Investigating Women's Travel Mode Selection Based on Trip in Bangladesh.

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2022

Investigating Women's Travel Mode Selection Based on Trip in Bangladesh.

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A THESIS SUBMITTED FOR THE DEGREE OF BACHELOR OF SCIENCE IN CIVIL ENGINEERING (TRANSPORTATION)

Department of Civil & Environmental Engineering

Islamic University of Technology

2022

APPROVAL

This is to certify that Fahmidul Islam’s dissertation, " **Investigating Women’s Travel Mode Selection Based on Trip in Bangladesh** " has been approved as meeting the requirements for the Bachelor of Science Degree in Civil Engineering.

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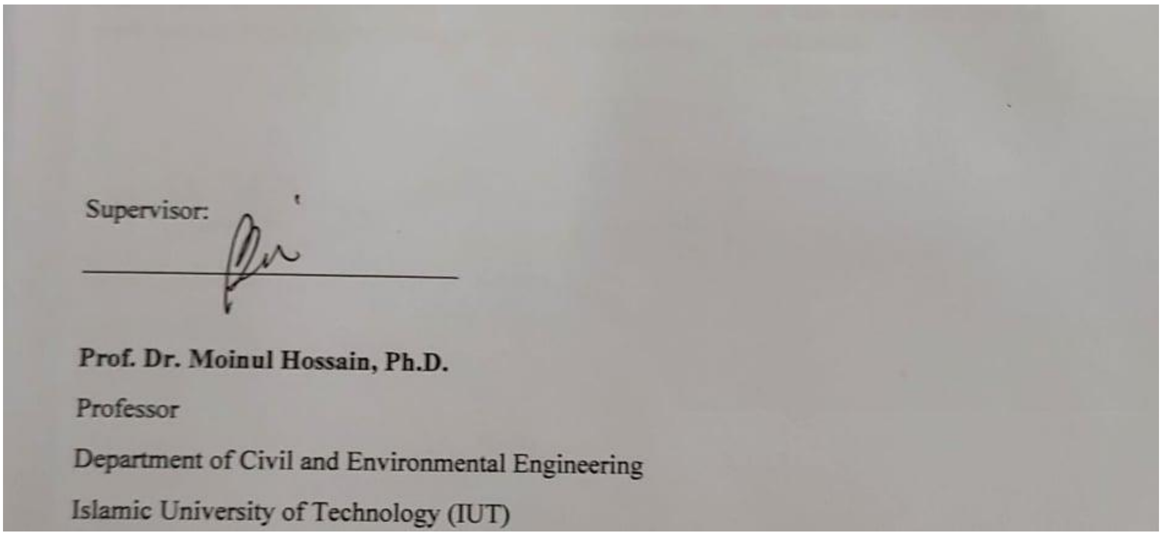

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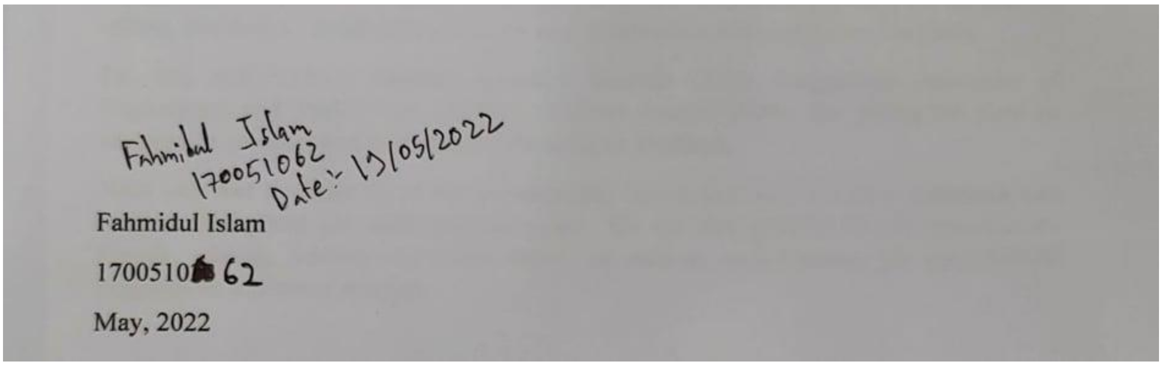
DECLARATION

We declare that the undergraduate research work reported in this thesis was completed under Professor Dr. Moinul Hossain's supervision. We've taken the necessary steps to ensure that the work is original and free of plagiarism. We can also make sure that the work has not been submitted for any other purpose except for publication.



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May, 2022

ACKNOWLEDGEMENT

"In the name of Allah, Most Gracious, Most Merciful"

All praise be to Allah (SWT) for allowing us to complete this research project. We would like to express our gratitude to our parents for providing us with the strength and dedication required to complete this thesis.

It is a great honor to express our heartfelt gratitude to our respected supervisor, Dr. Moinul Hossain, Professor of Civil and Environmental Engineering (IUT), for his tireless efforts, inspiration, invaluable guidance, and constructive criticisms over the years.

Dr. Md. Asif Raihan, Accident Research Institute (ARI), Bangladesh University of Engineering and Technology (BUET), deserves special thanks for taking the time to correct our mistakes and provide us with valuable feedback.

We'd also like to thank all of our departmental faculty and staff for their assistance and support throughout our undergraduate years. We are also grateful to our department's friends, seniors, juniors, and batch mates, as well as well-wishers, for their helpful suggestions and warm support.

DEDICATION

We dedicate this thesis to our parents, who gave up their time, commitment, and livelihood for many years so that we could pursue our dreams through education. Having parents who have been dedicated to each other for as long as ours has taught us the value of perseverance in achieving one's goals.

ABSTRACT

Several studies show that women are harmed by the current transportation system, which restricts their access to education and economic opportunities. As a result, their standard of living suffers. Thus, improving public transportation and infrastructure should be a top priority, with gender issues factored into the equation.

Women are more affected than men by various travel patterns caused by inadequate and poor public transportation services. This reality is exacerbated by conservative social norms that stigmatize women who arrive home late due to delays caused by inefficient public transportation.

Using GeNIe, a Bayesian model is created using data from a face-to-face survey conducted in various locations across Bangladesh.

Key words: Short Trip, long trip, trip duration, gender, monthly income, Bayesian analysis

Table of Contents

List of Figures

CHAPTER 1

INTRODUCTION

1.1. Background of the study

"Everyone has the right to freedom of movement and residence within the borders of each state," according to Article 13 of the Universal Declaration of Human Rights (UDHR). Individuals should be able to move from one place to another easily, freely, and safely, so mobility rights are considered basic rights. While Article 13 does not explicitly state that efficient transportation is a human right, citizens' right to mobility can only be realized if they have access to adequate transportation for their own safe and efficient mobility.(Fatmi & Habib, 2017; Nobis & Lenz, 2005)

Women cannot achieve gender equality in this context because current transportation systems are unsafe, violent, and inaccessible. Women's socioeconomic status will improve if they have access to transportation because it will encourage more women to enter the labor force. It will also encourage women to become active members of their communities and promote gender equality. Because women account for half of the world's population, women's empowerment will make sustainable development a reality.(sahar Aloul, 2018)

Both decision-makers and policymakers should consider the economic benefits for women as a result of increasing their access and use of public transportation, as well as the role this would play in achieving overall economic growth and sustainability.

1.2. Problem Statement

Because the goal of our research is to determine the diversity of women's travel mode selection based on trip length, the main focus is to determine precise trip generations in rural and urban areas.

It's critical to recognize that men and women have quite distinct travel requirements. It's also critical to secure women's safety when using public transportation, as they make up a larger portion of city travel for a variety of reasons, including the fact that they feel significantly less comfortable after dark. Even in the sight of daylight, they are harassed on public transportation(Tokey & Shioma, 2017).

Buses may account for a small percentage of total journeys, but they are a significant alternative to automobiles in low-density corridors that serve rural areas and small towns (Abdulsalam et al., 2013).

In the social sciences, cross-cultural approaches are common, but they have yet to catch on in transportation research. There hasn't been much research done to see if these models can forecast travel behavior in places other than the ones where the modal parameters were calculated(Nicolaidis & Krishnan, 1977).

The effect of misspecification was larger in forecasting than in the estimation of marginal rates of substitution, such as the subjective value of time, which was a significant finding(Cantillo et al., 2010).

1.3. Purpose &Objective

According to the International Labor Organization, the most significant barrier to women's involvement in the labor market in developing countries is poor access to and safety of transportation, which is predicted to reduce their participation likelihood by 16.5 percent.

Women's travel patterns are commonly acknowledged to differ from men's, and these variances are marked by persistent inequality. Women have less access to both private and public transportation in any given metropolitan location, while also shouldering a greater share of their household's travel burden and making more trips linked with reproductive and caregiving duties(Tokey & Shioma, 2017).

The success of global transportation networks in serving women's demands, as well as the unintended consequences of their development on women's lives, are poorly understood and documented(Turner & Fouracre, 1995)

The focal objectives of the study are:

1. To determine whether there is individual preference heterogeneity
2. To take into account the variation in trip distance
3. to ask information about duration of travel and alternative modes along with demographic and attitudinal question

1.4. Scope of the study

The study can be used to consider the uniqueness of various types of travel modes. Our research shows which mode of transportation women prefer during any trip. More research can be done to improve responses.

We can correlate with more appropriate variables to get better understanding about their travel mode choice behavior.

DCM method can provide more accuracy.

CHAPTER 2

LITERATURE REVIEW

Travel time plays a crucial factor in deciding which mode of transportation to choose. Diverse features of travelers, such as gender, arrival time, and other factors, lead to different behavior in terms of transport mode selection and, in particular, trip time preference(Luo et al., 2007). Several intercity mode choice models have been created and are used to anticipate traveler's preferences all over the world. Because transportation networks typically get large investments, this modeling is critical for planning.(Ben-Akiva et al., 1997). Models of travel demand are used to forecast demand for travel activities and to estimate the value commuters place on the many elements that influence their decisions(Abdulsalam et al., 2013). In the case of trip distance heterogeneity, the difference in travel times across the options may have a different effect depending on the trip distance. When the shortest way has a travel time of only two minutes, a route with a travel time five minutes longer than the shortest path is unlikely to be chosen, assuming all other variables are equal. When the shortest trip takes thirty minutes, the two routes are equivalent. In other words, longer journeys may have more variance in the error terms in the route choice model than shorter trips (Yamamoto et al., 2018).

The estimation of conventional mode choice models is commonly used to gain a better understanding of people's travel behavior, particularly their mode selection. Past choice data is used to calibrate these models. When no such data are available, data must be generated either directly by experimentation, such as demonstration projects, or indirectly, as in this case.(Nicolaidis & Krishnan, 1977).

The estimation of conventional mode choice models is commonly used to gain a better understanding of people's travel behavior, particularly their mode selection. Past choice data is used to calibrate these models. When no such data are available, data must be generated either directly by experimentation, such as demonstration projects, or indirectly, as in this case.(Nicolaidis & Krishnan, 1977)

Consumers are unable to distinguish a minor utility difference between two alternatives, which could be due to their low knowledge and perception skills, or because they just reduce the choosing task to save time (Pan & Zuo, 2020).

CHAPTER 3

METHODOLOGY & DATA

3.1. Introduction

This chapter presents the methodological approach used in this study in a step-by-step format. The goal of this study was to uncover the underlying factors that influence the selection of travel mode in developing countries and to establish a causal relationship between the factors. Because such factors are frequently interdependent and influenced by prior beliefs, conditional probability can be used to establish a causal relationship between them using the Bayesian Belief Network (BBN). This chapter will provide a brief but thorough introduction to Bayesian Belief Network (BBN), as well as a demonstration of its applicability to our research.

