MATHEMATICAL MODEL FOR BUYING BEHAVIOR OF INTERNATIONAL TRAVELLERS – A MULTINOMIAL LOGISTIC REGRESSION APPROACH

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DECLARATION

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Name of the Supervisor: Prof. T. S. G. Pieris

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Abstract

Predicting the future sales is required continuous attention in order to fulfill the consumer requirements. Disaggregating the sales in to micro level of the business would increase the prediction accuracy since the ground level requirements, trends and patterns are captured. Multinomial logistic regression is a technique that is to be used to model the outcomes with categorical response variable with more than two levels. In the study, the significant determinants for the brand wise purchasing decision of chocolates in a travel retail chain and its consequences are investigated. Multinomial logistics regression found that nationality of the consumers, time of purchase, preference for promotions and preference for weight of the products have significant impact on the chocolate brand choice. It was also found that these fours variables have no multicollinearity effect. The pseudo R2 value of the model confirms that only 44.9% of the variability is absorbed by the final model. The model has overall brand classification accuracy of 52.4. The buying preference for any brand of cholate is maximized during the 1st quarters. Mix and match promotion maximizes the preference for purchase of Mars and Mondelez brands while buy 3 get 1 free become the promotion that maximizes the buying preference for Nestle. Preference for weight category is variant for the 3 brands. The relative nationality wise probabilities of selecting a brand of chocolate for fixed levels of promotional preferences and product weight preferences are derived with the multinomial logistic transformation equations. When comparing the nationality wise brand selection probabilities, no significant changes to the probabilities were found according to the nationalities of the customers. It is recommending to carry out similar studies for other sales as well.

Keywords: Chocolate Purchase, International Travelers, Likelihood Ratio Test, Multicollinearity, Multinomial Logistic Regression,

DEDICATION….

…. May this research be dedicated to my ever-loving parents, Wife Indeewari and Daughter Sasmini **…….**

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LIST OF ABBREVIATIONS

Abbreviation	Description
ANN	Artificial Neural Network
ARIMA	Auto – regressive Integrated Moving Average
BPNN	Back – Propagation Neural Network
BIA	Bandaranaike International Airport
CF	Sharing packs – over 175 grams'
MIS	Management Information System
MLR	Multiple Linear Regression
MSE	Mean Square of Error
MSR	Mean Regression Sums of Square
OLS	Ordinary Least Square
POS	Point of Sales
SKU	Stock Keeping Unit
SSR	Regression Sums of Square
SST	Total Sums of Square
USD	United States Dollars
VIF	Variance Inflation Factor

CHAPTER 1

INTRODUCTION

1.1 General Background

Assume you are a shopper stepping to a famous retail shop to buy some confectionaries for your family. Your requirement may be to purchase some chocolate packs to share with your family members, relations and neighbors. You generally buy chocolates from Brand A over other reputed chocolate brand names, because of the high quality, taste and your loyalty to the brand. Out of the Brand "A" products, you prefer some exact product variant and your choice will not be changed because of the attractive promotional activities offered by the other brands or other products in the same brand. Therefore, this particular shopper exactly knows what to be purchased in what quantity and at what price, before he goes to the shop. His or Her purchasing decision will get more complicated if the shopper is interested in offers than the brand or product variant. For a shopper, these purchasing decisions are quite simple and straight forward as stepping to the shop and pick the product from the shelf. If the product is not available at the first shop, you are free to check at a different store or opt to a different variant from the same brand or to buy same product with different brand name.

But for the shop owner, there are many complex and sensitive decisions to be made to make sure the product is available in the shelf. If it is not being the case, it might be a lost sale if the shopper decides to try at a different shop. Therefore, out of stock situation cannot be accommodated at any cost. Inversely, having too much of stocks from the same variant might tie up the budget unnecessarily in a particular product. Hence, not available enough budget to build stocks of other products which another shopper is looking for. In the above explained scenario, it is considered only one product and shopper. When there are hundreds of products and thousands of shoppers with different product preferences and purchasing patterns, how would the complexity be to make the product available at the store.

In supply chain and logistics functions, the main task is to make the right product available at the right time in right quantity. Therefore, a lot of planning is involved in forecasting the demand in advance. With the complexity of the product portfolio and the customer preferences, it is much difficult to estimate the future sales with a simple method of forecasting. If there is a quantitative way to do the forecasting by incorporating the customer preferences, it will reflect the actual requirement for a particular product or product group based on the shopper entering pattern to the shop. If one can accurately forecast the future, then the availability challenge will be succeeded, and the only task will be to place the order with the supplier. Besides that, there are lead times involved for each and every task of the ordering process; requirement identification (forecasting), order processing, production, transportation, clearance and warehousing. Therefore, the challenge gets more tightened since it is required to see the future of the business not for the immediate next month, but for a month yet to come in 3 or 4 months' time. Therefore, planning in advance and accuracy of the planning will give competitive advantage over the competitors with the availability of products to cater the true potentials of the business. If the forecast can identify all the patterns in the sales, it will determine the actual stock levels to be maintained and the correct timing for the availability. If it is not identified accurately, there might be two extreme situations either to out of stock due to under estimation and over stock situation due to the over projection. Both situations will lead to a failure in customer service. It may be arguable whether the overstock situation also leads to a failure in the service level. Over stock to a certain product would not be a threat to the same product, but for other SKUs due to the unavailability of the funds to build the stocks as required. therefore, accuracy of the forecast plays a major role in the success of the business.

For this purpose, it is not sufficient to look at the previous months 'sales only, but also number of customers from different segments and how do they sensitive for the promotional activities and many others factors such as brand loyalty, sensitivity to prices. This understanding helps to make the right goods available in the right quantity at the right time.

Therefore, the two main questions that requires the answers are what the products that are searched by the consumers when the consumer characteristics are known and what will be the quantity requirement in coming months based on the consumer preferences.

1.2 Theoretical Background

The two questions which are raised in the above mentioned scenario can be answered with sales forecasting. There have been number of methods evolved for sales forecasting over the years due to the importance of the forecasting. With the intensified competition among the manufacturers and the specific needs of the consumers, there is no room for any business to have a lesser attention for the product availability. Hence the consistency in the accuracy level of the forecasting is a core requirement for any business segment. The more accurate estimates for the sales forecasts can increase the accuracy of the plans and decisions which are derived based on the forecast. The relative accuracy level of the decisions has a great influence on profitability, customer service levels and productivity of the business (Ouwehand, 2006).

There are number of statistical techniques been developed to predict the sales quantities. Time series analysis, moving average, trend line analysis and decomposition are the popular techniques which consider only the past sales quantities to derive the forecasting numbers based on the statistics and hidden patterns of the data set. Any external factors are not taken in to the consideration in above methods. However, in regression analysis method, it is considered the factors which influence for the sales numbers (Zhou, Huang, & Huang; Jelena & Vesna, 2006). Apart from the quantitative methods, there are qualitative techniques which are adopted to handle forecasting of markets with less or no data available (Jelena & Vesna, 2006).

Hierarchical forecasting is a technique which can be used when there are number of levels in the operations level (Ouwehand, 2006). This method is related to the aggregation and the disaggregation between the hierarchical levels in the business. Further to that, it has been identified the important of focusing the individual household or personal level for sales forecasting due to the intensified marketing and pricing pressure from the different manufactures (Allenby & Lenk, 1994).

For an individual person, selecting a commodity over a set of alternatives is involved making a choice among the discrete set of alternatives (Agresti, 2007). Mcfadden (1974) has derived a model of discrete choice from random utility theory. The theory says that an individual makes a decision in order to maximize the utility by selecting the alternative. The proportion of the utility gained by an individual by selecting a particular alternative over the total utility gained by the total number of alternatives is defined as the probability of selecting the alternative (Miskeen, Alhodairi, & Rahmat, 2013). The same probability can be defined by using logistic regression model due to the categorical feature of the dependent variable while the explanatory variable could be either in categorical or continuous form (Miskeen, Alhodairi, & Rahmat, 2013; Pavlyuk & Gromule, 2010). Usually, the logistic regression models have the capability of deriving the relationship between explanatory variables and the response variable which essentially to be a categorical variable. The logistic regression model has been used in many demographical analyses, studies on sociological issues, medical researches and buying behavior analyses over the years due to the capability of handling the categorical variables (Allenby & Lenk, 1994; Hoffmnan & Duncan, 1988; Lobel & Perakis, 2018; Miskeen, Alhodairi, & Rahmat, 2013; Pavlyuk & Gromule, 2010; Chan, 2005).

1.3 Research Problem

For any business that operates to sell consumer goods to its buyers is important to understand target market of the business and the actual needs of its target market. Proper understanding of the socio - economic background of the potential consumers would help to define the actual requirements and how to approach their requirements by making available the correct product mix along with the desired marketing activities such as promotions.

However, if the customer base is very wide and their socio - economic and cultural requirements are different, then it is important to identify the correct requirement at the right time and the right intensity of the requirement. A Travel Retail Shop can be a classic example for the number of different customers with different socio - economic backgrounds. Besides that, in the travel retail business, there are number of recognized brand names available for sales with more attractive sales and promotional activities. Therefore, purchasing decision of the shopper at a travel retail shop is absolutely complex to determine.

Duty free and Travel Retail is a global industry which involves selling goods to travelers who are travelling between countries or the international travelers (Spinks, 2015). Travelers can enjoy the prices lower than the local market due to the exemption from the payment of certain local taxes and excise duties. Perfumes and cosmetics, wines and spirits, confectionary, tobacco, fine foods and luxury goods are the key product categories that are being sold in duty free shops (Spinks, 2015). While international airports account for the majority of the travel retail, there are duty free and travel retail shops are available at border shops, onboard cruise and ferry vessels in international waters, onboard aircraft during international flights and at some international railway stations. It is reveals that the total sales value in the travel retail was 30 billion of Euro in 2008 (Spinks, 2015).

In travel retail business, it is expected to have complex target customer mix since the travelers all over the world can access to the travel retail shop. Their purchasing behaviors might differ based on their nationality. It is expected different cultural values, beliefs and behavioral patterns based on the nationality, thus the buying behavior would be different (Khaniwale, 2015). Therefore, what exactly a customer would choose to purchase would be a tougher decision that has to be taken by the planners to make the goods available. Therefore, it is suitable to focus on the sales quantities of a travel retail business in order to derive a relationship between the passenger's socio - economic characteristics and the purchasing patterns.

In Sri Lanka, though there were two international airports; Katunayake Bandaranaike International Airport (BIA) is the only one that is in the operating status. There are two core – category travel retail operators operating at BIA at arrival and departure lounges. Both operators are having same four core – product categories; Liquor and Beverage, Confectionary, Perfume and Cosmetics, and Tobacco. Since the business is fully relying on the air line travelers, economic and political stability contributes a lot for the prosperity of the business (Weissenberg, 2017). Apart from that, supply chain management system ensures correct inventory levels and availability of the goods. Innovative Marketing strategies play a major role in the business. Out of the two operators, it will be focused on one of the well – recognized operator and her sales volumes in terms of the quantities.

Confectionary category is the second largest revenue contributor to the business while beverage category gives the highest revenue. It is contributing around 25% ~ 30% of the total monthly revenue of the business. Thus the right product availability will always help to secure the revenue percentage due to the minimum loss sales. There are number of product segments in confectionary category based on the product characteristics such as base of the product, weight, shape etc. All the above mentioned product characteristics are developed by the manufactures to cater the different requirements of the consumers. Hence, the sales movements of the products are expected to be differed. Therefore, the requirement for a forecasting model which considers the travelers buying behavior is inevitable to improve the accuracy.

In the present study, it is tested how the characteristics of the international travelers are influential for the selection of a brand over set of brands in a particular product segment in Chocolate products. Association between the brand choice and the origin of the international passengers and their purchasing preferences (i.e.: purchasing behaviors) is tested. The relative odds and odd ratios are calculated by using the multinomial logistic regression model in order to determine how the brand choice preference is related with the change in the explanatory variables. With the parameter estimates of the multinomial logistic regression model, it is calculated the nationality wise probability of purchasing when the rest of explanatory variables are fixed.

1.4 Objectives

On view of the above the objectives of the study are to:

1. Define the brand selection problem in mathematical terms using multinomial logistic regression.
2. Determine the relationship between the selection of a particular brand of chocolate and passenger characteristics including country of origin (nationality) and purchasing behaviors.
3. Derive multinomial logistic regression model to determine significant factors and how the factors are influential for purchasing decision.
4. Determine how the different levels of the factors change the preference of selecting a brand over reference brand.
5. Calculate the nationality wise chocolate purchase probabilities when the factors are known.

1.5 Limitations

The study was carried out subject to the below mentioned limitations,

1. There are eighteen product segments under confectionary category and according to the eighty twenty theory, only several brands contribute for over 80% of the sales volumes and revenue of a product segment. Further, there are outbound passengers who belong to number of countries. However, out of the all, there are only 16 countries which gives 5 major nationality groups that contribute for more than 80% of the sales. Therefore, only the major brands and major nationalities are considered for the study to narrow down the scope to drill down into the depth.
2. The entire study is carried out based on the 2 secondary data sources, World Duty Free Group Lanka Limited and Department of immigration and Emigration. Based on the availability, data is collected from 2014 January to 2016 December. There is a restriction in the Management Information System in the World Duty Free to archive reports for more than 3 years old. Therefore, the study was confined to the afore - mentioned period.
3. Management Information System (MIS) of World Duty Free does not gather customer's demographic data such as age, gender of the purchasers, occupation related to each sales entry. Therefore, the other passenger related characteristics are not analyzed in terms of brand selection preferences.

1.6 Outline of the Dissertation

The report comprises with six chapters. Starting with the introduction in the Chapter one, the second chapter is dedicated to review the previous literature to analyze how the past studies are aligning to current type of research problems. Literature survey is carried out the areas of qualitative studies on the buying behavior analysis, application of different forecasting techniques, usability of disaggregated sales forecasting due to the complexity of the buying behavior and finally the applicability of multinomial logistic regression model for discrete choices is discussed.

The third chapter of materials and methods, is divided in to two sections of data collection and preparation and the methodology. Under data collection; types of data collected, interpretation of variables and basic statistics of the data are discussed. Under methodology section, it is discussed contingency tables, odds, Chi – Square test for association and theories of Multinomial Logistic Regression. Apart from that brief introduction for multiple linear regression is given. Finally, the steps of the model development are discussed.

In Results and Discussion, impacts of the explanatory variables for the brand choice, steps of Multinomial Logistic Regression model development, interpretation of parameter estimates and brand selection probabilities are discussed.

In the last chapter of the conclusion and recommendations, it is summarized the findings of the study. The suitability of the disaggregate sales forecasting model is discussed with the validation data set results. Further to that, under recommendation, it is discussed the suggestions to further improve study.

CHAPTER 2

LITERATURE REVIEW

Retail sales is influenced by many driving factors; both internal and external. Selecting a product or a brand over a set of alternatives is a human decision and directly related with the behavior pattern of the consumers of the target market (Lautiainen, 2015). It has been found out the positive relationship between the brand name and the buying behavior of the consumer (Shehzad, Ahmad, Iqbal, Nawaz, & Usman, 2014). Supply factors such as availability, plays a secondary role in the sales of a product. Consumers will not switch directly to the product what is available over his or her first preference. That option only comes to effect if the product that he is searching for is not available (Grubor, Milićević, & Djokic, 2016). Therefore, identifying the buying behavior of the consumers and managing the supply of the goods accordingly is the best way to optimize the selling quantities with the minimum cost of inventory holding (i.e.: storage, order processing, opportunity cost, etc.).

Number of researchers have done extensive studies in both qualitative and quantitative contexts on what are the factors influenced for the sales and how such factors can be used in sales forecasting purposes.

2.1 Qualitative Studies on Buying Behaviors

There are both internal and external factors that influences for the buying behaviors of the consumers. Khaniwale (2015) has categorized cultural and social factors as external factors influencing on the buying behaviors while personal and psychological factors as internal stimulus. Cultural factors which deeply influence on individual buying behavior, represents the norms, financial and moral values, convictions, attitudes and habits. Cultural factors have been further sub categorized as buyer's culture, sub - cultures and social classes (Khaniwale, 2015). It includes many aspects of the life such as believes, behaviors, ways of thinking, norms and ethics. In each culture, it contains different sub cultures such as nationalities, geographic regions, religions etc. Marketers can exploit these differences to segment the market into small groups and position their brands according to the market segment (Rani 2014). Under each cultures and sub - cultures, it can be found divisions based on the income level, profession and education level. Generally, people from a same social class of a culture and sub - culture have common interests and behaviors (Khaniwale 2015)

Influences from the outsiders on purchase decision is known as social factors in consumer buying behavior. It encompasses three aspects; membership group, family and group (Rani, 2014). When a person is living in the society, based on his or her connections and environment; the person would belong to social groups knowingly or unknowingly. These types of groups usually related to social relationships such as education, work or place of residence (Rani, 2014). Furthermore, preferences of the family members also play a great role for the purchasing decisions (Khaniwale, 2015).

Internal factors which have influence on buying behaviors, can be grouped as; personal factors and psychological factors. Individuals have different needs based on the age, gender, education level, profession and income level of the self. Under psychological factors, motivation, learning, his or her beliefs and attitudes also can influence for the purchasing behaviors (Khaniwale, 2015).

