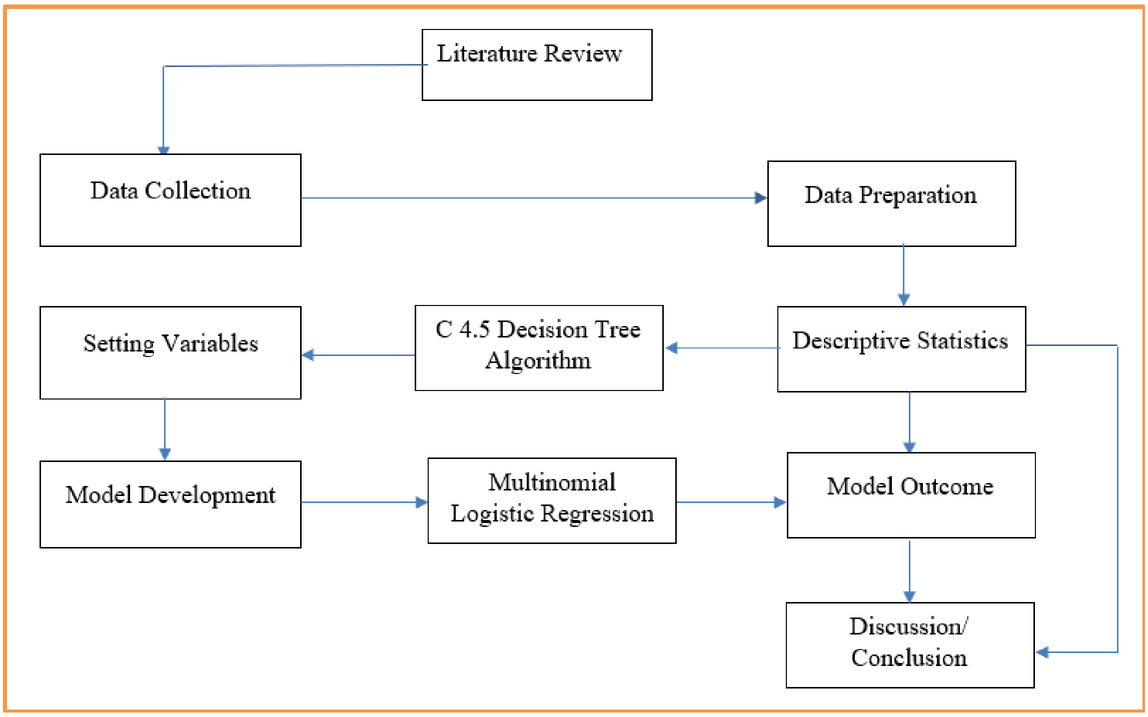

Figure 3-5: Work flow diagram

At the very beginning of our research after selecting the topics a lot of literature reviews were done to figure out the existing situation and the research gaps. With the help of literature, the questionnaire survey was set, and the data was collected. Then the data was analyzed firmly. The variables were categorized according to different guidelines. The variables were used in C 4.5 Decision Tree Algorithm and the significant or the important variables were extracted from the analysis according to the feature importance score of the variables. The variables were converted into dummy variables for better accuracy and output of the model. Then the extracted variables were used in Discrete Choice Moelling method as independent variables and Mode was the dependent variable. After that the coefficient for the variables were determined using Python Biogeme and the utility functions were defined. After that Multinomial Logistic Regression was applied to calculate the percentage of choosing a specific mode under a given situation.

3.4 C4.5 Decision Tree Algorithm

C4.5 algorithm, also called a decision tree, A flowchart-like structure may be found in C4.5. The flowchart has a node for the attribute value, branches for the test results and the class, and a node for the attribute value. The C4.5 algorithm is a development of the ID3 algorithm and has a classification mechanism. Due to its capacity to not limit branches in binary and distinct forms, C4.5 algorithm offers benefits over ID3 and CART algorithms.

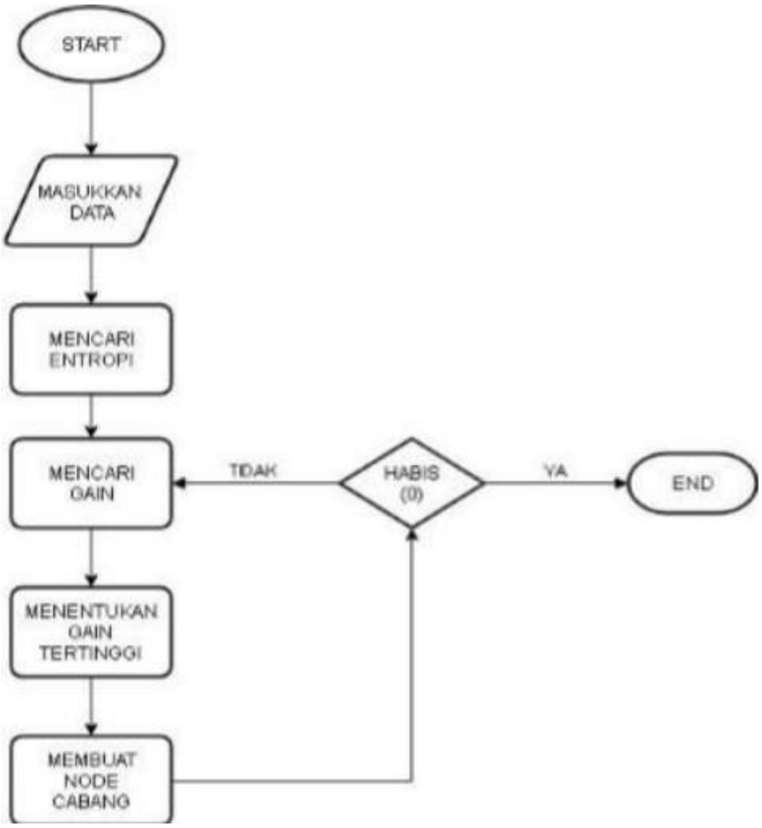

Figure 3-6: Flowchart for C 4.5 Algorithm

Depending on the current qualities' best gain value, choose attributes with roots. The gain is determined using the following formula:

$$Gain\ (A) = Entropi\ (S)) - \sum_{i=1}^{k} \frac{|Si|}{|S|} \times Entropi\ (Si)$$