An overall workflow can be used to describe the methodology process.

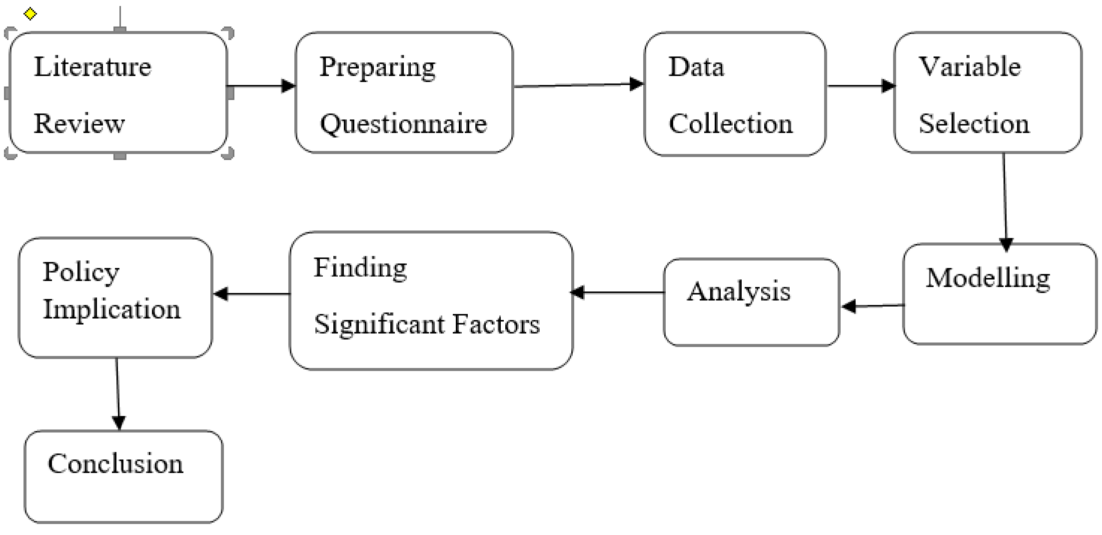

Figure 1: Workflow of Methodology

3.2. Methods

The Bayesian Belief Network (BBN) is used in this study to better understand the underlying relationship between variables like safety perception and demographic characteristics, as well as how they influence the use of safety restraints. A Bayesian network is a visual representation of a set of variables and their conditional dependencies. The conditional dependencies are visualized using a Directed Acyclic Graph (DAG), which is a useful tool for visualizing the probabilistic model, evaluating the relationship between random variables, and determining their posterior probability for given evidence. Each random variable in a DAG is referred to as a node, and arcs connect them. The nodes on the arc's origin side are known as mother nodes, while the rest are known as child nodes.

The Bayesian framework is based on the Bayes hypothesis, or Bayes rule.

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

The probability of A occurring is P(A), and the probability of B occurring is P(B). P(A|B) denotes the probability of A occurring if B has already occurred, and P(B|A) denotes the probability of B occurring if A has already occurred.

GeNIe 3.0 Academic Version was used for structural learning (network formation) and parameter learning in our research (preparation of CPT). GeNIe 3.0 is a computer program created at the University of Pittsburgh. This program can be used for decision-making and graphical representation of the union of probability and network occurrences. GeNIe is useful for analyzing noisy data and uncertainty measures and can be used to analyze Bayesian networks. Calculating a Bayesian network with a large number of interconnected nodes can be difficult at times, but GeNIe is well equipped to handle such problems.

At GeNIe software, a CSV file was used to learn new parameters for the Bayesian model. At genie software, we use the PC algorithm, which has six different algorithms. The PC algorithm is the most up-to-date constraint-based causal discovery method. However, the PC algorithm's runtime is exponentially proportional to the number of nodes (variables) in the worst-case scenario, making it inefficient when applied to high-dimensional data, such as gene expression datasets.

The Expectation Maximization (EM) algorithm is used by GeNIe. In the presence of latent variables, the EM algorithm is a method for performing maximum likelihood estimation. To maximize the estimation, EM first estimates the values of latent variables and then continues an iterative improvement process. The iteration process is divided into two steps: E-Step (Expectation Step) and M-Step (Measurement Step) (Maximization Step). The process is repeated until the two steps converge.

We can create a standard model for our objective after EM algorithm analysis and consider it a primary model because several modifying issues remain.

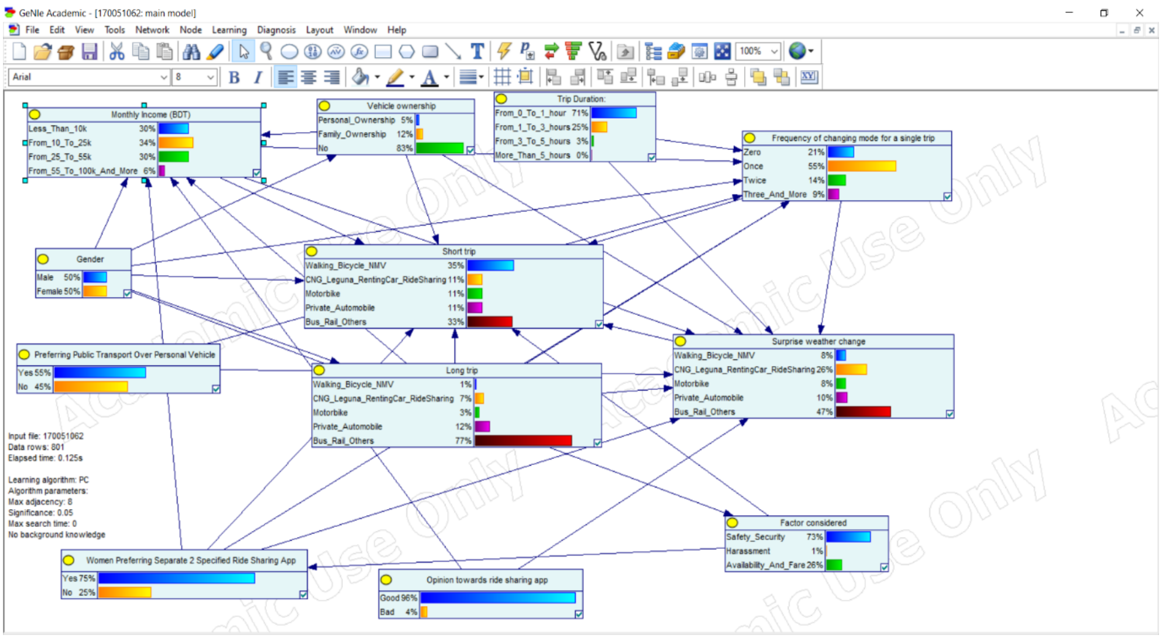

Figure 2: Primary model analysis at GeNIe

This is a probabilistic prior distribution. Following the update, the belief prior probability distribution appears. A prior probability distribution of an uncertain quantity is the probability distribution that would express one's beliefs about this quantity before some evidence is taken into account in Bayesian statistical inference.

It's interesting to note that it's the same as a descriptive statistic. As we analyzed our data, we noticed that different variables have different responses and characteristics, as well as their significance, so we built a Bayesian network, which is similar to descriptive statistical analysis. After that, considering the significance of the variable was done, (which is the most important factor to consider). It demonstrates the relationship between variables for example which variable is significant and which is not.

We must set a target variable to determine the significance of a variable. We can also set more than one target variable. The core variable that is considered an objective is the target variable. We’ve chosen Short Trip and Long Trip as our target variables in our study.

We wanted to see how women choose travel modes for short and long trips for our research. We have 12 variables, and Short Trip and Long Trip are both related to travel mode selection. Short Trip and Long Trip are the closest ones to set as target variables to assess the travel mode selection for rural and urban areas in Bangladesh based on our questionnaire and Bayesian model.

Assume that Short Trip and Long Trip are target variables, and that the red mark indicates the significance of the variable with the target variable (Dark red= very relatable, connected, influenced by target variable), (Light red= relatable, standard significant with target variable), (Light white= important but less significant), and (white= can be removed, no significance).

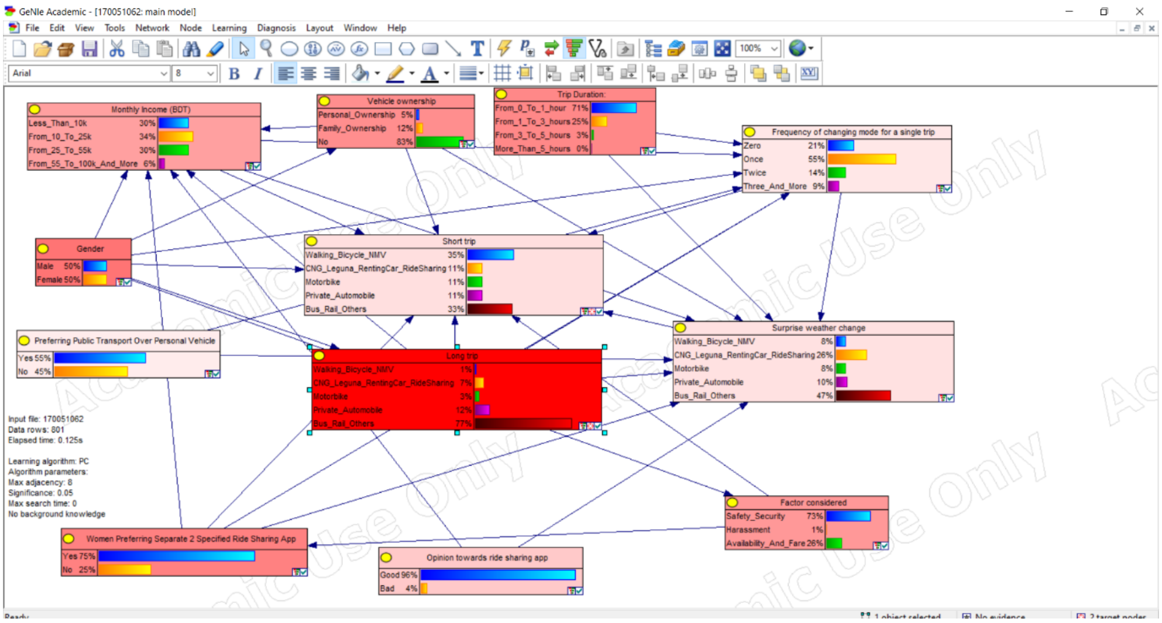

Figure 3: Sensitivity analysis

Irrelevant variables can be removed after sensitivity analysis. We found that all of the variables we chose were significant. The most important variables are gender, trip duration, vehicle ownership, monthly income, and factor considered. The remaining variables are less significant but still important. We also used SPSS to perform correlation analysis. The double star correlation or 99 percent significant variables will remain after the correlation in SPSS, and the remaining variables should be eliminated.