Based on the above-mentioned factors, it has been developed a consumer buying process with 6 stages namely; problem recognition, information search, evaluation of alternatives, purchase decision, purchase and post - purchase evaluation (Munthiu, 2009). Further to that, four types of consumer buying behaviors have been identified based on the decision-making pattern and information search (Rani, 2014). Routine response, limited decision making, extensive decision making and impulse buying. In routine purchases, very low involvement of searching and decision offer. Consumer goods such as soft drinks, snack foods are coming under this type of purchase. Impulse buying does not involve any planning or decision-making process since this type of purchases are done for very cheap products. It is made with no conscious planning and involves sudden decision making which is very random. In many shop floors, the products which are identified as impulse buyers are displayed near to the counters. While waiting in the queue to do the payments, shoppers tend to buy some very low value products due to the attractiveness of the product. Contrary to this, extensive, complex and high involvement in decision making is involved when buying unfamiliar, expensive and complex products such as vehicles, homes, computers etc. (Rani, 2014).

2.2 Studies on Buying Behaviors Regarding Food

Researchers from different parts of the world have conducted qualitative studies on food purchase behaviors, attitudes and perceptions. International Market Bureau which is attached to the Canadian Agriculture and Agri - Food Department has done a market analysis report about the behavior, attitudes and perception towards food products of the Hispanic - American consumers. The study was carried out by using persons with a culture or origin of Cuban, Mexican, Puerto Rican, South or Central American or other Spanish cultures regardless of race. In the report, it is emphasized the importance of identifying the diversified identities of the different nationalities rather than consider as one group “Hispanic". It is stated the opportunities for creating niche markets to the ethnically and generationally diverse Hispanic market place (The Hispanic-American Consumer Behaviour: Attitudes and Perceptions Toward Food

Products, 2013). It has been identified the important factors which influence on purchasing decision of food such as country of origin, income level, age, life style, family size and presence of children and acculturation level.

Lautiainen (2015) has done a study on the factors that affecting for the consumer buying decision in the selection of a coffee brand. It was revealed that there are relationships between social, personal and psychological factors and the coffee brand selection decision making process. Out of the factors; family, friends and neighbors are the most important. Additionally, consumers do their purchases with their beliefs and attitudes of psychological factors such as motivation, perception, beliefs and attitudes. When it comes to the coffee buying, consumers make impulse decisions other than following all the steps in the decision-making process.

Some of the market research and consultancy institutions have carried out intensive market analysis on Chinese chocolate market in order to find out the potential trends. It has been found out that out of the 32.1% of the Chinese consumers prefer on foreign brands of chocolates (Qian, 2012). The main factor that is considered when buying chocolate is taste (30%) followed by brand (18%) and price (17%). Sweet smelling milk as silk tasting, melting mouth, lasting flavor and smoothness were some of the characteristics that focused when purchasing chocolate brands in china. In a similar kind of study which has been carried out in central Europe, it has been identified recommendation from friends, brand of the chocolate and its price as the most affecting factors for consumption of chocolate. While personal experience, health restrictions and allergies play moderate role as factors affecting to chocolate consumption when flavor, quality and country of origin have least influence among Europeans (Kozelová, Matejková, Fikselová, & Dékányová, 2014).

In Indian context, there are some contradictory findings related to factors affecting on purchase of chocolate. Mittal and Ravinder (2012) have suggested that taste as the most influential factor for chocolate purchasing. Availability and price are the following factors which the consumers are mostly considered. Packing has the least importance. A large portion of consumers moderately consider about the packaging when they make a purchase. However, another study revealed that quality is the most affecting factor for chocolate consumption (Mythili & Sowmiya, 2013). Further to that; price, quantity, taste and brand image are the remaining factors. According to the study, availability and packaging are in 6th and 7th ranks respectively. Mythili and Sowmiya (2013) have further revealed that based on the age category, the buying preference get changes in terms of brand names.

Further, Mittal and Ravinder (2012) have pointed out how the brand loyalty and competitive effect are influential in Indian market. It shows that 65% of the respondents are highly brand loyal in order to buy same brand costly product or check for other shops. Only 30% are willing to go for another brand.

It is answered the question for whom the chocolate is purchased by Mittal and Ravinder (2012). Many of the Indians buy chocolate for children and for self always. Majority is rarely buying chocolate for gifting purposes. With the receiving party of the chocolate, the sub category of the chocolate purchased is differed. For children, toys might be the highly sought after category. But for gifting, it can be either sharing packs or luxurious chocolates if it is for lover.

As many studies been carried out, there are complex buying behaviors for chocolates based on the consumers' nationality and age group. In most of the studies, it has been trying to determine on relationships based on the percentages and not by having statistical procedures such as chi - square testing.

2.3 Applicability of Different Forecasting Techniques

Forecasting of the future sales is a common problem faced by many inventory planners. In terms of sales forecasting, it is much important to plan the availability of the correct product mix in order to cater the actual demand of the individual buyers. Besides that, correct forecasting would help to allocate the required company resources in a manner to achieve the anticipated sales (Jelena & Vesna, 2006). Anticipating the future market trends correctly would help to develop the correct business strategy in order to achieve the target revenues and volumes. Due to the importance of the forecasting, there are number of techniques and theories have been developed for forecasting by various researchers.

In the macro picture of forecasting, sales forecasting can be done by projecting the total market as one entity and by determining what will be the share that the company can acquire out of the total with the available resources which is called as aggregated sales forecasting. On the contrary, forecasting can be started from the individual product level in an individual business (Jelena & Vesna, 2006). Based on the time span and the scope of the forecasting, there are 3 different forecasts namely; short term, medium term and long term. In short term forecasting, the focus time span is three months' future. Short term sales fluctuations are considered when doing the forecast for routine operational matters such as production planning. Sales forecasting up to the individual Stock Keeping Unit (SKU) level which is focused in the current study is come under the short-term forecasting. Medium to long term forecasting are directly linked with the strategic and policy decisions taken by the top management level (Jelena & Vesna, 2006).

It has been identified series of important activities and procedures in the sales forecasting process (Futrell, 1998). The process starts with the identification of forecasting objectives which can be either to forecast the future sales or number of purchasers who purchase a product. Identifying the dependent variable and the independent variables are important to derive a relationship between the sales numbers and the respective driving factors for the sales. It has number of researches been carried out to identify how the different factors are influenced for the forecasting of sales (Kuzhda, 2012). Once the dependent variables are determined, forecasting procedure need to be developed. It is either quantitative forecasting technique or qualitative forecasting technique. According to the forecasting procedure which is going to be used and the independent variables determined, the relevant data should be collected. Minimum past data requirement for the sales forecasting is an area where there is no conclusion arrived. There are 2 opinions among the researchers regarding the amount of data or the time span of the past data. Though the common claim is to have as much as possible data, there are some contradictory views on the above claim as well (Hyndman & Kostenko, 2007). Due to the changes happened in the past sales trend, it is arguable whether the sales data which two or three years back are relevant for the forecasting. However, Hyndman and Kostenko (2007) are suggesting that the amount of data required is depend on the model which is used for the forecasting and the amount of random variation in the data set. With the available data set, calculation is done based on the assumptions made in the previous stages of the process. Once the results are arrived, it must be evaluated and validated the model by calculating the variances between the actual sales and forecasted sales. If only the model is passed from the validation stage, it can be used for the forecasting.

There are number of studies have been carried out to check the suitability of different forecasting techniques in the sales forecasting. Kuzhda (2012) has done a study on application of Multiple Regression Model on retail sales forecasting. With the changing environment, consumer's income and advertising cost has been changing which influence for the retail sales quantities. Zhou, Huang, & Huang have studied how the external factors are influenced in the stores sales. Promotional activities, competition, holidays, seasonality and the locality have been shortlisted as the explanatory variables for the retail sales. Random forest and gradient boosting methods have been used to see whether there are improvements compared to the benchmark model of linear regression. Random Forest method constructs a multitude of design trees. The actual sales are classified into the nodes of the design tree and mean value is calculated for each node which is used for prediction. Gradient boosting trees also generate the trees as an optimization algorithm. The results showed that gradient boosting has the highest ability to forecasting when compared to Linear and logistics regression.

Lee, Chen, Chen, Chen, and Liu (2012) have studied the suitable forecasting technique to predict the fresh food sales at a convenient store among the three techniques; logistic regression, moving average and Back - Propagation Neural Network (BPNN) methods. Apart from that Dreiseitl and Ohno-Machado (2002), Eguchi, Itoh, and Konishi

(2007), Horimoto, Lee, and Nakai (1997), Paruelo and Tomasel (1998) and Sargent (2001) have used the logistic regression, Moving Average and BPNN methods in many research areas related to forecasting due to the high fault tolerance capability and high-speed computability. It has been concluded in previous researches that BPNN has the better suitability among others. It is an Artificial Neural Network (ANN) based technique. ANN is developed by simulating the functions and natural formation of a biological neural network and used as an approximate function to find the output for given inputs. BPNN attempts to minimize the mean - square output error throughout the entire training data set (Lee, Chen, Chen, Chen, & Liu, 2012). Due to the high classification accuracy, BPNN has been identified as a good method for long term data though the method has problems with slow training speed and the likelihood of entering into a local minimum during the process. Besides that, the Logistic regression technique has relatively less complexity when there are less or no interaction terms or variable transformations are used (Dreiseitl & Ohno-Machado, 2002).

Alon, Qi, and Sadowski (2001) have studied how efficiently the forecasting can be done for the US aggregate retail sales which have strong trends and seasonal patterns. It has been used Artificial Neural Network (ANN) techniques with the traditional techniques such as Winter's Exponential Smoothing, ARIMA and Multivariate Regression. These traditional methods are very much capable of handling the trends and seasonal fluctuations (Alon, Qi, & Sadowski, 2001). ANN has been used for identifying and modeling data patterns that cannot be easily recognized by the traditional statistical methods. The results showed that the ANN has more capacity to handle data with strong trends and seasonal patterns followed by Box - Jenkins model. Further, the results showed more viability in multiple - step forecasting under stable economic conditions when using Winter's exponential smoothing technique.

Therefore, it cannot be concluded with exact method which can give the highest accuracy level when forecasting. Therefore, it is highly important to identify the forecasting objectives, explanatory and response variables and structure of the collected data in order to select the best way to do the forecasting.

2.4 Aggregate versus Disaggregate Sales Forecasting

Contrary to the aggregate sales forecasting, disaggregate sales forecasting is focusing on the individual product level and aggregate the numbers to get the final aggregate sales forecast. Rather than focusing on the macro level influential factors, factors which are influential for the sales of individual SKUs or individual consumers are important for the disaggregate sales forecasting. For an individual person who is attending to a store to purchase a particular product, the final decision is a choice has to be made among the several options. Therefore, it is important to identify the factors which are influential for a tentative consumer to make a choice to purchase a particular product among the several alternatives. There are number of studies been carried out on the consumer buying behavior analysis and how it affects to the actual sales of a product.

With the number of levels in the operations, the hierarchical forecasting is supposed to do sales predictions for items at different levels. Forecast of the lower level of the hierarchy are considered as members of the immediate higher level in the hierarchy. The level of hierarchy can relate to the dimensions such as type of products, time or locations (Ouwehand, 2006). As an example, national level forecasting is done by aggregating the area wise sales to derive the region wise sales and region wise sales are aggregated to calculate the national sales. This type of aggregation can be done either across the time; called temporal aggregation or across the series which is called as contemporaneous aggregation (Wei, 1978; Ouwehand, 2006). Under hierarchical forecasting techniques, aggregation and disaggregation are done in 2 methods namely; Bottom - up approach and Top - Down approach. In the bottom - up approach, the bottom layer forecasts are aggregated in order to improve the forecasts at aggregate levels. Top - down approach aims at improving the forecasts at the disaggregate ground levels by starting with aggregate level and then disaggregating the forecasts to SKU level. The disaggregation can be done with the historical proportions of aggregate demand or it can be forecasted the proportions (Gross & Sohl, 1990).

Furthermore, the focus of the bottom up approach is further narrowed down to the individual household or personal level who is actually doing the purchase (Allenby & Lenk, 1994). With the maturity of the market and the fixed market size, the manufactures and the sellers have minimum influential power over the buyers to make the profitability high. Hence the focus is shifted to pricing and marketing activities to increase the profit (Allenby & Lenk, 1994). To plan and evaluate the pricing and marketing activities effectively, identifying the buying behavior of the individual household is important. The way that the pricing and marketing activities are perceived by different households is different based on their demographic characteristics (Allenby & Lenk, 1994). With the escalated focus on the individual level buying decisions, the aggregation is to be started with the individual level.

When it comes to the behavioral decisions on purchasing of a product; the purchase decision to select a product can be defined as a subject to be chosen among a discrete set of options. Multi - category Logit model can be used to model how a person choices one product / subject over set of alternatives. Explanatory variables would be the factors that differentiate the purchasing pattern of the person while the response becomes the choice of the purchasers among all the possible products or options. The generalized model between the purchase choice and the number of factors is called as "Discrete Choice Model" (Agresti, 2007). Logit models are used to calculate the probabilities of selecting a choice among several other choices. If the choice is done from the two options, binary logistic model is used. If there are more than two options to pick one option, multinomial logistic model can be applied. Most of the behavioral analyses can be defined as discrete choices, hence the multinomial logistic regression can be applied in modeling. Transport demand modeling has been one of the key area which the Discrete Choice Model is used (Agresti, 2007).

2.5 Discrete Choice Model

Most of the actions or decisions we make in the life involve making choices over set of alternatives. Different behavioral patterns of the Individuals would impact for the decisions made. Decision maker is not necessarily to be individual person, but can be households, firms or any other decision-making units which the decisions be within its scope (Train 2002). Choices can be either for products over several alternatives or course of action which is followed among several options. This type of problems is described under discrete choice model. Traditional economic theories for consumer choices focused on utility maximization. Consumers are tending to choose the commodity over several other options which can maximize the utility of the consumer (Greene 2008).

Ben - Akiva and Lerman (1985) have proposed below mentioned sequential decision-making process for choices rather than a single choice at a specific time.

1. Definition of Choice problem - Identify the problem which the tentative solution is to make a choice
2. Generation of the alternatives - all the possible alternatives which can be chosen to be recognized
3. Evaluation of the attributes of the alternatives - evaluate the all alternatives in terms of the attributes of the alternatives
4. Choice – select one alternative based on the attributes of the alternatives
5. Implementation

In order to define the above process, it has to be identified 4 major elements; decision maker, alternatives, attributes of the alternatives and decision rule. As per the above framework, choice is dependent on the attributes of the alternatives rather than the alternatives themselves (Ben - Akiva & Lerman, 1985). Once the attributes of the alternatives are evaluated, decision maker makes the choice for the best alternative with some internal calculations based on the available information which can be identified as decision rule. Slovic, Fischhoff and Lichtenstein (1977) have classified the decision rules under 4 categories,

1. Dominance – it is considered that one alternative is better than other alternatives due to at least one attribute is better in one alternative over the same attribute in competing alternatives. In many cases, dominance does not lead to a unique choice, but to eliminate the worst alternatives from the choice set.
2. Level of Satisfaction - based on the personal beliefs and intuition of the decision maker, he or she sets the level of satisfaction for each and every attribute of the alternatives
3. Lexicographical rules - refers to the ordering of attributes by the importance. This importance is based on the judgment of the decision maker. According to the rule, the decision maker will choose the choices that has only the attributes he or she values.
4. Utility - refers to as attractiveness to the attribute of an alternative. This decision rule is mostly used in recent models.

With the above-mentioned frame work, there has been number of theories developed to calculate how likely a choice is selected. Discrete and probabilistic choice theories calculate the probability of a decision maker chooses a certain alternative subjected to maximize the utility function of the decision maker.

In the discrete choice modeling, it is assumed the rational behavior of the individuals, where the individuals are acting stratrgically to maximize the individual interests or utilities (Krstic and Krstic, 2015). Since the different individuals are having different values and beliefs, individual behaviors are not expected to be unique for every person for similar type of choice decsions. However, accrding to the rational behavior theory, it is assumed that the individuals' actions on same type of incident will follow same decision process and will be ended up with same choice irrespective to the psychological state of the individual at the time of decision making. The quality of the choice to be chose is determined by the amount of information that the decision maker poses. There are number of theories have been developed in discrete choice modelling in order to understand how the choices are made.