Where,

S: case set A: attribute

N: number of attribute attributes A

| Si |: number of cases on the i partition

| S |: number of cases in S

In order to get the highest attribute's gain value. One of the qualities used to choose the test attribute for each node in the tree is gain. The test attribute of a node is the one with the greatest information gain. In the meanwhile, the equation shows how entropy values are calculated:

$$\text{Entropi}\ (S) = -\sum_{i=1}^{k} \frac{|Si|}{|S|} \times (p_j \ log_2 p_j)$$

Where,

S: case set A: attribute

N: number of partitions S

Pj: proportion of S (Supangat et al., 2021)

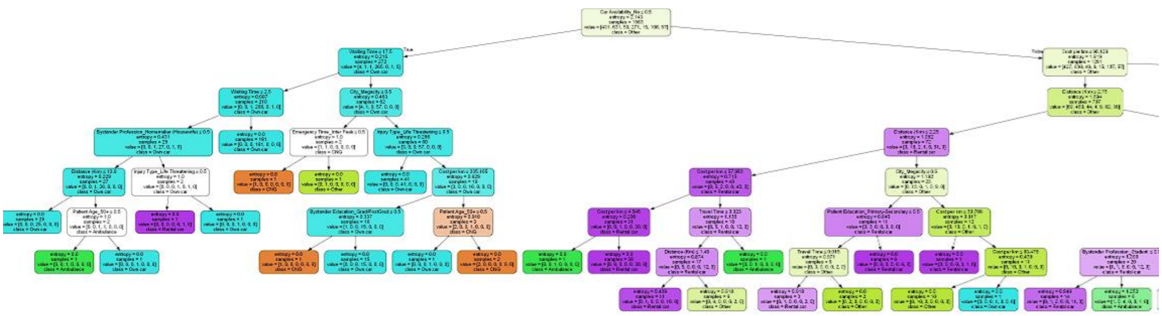

Figure 3-7: A portion of the decision tree generated in C 4.5

```
In [140]: print("Training Accuracy is: ", dt.score(X_train, y_train))
          print("Testing Accuracy is: ", dt.score(X_test, y_test))

          Training Accuracy is:  0.8841970569417786
          Testing Accuracy is:  0.8388746803069054

In [141]: final_fi =final_fi.sort_values('Feature Importance Score', ascending = False).reset_index(drop =True)
          final_fi

Out[141]:
```

	Variable	Feature Importance Score
0	Car Availability_No	0.364358
1	Distance (Km)	0.278346
2	Cost per km	0.236305
3	Waiting Time	0.057547
4	City_Megacity	0.014024
5	City_Township	0.006907
6	Patient Education_Primary-Secondary	0.006078
7	Travel Time	0.004909
8	Patient Profession_Employee	0.004237
9	Emergency Time_Off Peak	0.003740
10	Bystander Profession_Homemaker (Housewife)	0.003568
11	Injury Type_Life Threatening	0.002796
12	Bystander Profession_Student	0.002766
13	Patient Profession_Homemaker (Housewife)	0.002359
14	Bystander Income_10-35K (Low)	0.002270
15	Bystander Education_Grad/PostGrad	0.002087
16	Emergency Time_Evening Peak	0.001923

Figure 3-8:Determining the feature importance score using C 4.5 in Python

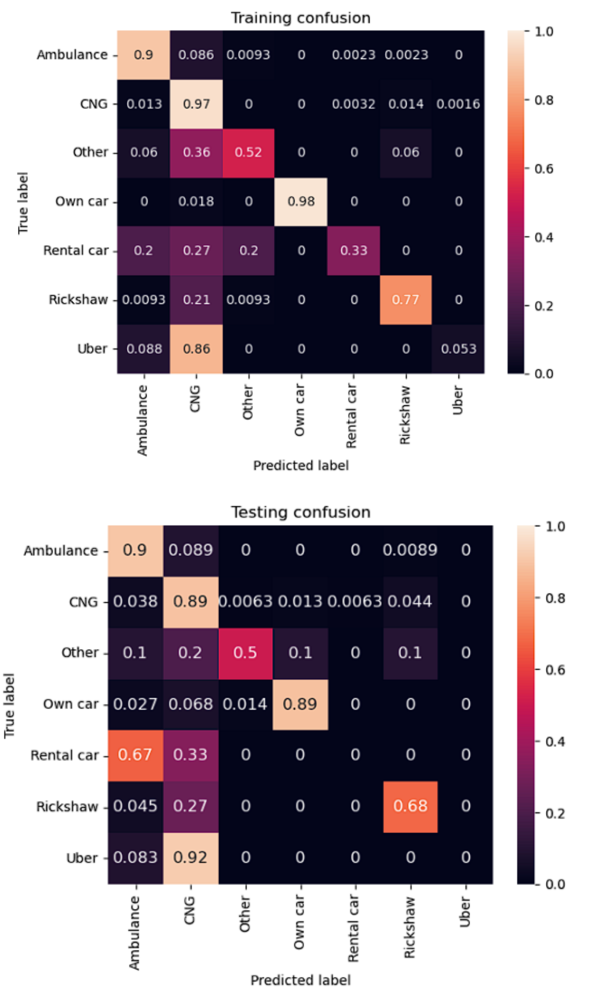

Figure 3-9: Training and Testing confusion matrix for C 4.5 analysis

3.5 Multinomial Logistic Regression

The variables that were retrieved from the C 4.5 analysis were entered here as independent variables, and the Biogeme program computed the coefficients for each of the variables. To calculate the coefficients, the Maximum Likelihood Estimation Method was utilized.