*Output1 [Document1] - IBM SPSS Statistics Viewer

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Correlations

		Gender	MonthlyIncomeBDT	Shorttrip	Longtrip	VehicleownershipPrivateautomobilelikecarmicrobus	TripDuration	Howmanytimesyouneedtochangeyourmodetomakethesinglet	Surpriseweatherchange	Factorconsidered	Opiniontowardsridesharingapp	WomenPreferringSeparate2SpecifiedRideSharingApp	PreferringPublicTransportOverPersonalVehicle
Gender	Pearson Correlation	1	-.189**	.231**	.051	.040	-.117**	-.127**	.055	-.211**	-.032	-.012	-.029
	Sig. (2-tailed)		.000	.000	.152	.260	.001	.000	.122	.000	.372	.728	.408
	N	801	801	801	801	801	801	801	801	801	801	801	801
MonthlyIncomeBDT	Pearson Correlation	-.189**	1	.233**	-.253**	-.317**	.206**	.064	-.121**	-.084*	.018	.120**	.117**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.071	.001	.017	.601	.001	.001
	N	801	801	801	801	801	801	801	801	801	801	801	801
Shorttrip	Pearson Correlation	.231**	.233**	1	-.021	-.118**	.234**	.188**	.147**	-.302**	.015	.319**	.013
	Sig. (2-tailed)	.000	.000		.548	.001	.000	.000	.000	.000	.679	.000	.718
	N	801	801	801	801	801	801	801	801	801	801	801	801
Longtrip	Pearson Correlation	.051	-.253**	-.021	1	.262**	-.134**	-.072*	.244**	.119**	.072*	-.145**	-.020
	Sig. (2-tailed)	.152	.000	.548		.000	.000	.041	.000	.001	.043	.000	.569
	N	801	801	801	801	801	801	801	801	801	801	801	801
VehicleownershipPrivateautomobilelikecarmicrobus	Pearson Correlation	.040	-.317**	-.118**	.262**	1	-.049	.252**	.078*	.142**	.058	-.009	-.205**
	Sig. (2-tailed)	.260	.000	.001	.000		.167	.000	.027	.000	.099	.809	.000
	N	801	801	801	801	801	801	801	801	801	801	801	801
TripDuration	Pearson Correlation	-.117**	.206**	.234**	-.134**	-.049	1	.422**	.173**	-.119**	.012	.233**	-.032
	Sig. (2-tailed)	.001	.000	.000	.000	.167		.000	.000	.001	.733	.000	.362
	N	801	801	801	801	801	801	801	801	801	801	801	801
Howmanytimesyouneedtochangeyourmodetomakethesinglet	Pearson Correlation	-.127**	.064	.188**	-.072*	.252**	.422**	1	.184**	-.096**	.089*	.287**	-.217**
	Sig. (2-tailed)	.000	.071	.000	.041	.000	.000		.000	.007	.012	.000	.000
	N	801	801	801	801	801	801	801	801	801	801	801	801
Surpriseweatherchange	Pearson Correlation	.055	-.121**	.147**	.244**	.078*	.173**	.184**	1	-.119**	.056	.144**	-.312**
	Sig. (2-tailed)	.122	.001	.000	.000	.027	.000	.000		.001	.115	.000	.000
	N	801	801	801	801	801	801	801	801	801	801	801	801
Factorconsidered	Pearson Correlation	-.211**	-.084*	-.302**	.119**	.142**	-.119**	-.096**	-.119**	1	.029	-.211**	.087*
	Sig. (2-tailed)	.000	.017	.000	.001	.000	.001	.007	.001		.418	.000	.014

Double click to edit Pivot Table | IBM SPSS Statistics Processor is ready | Unicode:ON | H: 982, W: 1359 pt.

Figure 4: Correlation part I

Longtrip	Pearson Correlation	.051	-.253**	-.021	1	.262**	-.134**	-.072*	.244**	.119**	.072*	-.145**	-.020
	Sig. (2-tailed)	.152	.000	.548		.000	.000	.041	.000	.001	.043	.000	.569
	N	801	801	801	801	801	801	801	801	801	801	801	801
VehicleownershipPrivateautomobilelikecarmicrobus	Pearson Correlation	.040	-.317**	-.118**	.262**	1	-.049	.252**	.078*	.142**	.058	-.009	-.205**
	Sig. (2-tailed)	.260	.000	.001	.000		.167	.000	.027	.000	.099	.809	.000
	N	801	801	801	801	801	801	801	801	801	801	801	801
TripDuration	Pearson Correlation	-.117**	.206**	.234**	-.134**	-.049	1	.422**	.173**	-.119**	.012	.233**	-.032
	Sig. (2-tailed)	.001	.000	.000	.000	.167		.000	.000	.001	.733	.000	.362
	N	801	801	801	801	801	801	801	801	801	801	801	801
Howmanytimesyouneedtochangeyourmodetomakethesinglet	Pearson Correlation	-.127**	.064	.188**	-.072*	.252**	.422**	1	.184**	-.096**	.089*	.287**	-.217**
	Sig. (2-tailed)	.000	.071	.000	.041	.000	.000		.000	.007	.012	.000	.000
	N	801	801	801	801	801	801	801	801	801	801	801	801
Surpriseweatherchange	Pearson Correlation	.055	-.121**	.147**	.244**	.078*	.173**	.184**	1	-.119**	.056	.144**	-.312**
	Sig. (2-tailed)	.122	.001	.000	.000	.027	.000	.000		.001	.115	.000	.000
	N	801	801	801	801	801	801	801	801	801	801	801	801
Factorconsidered	Pearson Correlation	-.211**	-.084*	-.302**	.119**	.142**	-.119**	-.096**	-.119**	1	.029	-.211**	.087*
	Sig. (2-tailed)	.000	.017	.000	.001	.000	.001	.007	.001		.418	.000	.014
	N	801	801	801	801	801	801	801	801	801	801	801	801
Opiniontowardsridesharingapp	Pearson Correlation	-.032	.018	.015	.072*	.058	.012	.089*	.056	.029	1	-.011	-.024
	Sig. (2-tailed)	.372	.601	.679	.043	.099	.733	.012	.115	.418		.766	.504
	N	801	801	801	801	801	801	801	801	801	801	801	801
WomenPreferringSeparate2SpecifiedRideSharingApp	Pearson Correlation	-.012	.120**	.319**	-.145**	-.009	.233**	.287**	.144**	-.211**	-.011	1	-.103**
	Sig. (2-tailed)	.728	.001	.000	.000	.809	.000	.000	.000	.000	.766		.004
	N	801	801	801	801	801	801	801	801	801	801	801	801
PreferringPublicTransportOverPersonalVehicle	Pearson Correlation	-.029	.117**	.013	-.020	-.205**	-.032	-.217**	-.312**	.087*	-.024	-.103**	1
	Sig. (2-tailed)	.408	.001	.718	.569	.000	.362	.000	.000	.014	.504	.004	
	N	801	801	801	801	801	801	801	801	801	801	801	801

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 5: Correlation part II

We modified this model and the relationship between variables after completing the correlation in SPSS. The main process of model modification is removing and connecting arcs. Changing variables is required to create a sensible model. After learning parameter sensibility, removing arc and including arc will change the significance of the variable. Also, ensure that the model is acyclic, and that the arc connections are frequently connected for a more logical purpose.

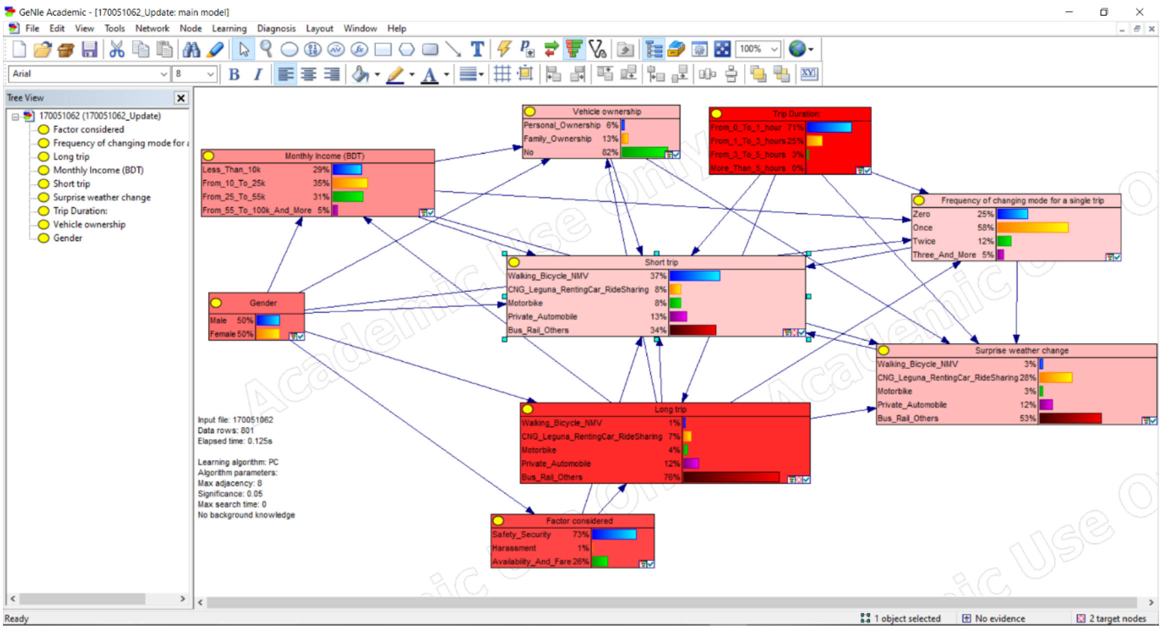

Figure 6: Modifying model at GeNIe

CHAPTER 4

ANALYSIS & RESULT

4.1. Introduction

This research investigates which travel mode women prefer during short and long trips. After completing data analysis using the BBN model, this chapter presents the study's main findings. The data from the survey was initially re-categorized and re-distributed using descriptive statistics. The data was then fine-tuned and fitted into a Bayesian network structure. The network's nodes were tweaked and tested to see how each variable affected the target variable. The model was subjected to several analyses, including sensitivity analysis and tornedo diagrams. The model's accuracy was also checked using the GeNIe software's built-in model validation feature.

This chapter discusses the research findings, which include descriptive statistics and important factors that influence mode selection during a trip.

ANALYSIS & RESULT

4.2.Descriptive Statistics

Firstly in the GeNIe software analysis process, we did parameter learning. For parameter learning, GeNIe uses the default EM (Expectation-Maximization) algorithm. After parameter learning, the marginal probabilities of all nodes in the network were calculated. For a given event of the target variable, the marginal probability is the sum or union of all the probabilities of events of other variables. The observation-based 'Short Trip' and 'Long Trip' variables were chosen as target variables in this study because they strengthen the models by removing the social desirability bias of self-reported data.

4.3.Model output & Explanation

The study shows how to choose a travel mode as an objective during a trip, so the model output will be the study's final declaration. The model's output is determined by the Bayesian model result and identification provided by genie software. Following the sensitivity analysis test, the validation process is the most important step in determining the trip destination's worth. The learning parameter and validation option will be executed first, and the validation process will take a few minutes to complete.