In Probsbilisitc choice theory, it is insisted that the probabilistic nature of the human behaviors, hence the human behavior cannot be understood with deterministic parameters. In the utility theory, it is stated that the decision maker will choose some alternative in order to match with his own beliefs and desires, which fulfills the utility of the decision maker (Anand, 1995). Multinomial choice models are used when there are more than two alternatives are available. It is assumed that the choice set of every decision maker is different from each other, as each individual has their own index of attributes and a different subset of the global set. McFadden (1974) has derived an equation to estimate the probability of selecting the brand j assuming an additive independent and identically distributed extreme value error for log marginal utility. Equation 2.1 shows the general view of the discrete choice model.

$$p_{i,t}(j) = \exp[y_{i,t}(j)] \Big/ \{\sum_{k=1}^{m} \exp[y_{i,t}(k)]\} \quad 2.1$$

Equation 2-1: Discrete choice model

Where,

j = indexes of the different brands ($j = 1,2, \dots, m$)

t = indexes of the order of the purchase occasions ($t = 1,2, \dots\dots T_i$)

T_i = total number of purchase occasions

i = indexes of the decison makers ($j = 1,2, \dots, h$)

$y_{i,t}(j)$ = function of a brand specific intercept and log of the other influential factors for the brand choice

$p_{i,t}(j)$ = probability of selecting brand j by the i^{th} individual decision maker at the purchasing occasion of i

This same format of equation is used in the multinomial logistic regression models in order to estimate the probability of a categorical dependent variable with related to the number of explanatory variables (Agresti, 2007). Therefore, the applicability of the multinomial logistic regression for the discrete choice model problem has been a widely discussed area in the previous researches on modeling the individual choices.
Small (2015) has done a study on travel demand by using the economic demand modeling which is developed based on the discrete choice model. The study focuses on the features that an individual is mostly values when the travel mode is chose. Travelers utility levels with respect to each mode of travel is calculated in terms of their features of speed, frequency, reliability, comfort and desired schedules. Aggregate model defines the total number of travels in a mode is related to the amount of industrial or residential developments, average transit time cost of transit, service quantity which can be identified in macro level. In order to calculate how likely to choose a particular choice among the set of alternatives is calculated by using the logistic regression model. Modal share of transit according to the models is lying between zero and one. The alternative method of disaggregate model or behavioral model is focused into the individual level of selecting a mode among the others when the individual explanatory variables are known. Results from the aggregate model and disaggregate model were compared. The results show that the disaggregate model is more suitable in predicting the travel mode choice. Ben-Akiva, Bottom, Gao, Koutsopoulos, and Wen (2007) have emphasized that a travel forecasting model

should be dynamic and disaggregate. In the convnetional travel demand models are not considering the individual level travel demand and considers the total amount of travel by users. Since the heterogenioty of the travellers are not considered in the conventional methods, it is expected to have biased results. Therefore, in the modern studies, individual level travel data is gathered with better set of explanatory variables. With the discrete choice modelling, the focus is given to the indivual level decision making process with unique set set of explanatory variables.

Hoffmnan and Duncan (1988) have studied how suitable to use logistic regression models in demographic analyses. Suitability of binomial logistic and probit models for binary choice problems and multinomial logit techniques for the choice among three or more categories have been tested. Multinomial probit models are not frequently used due to the complexity in calculations. Probit models or conditional logit models are more appropriate when the choice among the alternatives is modeled as a function of the characteristic of the alternatives rather than the characteristics of the individuals who make the choice (Hoffmnan & Duncan, 1988). The key difference between the conditional logit and multinomial logit is the unit of analysis. While individual become the unit of analysis in the Multinomial logistic model, set of alternatives become the unit of analysis for the conditional logit model. In conditional logistics model, individual level characteristics of the alternatives such as personal attributes can be accommodated.

Customer adoption process or switching from one option to another option can be determined as a process of making a choice to shift or not. Lobel and Perakis (2018) have used logit demand models to understand the customer adoption process to a certain technology of a solar panel. The possible choices that a customer is facing at each time step is defined as whether to purchase a solar panel or not. Demand to choose a solar panel during a time period is calculated with the number of potential customers and the probability of making the decision to purchase a solar panel. The probability of purchasing by a customer is called as adoption or diffusion rate. Logit demand model assumes that a customer is motivated with maximizing of utility with any choices he or she made.

2.6 Applicability of Multinomial Logistic Regression Model

Multinomial logistic regression model has been used in many areas with related to the behavioral analyses which is involved in making choices among several other alternatives which can be identified as categorical dependent variables (Pathak & Shi, 2014; Miskeen, Alhodairi, & Rahmat, 2013; Allenby & Lenk, 1994). For dependent variables with only two levels of categories, it is used binomial logistic regression while multinomial logistic regression is used for problems with categorical variables with more than 2 levels (Agresti, 2007). In discrete choice model problems, multinomial logit models are used to calculate the probability of an option to be chose based on the relative level of utility which is gained from the choice.

Peng & Nichols (2003) have developed a multinomial logistic model to predict the behavioral risks of adolescent. It has been defined three levels of self - injurious behaviors as low, medium and high. Four explanatory variables identified as gender, intention to drop out of school, family structure, self-esteem and emotional risk. Self - esteem and emotional risks are collected as continuous variables while the other 3 are nominal data. Goodness of fit and $\mathrm{pseudo}R^2$ tests have been used to check whether the model is adequately fit for the data set.

Similar type of study was carried out by Mohamad, Ali, Noor, & Baharum (2016) to determine the relationship between the demographic profiles and the workplace environment with the stress levels of the teachers. The multinomial response variable of stress level has been defined in three levels. Out of the 12 explanatory variables, it was found out 4 significant predictor variables by using 5 selection methods; forced entry, forward entry, backward elimination, foreword stepwise and backward stepwise. Goodness of fit test is carried out with Pearson - chi - squared test and deviance test to check whether the data set is adequately set for the data set. Likelihood ratio test is used to check whether the final model with 5 predictors variables are better at predicting the stress level than the null model. Diagnostic examinations were carried out with the standard error values of the predictor variables. Multi - collinearity among the predictor variables is ruled out with standard error values of predictor variables between zero to two (Mohamad, Ali, Noor, & Baharum, 2016).

Pathak and Shi (2014) have used multinomial logit model to derive a model for school selection and ranking problem in Boston. School ranking has been determined as a decision taken against the utility of each school programme provides. Both main effects and 2 way intractions of the explanatory variables are used in model development process using Maximum Likelihood method. Relative probability of selecting a particular school among other alternatives are calculated by the probabilities calculated in Logit Model. Relative odd ratios are calculated to find the relationship between school selection and the relavant influential factors. The key adverse implication that is indetified by the researchers is to independence of irrelavant alternatives which comes into effect when there are more than 2 options prevail and it assumes that substitution between choices follow the same proportional pattern.

Miskeen, Alhodairi, and Rahmat (2013) have used multinomial logit models to determine the mode of transport is chosen by the intercity travellers in Libya. Rather than focusiing on aggregate level demand, it is drilled down to the individual travellers level and find out how the travel mode choice varies with the demographical factors such as gender, nationality, age and purpose of travel etc. There are both continuous and categorical veriables among the explanatory variables. The mode choice decision is determined by the utility level that an individual gains by using a particular travel mode. Probability of choosing i^{th} mode has been defined as equal to the proportion of the utility which is gained over the utility gained by all modes. Relative utility function has been derived as a linear function of the explanatory variables. The mode choice is done among the intercity bus, Air plane and moter car; hence the problem becomes a multinomial logit problem to caclulate the relative probability of choosing a transport mode by a particular individual. The choosing probability is calculated with coefficients associated with explanatory variables and by substituting the value of relative explanatory varaibles. Since the results are given with related to selecting a motor car as the base case,relative coefficients shows the odd ratios which can be used to determine the relationship between the covariate and the response varialbe over the base category.

Pavlyuk & Gromule (2010) have done a same kind of study considering the mode of transport which is choosed to travel between particular 2 nodes in Latviya. Nested discrete choice model has been used to determine the mode of transport to be selecetd among car, coach and rail with the number of explanatory factors which are influenced for the decision. Contary to Miskeen, Alhodairi, and Rahmat (2013), Pavlyuk & Gromule (2010) have considered three types of factors influence for the mode choice decsion; travel specific factors (Departure time), passenger specific factors (age, income) and behavioral factors (time of arrival) whereas Miskeen, Alhodairi, & Rahmat (2013) have only considered the passenger specific factors. The researchers have faced the problems of selecting a suitable model between probit or logit model. The model for calculating the probabilitiy of selecting one mode is defined as a function of explanantory variables and vector of unknown coefficients. The function is defined as either standardized normal cumulative distribution fucntion (probit model) or cumulative logistics distribution fucntion (logit model). In the study, it is no systematic differences in the reults are found, hence logit model has been used.

Among the number of studies carried out in applicability of Discrete Choice Model for transport mode choice, Allenby and Lenk (1994) have studied on how the discrete choice model and logistic normal regression are used in modeling household purchase behaviors. The relative importance of focusing the marketing factors such as pricing, advertising and promotional activities and demographical factors such family size, income level and age have been increased in comodity market due to the maturity status of the market. In the fixed market size, manufacturers and marketers have to focus on new ways to increase the customer share with more customised pricing, advertising and promotional strategies to meet the exact requirements of the customers.

Allenby and Lenk (1994) have focused on how the pricing and advertising are influential for the purchase behaviors of the households based on their income level and family size. The behavioral patterns are specific to individual households, therefore the aggreagte store level data would not be useful for the modeling of brand choice decisions. Hence it is required to capturte the each and every brand choice decisions made by the households who do the purchases from the target store in order to identify the sensitivity to the changes in marketing factors. Scanner panel data includes all the related data for individual buying action. Further to the markering and demographic factors, the study is extended to check the impact from the past purchases and the previous brand choices for the brand choice in the current run. This effect is incorporated with an autoregressive error structure for the brand choice prababilities. Brand choice probabilites are calculated with a model derived incorporating the utility theory in the discrete choice model where the logistic regression is used.

The model was derived with several assumptions to the purchasing behaviors (Allenby & Lenk, 1994). It is assumed that the consumption of a brand in a product class is weakly separable from the consumption of the other goods. It allows to split the utility maximization problem in to 2 stage sub problems. Under the 1st stage, all the available expenditures are allocated among the product class which has several choices and all the other goods. In the second stage, a brand choice will be made among the alternatives in the product class. Apart from that, it is assumed that all the brands in the product class are perfect substitutions and would ensure the utility maximizing by choosing any brand.

CHAPTER 3

MATERIALS AND METHODS

This chapter elaborates a mathematical approach to the individual buying behavior of the chocolate products in the duty-free store and what are the steps have been used in the model development. Data collection and descriptive introduction to the categorical variables are included in the first half of the chapter along with the descriptive introduction on the data using marginal percentages. Theories behind the odds and odd ratios are discussed. The theoretical background of the multinomial logistic regression models is discussed along with derivation of logistic regression model, variable selection methods, model development steps, likelihood ratio test for significance of the model with the model acceptance criteria and model adequacy tests. Further, the steps of the study are descriptively elaborated.

3.1 Data Collection

The research is purely based on the secondary data sources which the data is already gathered from the real time computer systems. Therefore, the required data can be archived by running the quarries in the computer systems. Below are the types of the data which was gathered for the study.

1. Confectionary Sales Data from 2014 January to 2016 at the departure shop lounge – This is the core data set which is required to determine the relationships between passenger nationality and the brand choice decision. Individual sales entry at the departure shop is updated in real time by synchronizing both MIS and Point of Sales (POS) machines at the shop floor. Every sales entry is having a passport number where the system captures the nationality of the customer. However, other demographic information such as gender and age of the purchaser are not captured.
2. Product master sheet - This contains the confectionary sub category details with the sub category definitions, weight of the products, supplier details (brand), cost of the Goods etc. Based on the information, confectionary products will be categorized into product segments and weight categories according to their brands and product weights.
3. Actual Sales volumes – Brand wise sales quantities from January 2014 to December 2016 are collected to identify the product segments which are highly contributing for the sales volumes and values.
4. SKU wise promotional data – The MIS facilitates to archive data related to SKU wise promotional activities taken place on monthly basis.

5. Outbound Airline Passenger Data from 2010 January to 2016 December - Number of passengers who are passing the departure terminal of the Bandaranaike International Airport (BIA) is gathered. The data was collected from the Immigration and Emigration Department of Sri Lanka. Since the study is focusing on the purchasing pattern of the departure passengers, two types of the passengers need to be considered; Departure passengers and Transit passengers.

    Departure passengers – Number of passengers who are departing the country. This category includes 2 segments; Sri Lankans and non – Sri Lankans. A qualitative rational decision was taken to omit the Sri Lankan passengers from the study due to the less chance of buying chocolates when they leave the country. Hence the study is focused on the non – Sri Lankan passenger segment who are departing the country using the departure terminal.

    Transit Passengers – The passengers who are using Colombo International Airport to transit from one flight to another flight.

3.1.1 Data Filtering and Preparation

Once the above data was collected, initial data preparation was done in order to filter the data related to confectionary sales only. This was done by using VBA - Macros due to repetitiveness of actions in number of worksheets. Linking the data across the number of worksheets is done by using excel functions.

3.2 Identify the Key Product Segments in Chocolate

There are about 200 active Chocolate SKUs in the travel retail business which the study is focused on. The current list of the SKUs is further divided in to sub categories called segments based on the physical characteristics of the products such as weight, whether the product is cocoa based or sugar based, shape of the product and utility of the product. Currently the product portfolio is sub divided in to 18 segments based on the above one or more characteristics.

Utility refers to the purpose that a product is using. Familiar segment is focusing to the sharing utility of the buyer while toys are specially produced for children. Apart from that, weight category of a product plays an important role in identifying whether the product is designed for individual usage or sharing purposes. Chocolates with higher volumes or weights are used for sharing among number of people while chocolates with less volume is specialized for personalized sharing or even for personal consumption.

Table 3.1 shows that the Sharing Packs chocolates more than 175G is the highest contributor for the sales in terms of volume and value accounted for 42% and 50% respectively. Slab chocolates with more than 175G volume is the follower with 23% of the volume 20% of the value. Therefore, the study will be focused on the Familiar category over 175G which is easy to identified as sharing packs.

Table 3-1 Product segment wise volume and value - 2014 Jan to 2016 Dec

		Sold Volume		**Sold Value**	
Segment Code	**Description**	**Total (Units)**	**% from Total Volume**	**Total (USD)**	**% from Total Value**
CB	CHOCOLATE-CHOCOLATES OVER 175	107185	8%	1044902.82	10%
CF	CHOCOLATE-FAMILIAR OVER 175 GR	578188	42%	5143283.14	50%
CK	CHOCOLATE-TOY BELOW 175 GR	48761	4%	426849.19	4%
CQ	CHOCOLATE-TABLET BELOW 175 GR	87222	6%	361624.15	4%
CT	CHOCOLATE-TABLET OVER 175 GR	313554	23%	2087437.38	20%
GC	SWEETS-GUM PACK	60308	4%	136200.84	1%
	OTHERS	189133	14%	1001276.54	10%
	Total	**1384351**		**10,201,574.06**	

3.3 Brand Choice ($\mathbf{Y_i}$)

Brand choice decision is the response variable which is expected to be related with the factors listed as; passenger nationality, period of time the purchase occurs, consumer's preference for promotional activities and consumer's requirement for sharing. Therefore, the choice decision can be defined as a function of the above mentioned explanatory variables (factors),

$$\text{choice of a chocolate brand} = f(\text{passenger nationality, time of purchase,}$$

$$\text{preference for promotional activities, preference for sharing})$$

Since it is studied the relationship between the brand choice with number of factors influenced, the problem can be noted as equivalent to a multiple regression model. However, the below mentioned differences with compared to the multiple regression model can be identified,

1. Categorical variable as the response variable – In the multiple regression modelling, the response variable should be continuous variables while for multinomial logistic regression model, the response variable should be in categorical form.

2. Either continuous or categorical explanatory variables – In multiple regression modelling, explanatory variables should be in continuous form. However, in a logistic regression model, the explanatory variable can be either in continuous or categorical form. If the explanatory variable is a continuous variable, it is called as a covariate while if it is in categorical form, it is called as factors.

As discussed earlier, in the current study, the research problem would be defined as a logistic regression model due to the categorical form of the response variable.

There are 9 brand names under the above mentioned sharing packs over 175G category. As per the past sales volumes from 2014 January to 2016 December, three different brand names contribute for around 80% of the sales namely, Mars International Travel Retails, Mondelez Travel Retail and Nestle Travel Retails. Therefore, the categorical response variable for Brand choice would be comprised with 4 categorical levels with alternative other brands category which account for 20.26% from the total volume (Table 3.2). Hence the research problem would be defined as a multinomial logistic regression model.

Table 3-2 Brand wise volume contribution for Sharing Packs - Jan 2014 to Dec 2016

Brand Name	**Total Sales Volume (in units)**	**% from total sales volume**	**Categorical Level**
Mars ITR	257394	43.54%	1
Mondelez ITR	123115	20.83%	2
Nestle ITR	90844	15.37%	3
Other Brands	119768	20.26%	4
Total Volume	591121	100.00%	

3.4 Factors influential for Chocolate purchasing Decisions

The key factor which is focused in the study is the Nationality or country of origin of the chocolate buyer and how the characteristics of the buyers are influential for the buying decision. The factors are thoroughly discussed under below sections.

3.4.1 Nationality of the Passengers ($\mathbf{X_1}$)

Nationality of a person is cultural identity for each and every person. Therefore, based on the nationality of the person, his or her cultural values such as beliefs, attitudes would be different. Previous studies on the consumer buying behaviors would permit to consider the nationality as an influential factor for purchasing behaviors. In the current study, it is focused on how the nationality of the international passengers would be influential for the choice of a brand of the chocolate.

There are passengers from 16 countries which contribute to more than 2% of the total departure passenger numbers (including transit) when it considered the total departures from January 2010 to December 2016. Further, those 16 nationalities contribute for the 77% of the total passenger departures during the stipulated period.