3.5.1 Maximum Likelihood Estimation

A common strategy is maximum likelihood estimate of unknown parameters. A collection of values for the set of characteristics x_{in}, denoted x^k_{in}, and an observed choice make up an observation k. The person n and the alternative i are both connected to the qualities. $P^k_{in}(,)$ = $P_{in}(,,x^k_{in})$, where P_{in} is the probability function corresponding to the model under discussion, gives the likelihood that the model will repeat the observed decision. The likelihood, or likelihood of the model reproducing the entire sample if a sample of K observations is supplied, is given by

$$\mathcal{L}^*(\beta, \gamma) = \prod_{k=1}^{K} P^k_{in}(\beta, \gamma).$$

The maximum likelihood $\hat{\beta}$ $\hat{\gamma}$ estimators and are given by

$$(\hat{\beta}, \hat{\gamma}) = \text{argmax}_{\beta,\gamma}\, \mathcal{L}(\beta, \gamma),$$

where

$$\mathcal{L}(\beta, \gamma) = \ln \mathcal{L}^*(\beta, \gamma) = \sum_{k=1}^{K} \ln P^k_{in}(\beta, \gamma)$$

is the function of log-likelihood. In certain circumstances, the weights of the observations are adjusted to reflect their relative relevance in the population in order to balance their relative importance in the sample. In such situation, each observation would have a weight, and the log-likelihood function would be used.

$$\mathcal{L}(\beta,\gamma) = \sum_{k=1}^{K} \omega_k \ln P_{in}^{k}(\beta,\gamma)$$

(Bierlaire, 2003)

```
In [58]:  logprob = models.loglogit(V,av,Mode)

In [59]:  biogeme = bio.BIOGEME(database, logprob)
          biogeme.modelName= "Final_logit_Model 3"

In [60]:  results = biogeme.estimate()

          [15:05:00] < Warning >   Cannot read file __Final_logit_Model 3.iter. Statement is ignored.

In [61]:  pandasResults = results.getEstimatedParameters()

In [62]:  pandasResults
Out[62]:
```

	Value	Rob. Std err	Rob. t-test	Rob. p-value
Ambulance_B_999_Call	3.160646	0.852464	3.707660	2.091834e-04
Ambulance_B_Bystander_Income_10_35K_Low	-2.074091	0.326300	-6.356390	2.065497e-10
Ambulance_B_Bystander_Income_65K__High	3.389517	0.725760	4.670303	3.007554e-06
Ambulance_B_Bystander_Profession_Employee	0.314281	0.513733	0.611760	5.406965e-01
Ambulance_B_Bystander_Profession_Homemaker_Housewife	-0.597924	0.555570	-1.076235	2.818221e-01
...	...	...	...	...
RICKSHAW_B_Cost	-28.003259	2.480642	-11.288716	0.000000e+00
RICKSHAW_B_Waiting_Time	-0.002912	0.346924	-0.008393	9.933035e-01
UBER_B_Bystander_Income_35_65K_Mid	0.539886	0.383287	1.408567	1.589632e-01
UBER_B_Cost	3.133200	0.729596	4.294433	1.751400e-05
UBER_B_Waiting_Time	2.267644	0.371217	6.108674	1.004621e-09

Figure 3-10: Determining the coefficients using Python Biogeme

After Determining the coefficients, the utility functions were defined

$$V_{in} = \beta' \mathbf{x}_{in} = \sum_{k=1}^{K} \beta_k x_{ink}$$

Choice Probability :

$$\begin{aligned} P(i|C_n) &= P(U_{in} \geq U_{jn},\ \forall j \in C_n) \\ &= P(U_{in} - U_{jn} \geq 0,\ \forall j \in C_n) \\ &= P(U_{in} = \max_j U_{jn},\ \forall j \in C_n) \end{aligned}$$

For Binary Choice :

$$\begin{aligned} P_n(1) &= P(U_{1n} \geq U_{2n}) \\ &= P(U_{1n} - U_{2n} \geq 0) \\ &= P(\epsilon_{2n} - \epsilon_{1n} \leq V_{1n} - V_{2n}) \\ &= F_{\epsilon_{2n}-\epsilon_{1n}}(V_{1n} - V_{2n}) \qquad [\text{Univariate CDF of } \epsilon_{2n} - \epsilon_{1n}] \end{aligned}$$

Choice set: C_n,

J_n (>=2) alternatives are included in C_n.

$$
\begin{aligned}
P(i|C_n) &= P(V_{in} + \epsilon_{in} \geq V_{jn} + \epsilon_{jn},\ \forall j \in C_n) \\
&= P(\epsilon_{jn} - \epsilon_{in} \leq V_{in} - V_{jn},\ \forall j \in C_n)
\end{aligned}
$$

The Probability of choosing i under a given condition is :

$$
P(i|C_n = \{i, j\}) = \frac{e^{\mu V_{in}}}{e^{\mu V_{in}} + e^{\mu V_{jn}}}
$$

CHAPTER 4: ANALYSIS & RESULTS

4.1 Introduction

After analyzing the data with C4.5 and Multinomial logistic regression (MLR), the study findings are displayed in this chapter. The survey data was re-classified and re-structured. Variables are renamed and processed for analysis. The categorization of the variable was done in such a way that individual values don't skew the whole result.