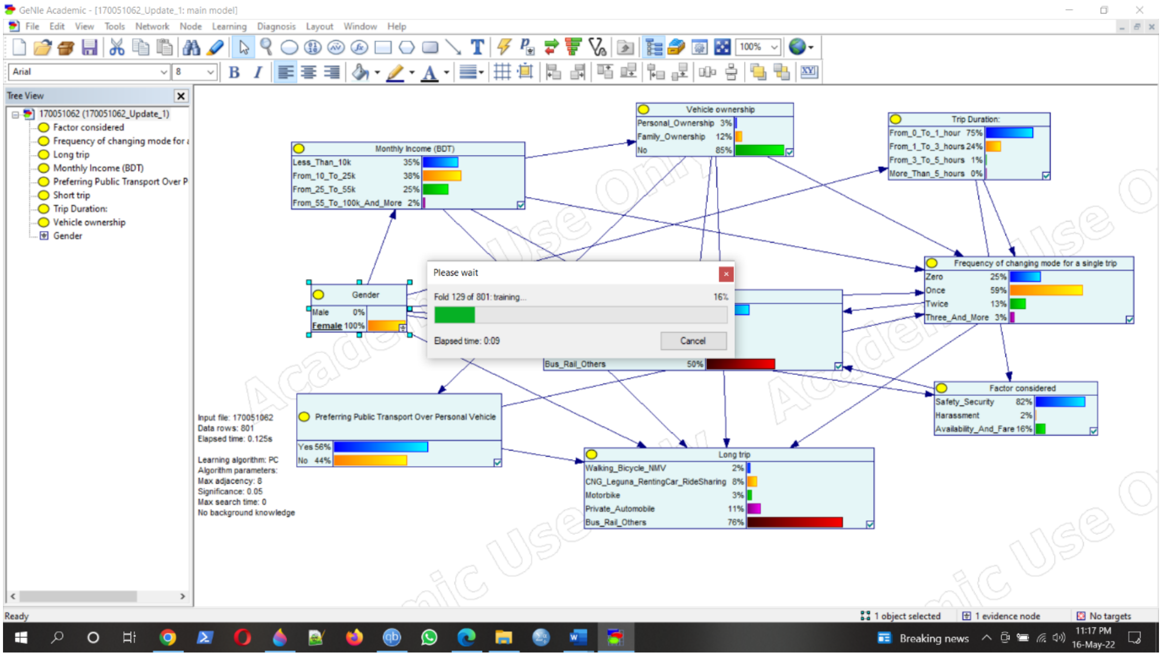

Figure 7: Validation Test of Model

Validation tests are performed using three algorithms. Here, we used the (leave one out) algorithm. It is an algorithm and software that generates a model structure on its own. The Leave One Out algorithm works by removing a target variable that is related to the study's goal. The rest of the variables will be trained, and the target variable will be left or eliminated. The impact of the other variables on the target variable is evaluated.

Approximately 30% of the data is used to train and develop the model. The remaining 70% of data will be fed into the model to match the 30% output data. The percentage of matching required to validate the model varies.

Following validation, we will use the ROC curve to evaluate the trip destination based on several criteria. The accuracy test, ROC curve, and confusion matrix all influence the validation outcome. The result of the validation is significant enough to determine the precise value of the objective. Because our main concern is trip destionation, these three criteria will help us evaluate it more precisely.

As we can see after validation, the accuracy test result is crucial in evaluating our objective.

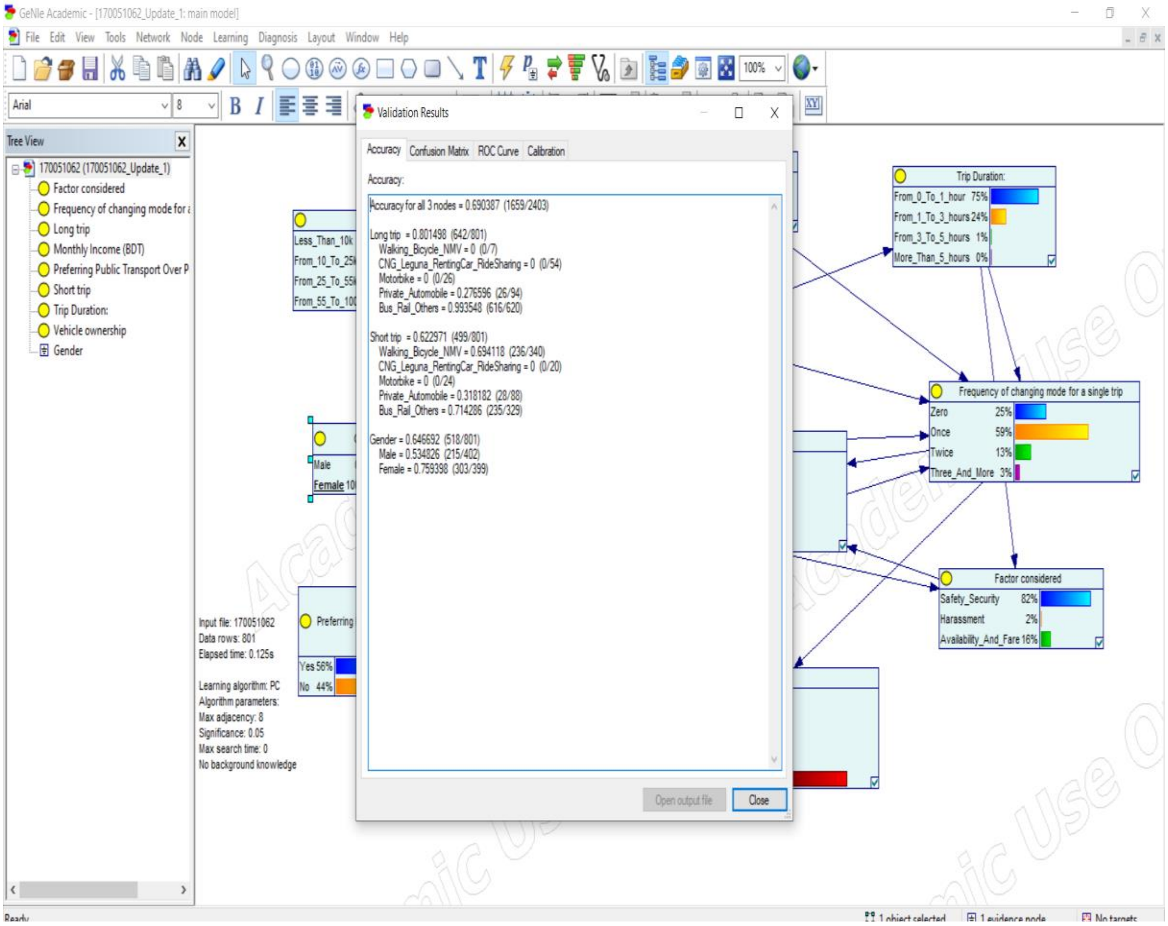

Figure 8: Accuracy

Results of ROC curves are shown below:

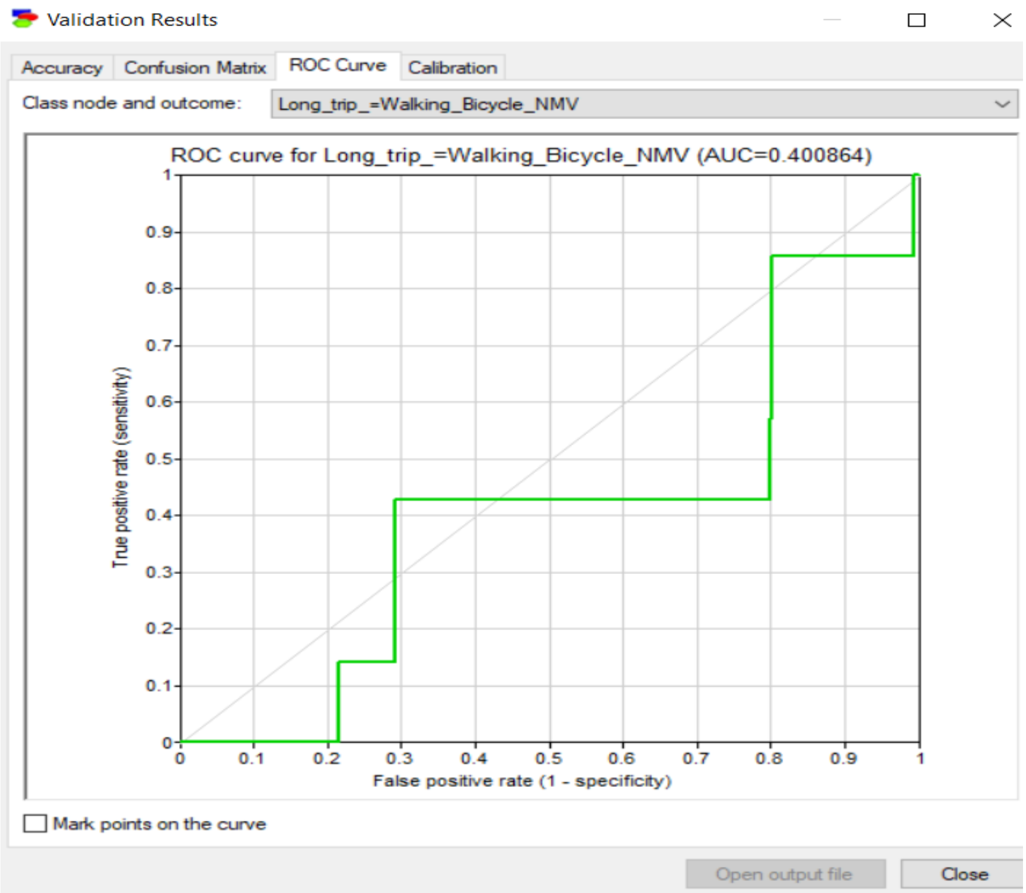

Figure 9: ROC for Long Trip (Walking,Bicycle,NMV)

Here, ROC curve is 0.400864

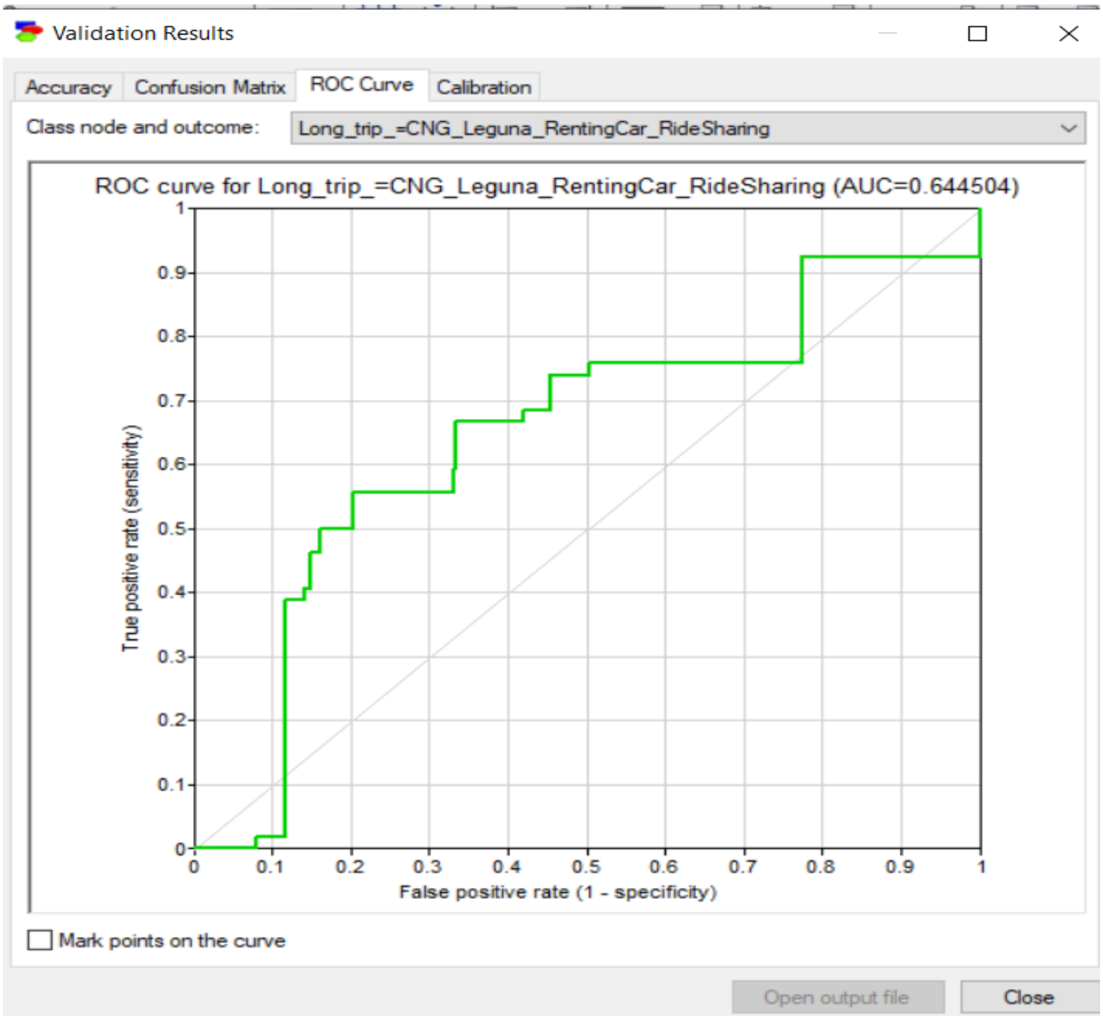

Figure 10: ROC for Long Trip (CNG,Leguna,Renting Car, Ride Sharing)