Table 3-3 Nationality wise total Departures - Jan 2010 to Dec 2016

Nationality	Total Pax. Outflow – (2010 to 2013)	Rank - from 2010 to 2013	Total Pax. Outflow – (2014 to 2016)	Rank - from 2014 to 2016	Total Pax. Outflow – (2010 to 2016)	Overall Rank (2010 to 2016)	Pax. Outflow % (2010 to 2016)
Indian	1156952	1	275257	2	1432210	1	19%
British	558518	2	244456	3	802976	2	10%
Chinese	175964	7	360397	1	536368	3	7%
Deutsch	312782	3	185754	4	498539	4	6%
Maldivian	250584	4	120245	6	370833	5	5%
French	228092	5	137004	5	365101	6	5%
Australian	207611	6	104154	8	311771	7	4%
Russian	135897	9	108006	7	243912	8	3%
American	144357	8	74237	9	218602	9	3%
Canadian	134391	10	59991	11	194392	10	3%
Japanese	117144	12	62834	10	179990	11	2%
Pakistani	132844	11	24380	21	157235	12	2%
Indonesian	96306	15	52403	12	148724	13	2%
Ukrainian	97827	14	45314	14	143155	14	2%
Malaysian	105947	13	36323	17	142283	15	2%
Dutch	82045	16	49533	13	131594	16	2%
Other	1184134		623978		1808112		24%
Total	5121395		2564266		7685797		

As per the above table 3.3, passengers from individual 16 countries contribute 77% of the total passenger out flow from 2010 January to 2016 December. The data has been presented under two separate periods intentionally to capture the differences within the study time period and the before the study period. Indians are the highest contributor for the departures from 2010 to 2016 with 19% contribution. British and Chinese are the followers with 10% and 7% contributions respectively. However, changes can be witnessed in the tourist departure profile in the two separate periods. From 2010 January to 2013 December, Indians were the highest departing passenger group while British were the follower. However, the Chinese were in the 7th position from 2010 to 2013. Interestingly, the number of Chinese was increased to the 1st position in 2014 to 2016 period while Indians and British becoming respective followers. Due to the economic and political relationships with the China, this trend would continue in the coming years as well. On the other hand, changes in the travelling behaviors and increased buying capacity of the Chinese citizens, it is inevitable to the Chinese travelers to become the most attractive passenger group for Sri Lankan travel retail industry. Out of the 16 nationalities, only 7 are from the Asian region while the others are from outside Asia. In the study, it will be analyzed the buying behavior in terms of the brand choice for the above motioned traveler groups from the 16 nationalities.

Grouping of Passenger Nationalities

If it is not used any grouping for the nationalities, it has to be used 16 levels in the multinomial logistics regression model, which gives great difficulties in the handling of the data and interpretation of the data. On the other hand, there are chances of not delivering significant answers and analyzer might face difficulties in results interpretation, which would futile the entire effort. Therefore, it was used a rational method to merge the passenger nationalities in to a reduced number of levels.

The respective countries of the nationalities are located in different continents itself, namely North America, Europe, Asia and Australia. Qualitative cultural similarities were considered in categorizing the nationalities.

1. Category 1 – North America

Both United States and Canada are located in the same geographical region of North American Continent. On the other hand, both nationalities are having the same cultural influences gained from the British and Spanish masters while there are different American cultural identities as well. Therefore, passengers from United States of America and Canada are grouped under North America.

2. Category 2 – Europe and Australia

There are seven European countries in the top passenger list which can be categorized under single group of nationality. Except for the two Soviet countries, all the other countries are having European main cultural influences developed with the Christianity. Hence it is reasonable to group the countries into one cluster. Additionally, due to the identical political groups and environmental groups, both Russia and Ukraine also categorized under Europe. Though the Australia is located in completely different geographical location, it is a country where the so – called civilization was done by the British invaders. Therefore, the leading culture in Australia is very much close to the Britain. Hence Australians also grouped under Europe.

3. Category 3 – East and South East Asia

China, Japan, Malaysia and Indonesia are located in the east and south east part of Asia. Though in Malaysia and Indonesia, there are leading Muslim cultures due to the

Islamic invades. All of these countries are having the Chinese cultural background. Therefore, the 4 countries were grouped as East and South East Asia.

4. Category 4 – South Asia

There are three south Asian countries which shows the top ranking international traveler outflow form the island, India, Pakistan and Maldives. The three countries were clustered as South Asia due to the relative geographical location in the world and cultural ties with each other from the past.

5. Category 5 - Other

All the other countries which are not included in the above list were considered under other category.

Therefore, the 16 nationalities were grouped in to 4 groups and the rest of the countries were clustered as one total group (Table 3.4). Hence the nationality of the air travel passengers would be determined as a categorical factor in the multinomial logistic regression model with 5 levels

Table 3-4 Levels of the nationality group

Nationality Group	Individual Nationalities	Categorical Level
North America	American, Canadian	1
Europe + Australia	British, French, German, Netherlands, Russian, Ukrainian, Australian	2
East and South East Asia	Chinese, Japanese, Malaysian, Indonesian	3
South Asia	Indian, Pakistani, Maldivian	4
Other	All the other nationalities	5

Nationality Wise Tourist Outflow and Purchase Quantities

Table 3.5 shows the summary of the customers' nationality wise purchasing quantities and the total number of passengers who depart the country from January 2014 to December 2016. Respective percentages from the total passenger outflow and total purchasing quantities are shown. As per the Table 3.5, passengers from North American region contribute for the lowest quantity purchases and the passenger outflows. From the total passenger outflow of the period, passengers from the other country category account for the highest percentage of 48% while they are contributing only 30% of the sales volumes. Considering the total quantity purchases, South Asians contribute for the highest portion of 41% from the total while they are accountable only for 17% of the total passenger outflows.

Table 3-5 : Region wise Departures and Chocolate Purchase volumes - Jan 2014 to Dec 2016

Country of Origin	Total Departure passengers	% from Total Departure Passengers	Total Purchases (units)	% from Total Purchases
North America	134,228	3%	15,327	1%
Europe + Australia	874,221	20%	107,913	10%
East and South East Asia	511,957	12%	181,758	18%
South Asia	761,468	17%	419,882	41%
Other	2,141,239	48%	305,913	30%
Total	4,423,113		1,030,793	

In order to test whether there are statistically significant relationships between the nationality wise purchase quantities and nationality wise passenger outflow numbers, correlation coefficients between volumes and passenger outflows were calculated. As per the results shown in the Table 3.6, it can be observed strong correlation between sales quantities and passenger outflows of South Asians with the value of 0.756. for all the other nationality groups, it is shown moderate relationship since the correlation coefficient lie between 0.500 to 0.700.

Table 3-6 : Nationality wise Correlation between purchasing quantities and passenger outflow

Nationality	Correlation Coefficient	P – value	Significant	Conclusion
North America	0.603	0.00	Significant	Moderate Correlation
Europe + Australia	0.675	0.00	Significant	Moderate Correlation
East and South East Asia	0.542	0.00	Significant	Moderate Correlation
South Asia	0.756	0.00	Significant	Strong Correlation
Other	0.54	0.00	Significant	Moderate Correlation

3.4.2 Time of Purchase (X_2)

Previous studies on the behavioral patterns related to chocolate consumption do not give evidences on how the relative period of the year for consumption is linked with the selection of a particular brand. However, with the different cultural influences of the passengers, they tend to do purchases during certain time periods of the year with influential travel patterns. As an example, Muslims in all over the world are obeying to the Ramadan Fasting and during the early part of the Ramadan season, they do not travel a lot and they do not purchase sweets as well. However, once the fasting is over, they tend to start travelling and consume sweets to personal consumption and as a gift. Further, in Christian countries, passengers tend to give away gifts during the December Christmas seasons.

Apart from that, tourists travel pattern to Sri Lanka shows seasonality (Relations, Annual Statistical Report - 2016, 2016). This seasonality has a direct relationship with the island's weather conditions and the leisure activities (i.e.: cultural activities). Based on the above factors, there are seasons where the travelers are arriving to the country.

Since the travel retail business is solely dependent on the tourist flow of the country, it can be identified the positive correlation between the total of sold volumes in the departure lounge shop in terms of individual units and the total number of passengers departed the country (Table 3.6). Hence, it can be suspected the existence of the relationship between the seasonality and the purchase decision of the travelers. Therefore, in the study, it was considered the season of the year as an explanatory variable for the brand choice decision. The entire one – year period from January to December was grouped in to 4 quarters. The variable was defined as a categorical variable with four levels (Table 3.7).

Table 3-7 Levels of the time of purchase

Period of the year (Quarter)	Categorical Level
January to March (Q 1)	1
April to June (Q 2)	2
July to September (Q 3)	3
October to December (Q 4)	4

3.4.3 Preference for Promotions ($\mathbf{X_3}$)

In order to grab the consumer attraction, there are marketing and promotional activities being planned focusing the end consumers. These promotions are focused on the price sensitivity of the consumers which has been discussed as an influential factor for the purchasing behavior of the consumers.

In the business, there has been 3 types of promotional activities are carried out for confectionary goods.

1. Product discount – Buy a certain quantity from a product and get free quantity from the same product. Under this category, there are several

promotional activities such as buy 1 get 1 free (1+1), buy 2 get 1 free (2+1) and buy 3 get 1 free (3+1).

2. Cash discounts – Buy a certain quantity from a product and get a cash discount.
3. Mix and Match promotions – This is an extended mechanism for the product discount promotions. Buy a certain quantity from a product and get a free quantity from some of the designated other product.

Impacts for the overall sales performances are different for each type of promotions. Therefore, the estimated incremental sales quantity should be considered separately for each type of promotion activities.

From the product discounts promotions, buy 2 get 1 free and buy 3 get 1 free are the commonly used promotional mechanisms which are popular among the customers as well as within the business due to the relative price advantage to the customer and hike in the sales for even more than three times than the ordinary months' sales. Consumers tend to go for buy 2 get 1 free promotion than the buy 3 get 1 free because the consumer's wish to differentiate his basket with several products rather than having the same product. On the other hand, in a 2 + 1 promotion, the consumer gets a 50% discount while he only gets 33% discount when he purchases a product from 3 + 1 promotion. 1 + 1 promotions are not widely used in the business since it gives 100% discount for the consumer. It is used as a precautionary method to deplete the SKUs with high inventory levels or with the expiration risk. Therefore, this promotion activity is not used for a longer period, thus the impact is not in a considerable level. Hence the buy one get one free promotion is combined with buy 2 get 1 free promotion category.

Cash discount promotions also give impact to increase the sales quantities. However, the discount amount which is given in the cash discounts promotions are relatively lower than in the product discount promotions.

Apart from that, mix and match type of promotions are also used to increase the sales of a slow moving product. A slow moving or non – moving product is bundled with the fast moving product to increase the sales rate of the fast moving product while depleting the slow moving product as well. Mix and match promotion type also used for the quick depletion, it does not increase the sales as much as 1 + 1 do. However, mix and match promotions are running for reasonably higher time period when compared to buy 1 get 1 free which are activated only for several days or few weeks. Therefore, the cumulative impact is higher for the mix and match promotions.

In the study, it was considered the consumers' preference for the promotional activities as an influential factor for the brand choice. It was assumed that the consumer's preference was reflected from the product that he or she purchases. For instance, if the consumer was preferred for a product discount promotion than a cash discount, he or she tends to purchase a product with a product discount promotion.

In the study, the explanatory variable of consumer preference for promotions has been has been defined as a categorical variable with 5 levels. As elaborated above, 1+1 promotion is not considered in a separate categorical level and has been included in 2+1 promotion category (Table 3.8).

Table 3-8 Levels of the Promotion Type

Promotion Type	Categorical Level
2 + 1 (buy 2 get 1 free)	1
3 + 1 (buy 3 get 1 free)	2
Save Dollar (Cash discounts)	3
Mix and match	4
Other (no promotions)	5

3.4.4 Preference for Product Weight ($\mathbf{X_4}$)

Different consumers are having different types of requirement when purchasing a particular product. In the study, it is focused on the purchasing of the sharing packs products only. The segment is designed for sharing purposes. To cater the different needs of the consumers, there are products with different product weights. Based on the volume requirement of the consumers, it can be selected the different products with different product weights. Hence the volume of the product is a decision that is taken by the consumer based on his or her requirement to sharing. In the study, it was considered the converse of the above. It was assumed that the volume of the product which was purchased was perfectly matched with the actual need of the consumer. Therefore, it was assumed that actual weight of the product purchased was equivalent to the actual need of the consumer for the sharing.

$$\text{need of the consumer to purchase a particular volume of chocolate} = \\ \text{volume of the chocolate which is actually purchased by the consumer}$$

There are chocolate products from 50g of weight to over 1000g of weight in the Sharing pack segment. However, out of this product weight range, most of the SKUs are within 290 grams to 1000 grams range. Based on the number of individual consuming units in a pack, it was grouped the products in to 5 hypothetical groups (Table 3.9). Based on the number of individual consuming units, consumers sharing requirement also divided in to 5 groups to match each weight categories. Table 3.9 defines the sharing requirement of the consumers, based on the weight category that the product is belonged to.

Table 3-9 Definition of the Sharing Requirement based on the product volume group

Preference for weight	Sharing Requirement Group
0 – 290 g	Requirement to share among the individual persons – very low sharing requirement
291 g – 490 g	Requirement to share among the family members. – low sharing requirement
491 g – 710 g	Requirement to share among the moderate group of members – moderate sharing requirement
711 g – 1000 g	Requirement to share among the higher number of members in the in a group – high sharing requirement
Other (> 1000 g)	Requirement to share among very higher number of members in the group. – very high sharing requirement

Based on the above sharing requirement groups, the sharing requirement variable was defined as a 5 – level categorical variable (Table 3.10).

Table 3-10 Levels of the Sharing Requirement (per unit volume)

Preference for Weight	Sharing Requirement	Categorical Level
0 – 290 g	Very low sharing requirement	1
291 g – 490 g	Low sharing requirement	2
491 g – 710 g	Moderate sharing requirement	3
711 g – 1000 g	High sharing requirement	4
Other (> 1000 g)	Very high sharing requirement	5

3.5 Data Preparation for Logistic Regression

It was considered a period of 24 months starting from January 2014 to December 2015 in order to collect the brand choice data of the passengers who are selecting to purchase products from Sharing packs – over 175 grams' (CF) product segment. During the stipulated period, there were 177,559 purchasing occasions of Sharing packs by all the passengers who entered to the shop. Brand selection decisions in the above mentioned purchasing occasions were gathered with the dependent variables of nationality group of the passenger, preference for promotional activities, preference for weight of the product and period of the year of the purchase. The data was retrieved from the Point of Sales terminal database where it captures all the passenger wise transactions with their passport details to trace back the identity of the customer. However, this transaction report does not capture some of the product oriented data such as product segment, available promotional activity. Hence, data from the MIS was collected regarding the product segment and relative promotional activities as an MIS report. Then the separate reports were linked and one master data set was developed. Due to the high number of records, data was used in summarized form for the data analysis rather than having individual records in the SPSS. "Weight Case" function of the SPSS package was used to simulate the individual passenger purchasing decision when the cumulative results are fed as the input data. The data set was weighted by the number of purchasing occasions under each brand name.

3.5.1 Basic Statistics of Brand Choice Data

Below table 3.11 shows the marginal percentages considering each explanatory variable and the response variable.

Out of the total respondents of 177,559 passengers, 39.9% is preferred to purchase Mars brand as their sharing pack product from the duty-free shop. Mondelez and Nestle brands secure 19.7% and 18.3% preference from the total passengers travelled via Colombo international airport from January 2014 to December 2015. Apart from that, there is a fairly high quantity with 22.1% of passengers who select other brands as well.

When it is considered the Nationality of the purchasers, the tourists with American origin has only 1% contribution for the total purchasers. Europe and Australian segment and the East and South East Asians contributes for 7.2% and 9.2% from the total number of passengers who do purchases from the duty-free shop. South Asians are the main contributor for the sales in terms of passengers who do purchases. Therefore, it can be suspected that the purchasing pattern of the south Asians would impact mostly for the selling quantities of Chocolate.

The time of the year when the passengers are doing shopping at the duty-free shop, out of the total passengers who purchase sharing packs, 26.2% of passengers have done purchases in the 4th quarter of the year. During the 1st quarters of the stipulated years, only 24% of the passengers who do shipping to purchase sharing packs. However, according to the past passenger movement pattern, 27% of the total passengers departed from Sri Lanka during the 1st and 3rd quarters of the year. Apart from that, during the 2nd quarter it is only 21% from the total outflow, while 4th quarter is accounted for 24%. Above mentioned statistics show that there are differences between the quarter wise percentage of the passengers who travel via Sri Lanka and quarter wise percentage of the passengers who do purchases from the duty free shop. This is an indication that there are some other factors which affect for the purchasing.

Total number of passengers who do purchases based on their preferences for the sales promotions given, the most of the passengers tend to go for buy 3 get 1 free promotion with 26.6% of the total purchasers followed by buy 2 get 1 free has accounted for 25.2% from the sample. Interestingly, 32.3% of the passengers do not interested in promotions when they choose a product. Dollar off (cash discounts) promotions are attracted by 10.3% while mix and match promotions are attracted by only 5.6% from the total passengers. Therefore, it is questionable whether to have those 2 types of promotions in the business.

When it is considered the sharing requirement or the preference for product weight of the passengers, 53.8% of the passengers have low sharing requirement, thus they are interested in sharing packs with a volume range from 291g – 490g. 26.6% of the passengers are interested in moderate volume sharing packs with around 47,000 of passenger’s choice. There are only 6.3% of passengers who have high sharing requirement. Considerable amount of passengers around 23,000 are having very low or very high sharing requirements either for personalized purchases with sharing packs with low volumes or very high sharing requirements.