4.2 Descriptive Study

We had data of 2008 emergency patients. We processed the data and for Multinomial Logistic Regression, the dependent variable was the mode of the vehicle used for that emergency purpose. Several socio-demographic and personal data were used as independent variables. 52% of the patients were aged between 18 and 50. Almost 95% of the patients were aged between 18 and 50. 79% of the by-standers were low-income group.

4.3 C4.5

4.3.1 Model development & analysis

To determine the important variables in mode choice of emergency patients, Decision tree and C4.5 was used to find out the important factors that yields the highest information gain. We took 20 variables to analyze. The models include Numerical and categorical data

The model's dependent variable was mode of emergency transport, which was categorized as 6 categories which are Ambulance, CNG, Rickshaw, Own car, Rental car, Uber, Others.

According to C4.5 analysis, among 20 variables, we got 4 variable that significantly controls the mode choice of an emergency patient.

Table 4-1: C4.5 Outcomes (importance score of variables)

S.N.	Independent variable	Importance Score
0	Car Availability_No	0.364358
1	Distance (Km)	0.278346
2	Cost per km	0.236305
3	Waiting Time	0.057547
4	City_Megacity	0.014024
5	City_Township	0.006907
6	Patient Education_Primary-Secondary	0.006078
7	Travel Time	0.004909
8	Patient Profession_Employee	0.004237
9	Emergency Time_Off Peak	0.00374
10	Bystander Profession_Homemaker (Housewife)	0.003568
11	Injury Type_Life Threatening	0.002796
12	Bystander Profession_Student	0.002766
13	Patient Profession_Homemaker (Housewife)	0.002359
14	Bystander Income_10-35K (Low)	0.00227
15	Bystander Education_Grad/PostGrad	0.002087

16	Emergency Time_Evening Peak	0.001923
17	Patient Age_50+	0.001839
18	City_Outer-Megacity	0.001637
19	Patient Education_Grad/PostGrad	0.00153
20	Emergency Time_Inter Peak	0.000774

The values are shown in the graph

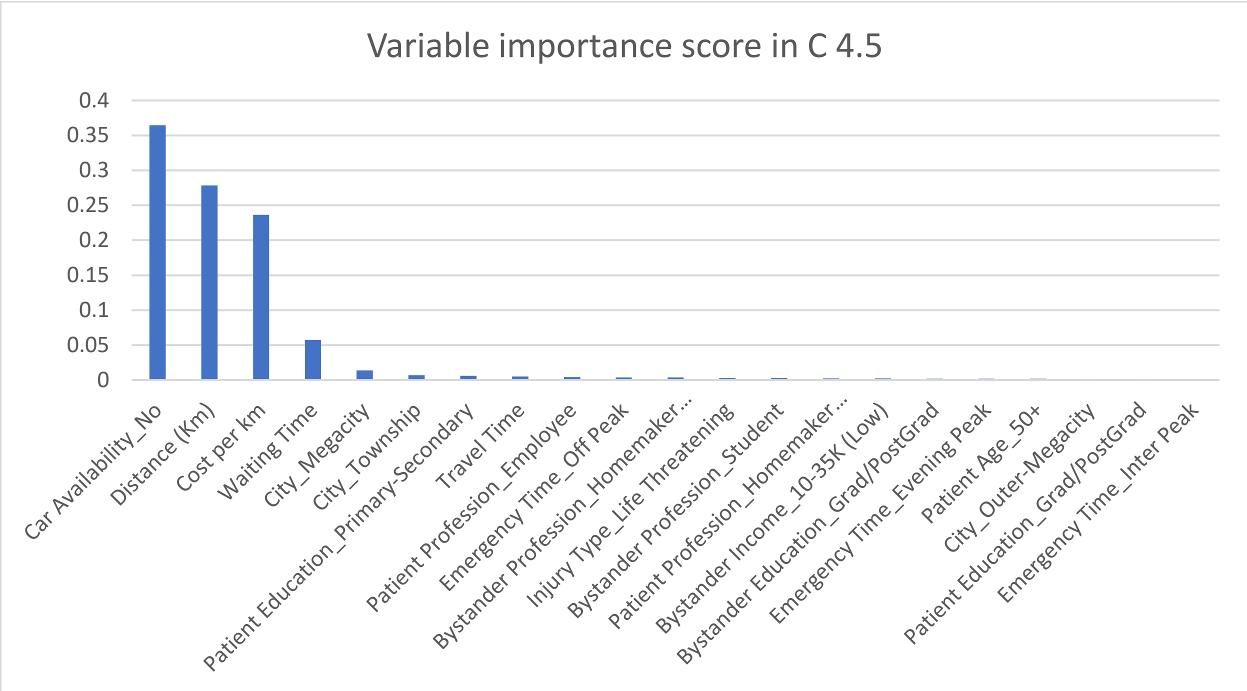

Figure 4-1: Visual representation of the importance score of the variables

4.3.2 Result interpretation

The graph here shows that Car availability, Distance per km, Waiting time, and megacity significantly controls the mode choice, where Car availability is the most important variable with an importance score of 0.36. Income of the patient, bystander's income and peak time does not significantly

4.4 Multinomial Logistic Regression (MLR)

4.4.1 Model development

Important variables are taken in account and used as input in the logistic regression model. The model utilized the data to assess the level of impact on the mode choice of an emergency patient. The model also analyzed the significance of the impact.