Here, ROC curve is 0.644504

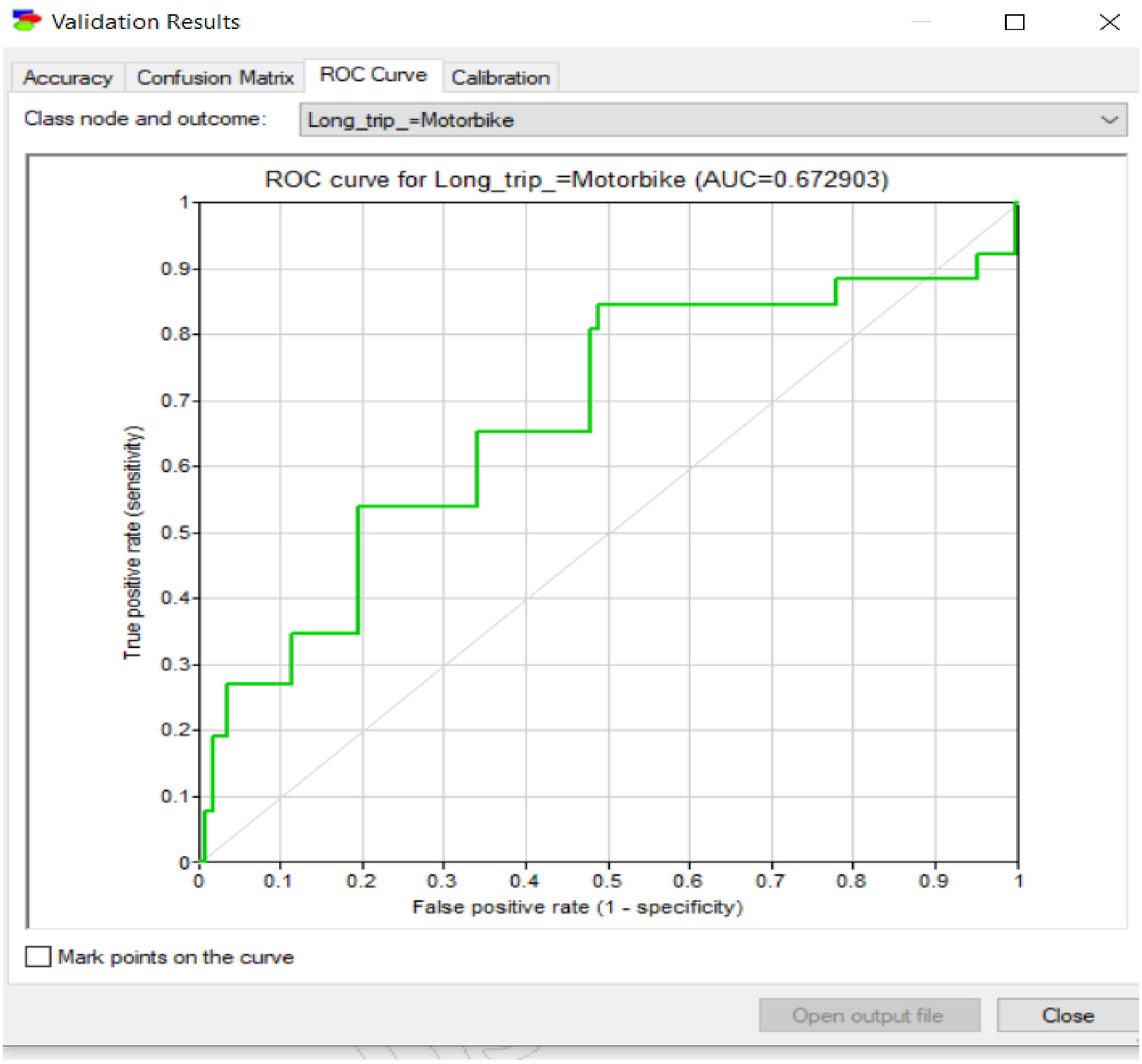

Figure 11: ROC for Long Trip (Motorbike)

Here, ROC curve is 0.672903

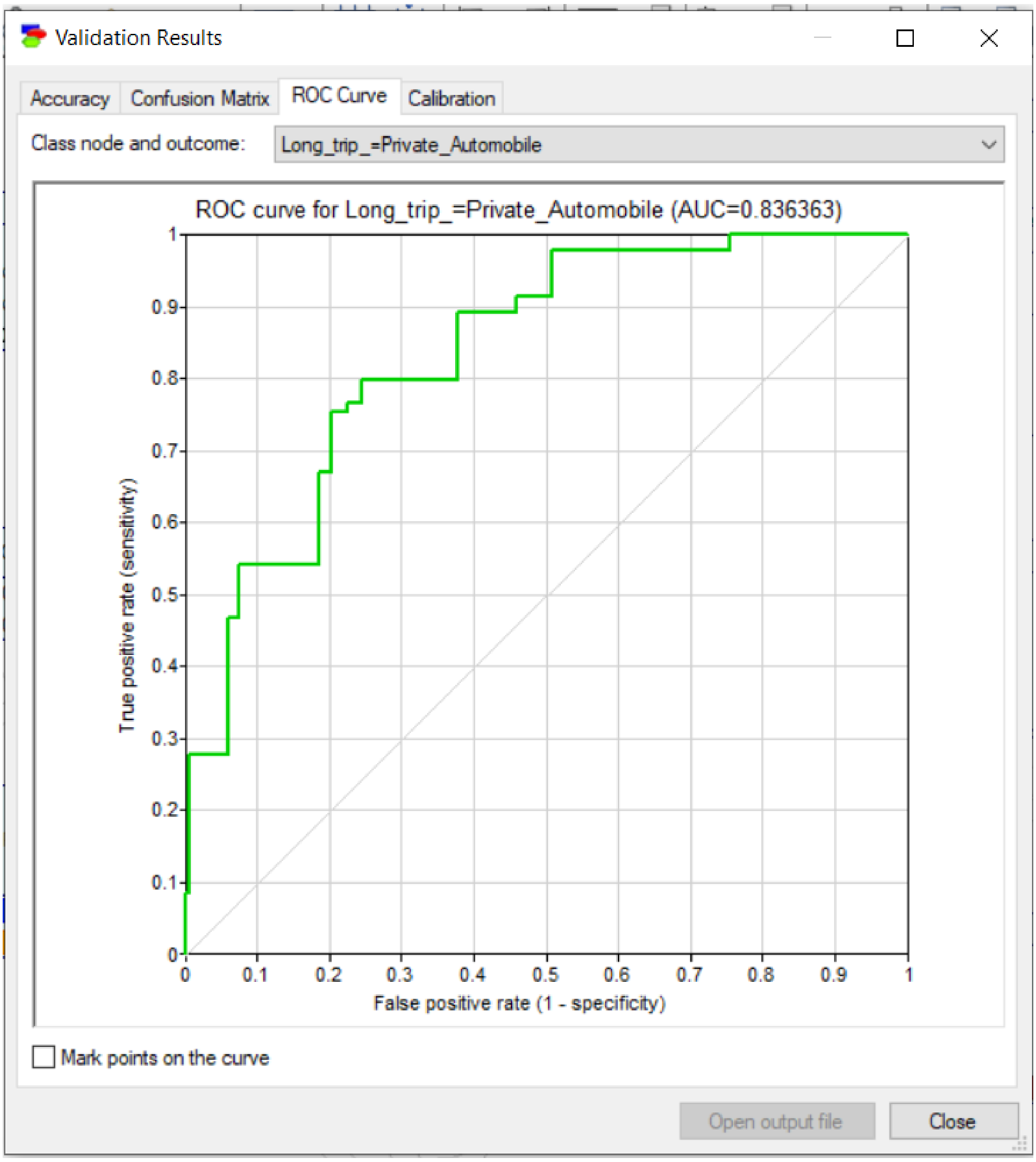

Figure 12: ROC for Long Trip (Private Automobile)

Here, ROC curve is0.836363

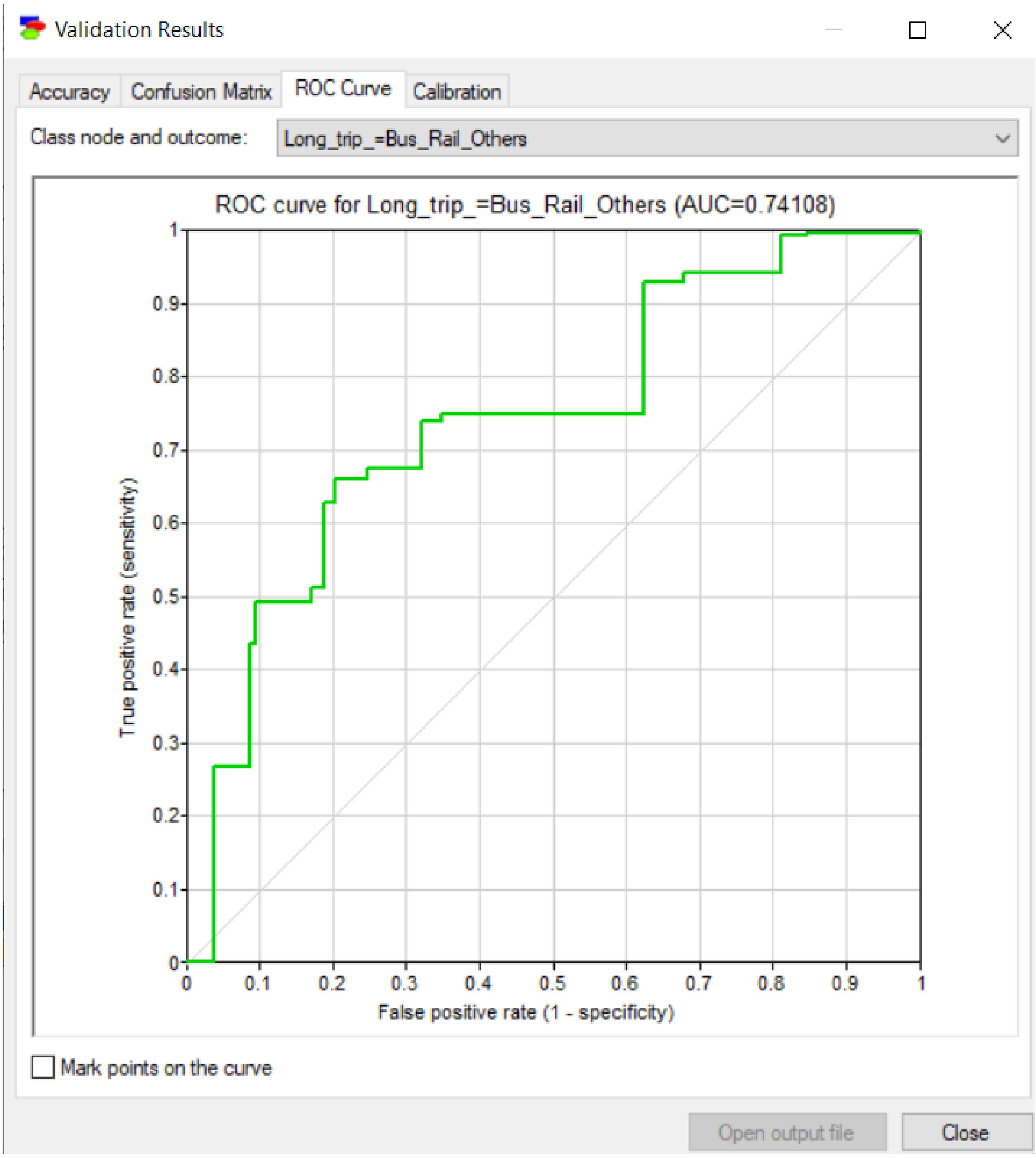

Figure 13: ROC for Long Trip (Bus,Rail,Others)