Table 3-11 Case Processing Summary

Variables	Description of Levels of Category	N	Marginal Percentage
Brand Choice (Y_i)	Mars	70920	39.9%
	Mondelez	35016	19.7%
	Nestle	32470	18.3%
	Other	39153	22.1%
Nationality of the Passengers ($\mathbf{X_1}$)	America	1752	1.0%
	Europe + Australia	12765	7.2%
	East and south east Asia	16381	9.2%
	South Asia	107538	60.6%
	Other	39123	22.0%
Time of Purchase ($\mathbf{X_2}$)	Jan to March - Q1	42606	24.0%
	April to June - Q2	43767	24.6%
	July to September - Q3	44731	25.2%
	October to December - Q4	46455	26.2%
Preference for Promotions ($\mathbf{X_3}$)	buy 2 get 1 free	44833	25.2%
	buy 3 get 1 free	47317	26.6%
	dollar off	18227	10.3%
	mix and match	9890	5.6%
	others (no promotions)	57292	32.3%
Preference for Product Weight (X_4)	0 – 290	17152	9.7%
	291 – 490	95580	53.8%
	491 – 710	47296	26.6%
	711 – 1000	11255	6.3%
	> 1000	6276	3.5%
Valid		177559	100.0%
Missing		0	
Total		177559	
Subpopulation		399	
The dependent variable has only one value observed in 106 (26.6%) subpopulations.			

3.6 Theoretical Background

In the present study, it is studied the relationship between characteristics of the international travelers and the selection of a brand over set of brands in a particular product segment in Chocolate products. The current study is focused on deriving a mathematical model to forecast the sales quantities based on the consumer characteristics and their buying behavioral patterns. Hence, the Brand preference among the number of consumer groups based on their nationality and behavioral patterns were considered. In the mathematical point of view, selecting a particular brand of chocolate among the number of brands is a problem which involves selecting a categorical choice as the response variable with given characteristics of the passengers which can be identified as categorical or continuous explanatory variables. Contingency tables and Pearson Chi – Square Test for association are the two basic statistical techniques to be used to summarize the data set and check whether there are relationships between the categorical variables. In addition to that, respective purchase decision is made by the consumer in order to maximize the utility of the purchasing decision which is discussed under discrete choice modeling. As per the previous studies, it was used multinomial logistic regression model as the primary statistical technique to predict the buying behavior of the consumers. SPSS and Minitab statistical packages were used for the data analyzing purposes.

3.7 Odds

In any study carried out by using a sample, it is required to identify whether there are relationships between the variables. Odds and odd ratios are to be used to measure the strength of the relationship between the categorical variables in 2 X 2 contingency table.

Odds is defined by,

$$\text{odds of success} = \frac{\text{probability of success}}{\text{probability of failure}} = \frac{p}{(1-p)} \qquad (3.1)$$

Equation 3-1: Odds

Odds is a different way of expression for the probability. As shown in the equation 3.1, it is defined as the probability of an event divided by the probability of the event not happening. The odd value is non - negative and ranges from zero to infinity.

3.7.1 Odd Ratio

Odd ratio is calculated by dividing the odds of the outcome in one group by the odds of the outcome in other group (Equation 3.2). Odd ratio value is always to be a non - negative and ranges from zero to infinity.

$$\text{Odd Ratioodd Ratio } (\theta) = \frac{\text{odds of success within row 1}}{\text{odds of success within row 2}} = \frac{\frac{p_1}{(1-p_1)}}{\frac{p_2}{(1-p_2)}} \quad (3.2)$$

Equation 3-2: Odd Ratio

Small differences in proportions and the odd ratios with value close to one indicate that there is very weak association between the 2 groups.

$$\text{odds}_1 = \text{odds}_2$$

Therefore the baseline for the comparison is $\theta = 1$, where there is no association or independent from each other. Association type is derived as where the odd ratio falls on which side from $\theta = 1$.

1. $\theta > 1$ - Odds of success in the row 1 is higher than the row 2. Thus it can be constituted that there is more likely to have successes in subjects in the row 1 than the subjects in the row 2.

   $$\frac{P_1}{P_2} = \theta > 1$$

   $$P_1 > P_2$$

2. $\theta < 1$ - Odds of success in row 1 is lower than row 2. Thus it can be constituted that there is less likely to have successes in the subjects in row 1 than the subjects in the row 2.

   $$\frac{P_1}{P_2} = \theta < 1$$

   $$P_1 < P_2$$

Odd ratios which are farther from $\theta = 1$ to either side represent strong relationship than the closer ones.

3.7.2 Difference of Log Odds

The difference between the two log odds can be used to compare the two proportions such as Brand preference 1 vs. brand preference 2.

$$\text{difference of log odds} = \text{logit}\,(p_i) - \text{logit}\,(p_2)$$

$$= \log\left(\frac{p_1}{1-p_1}\right) - \log\left(\frac{p_2}{1-p_2}\right)$$

$$= \log\left(\frac{p_1}{1-p_1} \bigg/ \frac{p_2}{1-p_2}\right)$$

$$= \log\left(\frac{p_1(1-p_2)}{p_2(1-p_1)}\right)$$

$$= \log(OR_{1,2})$$

This difference is called as log odd ratio and it compare proportions across the group.

3.8 Logistic Regression Model

Logistic regression models are used in analyzing the association between a categorical dependent variable and a set of independent variables (explanatory variables). Most of the real world problems are having categorical outcomes, hence the logistic regression is widely used in the problems related to social sciences.

Logistic regression models can be grouped into three main categories based on the characteristics of the categorical dependent variable.

1. Binary Logistic Regression model – It is used to model a binary (two - level) outcome / response problems such as yes or no, male or female.

However, in some instances, there are more than two levels in the categorical dependent variable. Therefore, it has been extended the binary logistic regression model to fit for such type of problems. For the binary outcomes, there is no difference with the ordered or not ordered outcomes. However, for levels with more than two, it has become questionable whether the levels can be ordered or not. With the ability to order the responses or not, there are two types of logistic regression models are developed.

2. Ordinal (ordered) Logistic Regression Model - This is used to model the categorical response variable with an order. Low, medium and high is a tentative ordinal levels in the categorical response variable. It is also called as Ordinal Multinomial Logistic Regression.
3. Nominal (unordered) Logistic Regression Model - This type of regression models is used to model a multilevel response variable which has no natural ordering. As an example it can be considered marital status as married, unmarried, divorced or widowed. Multinomial logistic model is the famous way of calling this model.

For logistic regression models, there are no limitations for the explanatory variables as it can be either continuous explanatory variable or categorical explanatory variable or the both types of variables can be included in the model. If the explanatory variables are in continuous form, it is called as covariates while for the continuous explanatory variables, it is called as factors.

The basic outputs of the logistic models are odds and odd ratios and the probability of occurring the particular categorical outcome and the classification table. In the classification table, it is calculated the percentage of the correctly classified number of outcomes against the actual category.

3.8.1 Logistic Regression and Discriminant Analysis

Discriminant Analysis also gives an alternative way of calculating (estimating) the category that the individual unit is belonged to. However, logistic regression model is far widely used in categorical data analysis than the Discriminant Analysis due to the assumptions made in the latter. In Discriminant Analysis, it is assumed the normal distribution of the independent variable which is not required for Logistic Regression. For a large data set, testing of normality gives further complexity to the analysis, hence many researchers and statisticians have considered logistic regression model as more versatile and better suited model compared to Discriminant analysis.

3.8.2 Logistic Curve

The logistic function models the S – curve shaped growth type. In the beginning of the curve, the growth shows an exponential pattern. As saturation begins, the growth rate reduces to a constant level and then the growth reduces at an exponential rate to stops the growth at the maturity. Below shown Equation 3.3 depicts the logistic function.

$$y\ (x) = \frac{e^{(a+bx)}}{1 + e^{a+bx}} \quad (3.3)$$

Equation 3-3: Logistic Function

The plot of y (x) is shown in figure 3.1.

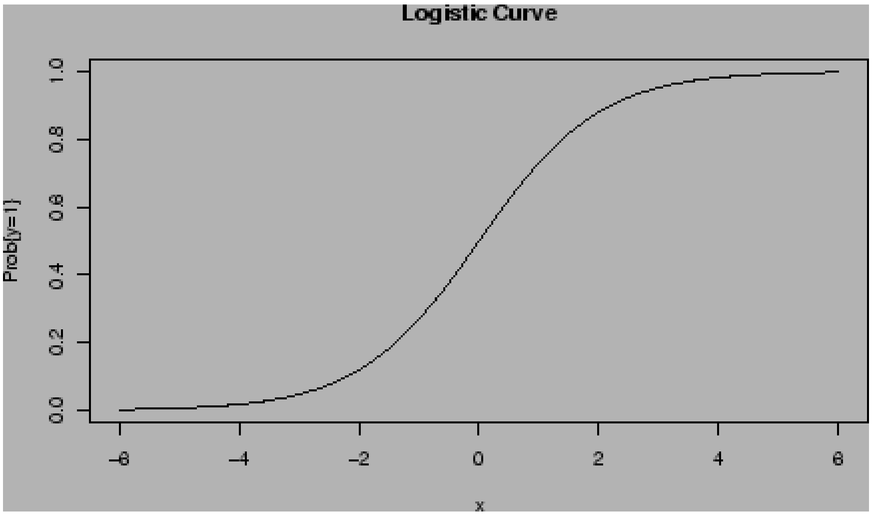

Figure 3-1 Logistic Curve

Source: https://www.stat.ubc.ca/~rollin/teach/643w04/lec/node46.html

3.8.3 Logistic Transformation

In the multiple regression model, a set of explanatory variables are used to estimate the mean of a continuous dependent variable. Similarly, in logistic regression model, it is estimated the logit of the probability of the categorical variable as a linear function of number of explanatory variables. Equation 3.4 shows the logit transformation which is defined as below,

$$\text{logit}\ (\text{p}) = \log\left(\frac{\text{p}}{1-\text{p}}\right) \quad (3.4)$$

Equation 3-4: Logit Transformation

Where,

$\text{p} = \text{probability of success in the dependent categorical variable (assumption}$
$\text{: dependent categorical variable has only 2 levels)}$

$(1 - \text{p}) = \text{probability of failiure in categorical dependent variable}$

$$\left(\frac{\text{p}}{1 - \text{p}}\right) = \text{odds of success}$$

The probability of any event is ranged from zero to one and the respective logit ranges from minus infinity to plus infinity while tie zero logit occurs when $\text{p} = 0.5$. The inverse logit transformation is called as logistic transformation (Equation 3.5)

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right) = e^{l} \qquad\qquad p = \text{logistic}(l) = \frac{e^{l}}{(1+e^{l})} \quad (3.5)$$

Equation 3-5: Logistic Transformation

Where,

$l = a + bx_1 + cx_2 + \cdots$

In the logistic regression model, it is derived a linear and additive relationship between the explanatory variable and the log odds of the event. Hence the log odds can be estimated with the explanatory variables.

Let us assume a scenario where an individual faces a choice decision which has J number of categorical responses. The response of the categorical dependent variable is assumed to be a function of p number of explanatory variables. Where,

$n = \text{number of decison making units } (i = 1, 2, 3 \ldots\ldots, n)$

$J = \text{nominal categories of the response variable}$

$\text{if } J > 2 = \text{multinomial logistics regression model}$

$(J - 1) = \text{numberof non} - \text{overlapping models}$

$J = \text{reference category}$

$Y = \text{multinomial response variable with J nomial categories}$

$Y_i = \text{value of the multinomial response variable for } i^{th} \text{ decision unit}$

$X_p = \text{predictor variable p}$

$p = \text{index of the predictor variable } (p = 0, 1, 2, \ldots\ldots P)$

$X_1, X_2, \ldots\ldots X_{P-1} = \text{multiple predictor variables}$

$\beta = \text{parameter of the explanatory variable } (\beta = \beta_o, \beta_1, \ldots\ldots.., \beta_{p-1})$

$X_{i,p-1} = \text{explanatory variable of the } (p-1)^{th} \text{ variable for the } i^{th} \text{ decision unit}$

The J^{th} category is considered as the reference category.

$$\log_e\left(\frac{P\ (Y_i = 1|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}{P\ (Y_i = J|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}\right) = \beta_{10} + \beta_{1,1}X_1 + \dots + \beta_{1,1}X_{p-1} = \acute{\beta_1}X_i$$

$$\log_e\left(\frac{P\ (Y_i = 2|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}{P\ (Y_i = J|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}\right) = \beta_{20} + \beta_{2,1}X_1 + \dots + \beta_{2,1}X_{p-1} = \acute{\beta_2}X_i$$

..

..

$$\log_e\left(\frac{P\ (Y_i = j-1|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}{P\ (Y_i = J|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}\right) = \beta_{j-1,0} + \beta_{j-1,1}X_1 + \dots + \beta_{j-1,1}X_{p-1}$$

$$= \acute{\beta}_{j-1}X_i$$

Therefore, the general logit model for the j^{th} category is,

$$\log_e\left(\frac{P\ (Y_i = j|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}{P\ (Y_i = J|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}}\right) = \log_e\frac{P_{ij}}{P_{iJ}} = \log_e\left(\frac{P_{ij}}{1 - \sum_{j=1}^{J-1} P_{ij}}\right) \ (3.6)$$

$$= \beta_{j,0} + \beta_{j,1}X_1 + \dots + \beta_{j,p-1}X_{p-1} = \acute{\beta_j}X_i$$

Equation 3-6: General form of Multinomial Logistic Regression

$$P_{ij} = P\ (\text{success in } j^{th} \text{ category})$$

$$= P\ (Y_i = j|X_{i,1}, X_{i,1}, \dots, X_{i,p-1}) = \frac{\exp(\acute{\beta_j}X_i)}{1 + \sum_{j=1}^{J-1}\exp(\acute{\beta_j}X_i)}\ , j < 1\ (3.7)$$

Equation 3-7: General form of Multinomial Logistic Transformation

Above mentioned equations 3.6 and 3.7 show the general form of the Multinomial Logistic Regression and the general form of Multinomial Logistic Transformation respectively.

3.8.4 Interpretation of Multinomial Regression Coefficient

The interpretation of the estimated regression coefficients in the multinomial logistic regression posses' complex steps when compared to the multiple linear regression. The complexity arises with the nonlinear relationship between X (explanatory variable) and Y (response variable). Furthermore, if the dependent variable has more than two unique values, there are several regression equations to be derived which increase the complexity further.

For a model with a binary dependent variable (Y) and a single independent variable (X), the logistic regression equation is,

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X$$

If it is considered a unit increase in X, the logistic regression equation becomes,

$$\log\left(\frac{p'}{1-p'}\right) = \beta_0 + \beta_1 X + \beta_1(1)$$

By taking the difference between the 2 equations, the parameter estimate for the slope can be isolated,

$$(\beta_0 + \beta_1 X + \beta_1(1)) - (\beta_0 + \beta_1 X) = \log\left(\frac{p'}{1-p'}\right) - \log\left(\frac{p}{1-p}\right)$$

$$\beta_1 = \log\left(\frac{p'}{1-p'}\right) - \log\left(\frac{p}{1-p}\right)$$

$$= \log\left(\frac{\left(\frac{p'}{1-p'}\right)}{\left(\frac{p}{1-p}\right)}\right)$$

$$\beta_1 = \log\left(\frac{odds'}{odds}\right)$$

$$\exp(\beta_1) = \left(\frac{\left(\frac{p'}{1-p'}\right)}{\left(\frac{p}{1-p}\right)}\right) \quad (3.8)$$

Equation 3-8: Calculate the parameter estimate of Logistic regression

Therefore, the exponential of the parameter estimate shows the odd ratio of the response of interest for an observation in any group related to the base group (Equation 3.8).

3.8.5 Model Selection Problem

With the number of factors and covariates influencing for the categorical response variable in the logistic regression model, it is important to specify the factors and covariates to be included in the final model. By default, all the main effects are included in the model. However, it is allowed to specify other types of relationships between the factors to be included in the model.

1. Main Effects Model - uses only the selected variables and creates a model contains the main effects terms from covariates and factors, without the interaction between the factors
2. Full Factorial Model - Contains all main effects and all factor-by-factor interactions. It does not contain covariate interactions
3. Custom Model - Manual inclusion of the factors, covariates main effects and respective interactions between selected factors and covariates are allowed under this model as forced entry or a stepwise inclusion term.

In the SPSS package, the user can create a custom model to specify subsets of factor interactions or covariate interactions or request stepwise selection of model terms.

3.8.6 Specify Model in Custom Model

In the SPSS, it is facilitated to control the inclusion of the specified covariates and factors in the model with statistical procedures.

1. Forced Entry Terms – Specified terms are always included in the model.
2. Stepwise Terms – Specified terms are included in the model according to one of the following user - selected Stepwise Methods:
    1. Forward entry – Begins with the no terms included in the model. At each step, the most significant term is added to the model until none of the stepwise terms left out of the model would have a statistically significant contribution if added to the model.
    2. Backward elimination – Begins with all terms are included in the model. At each step, the least significant stepwise term is removed from the model until all of the remaining stepwise terms have statistically significant contribution to the model.
    3. Forward stepwise – This method begins with the models that would be selected by the forward entry method. From there, the algorithm alternates between backward elimination on the stepwise terms in the model and forward entry on the terms left out of the model. This continues until no terms meet the entry or removal criteria.
    4. Backward stepwise – This method begins with the model that would be selected by the backward elimination method. From there, the algorithm alternates between forward entry on the terms left out of the model and backward elimination on the stepwise terms in the model. This continues until no terms meet the entry or removal criteria.