4.4.2 Model evaluation

Maximum Likelihood Estimation (MLE) has beeen used to estimate the Multinomial Logistic regression model. Pseudo R-squared value of if the model is 0.84 which indicated that this model can predict and explain 84% of the mode choice of an emergency patient. P value of the model also tends to 0, which means the model is significant. We considered P value to be less than 0.05 as significance level

Table 4-2: Multinomial Logistic Regression Outcomes

Ambulance	Value	Rob. Std err	Rob. t-test	Rob. p-value
Ambulance_B_Day	2.36	0.463	5.11	3.26E-07
Ambulance_B_Cost	8.49	1.68	5.04	4.69E-07
Ambulance_B_Waiting_Time	4.19	0.868	4.83	1.36E-06
Ambulance_B_Car_Availability	-6.64	1.66	-3.99	0.000065
Ambulance_B_Patient_Profession_Student_	-2.55	0.652	-3.9	9.48E-05
Ambulance_B_Cost_per_km	2.88	0.742	3.88	0.000105
Ambulance_B_Bystander_Income_10_35K_Low	-3.57	0.974	-3.67	0.000245

Ambulance_B_999_Call	3.28	1.08	3.02	0.00253
Ambulance_B_TT	-0.776	0.333	-2.33	0.0197
Ambulance_B_Distance_(Km)	0.958	0.458	2.09	0.0363
Ambulance_B_Injury_Type_Minor_Injury	1.35	0.654	2.06	0.0398
Ambulance_B_Bystander_Profession_Student_	2.93	1.49	1.97	0.0487
Ambulance_B_Injury_Type_Not_Life_Threatening-but_will_cause_long_term_damage	-1.59	0.806	-1.97	0.0492
OwnCar	**Value**	**Rob. Std err**	**Rob. t-test**	**Rob. p-value**
OwnCar_B_Bystander_Profession_Homemaker_Housewife	-0.0094	3.24E-09	-2900000	0
OwnCar_B_Bystander_Profession_Others	-0.138	3.21E-07	-429000	0
OwnCar_B_Car_Availability	27.6	1.8	15.4	0
OwnCar_B_Day_day	-7.83	0.921	-8.5	0
OwnCar_B_Patient_Education_Illiterate	-0.0656	1.65E-05	-3970	0
OwnCar_B_Patient_Profession_Others	-0.141	5.44E-06	-25900	0

OwnCar_B_Injury_Type_Minor_Injury	-5.41	0.904	-5.98	2.19E-09
OwnCar_B_Bystander_Income_10_35K_Low	-6.67	1.39	-4.79	1.65E-06
OwnCar_B_TT	0.979	0.211	4.64	3.42E-06
OwnCar_B_Bystander_Income_35_65K_Mid	5.29	1.22	4.33	1.49E-05
OwnCar_B_Patient_Profession_Student_	3.69	1	3.68	0.000229
OwnCar_B_Injury_Type_Not_Life_Threateningbut_will_cause_long_term_damage	3.19	0.923	3.46	0.00054
OwnCar_B_Distance_(Km)	-2.91	0.872	-3.34	0.000845
OwnCar_B_Emergency_Time_Morning_Peak	-2.07	0.652	-3.17	0.0015
OwnCar_B_Cost_per_km	-8.99	2.86	-3.14	0.00167
OwnCar_B_Patient_Profession_Homemaker_Housewife	-2.6	0.847	-3.07	0.00211
OwnCar_B_Patient_Education_GradPost-Grad	3.42	1.16	2.95	0.00315
OwnCar_B_Emergency_Time_Inter_Peak	-2.61	0.976	-2.68	0.0074
OwnCar_B_Patient_Profession_Employee	-2.51	0.985	-2.55	0.0108
OwnCar_B_Waiting_Time	-4.8	1.9	-2.53	0.0115
OwnCar_B_Bystander_Profession_Student_	-2.91	1.16	-2.51	0.0122
ASC_OwnCar	-1.56	0.705	-2.22	0.0265

CNG	Value	Rob. Std err	Rob. t-test	Rob. p-value
CNG_B_Bystander_Profession_Home-maker_Housewife	-7.29	1.23	-5.91	3.4E-09
CNG_B_Day_day	1.81	0.382	4.74	2.17E-06
CNG_B_Injury_Type_Minor_Injury	1.16	0.314	3.68	0.000229
CNG_B_Cost_per_km	2.64	0.756	3.49	0.000488
CNG_B_Waiting_Time	2.01	0.644	3.12	0.00179
CNG_B_Bystander_Profession_Student_	2.94	0.954	3.08	0.00204
CNG_B_Emergency_Time_Inter_Peak	1.31	0.46	2.84	0.0045
CNG_B_Bystander_Profession_Others	6.68	2.43	2.75	0.00597
CNG_B_TT	0.448	0.186	2.41	0.0161
CNG_B_Car_Availability	-2.3	0.961	-2.39	0.0169
ASC_CNG	2.58	1.1	2.35	0.0187
CNG_B_Patient_Education_Illiterate	1.56	0.771	2.02	0.0438
CNG_B_Patient_Education_PrimarySecond-ary	1.32	0.659	2	0.0458
CNG_B_Bystander_Income_35_65K_Mid	3.54	1.8	1.96	0.0499