Here, ROC curve is 0.74108

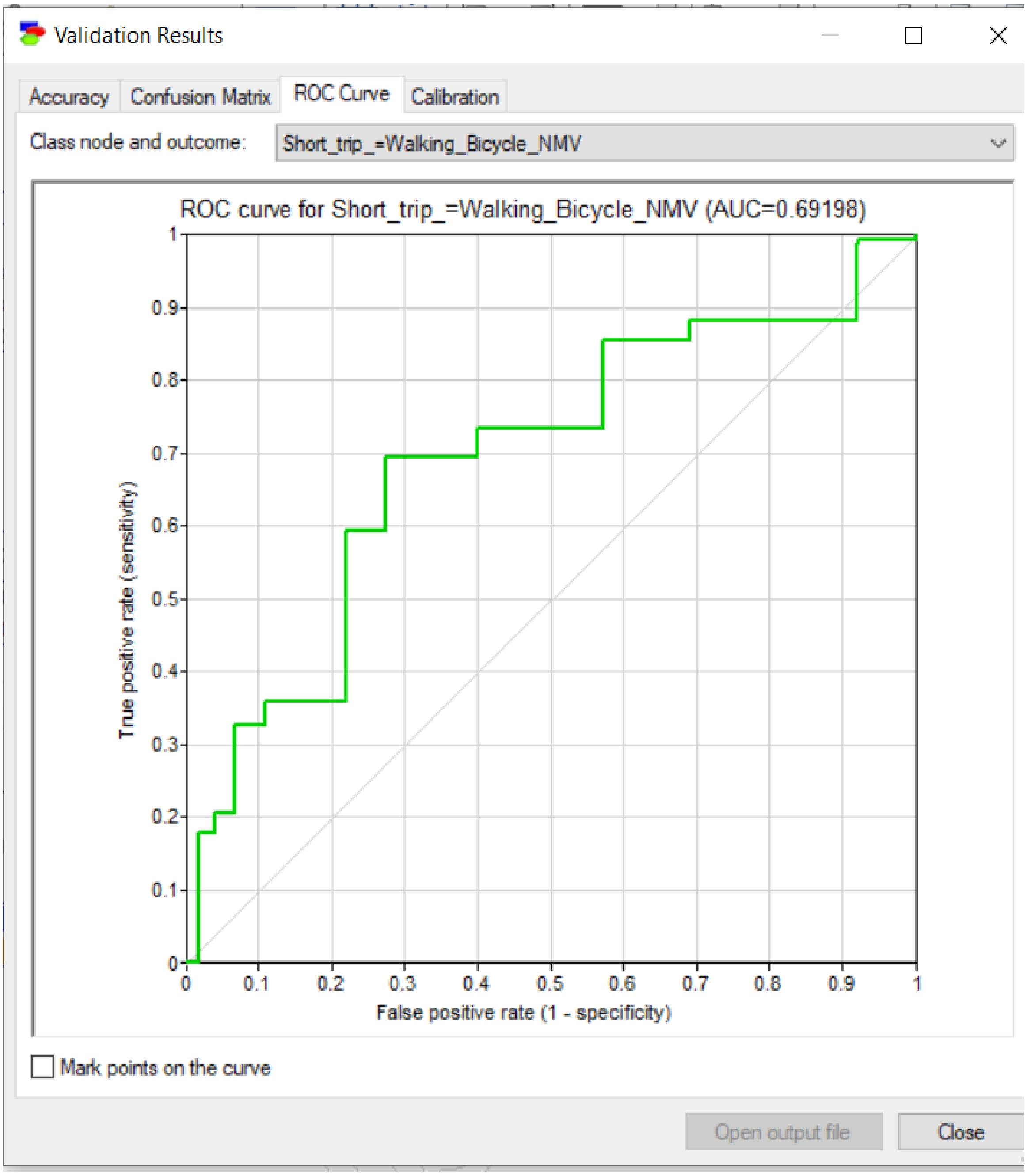

Figure 14: ROC for Short Trip (Walking,Bicycle,NMV)

Here, ROC curve is 0.69198

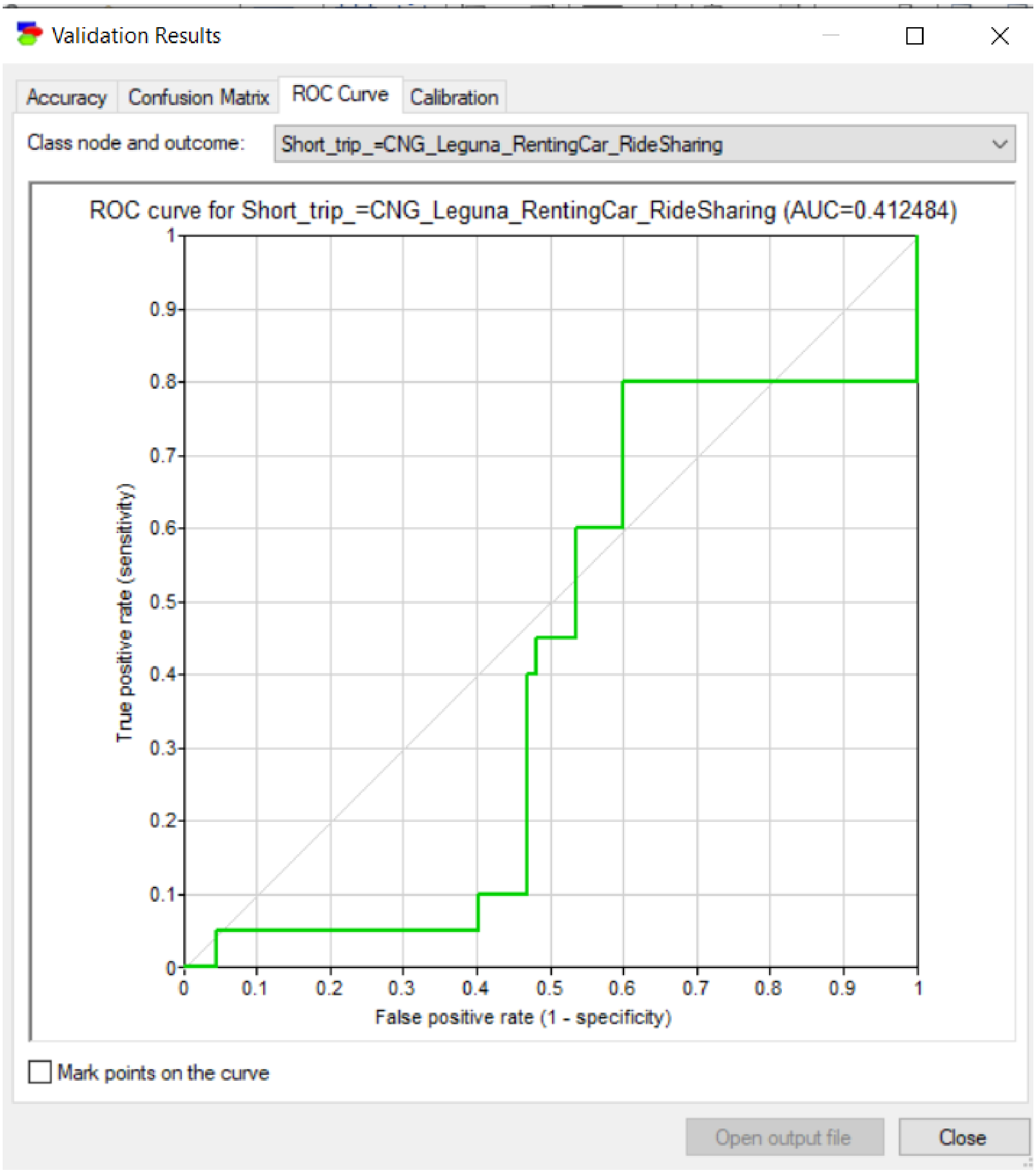

Figure 15: ROC for Short Trip (CNG, Leguna, Renting Car, Ride Sharing)

Here, ROC curve is 0.412484

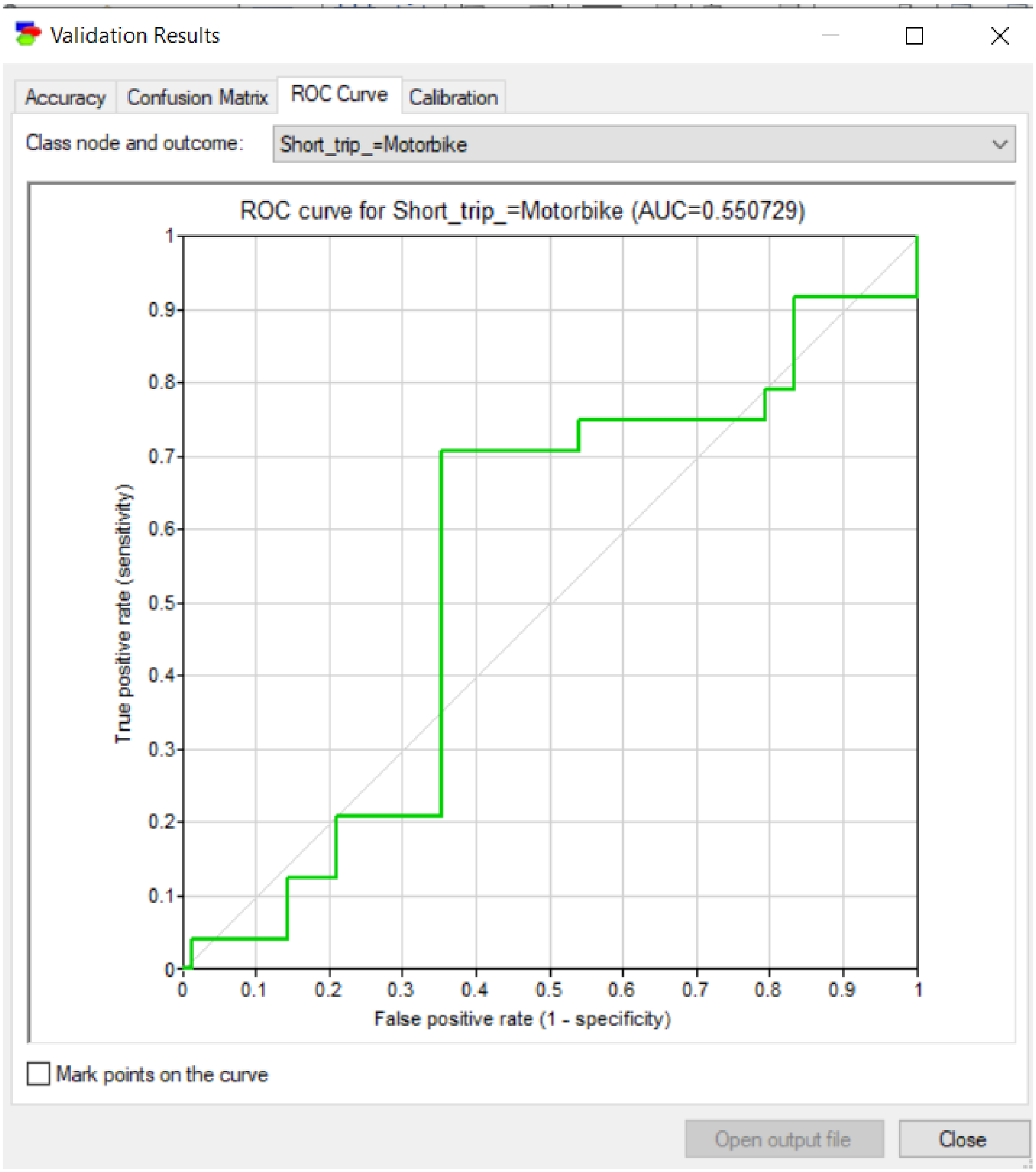

Figure 16: ROC for Short Trip (Motorbike)