3.8.7 Significance of Explanatory Variables

Once the model is fitted with the specified explanatory variables, it has to be statistically tested whether the explanatory variables in the final model are statistically significant, hence the explanatory variable should be included in the final model.

Below are the statistical procedures to be used to test the significance of the explanatory variables in the logistic regression model.

Likelihood Ratio

The likelihood ratio test is defined as,

$$\text{Likelihood Ratio (L)} = -2 * \text{difference between the log likelihood of the 2 models}$$

The distribution of the LR statistic is closely approximated by the chi-square distribution for large sample sizes. The degrees of freedom (DF) of the approximating chi-square distribution is equal to the difference in the number of regression coefficients in the two models. The test is named as a ratio rather than a difference since the difference between two log likelihoods is equal to the log of the ratio of the two likelihoods (Equation 3.9).

$$\text{LR} = -2[\text{L}_{\text{subset}} - \text{L}_{\text{full}}]$$

$$\text{LR} = -2\left[\ln\left(\frac{\text{l}_{\text{subset}}}{\text{l}_{\text{full}}}\right)\right] \quad (3.9)$$

Equation 3-9: Likelihood Ratio

Where,

$\text{L}_{\text{full}} = \text{log likelihood of the full model}$

$\text{L}_{\text{subset}} = \text{log likelihood of a subset of the full model}$

Likelihood Ratio Test

Below is the hypothesis test which is used to check the significance of the coefficients of the explanatory variables in the model.

$\text{H}_0 = \text{reduced model is true}$

Vs.

$\text{H}_1 = \text{current model is true}$

In the reduced model, it is omitted the arbitrary group of coefficients of the explanatory variables from the model by setting them equal to zero which indicate no relationship with the response variable. In the current model, the coefficients are included the model.

The likelihood ratio statistic is,

$$\Delta G^2 = -2\left(\log\left(\text{likelihood from reduced model}\right)\right) - \left(-2\log(\text{likelihood from current model}\right) \sim \chi_k^2$$

Null hypothesis is rejected if,

$$p\ (\Delta G^2) < 0.05$$

The degree of freedom is equal to the number of coefficients in the model. In the SPSS output panel, the reduced model is the model with “only intercept” model (no predictor variables) and current model is the model fitted with “intercept and covariates”. If the null hypothesis is rejected, it is affirmed that the current model is true which includes the intercept and covariates.

Deviance

As mentioned earlier in likelihood ratio, if the full model become the saturated model, the Likelihood Ratio is called as the Deviance. In the saturated model, it is included all possible terms including interactions which gives the predicted values equal to the original values.

$$D = -2[L_{\text{reduced}} - L_{\text{saturated}}]$$

3.8.8 Model acceptance criteria

Pseudo - R Squares –

This statistics is similar to the R^2 discussed in the Ordinary Least Square (OLS) regression models. It shows the percentage of the variability of the dependent variable is explained by the fitted model. There are 2 methods of calculating the Pseudo R – square in the logistic regression models; Cox and Snell's R – Square (Equation 3.10) and Nagelkerke’s R-square (Equation 3.11).

Cox and Snell's R - Square:

$$R^2 = 1 - \left[\frac{L_{(\text{M intercept})}}{L_{(\text{M full})}}\right]^{2/n} \quad (3.10)$$

Equation 3-10: Cox and Snell's R - Square

Nagelkerke’s R-square:

$$R^2 = \frac{1 - \left[\frac{L_{(M\ intercept)}}{L_{(M\ full)}}\right]^{2/n}}{1 - \left[L_{(M\ intercept)}\right]^{2/n}} \quad (3.11)$$

Equation 3-11: Nagelkerke’s R-square

Where,

$L_{(M\ intercept)}$ = likelihood of the intercept only model

$L_{(M\ full)}$ = likelihood of the full model

However, these matrices do not represent the amount of the variance in the outcome variable is explained by the predictor variables. Therefore, these test statistics should be interpreted and used with great caution due to some disadvantages embedded in the two statistics. Cox and Snell's R - squared has the disadvantage of not achieving its maximum value of one for the discrete models even when the model predicts all the variables properly. This has been improved in the Nagelkerke’s R-square which gives the ability to achieve the maximum value of the $R^2$when the model predicts the data properly (Aziz, Ali, Nor, Baharum, & Omar, 2016).

3.8.9 The Classification Table

It provides a systematic way of evaluating the predictor accuracy of the logistic regression model by comparing the outcome variables predicted by the model and the actual outcome variable under each response category in the selected sample. The table gives the number of cases that are predicted correctly by the final accepted model compared to the actual outcome of the case. If the percentage is relatively high, it can be identified as a good model which fits for the data set.

3.8.10 Model Diagnostic Tests

Generally, there are 3 types of errors which give adverse impact on the model fit in regression models namely; Multicollinearity, Outliers and Influential Observations. Outliers and influential observations are discussed in Simple regression models while multicollinearity occurs in multiple regression forms due to the high correlation among the explanatory variables it selves. In the study, it is only used Multicollinearity as a model diagnostic test.

Multicollinearity

There is no unique statistical test to check the multicollinearity in multinomial logistic regression models. However, it can be tested with the magnitude of the standard errors of each estimated coefficient (Aziz, Ali, Nor, Baharum, & Omar, 2016). If the standard error values of the estimated coefficients are over 5, it indicates the occurrence of the multicollinearity among the predictor values.

3.9 Steps of the Model Development

Having discussed the theoretical background of the regression model development, it is discussed the steps model derivation process for the chocolate brand preference for the air travelers depart from Sri Lanka.

3.9.1 Identifying the Target Group

There are around 200 active SKUs of Chocolate in the duty-free shop which are supplied by 21 suppliers that are fallen under 18 product segments. However, only few of the SKUs are contributing for considerable portion of the sales in terms of value and the volume. Generally, in a study, it is important to narrow down the study to a target group and derive the results for the target group and generalize the results to the population. Therefore, the sales in terms of the volume and values from 2014 January to 2016 December will be analyzed to identify the main contributors for the sales by the product segment and the respective brand names. On the other hand, assuming the relationship between the sales volumes and the number of airline passengers who depart through the departure lounge, the main nationalities of the airline passengers who travel mostly via Colombo International Airport is selected. Therefore, the buying behaviors of those passenger nationalities will be considered in the study.

3.9.2 Definition of the Response Variable and Explanatory Variables

In the multinomial logistic regression procedures, a relationship between higher (>2) level of categorical response variable and the number of categorical explanatory variables (factors) or continuous response variables (co –variates) will be tested. Therefore, the identification of the factors and co – variates and their relationship with the response variable is important. Since the problem is defined as a multinomial logistic regression problem, response variable need to be defined as a categorical variable with higher number of levels. Apart from that, any categorical explanatory variables should be grouped in meaningful categories.

3.9.3 Two – way Contingency Tables

Two-way contingency tables will be derived in order to analyze the relationships between the explanatory variables and the response variable by using the Pearson –

Chi Squared Test and Likelihood Ratio test are derived to analyze the relationship between the explanatory variables and response variables.

3.9.4 Derive the Multinomial Logistic Model

A multinomial logistic regression model will be derived between the categorical response variable of brand selection and categorical explanatory variables. In order to test the significant explanatory variables to be included in the model, four step – wise variable selection procedures to be used. All the model acceptance criteria will be tested in order to accept the model. Significance of the Log likelihood of the final model and significance of the log likelihood of each effect would be tested to check the significance of the model.

3.9.5 Calculate the Probability of Brand Selection

Relative consumer nationality wise probabilities of selecting a chocolate brand over will be calculated with the odd ratios and logistic transformation of odd ratios. Calculations to be performed in fixed levels of explanatory variables.

CHAPTER 4

RESULTS AND DISCUSSION

This chapter is dedicated to the results of the data analysis and interpretation of the results. Topics of this chapter is lined under 3 main areas; impact of explanatory variables on response variable, deriving the multinomial logistic regression model and interpretation of the parameter estimates. Impacts are discussed with the Pearson Chi – Square test for association and likelihood ratio Chi – square test. Apart from that, cross tabulation tables are interpreted with row percentage. Under multinomial logistic regression model development; steps of the model derivation and significance of the model are discussed with interpretation of the results. Parameter estimates for different brands relative to the alternate other brands are discussed with the odds. Finally, brand selection probabilities are calculated.

4.1 Impact of Explanatory Variables on Brand Preference

In order to test whether there are associations between each of the explanatory variable and the response variable, Chi-Square analyses for frequency tables were carried out. Results obtained from SPSS are shown below.

4.1.1 Impact of Nationality on Brand Preference

Table 4-1: Relationship between Nationality vs. Brand Preference

	Value	**Degree of Freedom**	**Asymp. Sig. (2-sided)**
Pearson Chi-Square	2819.071	12	0.000
Likelihood Ratio	2762.981	12	0.000
N of Valid Cases	177559		

Above shown table 4.1 indicates the results of the Pearson Chi – Square test and Likelihood Ratio test for the association between Nationality and Brand preference. As the P – value is less than 0.05, the null hypothesis is rejected in favor of no association between Nationality of the customer and their brand preference. Therefore, it can be concluded with 0.05 level of significance that there is a significant association between Nationality of the customers and the brand preference.

Table 4-2 : Cross Tabulation - Nationality vs. Brand Preference

			Brand Preference				Total
			Mars	Mondelez	Nestle	Other	
Nationality	North America	Count	553	394	406	399	1752
		% within Nationality	31.6%	22.5%	23.2%	22.8%	100.0%
	Europe and Australia	Count	4224	2575	2665	3301	12765
		% within Nationality	33.1%	20.2%	20.9%	25.9%	100.0%
	East and South East Asia	Count	5014	3456	2485	5426	16381
		% within Nationality	30.6%	21.1%	15.2%	33.1%	100.0%
	South Asia	Count	44760	21083	18174	23521	107538
		% within Nationality	41.6%	19.6%	16.9%	21.9%	100.0%
	Other	Count	16369	7508	8740	6506	39123
		% within Nationality	41.8%	19.2%	22.3%	16.6%	100.0%
Total		Count	70920	35016	32470	39153	177559
		% within Nationality	39.9%	19.7%	18.3%	22.1%	100.0%

Above mentioned table 4.2 shows the cross tabulation between the Nationality of the customers and the brand preference with the row percentages which describes the percentage of customers based on the nationality who purchase particular brand of chocolate. For all the customers except who belong to East and South East Asian region, would purchase Mars brand chocolates as the highest preferring brand of chocolate. For East and South East Asians, they are preferring to purchase alternative brands rather sticking to popular brands of Mars, Mondelez or Nestle with 33.1% of preference. Comparing to North Americans and Europeans, South Asians and Customers who belong to other nationalities are willing to purchase Mars with a percentage of 41.6% and 41.8% respectively.

Out of the nationality wise buying preference percentages, North Americans are having the highest percentage of purchasing Mondelez and Nestle brands with 22.5% and 23.2% respectively. Out of the customers who select Mondelez brand, South

Asians and Other nationality groups are the lowest percentages among their nationality groups to select Mondelez. The same pattern can be identified for the Nestle brand chocolates as well.

Out of the total customers, 39.9% are willing to purchase Mars brand chocolates while 22.1% are preferring to purchase alternate other brands. Customers are willing to purchase Mondelez and Nestle brands with percentages of 19.7 and 18.3 respectively irrespective to the nationality.

4.1.2 Impact of Time of purchase on Brand Preference

Table 4-3: Relationship between Time of Purchase vs. Brand Preference

	Value	Degree of Freedom	Asymp. Sig. (2-sided)
Pearson Chi-Square	555.117	9	.000
Likelihood Ratio	561.229	9	.000
N of Valid Cases	177549		

Above shown table 4.3 indicates the results of the Pearson Chi – Square test and Likelihood Ratio test for the association between Time of Purchase and Brand preference. As the P – value is less than 0.05, the null hypothesis is rejected in favor of no association between time of the purchase occurs and the brand preference. Therefore, it can be concluded at the 0.05 level of significance that there is a significant association between time of chocolate purchase and the brand preference.

Below mentioned table 4.4 shows the cross tabulation between the time of the chocolate purchase and the brand preference with the row percentages which describes the percentage of customers based on the time of purchase on particular brand of chocolate. During the period of analysis, Mars brand chocolates are the highly preferred chocolate brand irrespective to the time of the purchase. Except for 3rd quarter of the year, in reaming 3 quarters, more than 40% of the consumers are tend to buy Mars brand where as it has dropped to 37.3% in the 3rd quarter of the year. For the remaining brands, percentage of preference is different during the 4 quarters.

Table 4-4 : Cross Tabulation – Time of Purchase vs. Brand Preference

			Brand Preference				
			Mars	**Mondelez**	**Nestle**	**Other**	**Total**
Purchasing time	Quarter 1 (Q1)	Count	17244	9272	7821	8269	42606
		% within Purchasing time	40.5%	21.8%	18.4%	19.4%	100.0%
	Quarter 2 (Q2)	Count	17709	7919	8258	9881	43767
		% within Purchasing time	40.5%	18.1%	18.9%	22.6%	100.0%
	Quarter 3 (Q3)	Count	16703	9362	8310	10356	44731
		% within Purchasing time	37.3%	20.9%	18.6%	23.2%	100.0%
	Quarter 4 (Q4)	Count	19264	8463	8081	10647	46455
		% within Purchasing time	41.5%	18.2%	17.4%	22.9%	100.0%
Total		Count	70920	35016	32470	39153	177559
		% within Purchasing time	39.9%	19.7%	18.3%	22.1%	100.0%

If it is considered the brand preference percentages in each quarter of the year, Nestle brand chocolates have the lowest buying percentages during the first, third and fourth quarters of the year. During the second quarter, Mondelez has the lesser preference to be chose compared to the other brands. Therefore, the sales force can work on to boost sales for the problematic brands during the respective periods of the year.

4.1.3 Impact of Preference for Promotions on Brand Preference

Below shown table 4.5 indicates the results of the Pearson Chi – Square test and Likelihood Ratio test for the association between Preference for the Promotional Activities by the customers and Brand preference. As the P – value is less than 0.05, the null hypothesis is rejected in favor of no association between preference for the promotional activity and the brand preference. Therefore, it can be concluded at 0.05 level of significance that there is a significant association between customer's preference for the promotion and the brand preference.

Table 4-5: Relationship between Preference for Promotion vs. Brand Preference

	Value	**Degree of Freedom**	**Asymp. Sig. (2-sided)**
Pearson Chi-Square	41740.725	12	0.000
Likelihood Ratio	45820.505	12	0.000
N of Valid Cases	177559		

Below cross tabulation table of 4.6 shows how the percentage of preference for the brand of chocolate differs based on the preference of promotional activities by the customer. Compared to the results in nationality and time of purchase, it can be seen much differences in the percentage of preferences for a brand.

Passengers who are preferring a promotion of buy 2 get 1 free or buy 3 get 1 free, mostly will tend to select the Mars brand with a 30.3% and 48.8% respectively against the promotion wise total customers. However, for customers with preference for cash discounts than the product discounts are preferring 49.9% from the total cash discount passengers to opt to an alternative other brand rather than selecting Mars, Mondelez or Nestle brands. Out of the 35.7% of the passengers who prefer buy 3 get 1 free promotion tend to select Mondelez brans chocolates. From the passengers who prefer buy 2 get one free promotion, 26.5% are selecting Nestle brand chocolates. When there are Mix and Match promotions, most of the passengers are tend to purchase Mars brand chocolates with 78.8%. For the customers who like to have mix and match promotions are not interested in purchasing Nestle brand chocolates. The customers who do not interested in any promotions are tend to purchase Mars brand chocolates with 40.1% preference.

Table 4-6 : Cross Tabulation – Preference for Promotions vs. Brand Preference

			Brand Preference				Total
			Mars	Mondelez	Nestle	Other	
Promo Category	Buy 2 get 1 free (2+1)	Count	13562	9900	11895	9476	44833
		% within Promo Category	30.3%	22.1%	26.5%	21.1%	100.0%
	Buy 3 get 1 free (3+1)	Count	23079	16881	4670	2687	47317
		% within Promo Category	48.8%	35.7%	9.9%	5.7%	100.0%
	Cash Discounts (Dollar Off)	Count	3504	3144	2478	9101	18227
		% within Promo Category	19.2%	17.2%	13.6%	49.9%	100.0%
	Buy a product and get different product free (Mix and Match)	Count	7790	1793	0	307	9890
		% within Promo Category	78.8%	18.1%	0.0%	3.1%	100.0%
	Other (No Promotions)	Count	22985	3298	13427	17582	57292
		% within Promo Category	40.1%	5.8%	23.4%	30.7%	100.0%
Total		Count	70920	35016	32470	39153	177559
		% within Promo Category	39.9%	19.7%	18.3%	22.1%	100.0%

4.1.4 Impact of Preference for Weight Category on Brand Preference

Table 4-7: Relationship between Preference for Weight Category vs. Brand Preference

	Value	Degree of Freedom	Asymp. Sig. (2-sided)
Pearson Chi-Square	44745.388	12	0.000
Likelihood Ratio	44361.646	12	0.000
N of Valid Cases	177559		

Results of the Pearson Chi – Square test and Likelihood Ratio test for the association between preference for the product weight and Brand preference are shown in the table 4.7. As the P – value is less than 0.05, the null hypothesis is rejected in favor of no association between preference for the product weight and the brand preference. Therefore, it can be concluded at 0.05 level of significance that there is a significant association between preference for the product weight and the brand preference.