RENTAL CAR	Value	Rob. Std err	Rob. t-test	Rob. p-value
RENTALCAR_B_Patient_Profession_Others	-7.16	1.21	-5.94	2.91E-09
RENTALCAR_B_Cost	9.73	1.69	5.76	8.22E-09
RENTALCAR_B_Car_Availability	-7.79	1.52	-5.14	2.81E-07
RENTALCAR_B_Bystander_Profession_Homemaker_Housewife	6.77	1.52	4.47	7.97E-06
RENTALCAR_B_Patient_Profession_Homemaker_Housewife	2.46	0.656	3.75	0.000175
RENTALCAR_B_Bystander_Income_35_65K_Mid	-6.6	1.84	-3.59	0.000332
RENTALCAR_B_Injury_Type_Not_Life_Threatening-but_will_cause_long_term_damage	-2.64	0.817	-3.23	0.00123
RENTALCAR_B_999_Call	4.25	1.34	3.17	0.0015
RENTALCAR_B_TT	-1.05	0.349	-3.02	0.00255
RENTALCAR_B_Bystander_Profession_Employee	3.72	1.29	2.89	0.00383
RENTALCAR_B_Bystander_Profession_Others	-10.3	3.68	-2.8	0.00504
RENTALCAR_B_Patient_Education_PrimarySecondary	-2.44	0.97	-2.51	0.0119

RENTALCAR_B_Bystander_Income_10_35K_Low	3.31	1.34	2.47	0.0134
ASC_RentalCar	-3.03	1.25	-2.42	0.0156
RENTALCAR_B_Bystander_Profession_Student_	-3.2	1.34	-2.39	0.0169
RENTALCAR_B_Injury_Type_Minor_Injury	1.36	0.598	2.27	0.0233
RICKSHAW	**Value**	**Rob. Std err**	**Rob. t-test**	**Rob. p-value**
RICKSHAW_B_Bystander_Income_65K__High	-0.00615	3.76E-11	-1.6E+08	0
RICKSHAW_B_Car_Availability	-12.8	1.23	-10.4	0
RICKSHAW_B_Cost	-21.3	4.21	-5.07	3.95E-07
RICKSHAW_B_Cost_per_km	3.14	0.833	3.76	0.000168
RICKSHAW_B_Day	1.67	0.537	3.11	0.0019
RICKSHAW_B_Patient_Education_GradPostGrad	-3.04	0.995	-3.05	0.00226
RICKSHAW_B_Bystander_Profession_Employee	-2.76	1.06	-2.61	0.00899
RICKSHAW_B_TT	0.491	0.194	2.53	0.0114
RICKSHAW_B_Waiting_Time	1.76	0.703	2.5	0.0125

RICKSHAW_B_Bystander_Income_10_35K_Low	7.91	3.2	2.47	0.0134
RICKSHAW_B_Bystander_Profession_Others	5.94	2.47	2.41	0.0159
RICKSHAW_B_Patient_Education_PrimarySecondary	1.71	0.803	2.13	0.033
OTHER	**Value**	**Rob. Std err**	**Rob. t-test**	**Rob. p-value**
OTHER_B_Patient_Profession_Others	4.72	1.05	4.49	7.18E-06
OTHER_B_999_Call	-5.34	1.25	-4.28	1.91E-05
OTHER_B_Cost	5.15	1.41	3.65	0.000264
OTHER_B_Patient_Education_PrimarySecondary	2.53	0.738	3.43	0.000596
OTHER_B_Day	1.67	0.502	3.34	0.000844
OTHER_B_Bystander_Income_35_65K_Mid	3.81	1.24	3.07	0.00216
OTHER_B_Patient_Education_SSCHSC	2.6	0.865	3	0.00266
OTHER_B_Emergency_Time_Morning_Peak	1.49	0.52	2.87	0.00416
OTHER_B_Cost_per_km	2.35	0.852	2.76	0.00575
OTHER_B_Distance_(Km)	0.91	0.333	2.73	0.00634
OTHER_B_Patient_Profession_Homemaker_Housewife	-2	0.744	-2.68	0.00734

OTHER_B_Bystander_Profession_Employee	-2.35	0.892	-2.63	0.00848
ASC_Other	2.19	0.846	2.59	0.0096
OTHER_B_Injury_Type_Minor_Injury	0.928	0.425	2.18	0.0291
OTHER_B_Patient_Profession_Student_	-1.23	0.575	-2.15	0.0317

4.4.3 Utility functions

$V_{Ambulance}$=

2.36*Ambulance_B_Day+8.49*Ambulance_B_Cost+4.19*Ambulance_B_Waiting_Time +(-6.64)*Ambulance_B_Car_Availability+(-2.55)*Ambulance_B_Patient_Profession _Student+2.88*Ambulance_B_Cost_per_km+(-3.57)*Ambulance_B_Bystander_Income _10_35K_Low+3.28*Ambulance_B_999_Call+(-0.776)*Ambulance_B_TT +0.958*Ambulance_B_Distance_(Km) +1.35*Ambulance_B_Injury_Type_Minor_Injury+2.93*Ambulance_B_Bystander_Profession_Student+(-1.59)*Ambulance_B_Injury_Type_ Not_Life_Threateningbut_will_cause_long_term_damage