Here, ROC curve is 0.550729

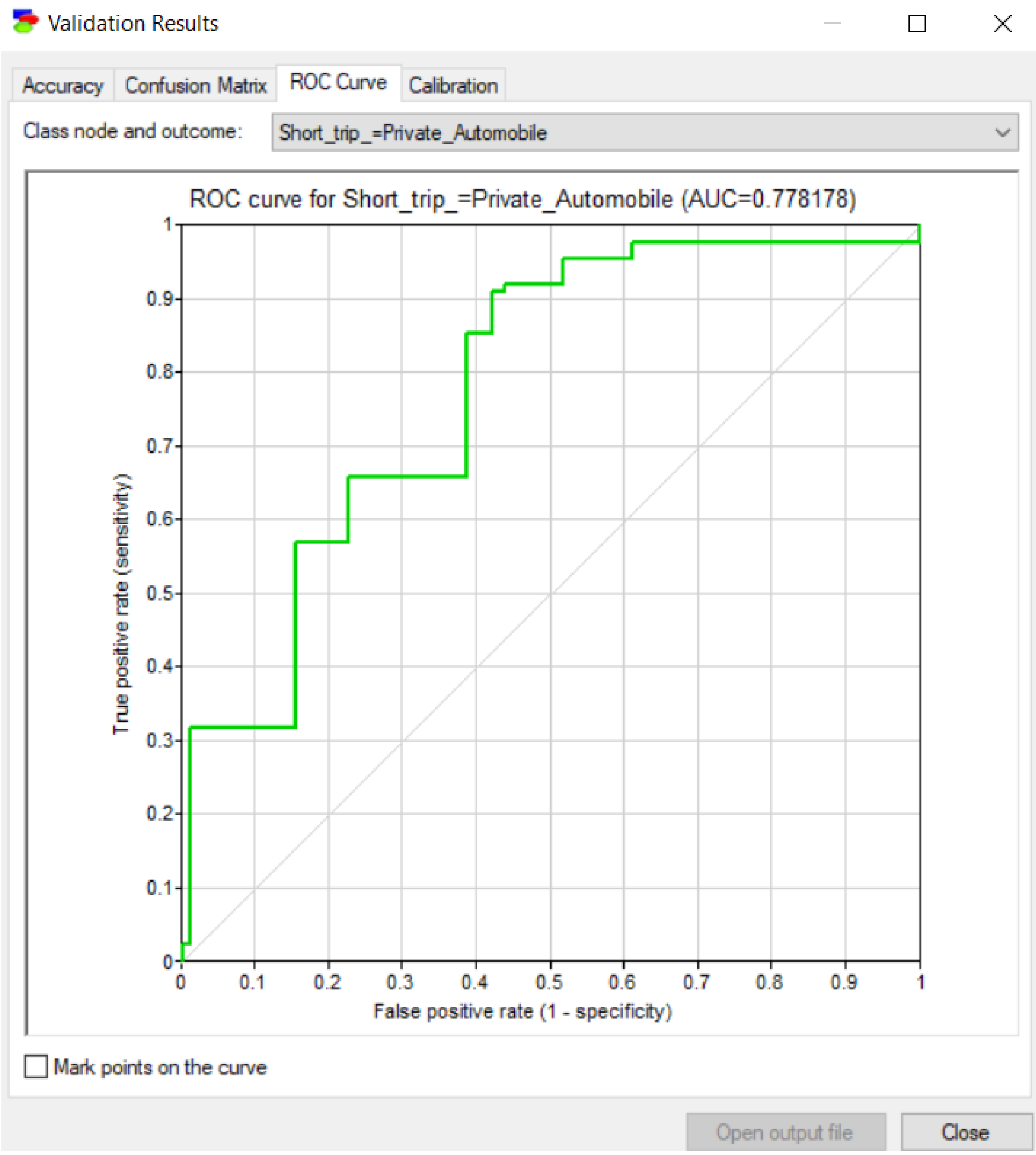

Figure 17: ROC for Short Trip (Private Automobile)

Here, ROC curve is 0.778178

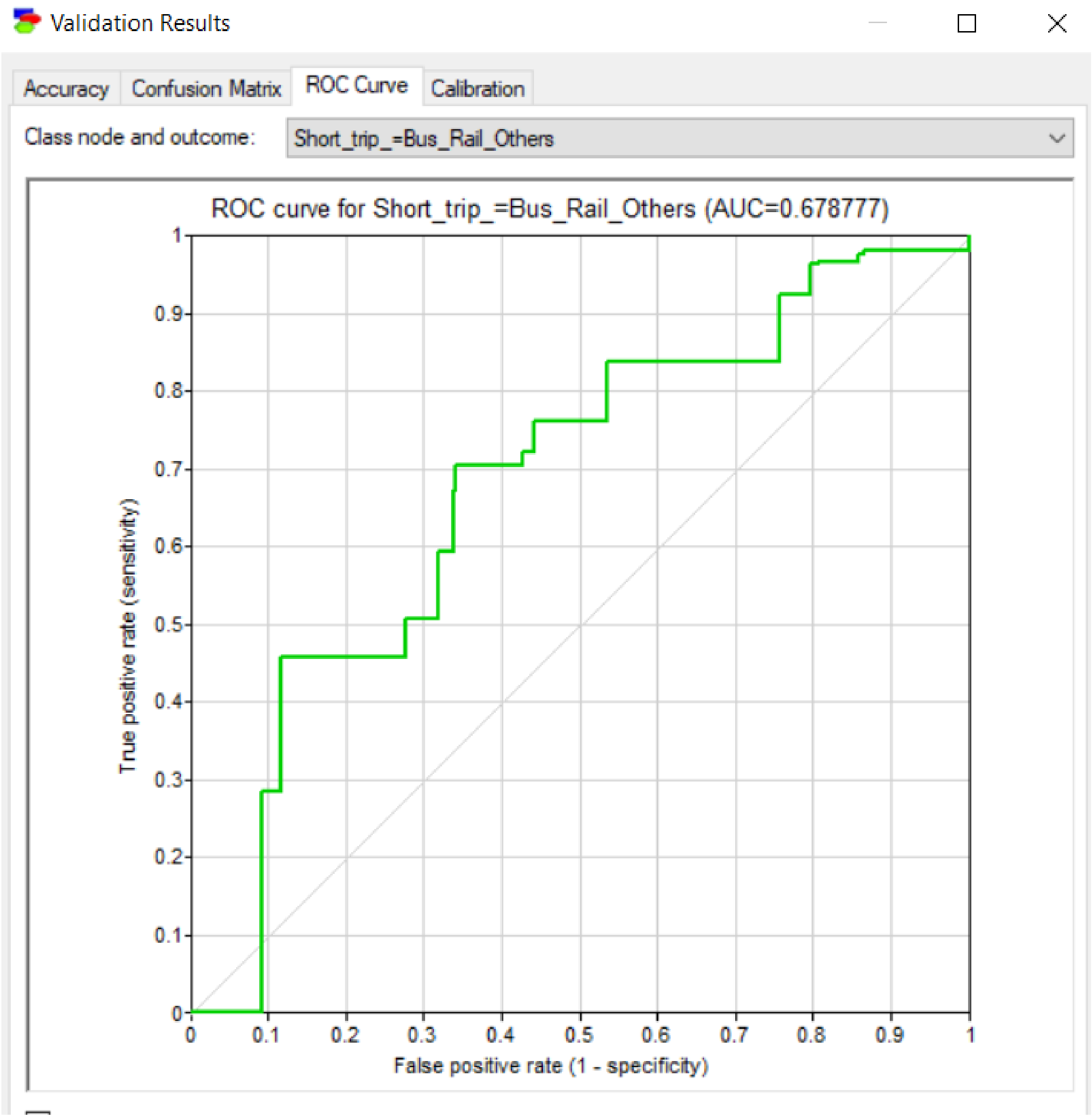

Figure 18: ROC for Short Trip (Bus, Rail, Others)

Here, ROC curve is 0.678777

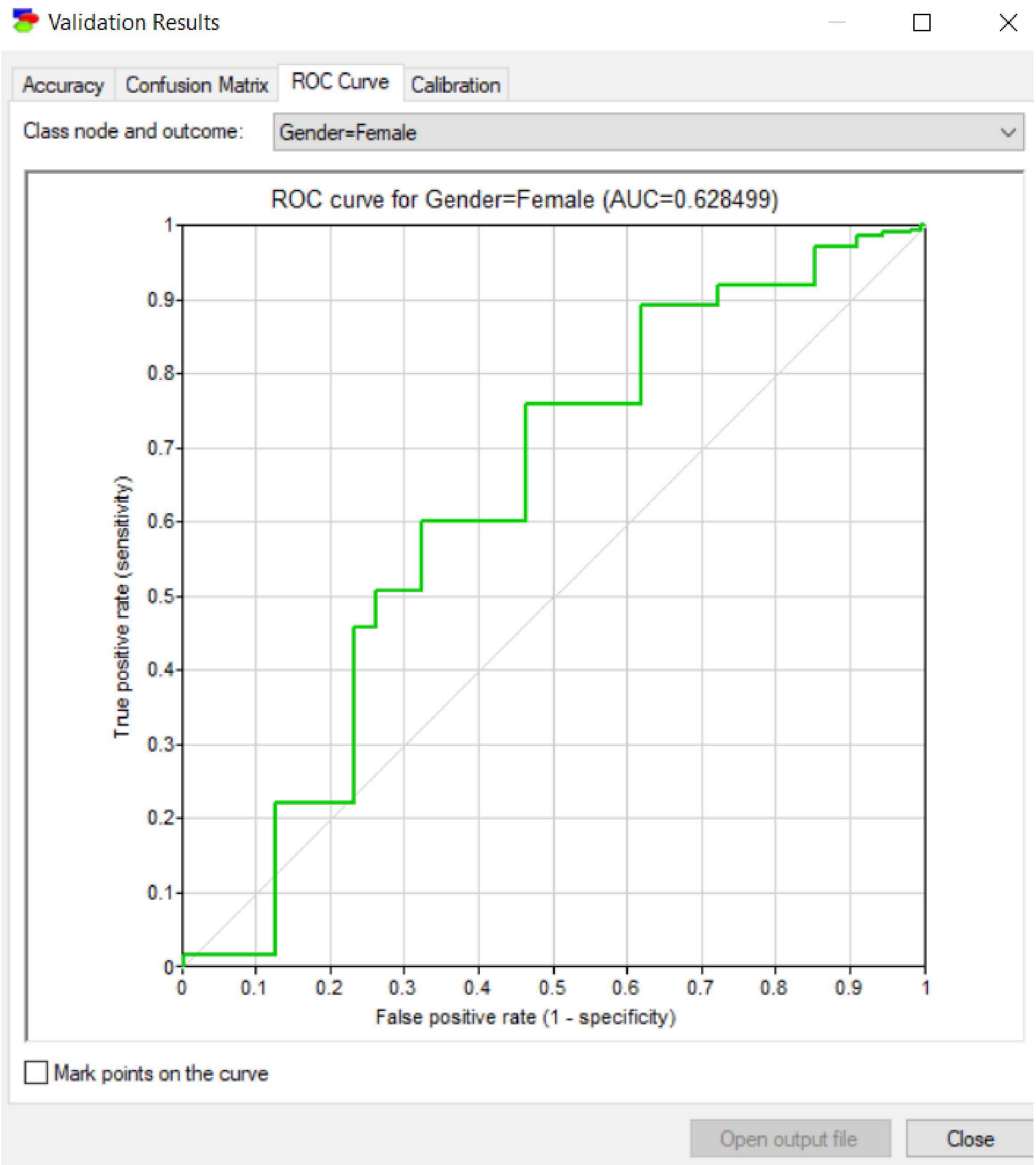

Figure 19: ROC Curve for Gender(Female)