Below cross tabulation table of 4.8 shows how the percentage of preference for the brand of chocolate differs based on the preference for the weight product by the customer. Passengers who are preferring to purchase products with a weight from 290 grams to 491 grams and 500 grams to 710 grams are preferred to purchase Mars chocolates with percentages of 46 and 42.7 respectively. Therefore, the passengers with a requirement of low sharing requirement and moderate sharing requirement are willing to purchase Mars chocolates. However, out of the total customers with very low sharing requirement (0 – 290g), 33% are preferring to purchase Mondelez brand chocolates while 30.9% are preferred to buy Nestle chocolate. Customers who want to purchase chocolate with more than 1000 grams are willing to purchase alternative brands of chocolates with 35.8% rather than selecting Mars, Mondelez or Nestle. There is zero preference for the Mondelez brand chocolates from the customers who prefer to have very high sharing requirements.

Table 4-8 : Cross Tabulation – Preference for Product Weight vs. Brand Preference

			Brand Preference				**Total**
			Mars	**Mondelez**	**Nestle**	**Other**	
Preference of Weight category	0 – 290 (grams)	Count	2770	5663	5304	3415	17152
		% within Weight category	16.1%	33.0%	30.9%	19.9%	100.0%
	291 – 490 (grams)	Count	43985	26940	10597	14058	95580
		% within Weight category	46.0%	28.2%	11.1%	14.7%	100.0%
	491 - 710 (grams)	Count	20219	1894	10502	14681	47296
		% within Weight category	42.7%	4.0%	22.2%	31.0%	100.0%
	711 - 1000 (grams)	Count	2754	519	5963	2019	11255
		% within Weight category	24.5%	4.6%	53.0%	17.9%	100.0%
	Other (> 1000 grams)	Count	1192	0	104	4980	23428
		% within Weight category	19.0%	0.0%	1.7%	79.3%	100.0%
Total		Count	70920	70920	35016	32470	39153
		% within Weight category	39.9%	39.9%	19.7%	18.3%	22.1%

4.1.5 Correlation between Explanatory variables and Response Variable

In order to test the correlation between the response variables and the explanatory variables, it was carried out the Rank Correlation Coefficient test (Spearman Correlation) for the categorical variables. Below mentioned table 4.9 shows the summary of the correlation coefficients and the respective p values in order to test whether there is significant correlation between the 2 variables.

Table 4-9: Correlation between response variable and explanatory variables

Response Variable	Explanatory variable	Rank Correlation Coefficient	Approx. Sig.	Conclusion
Brand Preference	Nationality	-0.076	0.000	Sig. Correlation
	Purchasing Time	0.014	0.000	Sig. Correlation
	Promo preference	0.044	0.000	Sig. Correlation
	Preference for weight	0.139	0.000	Sig. Correlation

As shown in the table 4.9, for all the pairs of variables, it can be concluded the correlations are significantly different from zero at the significance level of 0.05. However, if it is considered the correlation coefficient values for each pair, none of the pairs showed strong relationship with the explanatory variable brand preference. In fact, they show weak relationships. Nationality shows a negative correlation of -0.076 with the brand Preference and purchasing time shows the minimum relationship of 0.014. The preference for the sharing show relatively higher relationship compared to others with a value of 0.139.

4.2 Develop a Multinomial Logistic Model

As association of all 4 variables were significant on the Brand Preference, a multinomial logistic regression model was developed by taking all 4 explanatory variables simultaneously. In this case, all four types of step wise variables selection methods, namely; (1) Forward Entry (2) Backward Elimination (3) Forward Stepwise and (4) Backward Stepwise methods were applied. Additionally, to select the significant variables to be included in the model, both Likelihood Ratio and Wald tests were applied as the variable removal test. Table 4.10 summarizes whether the 4 explanatory variables are significant to be included in the multinomial logistic regression models developed using different variable selection methods and variable removal test. Probability of entry and probability of removal were considered as 0.05. It was found out that the identified significant variables were variant of the type of variable selection method and as type of variable removal criteria.

When using Forward Entry and Forward Stepwise methods as the variable selection method, it was found out that the Preference for Promotion is not significant to be included in the final model irrespective to the likelihood ratio test and Wald test as the test for variable removal. However, when the Backward Elimination and Backward Stepwise methods are used, all the four variables were significant to be included in the final model irrespective to the variable removal test. Therefore, in order to arrive a final determination on the variables, it was considered other relevant statistics such as Pseudo R – Square and Classification Accuracy.

In the Table 4.10, the Negelkerke Pseudo R – Square values for the 8 different models are shown below. For the 4 multinomial logistic regression models which are derived with Forward Entry and Forward Stepwise methods have Pseudo R – Squared value of 0.253, which means that 25.3% of the variability of the brand choice variable is explained by the model. On the other hand, the 4 models which are derived with Backward Elimination and Backward Stepwise variable selection methods have achieved Pseudo R – Squared value of 0.449. therefore, it can be statistically shown that the 4 – explanatory variable models are capable of explaining the higher variability of the dependent variable than the 3 – explanatory variable models.

Further to that, 4 backward models have achieved around 52.4% of classification accuracy while the 4 models with Forward Entry and Forward Stepwise selection methods have achieved only 46.1% of classification accuracy from the total 177559 purchasing occasions.

Therefore, it can be concluded that the multinomial logistic regression model with all four explanatory variables is better fitted for the data set than the logistic regression model with 3 explanatory variables included. Hence the final model would be derived with Backward Elimination method with Likelihood Ratio test as the variable removal test.

Table 4-10: Significance of the Explanatory Variables in Different Model Development Methods

Variable Selection Method		**Forward Entry Method**		**Backward Elimination**		**Forward Stepwise**		**Backward Stepwise**	
Variable Removal Test		**Likelihood Ratio**	**Wald Test**	**Likelihood Ratio**	**Wald Test**	**Likelihood Ratio**	**Wald Test**	**Likelihood Ratio**	**Wald**
Explanatory Variable	**Nationality (X1)**	Sig	Sig	Sig	Sig	Sig	Sig	Sig	Sig
	Time of Purchase (X2)	Sig	Sig	Sig	Sig	Sig	Sig	Sig	Sig
	Promotion Preference (X3)	not sig	not sig	Sig	Sig	not sig	not sig	Sig	Sig
	Weight Preference (X4)	Sig	Sig	Sig	Sig	Sig	Sig	Sig	Sig
Pseudo R-Square	**Nagelkerke**	0.253	0.253	.449	.449	0.253	0.253	.449	.449
Classification Accuracy		46.10%	46.10%	52.40%	52.40%	46.10%	46.10%	52.40%	52.40%

4.2.1 Multinomial Logistic Regression Model

As all the four explanatory variables are significant to be included simultaneously in the model, it was fitted a Multinomial Logistic Regression Model with all the 4 explanatory variables and the SPSS outputs are discussed below.

Steps of the Multinomial Logistic Model Development

Below table 4.11 shows the summary of the steps in the model development process. Under Step – wise variable selection methods, Backward Elimination method was used to build the model with probability of entry and probability of removal were considered as 0.05 and Likelihood ratio test as the variable removal test. In the Backward Elimination method, modeling starts with all terms included with the intercept. At each step, the least significant stepwise term is removed from the model by considering the removal probability of 0.05 until all of the remaining stepwise terms have statistically significant contribution to the model. As the variables are removed from the initial final model, the -2 Log Likelihood Ratio increases.

As per the Table 4.11 which depicts the step summary of the backward elimination method, there were no variables to be removed from the full model with 4 explanatory variables since all the variables are significant. The test statistics of the -2 Log Likelihood Ratio for the reduced model which excludes each variable at a time from the final model are in the rejection region of the null hypothesis. Hence, it is confirmed that the removal of the variable is not significant. Therefore, the final model with all four variables was not changed in the steps of the Backward Elimination method.

Table 4-11: Step summary of the Backward Elimination Method

Step Summary

Model	Action	Effect(s)	Model Fitting Criteria	Effect Selection Tests
			-2 Log Likelihood	Chi-Square
0	Entered	<all>	72070.794	

Stepwise Method: Backward Elimination

The chi-square for removal is based on the likelihood ratio test.

Table 4-12: Model Fitting Information of the Entry Method

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	167933.000			
Final	72070.794	95862.206	45	0.000

Above mentioned Model Fitting Information table 4.12 shows whether the final model or the model with specified explanatory variables is statistically significant than compared to the intercept only model which excludes all the explanatory variables from the model. The final model has been arrived at through an iterative process as discussed earlier. By including the predictor variables and maximizing the log likelihood of the outcomes seen in the data, the "Final" model should improve upon the "Intercept Only" model. This can be seen in the differences in the -2(Log Likelihood) values associated with the two models ("Intercept only" and "Final") and the p value with respect to the Chi - Square value and the Degree of Freedom. The likelihood of the model is used to test of whether at least one of the predictors' regression coefficients which are included in the model are zero. The null hypothesis of the test is all the regression coefficients of the model are equal to zero or the "Intercept Only" model is accepted.

The likelihood Ratio (LR) Chi – Square statistics is calculated by;

$$2 * \mathrm{L(null\ model)} - \left(-2 * \mathrm{L(fitted\ model)}\right) = 167933.00 - 72070.794 = 95{,}862.206$$

where the null model is the "Intercept Only" model while the "Fitted Model" is arrived by an iterative process. Since the p – value is (p = 0.000) significant at the 0.05 level, the null hypothesis is rejected. Therefore, it can be concluded at the 0.05 level of significance that the all the predictor variables in the final model are significantly different from zero. In other words, at least one of the coefficients of predictor variables are not equal to zero in the final model. Hence the final model with 4 predictor variables are accepted.

4.2.2 Significance of Effects

The likelihood ratio test for each effect is tested to check whether the effect of the explanatory variables is significantly different from zero. The Chi – Square statistics is calculated by calculating the difference in -2 Log Likelihood between the final model and the reduced model. Reduced model is formed by omitting the specific effect from the final model at a time. The null hypothesis is defined as the parameter estimates of the effect is zero. If the null hypothesis is rejected, it can be concluded that the parameter estimates of the effect are significantly different from zero, hence the explanatory variable has an effect for the brand choice decision. As shown in the table 4.13, it can be confirmed that Nationality of the passengers, Time of the purchasing, Preference for the promotional activities and preference for weight category are the significant effects which can influence for the brand selection of the purchasers.

Table 4-13: Effect wise likelihood ratio test results for Backward Elimination method

Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	72070.794	0.000	0	
Weight Preference	117997.552	45926.758	12	0.000
Time of purchasing	74259.369	2188.575	9	0.000
Nationality of Passenger	74239.078	2168.284	12	0.000
Preference for Promotion	120228.032	48157.238	12	0.000

4.2.3 Goodness of Fit Test

Though the above model fitting summary statistics show that the final model is accepted, it was derived a contradictory result for Goodness of Fit test which is shown in the table 4.14. It is tested under null hypothesis whether the final model fits the data or not. As per the test statistics, p = 0.000 is laid within the rejection region of the null hypothesis, which concludes that the model does not fit for the data set. However, since the other statistics show the significance of the model, the test Goodness of Fit test statists were ignored and study was continued.

Table 4-14: Results of the Goodness of Fit test – Backward Elimination Method

Goodness-of-Fit Test

	Chi-Square	df	Sig.
Pearson	85392.445	1149	0.000
Deviance	69280.333	1149	0.000

4.2.4 Results of Pseudo R – Square

Below table 4.15 shows the three Pseudo R – Squared values. Multinomial Logistic Regression model does not have an equivalent to the R – squared value which is found in Ordinary Least Square (OLS) regression models. Generally, R – squared value in OLS Regression determines the proportion of the variance of the response variable explained by the explanatory variables. There are number of Pseudo R – Squared statistics which give contradictory results, hence the contradictory conclusions as well. Cox and Snell and Mcfadden R – Squared statistics are not used for decision making due to the inappropriateness studied in early studies. The Nagelkerke R – Square indicates that 44.9% of the total variation in brand choice is explained by the explanatory variables. It is a relatively positive sign for the appropriateness of the model.

Table 4-15: Results for Pseudo R - Square – Backward Elimination Method

Pseudo R-Square

Cox and Snell	.417
Nagelkerke	.449
McFadden	.203

4.2.5 Classification Table

Below mentioned table 4.16 shows the prediction accuracy of the brand from the model against the actual brand choice of the individual purchasers considered in the study. For the selection of Mars and Mondelez brands, the prediction accuracy is over 50%. Out of the 70,920 passengers who actually select Mars as their sharing pack brand, it has been predicted 50650 passengers as brand “Mars” selectors by using the multinomial logistic regression model derived with Backward Elimination method. Therefore, it shows an accuracy percentage of 71.4%. With the current model it has been misclassified 20,270 occasions which the actual brand selection is Mars, but the model has predicted a different brand name. There are 9,000 passengers whose actual brand selection is Mars has been predicted as Mondelez, 4,131 passengers as Nestle purchasers and 7,139 as other brands.

Overall classification accuracy for the Mondelez purchasers is 57%. Out of the 35,016 of total passengers who actually choose Mondelez, model has predicted as 19,959 passengers purchasing Mondelez itself with 57.0% accuracy level. There is a misclassification percentage of 43% with 15,057 purchasers being classified inaccurately. As the classification accuracy is around 57.0%, the proposed model is suitable to predict the Mondelez selectors when the explanatory variables are known.

For Nestle brand, out of 32,470 Nestle purchasing customers, it was only capable of predicting 9,992 purchasers as purchasing Nestle as their sharing pack brand which is only 30.8% classification accuracy. Out of the total Nestle purchasers, it was classified 12,299 purchasers as Mars buyers which is 37.8% from the total. Therefore, it is not a good model to predict the Nestle purchasers due to the low classification accuracy percentage.

Table 4-16: Classification Accuracy of the Entry Model

Classification Accuracy

Observed	Predicted				
	Mars	Mondelez	Nestle	Other	Percent Correct
Mars	50650	9000	4131	7139	71.4%
Mondelez	13099	19959	1144	814	57.0%
Nestle	12299	6575	9992	3604	30.8%
Other	19605	1552	5612	12384	31.6%
Overall Percentage	53.9%	20.9%	11.8%	13.5%	52.4%

For airline passengers who purchase other brands as their sharing pack brand, the classification accuracy remains at 31.6% with correctly classifying 12,384 purchasers out of total purchasers of 39,153 during the study period. There are 26,769 purchasers have been inaccurately classified to other 3 brands which is a 68.4% inaccuracy level. Therefore, for other brands also, it is not recommended to use the final model to predict the Other brand purchasers.

However, the overall classification accuracy is 52.4%. Hence the proposed model can be accepted as an acceptable model to predict the buying behaviors of the departure and transit passengers when the nationality, time of purchasing in the year, preference for promotions and sharing preference (preferred product weight) are known.

4.3 Interpretation of Parameter Estimates

In this section, it is deeply discussed the parameter estimates for each brand derived from the forward entry method compared to the base category of alternative other brands. Under interpretations, it will be discussed 2 main areas; significance of the regression coefficients and Odds. With the odd ratios, it is discussed how the preference for purchase of a brand relative to the other brands differs with the levels of the factors. SPSS results of the parameter estimates are shown in three separate tables with each brand of chocolate against the alternative other brands.

4.3.1 Mars Relative to Other Brands

Significance of Parameter Estimates

Below shown table 4.17 summarizes the parameter estimates and the exponential of the parameter estimates which elaborates the odds and odd ratios with other statistical results comparing Mars with Other brand category. The Wald test statistics is tested for Mars relative to other brands. The Wald test statistics for the sales in the 1st quarter is 0.005 with an associated p – value of 0.807. With the significance level of 5%, we would fail to reject the null hypothesis and conclude with that the regression coefficient for sales of Mars brand chocolates compared to other brands during the quarter 1 has not been found statistically different from zero. All the other regression coefficients are found statistically different from zero due to there are no Wald test statistics with associated p – values > 0.05. A diagnostic examination was conducted on the multinomial logistic regression model with 4 predictor variables in order to check the multicollinearity among the predictor variables. Value of the standard errors of the predictor variables are analyzed. As seen in the table, standard errors of the predictor variables lie between 0 and 2, it can be confirmed that the no multicollinearity among the predictors.