$V_{Own\ Car}$=

(-0.0094)*OwnCar_B_Bystander_Profession_Homemaker_Housewife+(-0.138)*OwnCar_B_Bystander_Profession_Others+27.6*OwnCar_B_Car_Availability+(-7.83)*OwnCar_B_Day_day+(-0.0656)*OwnCar_B_Patient_Education_Illiterate+(-0.141)*OwnCar_B_Patient_Profession_Others+(-5.41)*OwnCar_B_Injury_Type_Minor_Injury+(-6.67)*OwnCar_B_Bystander_Income_10_35K_Low +0.979*OwnCar_B_TT+5.29*OwnCar_B_Bystander_Income_35_65K_Mid +3.69*OwnCar_B_Patient_Profession_Student_+3.19*OwnCar_B_Injury_Type_Not _Life_Threateningbut_will_cause_long_term_damage+(-2.91)*OwnCar_B_Distance_ (Km)+(-2.07)*OwnCar_B_Emergency_Time_Morning_Peak+(-8.99)*OwnCar_B _Cost_per_km+(-2.6)*OwnCar_B_Patient_Profession_Homemaker_Housewife +3.42*OwnCar_B_Patient_Education_GradPostGrad+(-2.61)*OwnCar_B_Emergency

_Time_Inter_Peak+(-2.51)*OwnCar_B_Patient_Profession_Employee+(-4.8)*OwnCar _B_Waiting_Time+(-2.91)*OwnCar_B_Bystander_Profession_Student_+(-1.56) *ASC_OwnCar

V_{CNG}=

2.58*ASC_CNG+ (-7.29)*CNG_B_Bystander_Profession_Homemaker_Housewife +1.81*CNG_B_Day_day+1.16*CNG_B_Injury_Type_Minor_Injury +2.64*CNG_B _Cost_per_km+2.01*CNG_B_Waiting_Time+2.94*CNG_B_Bystander_Profession_Student_ +1.31*CNG_B_Emergency_Time_Inter_Peak+6.68*CNG_B_Bystander_Profession_Others+0.448*CNG_B_TT+ (-2.3)*CNG_B_Car_Availability +1.56*CNG_B_Patient_Education_Illiterate+1.32*CNG_B_Patient_Education_PrimarySecondary +3.54*CNG_B_Bystander_Income_35_65K_Mid+(-1.09)*CNG_B_Patient_Education_ GradPostGrad

$V_{RENTAL\ CAR}$=

(-7.16)*RENTALCAR_B_Patient_Profession_Others+9.73*RENTALCAR_B_Cost+(-7.79)*RENTALCAR_B_Car_Availability+6.77*RENTALCAR_B_Bystander_Profession_Homemaker_Housewife+2.46*RENTALCAR_B_Patient_Profession_Homemaker_Housewife+(-6.6)*RENTALCAR_B_Bystander_Income_35_65K_Mid+(-2.64)*RENTALCAR_B_Injury_Type_Not_Life_Threateningbut_will_cause _long_term_damage+4.25*RENTALCAR_B_999_Call+(-1.05)*RENTALCAR _B_TT+3.72*RENTALCAR_B_Bystander_Profession_Employee+(-10.3)*RENTALCAR_B_Bystander_Profession_Others+(-2.44)*RENTALCAR_B_Patient_Education_PrimarySecondary+3.31*RENTALCAR_B_Bystander_Income_10_35K_Low+(-3.03)*ASC_RentalCar+(-3.2)*RENTALCAR_B_Bystander_Profession_Student_+1.36*RENTALCAR_B_Injury_Type_Minor_Injury

$V_{RICKSHAW}$=

(-0.00615)*RICKSHAW_B_Bystander_Income_65K__High+(-12.8)*RICKSHAW _B_Car_Availability+(-21.3)*RICKSHAW_B_Cost+3.14*RICKSHAW

_B_Cost_per_km+1.67*RICKSHAW_B_Day+(-3.04)*RICKSHAW_B_Patient_Education_GradPostGrad+(-2.76)*RICKSHAW_B_Bystander_Profession_Employee +0.491*RICKSHAW_B_TT+1.76*RICKSHAW_B_Waiting_Time+7.91*RICKSHAW _B_Bystander_Income_10_35K_Low+5.94*RICKSHAW_B_Bystander_Profession _Others+1.71*RICKSHAW_B_Patient_Education_PrimarySecondary

V_{OTHER}=

+2.19*ASC_Other+4.72*OTHER_B_Patient_Profession_Others+(-5.34)*OTHER_B_ 999_Call +5.15*OTHER_B_Cost+2.53*OTHER_B_Patient_Education_PrimarySecondary+1.67*OTHER_B_Day+3.81*OTHER_B_Bystander_Income_35_65K_Mid +2.6*OTHER_B_Patient_Education_SSCHSC+1.49*OTHER_B_Emergency _Time_Morning _Peak +2.35*OTHER_B_Cost_per_km +0.91*OTHER_B_Distance_(Km)+(-2)*OTHER_B_Patient_Profession_Homemaker_Housewife+(-2.35)*OTHER_B_Bystander_Profession_Employee+0.928*OTHER_B_Injury_Type _Minor_Injury+(-1.23)*OTHER_B_Patient_Profession_Student

4.4.4 Result interpretation

Here, the dependent Categorical variable Ambulance is set to base as a result the constant for Ambulance is 0. Results suggest that the most preferable random choice of this community is Rickshaw as the intercept of this mode is the highest. It is due to high availability and accessibility and the destination is close. The second priority is CNG as in terms of availability it comes second. CNG is rapid, easily accessible, and reliable. The probability of choosing these modes decreases with the severity and waiting time increase.