Here, ROC curve is 0.628499

The ROC curve is critical in determining the goal with precise values for the target variables. The ROC curve can display the ranges of possible accuracy, and GeNIe's decision criterion is just one point on the curve. A different sensitivity and specificity will result from selecting a different point. A confusion matrix, also known as an error matrix, is a table layout that aids in visualizing a model's performance. Each column in a confusion matrix represents the actual class, while each row represents the predicted class. The following is the model's confusion matrix:

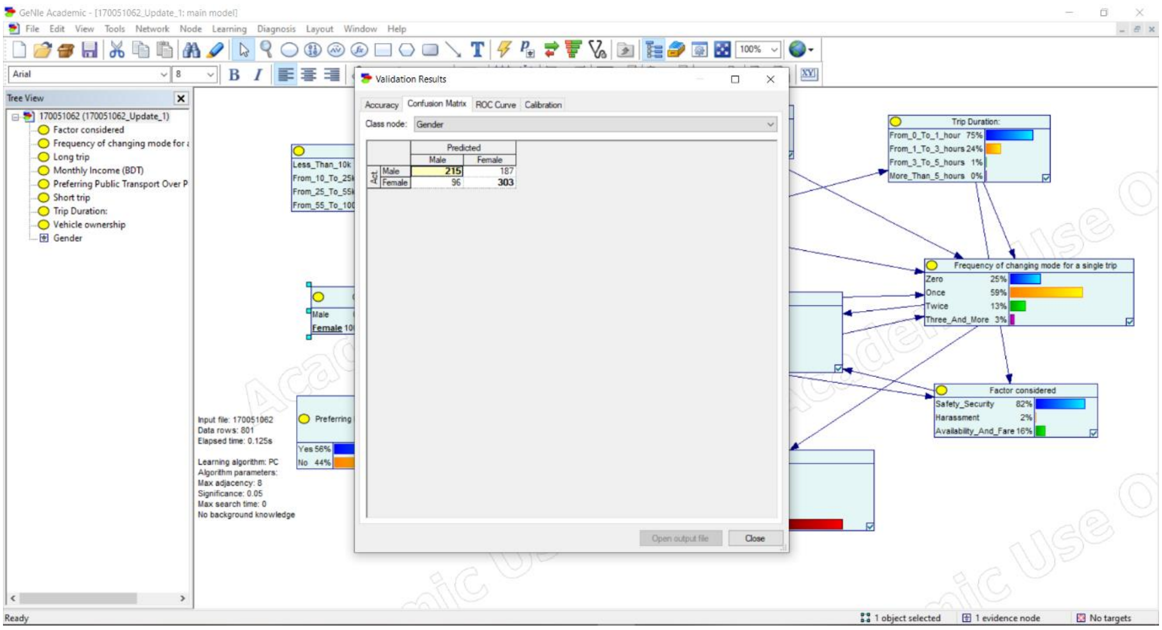

Figure 20: Confusion Matrix

Following validation, the final model network for the trip destination can be precisely determined.

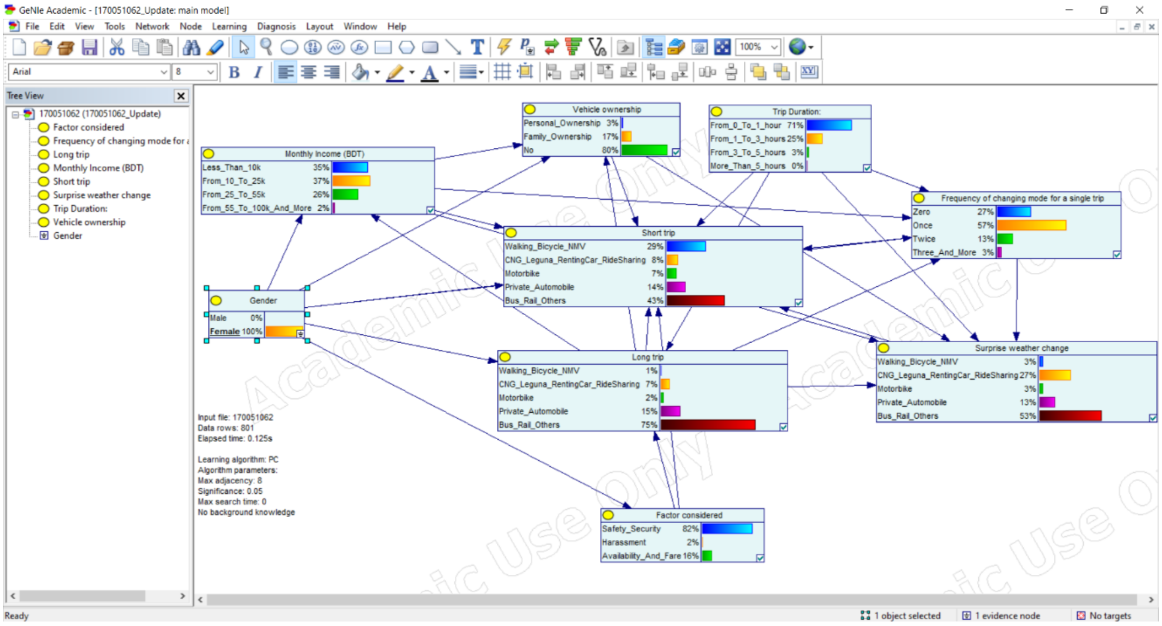

Figure 21: Updated network for Short Trip and Long Trip

Sensitivity Analysis:

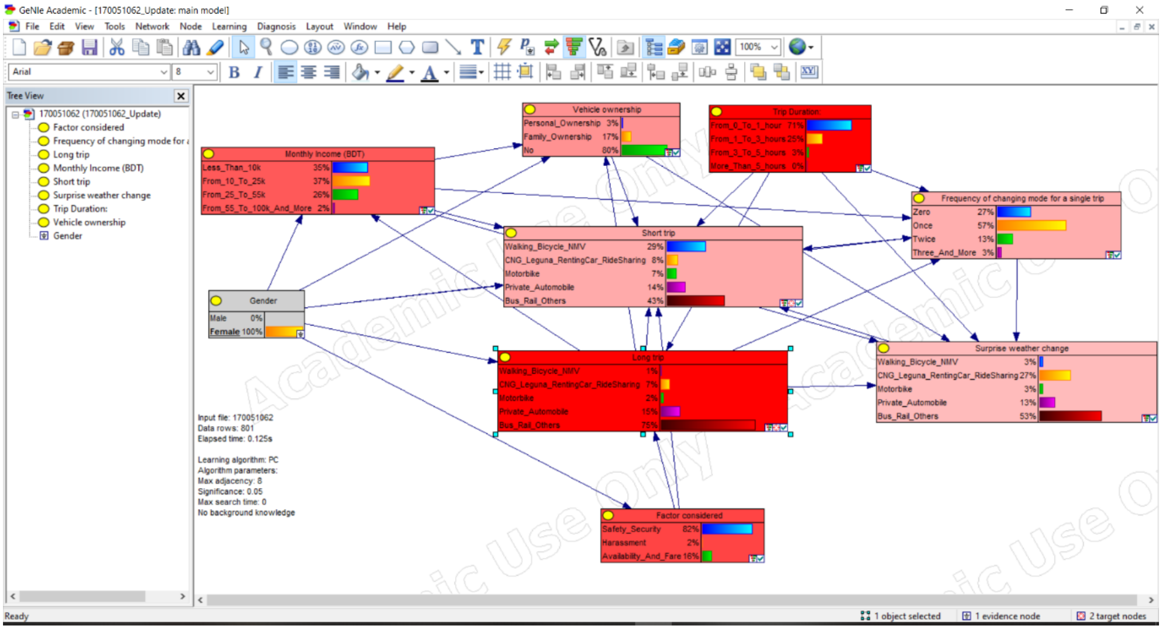

Figure 22: Final model for Short Trip and Long Trip

CHAPTER 5

CONCLUSION & RECOMENDATION

5.1. Introduction

In Bangladesh, a staggering 94 percent of women who commute by public transportation have experienced some form of sexual harassment, whether verbal, physical, or other. Traveling by public transportation has become a nightmare for women, particularly those who are younger and must use it on a regular basis because it is the cheapest option. Women's rights and safety in public transportation are not guaranteed, and as a result, women are unable to contribute to various development sectors. Furthermore, due to sexual harassment, 13% of women avoid taking public transportation. Many women in Dhaka may be forced to limit their movements or activities because they feel unsafe using public transportation. Bangladesh Road Transport Corporation currently operates 16 single- and double-decker buses on 13 city routes exclusively for women, with only two trips per day — one in the morning and one in the afternoon. Female passengers and women's rights activists have criticized the service, urging the authorities to provide more seats for female passengers on mainstream public buses to alleviate their suffering. Despite our many achievements, Bangladesh still has a long way to go in terms of public transportation. As a result, the news that Bangladesh's West Zone will receive 40 new locomotive engines aimed at improving passenger service in the region is welcome.

Because the study covers both urban and rural areas and Bangladesh is a densely populated country, women’s mode selection during a trip is a critical one to execute. For most of the time both for long and short trips, women gives higher priority to Public Transportation Services (Bus, Rail).

5.2. Major Findings

- ❑ Short Trips:
- 35% women preferred NMV, Walking & Bicycle
- 33% women preferred bus due to Safety & Security purpose
- ❑ Long Trips:
- 77% Women preferred Bus and Rail
- 12% preferred private vehicles
- Most considered factor was Safety & Security

Female having high income (55k to 100k) prefers Public transport over car (55%).

For long trips they prefer private automobile (61%) whereas 69% women income (25k to55k) prefers bus for long trips.

We can say that implementing proper NMV lanes can improve the structure& standard. Again, we can improve Public Transportation& service quality so that the men who currently prefer NMV for short trips will switch to Public Transportation. Thus, in both types of trips, men and women will choose public transportation.

5.3. References

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