The model doesn't find any significant relation between model choice and the patient's gender. The coefficient of waiting time for all modes is negative, which means the probability of choosing an ambulance is high when the waiting time increases. Patients tend to wait for an ambulance if the severity of the injury is high. If the patient is a student, then the utility of an ambulance decreases by 2.55. If the patient calls 999 for an ambulance, then the probability of choosing ambulance increases but in case of a rental car, the coefficient is higher than that of the ambulance. It suggests that patients call for an ambulance in emergency situations and most of the time they have to choose a rental car instead of an ambulance, possibly due to an ambulance's unavailability. Values suggest that patients prefer to wait for an ambulance and are ready to spend more as it seemingly provides safety and comfort. Car availability significantly decreases the utility of Ambulances.

Availability of Own car increases the utility of own car as the selected mode by 27.6. But if the cost of travel increases by 1 unit, the utility of this mode will decrease by 8.99. During the morning peak, own car may not be preferable due to some extra facilities provided by ambulance.

Data suggests that mid-income group patients choose CNG as their emergency transport mode. During interpeak, the utility of CNG increases by 1.31. CNG is a favorable option for minor injury patients. CNG is less preferable to highly educated people. According to the result, probability of patients calling 999 for ambulance yet choosing a rent car is 0.73.

CHAPTER 5: CONCLUSION & RECOMMENDATIONS

5.1 Introduction

As Bangladesh is a developing country and emergency medical service is still in jeopardy, so the goal of the study was to improve this situation based on the factors that are responsible for the choice of modes. Our main goal was to model how different variables of impact the mode choice behavior of an emergency patient. A thorough questionnaire survey was done for this project where the socioeconomic, demographic, preferences of the patients and bystanders were obtained. The key factors were obtained through C4.5 decision tree algorithm and the model for mode choice was then obtained by Multinomial Logit Regression Analysis.

5.2 Major Findings

This study was conducted to find out how different variables like income, waiting time, distance, cost per km etc. controls the mode choice of the patients. The study also analyzed the mode choice behavior of the community. Some of the major findings are as follows-

- Rickshaw is the base choice for emergency patients of the community, which means if there is no constraint on them, they will choose Rickshaw as it is highly available and accessible.
- The probability of not getting an ambulance even though he has called for an ambulance is 0.73.
- Probability of choosing a rickshaw is high when the patient has minor injury or his income is low.
- Car owners tend to choose their own car for emergency travel if available.
- Utility of Ambulance increases with the increase in Severity.

5.3 Policy Implication

The government's directives should be changed in light of the research findings since the emergency medical situation has been a significant impediment to our progress. The possible policies that can be implemented by the government for the betterment of the sector are as stated:

- CNG can be equipped with some basic emergency facilities as most people use CNG as their preferred mode and they are more accessible.
- Ambulances with trained personnel can be allotted in the accessible zones of a town for transfer so that reaction time can be reduced up to a certain level.
- Getting an ambulance after calling 999 should be assured.
- Advertising can be done through social media, news and recreational platform so that public are more informed and aware about their immediate action after an emergency situation through which reaction and response time can be lessened.
- Sufficient Ambulances should be located near Hospitals outside mega-city so that people don't have to use Rental car to come to mega-city for better treatment.
- The hospitals in a district's suburban areas should focus on enhancing the quality of service, and the medical facilities in the pivotal zone of the district should increase service effectiveness.
- Designing and executing educational courses at state-wide institutions and training institutions.

5.4 Limitation and Future Scope

The significance of the study can be seen from a variety of aspects. This study targeted to find the relationship between some independent variables and the mode choice of the patient of Bangladesh. But the data for this don't cover the whole country There were lots of the data for megacity Dhaka, some surrounding areas, and some townships. The dataset has a lot of data on CNG, Ambulance which may cause inclination of the results to some specific modes.

The results cannot show all the relations between mode selection and independent variables significantly. Maybe it is because of too much variation between data. A complete analysis can be done which overcomes our limitation and shows all the relationships between dependent and independent variables significantly and represents the whole country.

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Appendix

EMS Questionnaire

Event Specific (socio-economic)

1. What is the age of the patient?

   ☐ <18 ☐ 18 – 50 ☐ 50+

2. What is the sex of the patient?

   ☐ Male ☐ Female ☐ Transgender

   ☐ Prefer not to say

3. What is the income of the patient (in BDT)?

<10k	10-15k	15-20k	20-25k	25-35k
35-45k	45-55k	55-65k	65-100k	100k+

4. What is the education level of the patient?

   ☐ Illiterate/ No formal education

   ☐ Primary/ Secondary

   ☐ SSC/HSC

   ☐ Postgraduate / Kamil/ Graduate / Fazil

   ☐ Student

   ☐ Home Maker (Housewife)

   Other: ______________________

5. How severe was the emergency?

   ☐ Severely life threatening

   ☐ Life threatening

   ☐ Not life threatening but will cause long term damage

   ☐ Minor injury / will not cause long term damage

   ☐ Non injury/ neutral / recovered

6. Did the patient have similar medical history before?

   ☐ Yes ☐ No ☐ Don't know

7. Who brought the patient to the hospital? (MA)

   ☐ Family/Relative ☐ Neighbor ☐ Bystander

   ☐ Others (Specify): _____________

8. What is the age of the person who brought the patient to the hospital?

☐<18 ☐18 – 25 ☐25 – 35 ☐35 – 50 ☐50 – 60 ☐60 – 65 ☐≥65

9. What is the sex of the person who brought the patient to the hospital?

   ☐ Male ☐ Female ☐ Transgender

   ☐ Prefer not to say

10. What is the income of the person who brought the patient to the hospital (in BDT)?

   <10k ☐ 10-15k ☐ 15-20k ☐ 20-25k ☐ 25-35k
   ☐
   35-45k 45-55k ☐ 55-65k ☐ 65-100k ☐ 100k+