Interpretation of Odds

1. Nationality of the Purchasers

Multinomial logit for all the nationality groups related to the other nationality group (other origin passengers) are lower for preferring Mars relative to other brands given all the other predictor variables held constant or irrespectively to the predictor variables. Therefore, comparing Mars to other brands, it is less likely to do purchase Mars brand sharing packs by North Americans, Europeans, East and south east Asians and south Asians compared to other nationalities (Table 4.17). However, the preference of purchase Mars chocolates over other brands for South Asians would reduce by only 0.254 units while the preference of the East and South East Asians would drop by 0.899 units. Therefore, the preference to select Mars chocolates over other brands by each nationality group compared to other nationality group can be ordered as below,

$$\text{East Asians} < \text{Europeans and Australian} < \text{North Americans} < \text{South Asians} < \text{Other Nationalities}$$

2. Purchasing Time

As per the results shown in Table 4.17, Multinomial logit for purchasing time – Quarter 1 related to category – quarter 4 is only 0.005 units higher for preferring Mars relative to Other brands given all other predictor variables held constant. Therefore, comparing

Table 4-17: Parameter Estimates for Mars relative to other brands

Brand Preference		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Mars	Intercept	-.954	.041	539.567	1	.000			
	[Weight Pref. = 0 g – 290 g]	.900	.045	406.681	1	.000	2.459	2.253	2.684
	[Weight Pref. = 291 g – 490 g]	2.059	.037	3103.447	1	0.000	7.835	7.288	8.424
	[Weight Pref. = 492 g – 710 g]	1.221	.037	1090.445	1	.000	3.391	3.154	3.646
	[Weight Pref. = 711g – 1000 g]	.824	.049	283.986	1	.000	2.280	2.071	2.509
	[Weight Pref. = > 1000]	0			0				
	[Purchasing time= Quart 1]	.005	.020	.060	1	.807	1.005	.966	1.045
	[Purchasing time= Quart 2]	-.326	.020	269.471	1	.000	.722	.694	.751
	[Purchasing time= Quart 3]	-.184	.019	91.917	1	.000	.832	.801	.864
	[Purchasing time= Quart 4]	0			0				
	[Pax Nationality = North America]	-.576	.074	60.656	1	.000	.562	.486	.650
	[Pax Nationality = Europe and Aus.]	-.690	.030	526.545	1	.000	.502	.473	.532
	[Pax Nationality = East Asia]	-.899	.027	1082.892	1	.000	.407	.386	.429
	[Pax Nationality = South Asia]	-.254	.018	192.672	1	.000	.776	.748	.804
	[Pax Nationality = Other Origin]	0			0				
	[Promo Pref.= 2+1]	.394	.019	412.416	1	.000	1.483	1.428	1.541
	[Promo Pref.= 3+1]	1.824	.023	6051.974	1	0.000	6.194	5.915	6.485
	[Promo Pref.= Save Dollar]	-.889	.024	1394.355	1	.000	.411	.392	.431
	[Promo Pref.= Mix n match]	3.288	.061	2913.398	1	0.000	26.793	23.778	30.191
	[Promo Pref.= No Promo]	0			0				

Mars to Other brands, it is more likely to do purchases during the 1st quarter of the year over 4th quarter. However, during the 2nd and 3rd quarters of the year, it is less likely to purchase Mars brand chocolates comparing to other brands in the sharing pack segment by lowering the preference by 0.326 and 0.184 units respectively.

Therefore, the relative preference for Mars brand chocolates over the other brands during each quarters of the year compared to 4th quarter can be listed as,

$$\text{Quarter 2} < \text{Quarter 3} < \text{Quarter 4} < \text{Quarter 1}$$

3. Preference for Promotions

Multinomial logit for promotional preference for dollar off promos related to other types of promotions is 0.889 units lower for preferring Mars relative to other brands given all the other predictor variables held constant in the model (Table 4.17). Therefore, in simple words, it is less likely to select products with dollar off promos over no promotions compared to Mars brand sharing packs over other brands sharing packs. However, comparing to Mars brand over other brands, it is more likely to select products with 2+1, 3+1 and mix and match promotions over no promotions. The preference to purchase Mars brand chocolates over other brands would increase by 3.288 units when there is a Mix and Match promotion over no promotion situation. Compared to buy 2 get 1 free and buy 3 get 1 free promotion over no promotion, the relative preference for Mars compared to other brands would increase by 0.394 and 1.834 units only.

Below is the preference order for promotion activities over no promotion activities,

$$\text{dollar off} < \text{no promo} < \text{buy 2 get 1 free} < \text{buy 3 get 1 free} < \text{mix and match}$$

Therefore, when there is a promotion campaign is started to Mars brands sharing packs over other brands, it is more likely to purchasers go for Mars chocolates sharing packs except for products with dollar off promotions. Thus it is an indication that, dollar off promotion is not a successful promotion type that can be used for Mars brand sharing packs.

4. Preference for Weight Category

Multinomial logit for weight category one (0 g – 290 g) related to weight category four (> 1000g) is 0.900 units higher for preferring Mars relative to Other brands given all other predictor variables in the model are held constant (Table 4.17). In other words, comparing to Mars Brand to other brands, it is more likely to purchase for weight category of 0 g to 291 g over more than 1000g weight category chocolates. Apart from that, multinomial logits for all the other weight categories compared to over 1000g weight category show increases in the preference for buying Mars chocolates over other branded chocolates.

The order of increasing the preference of purchase Mars chocolates over other brands compared to weight over 1000 shows as below,

$$(\text{over } 1000\text{g}) < (710\text{ g} - 1000\text{ g}) < (0\text{ g} - 290\text{ g}) < (491\text{ g} - 710\text{ g}) < (291\text{ g} - 490\text{ g})$$

Therefore, for customers with low and moderate sharing preferences over very high sharing preferences would like to choose Mars brand chocolates compared to other brand chocolates.

4.3.2 Mondelez relative to Other brands

Significance of Parameter Estimates

Below shown Table 4.18 elaborates the parameter estimates and the exponential of the parameter estimates which describe the odds and odd ratios with other statistical results comparing Mondelez with Other brand category. The Wald test statistics for the Mondelez sales for the North Americans is - 0.183 with an associated p – value of 0.035. However, with the significance level of 5%, we would fail to reject the null hypothesis and conclude with that the regression coefficient for selection of Mondelez chocolates over other brands by North Americans has been found statistically significant from zero. All the other regression coefficients are found statistically significant from zero due to there are no Wald test statistics with associated p – values > 0.05. Standard errors of the predictor variables are analyzed in order to check the multicollinearity among the factors. As seen in the table 4.18, standard errors of the predictor variables lie between 0 and 2, thus it can be confirmed that the no multicollinearity among the predictors.

Interpretation of Odds

1. Nationality of the Purchasers

Multinomial logit for all the consumers' groups from one to four (i.e.: North Americans, Europeans and Australians, East and South East Asia and South Asia) nationality groups related to the other nationality (other origin consumers) group are lower for preferring Mondelez relative to other brands given all the other predictor variables held constant (Table 4.18). Therefore, comparing Mondelez to other brands, it is less likely to do purchases by North Americans, Europeans, East and south east Asians and south Asians compared to other origin nationalities.

If the individual nationality groups are considered over the other nationality group, the highest reduction in the preference is shown by East Asians followed by Europeans and Australians. The lowest reduction in the preference is shown by North Americans with 0.183 units than the other nationalities. The nationality wise preference order for Mondelez chocolates over other brands can be shown as below,

$$\text{East Asians} < \text{Europeans and Australians} < \text{South Asians} < \text{North Americans} < \text{Other Nationalities}$$

2. Purchasing Time

Multinomial logit for preferring Mondelez brand relative to other brand chocolates in quarter one and quarter three related to quarter four are respectively 0.738 and 0.353 units higher given all other predictor variables held constant (Table 4.18). Therefore, comparing Mondelez to Other brands, it is more likely to do purchases during the January to March (first quarter) and July to September (third quarter) over the sales in October to December (fourth quarter). However, during the 2^{nd} quarter of the year, it is shown 0.076 units lower for preferring Mondelez sharing packs over the other brand sharing packs when all the other predictor variables held constant. It is an indication for the sales and marketing departments to focus on the special activities to boost the sales during the April to June period of the year.

The order of preference to choose Mondelez chocolates over other brands shown below,

$$\text{Quarter 2} < \text{Quarter 4} < \text{Quarter 3} < \text{Quarter 1}$$

3. Preference for Promotions

As shown in the above table (4.18), Multinomial logit for all the promotional activities related to no promotion category are higher for preferring Mondelez relative to other brands given all the other predictor variables held constant in the model. For mix and match promotions related to no promotion, it shows the highest unit increase in preference of 4.101 units for Mondelez with respective to other brands category. Apart from that 3 + 1 promotion shows 3.827 units increase and 2 + 1 promotion shows 3.243 units increase in preference comparing to no promotion with respective to Mondelez sharing chocolates over other brands sharing pack chocolates. For dollar off promotions related to no promotion, the multinomial logit shows only 1.409 units increase in preferring Mondelez over other chocolate brands when all the other predictor variables held constant. Therefore, having dollar off promotion activities over no promotions will not give much rising for the preference to purchase Mondelez sharing packs over other brands sharing packs with compare to 2+1, 3+1 and mix and match promotions. Hence, it is questionable to have Dollar off promotions for Mondelez chocolates as well.

Below is the relative order of the preference for promotional activities for Mondelez brand chocolates over other brands,

$\text{no promo} < \text{dollar off} < \text{buy 2 get 1 free} < \text{buy 3 get 1 free} < \text{mix and match}$

4. Preference for Weight Category

According to the results shown in Table 4.18, multinomial logit for preference for all weight categories related to weight category preference for over 1000g show higher number of unit increases for preferring Mondelez relative to Other brands given all other predictor variables in the model are held constant. The situation arises since there are no products offered by Mondelez brand with volume of more than 1000 grams. Therefore, it can be concluded that, comparing to Mondelez sharing packs to other brands sharing packs, it is more likely to purchase sharing packs with volume of less than 1000g compared to over 1000g sharing packs. However, if the multinomial logit is re – evaluated except for over 1000g packs, the highest preference is shown for 0g – 290g weight category followed by 291g – 490g category. The 491g – 710g weight category shows the minimum increase in the buying preference.

The order of increasing the preference of purchase Mondelez chocolates over other brands compared to weight over 1000 shows as below,

$(\text{over } 1000\text{g}) < (491 \text{ g} - 710 \text{ g}) < (710 \text{ g} - 1000 \text{ g}) < (291 \text{ g} - 490 \text{ g}) < (0 \text{ g} - 290 \text{ g})$

Table 4-18: Parameter Estimates for Mondelez relative to other brands

Brand Preference		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Mondelez	Intercept	-23.626	.062	145836.707	1	0.000			
	[Weight Pref. = 0 g – 290 g]	22.711	.059	149242.424	1	0.000	7.30E+09	6.51E+09	8.19E+09
	[Weight Pref. = 291 g – 490 g]	22.064	.053	171399.618	1	0.000	3.82E+09	3.44E+09	4.24E+09
	[Weight Pref. = 492 g – 710 g]	18.718	.057	109287.990	1	0.000	1.35E+08	1.21E+08	1.50E+08
	[Weight Pref. = 711g – 1000 g]	19.470	0.000		1		2.86E+08	2.86E+08	2.86E+08
	[Weight Pref. = > 1000]	0			0				
	[Purchasing time= Quart 1]	.738	.025	857.949	1	.000	2.092	1.991	2.198
	[Purchasing time= Quart 2]	-.076	.025	9.048	1	.003	.926	.881	.974
	[Purchasing time= Quart 3]	.353	.024	209.903	1	.000	1.423	1.357	1.493
	[Purchasing time= Quart 4]	0			0				
	[Pax Nationality = North America]	-.183	.086	4.467	1	.035	.833	.703	.987
	[Pax Nationality = Europe and Aus.]	-.357	.037	93.793	1	.000	.700	.651	.752
	[Pax Nationality = East Asia]	-.470	.033	198.474	1	.000	.625	.586	.667
	[Pax Nationality = South Asia]	-.186	.023	67.779	1	.000	.830	.794	.868
	[Pax Nationality = Other Origin]	0			0				
	[Promo Pref.= 2+1]	3.243	.029	12792.110	1	0.000	25.613	24.214	27.094
	[Promo Pref.= 3+1]	3.827	.030	16254.115	1	0.000	45.905	43.282	48.686
	[Promo Pref.= Save Dollar]	1.409	.031	2061.154	1	0.000	4.093	3.851	4.349
	[Promo Pref.= Mix n match]	4.101	.068	3632.603	1	0.000	60.414	52.871	69.033
	[Promo Pref.= No Promo]	0			0				

4.3.3 Nestle respective to Other Brands

Significance of Parameter Estimates

It is tested the Wald test statistics for Nestle brands chocolates of Sharing packs relative to other brands as shown in the below Table 4.19. The Wald test statistics for the sales of chocolates in mix and match promotion category is -17.421 with an associated p – value of 0.957. With the 0.05 level of significance, we would fail to reject the null hypothesis and conclude with that the regression coefficient for sales of chocolates with mix and match promotional activities has not been found statistically significant from zero. All the other regression coefficients are found statistically significant from zero due to there were no Wald test statistics with associated p – values > 0.05. A diagnostic examination is conducted on the multinomial logistic regression model with 4 predictor variables to check the prevalence of the multicollinearity among the predictor variables. Standard errors of the predictor variables are analyzed. As seen in the table, standard errors of the predictor variables lie between 0 and 2, it can be confirmed that the no multicollinearity among the predictors.

Interpretation of Odds

1. Nationality of the Purchasers

Multinomial logit for all the consumers' groups from one to four (i.e.: North Americans, Europeans and Australians, East and South East Asia and South Asia) nationality groups related to the other nationality (other origin consumers) group are lower for preferring Nestle branded chocolates relative to other brands given all the other predictor variables held constant (Table 4.19). Therefore, comparing Nestle to other brands, it is less likely to do purchases by North Americans, Europeans, East and south east Asians and south Asians compared to other origin nationalities.

When the individual nationality groups are considered over the other nationality group, the highest reduction in the preference is shown by East Asians followed by South Asians with 0.934 and 0.548 units respectively. The lowest reduction in the preference is shown by North Americans with 0.250 units compared to the other nationalities. The nationality wise preference order for Nestle chocolates over other brands can be shown as below,

$$\begin{aligned}&\text{East Asians} < \text{South Asians} < \text{Europeans and Australians} < \text{North Americans}\\&\quad < \text{Other Nationalities}\end{aligned}$$

2. Purchasing Time

Multinomial logit for preferring Nestle brand chocolates relative to other brand chocolates in quarter one to quarter three related to quarter four are higher when given all other predictor variables held constant (Table 4.19). Therefore, comparing Nestle to Other brands, it is more likely to do purchases during the first 9 months from January to September over the sales in October to December (fourth quarter).

When the individual quarters are considered over the last quarter of the year, the highest increase in the preference is shown during the 1st quarter of the year followed by the preference increment in third quarter of the year with 0.148 and 0.129 units respectively. The lowest increment in the preference is shown during the second quarter of the year with only 0.096 units compared to the fourth quarter.

The quarter wise preference order for Nestle chocolates over other brands can be shown as below,

$$\text{Quarter 4} < \text{Quarter 2} < \text{Quarter 3} < \text{Quarter 1}$$

3. Preference for promotions

As shown in the below table 4.18, Multinomial logit for buy 2 get 1 free and buy 3 get 1 free promotional activities related to no promotion category are higher for preferring Nestle brand chocolates relative to other brands given all the other predictor variables held constant in the model. For buy 3 get 1 free promotions related to no promotion, it shows the highest unit increase in preference of 1.004 units for Nestle with respective to other brands category. Apart from that buy 2 get one free promotion shows 0.706 units increase in preference comparing to no promotion with respective to Nestle sharing chocolates over other brands sharing pack chocolates. For dollar off promotions and mix and match promotions related to no promotion, the multinomial logit show decreases in preferring Nestle over other chocolate brands when all the other predictor variables held constant. The preference in Nestle sharing packs over other brand sharing packs is reducing by 17.421 units compared to mix and match promotions with no promotions for Nestle brands. Apart from that, when there is a dollar off promotion is activated over no promotion, the preference for choosing Nestle chocolate over other brands is reducing by only 0.579 units. Therefore, having dollar off promotion and mix and match promotion activities over no promotions will not give much rising for the preference to purchase Nestle sharing packs over other brands sharing packs with compare to buy 2 get 1 free and buy 3 get 1 free. Hence, it is questionable to have Dollar off and mix and match promotions for Nestle chocolates as well.

Below is the relative order of the preference for promotional activities for Nestle brand chocolates over other brands,

$$\text{mix and match} < \text{dollar off} < \text{no promo} < \text{buy 2 get 1 free} < \text{buy 3 get 1 free}$$

4. Preference for Weight Category

Multinomial logit for weight category one (0 g – 290 g) related to weight category four (> 1000g) is 4.268 units higher for preferring Nestle relative to Other brands given all other predictor variables in the model are held constant (Table 4.19). In other words, comparing to Nestle Brand to other brands, it is more likely to purchase for weight category of 0 g to 290 g over more than 1000g weight category chocolates. Apart from that, multinomial logits for all the other weight categories compared to over 1000g weight category show increases in the preference for buying Nestle chocolates over other branded chocolates.

The order of increasing the preference of purchase Nestle chocolates over other brands compared to weight over 1000 shows as below,

$$(\text{over } 1000\text{g}) < (491\text{ g} - 710\text{ g}) < (291\text{ g} - 490\text{ g}) < (0\text{ g} - 290\text{ g}) < (710\text{ g} - 1000\text{ g})$$

Therefore, for customers with very low and high sharing preferences over very high sharing preferences would like to choose Nestle brand chocolates compared to other brand chocolates. Customers with low and moderate sharing preference would prefer less to choose Nestle chocolates over other brand chocolates when compared to customers with very low and high sharing preferences.

Table 4-19: Parameter Estimates for Nestle relative to other brands

Brand Preference		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Nrstle	Intercept	-3.493	.103	1160.681	1	.000			
	[Weight Pref. = 0 g – 290 g]	4.268	.102	1736.600	1	0.000	71.387	58.404	87.257
	[Weight Pref. = 291 g – 490 g]	3.403	.101	1143.528	1	.000	30.065	24.682	36.620
	[Weight Pref. = 492 g – 710 g]	3.159	.100	990.133	1	.000	23.557	19.349	28.681
	[Weight Pref. = 711g – 1000 g]	4.619	.103	2008.576	1	0.000	101.437	82.882	124.146
	[Weight Pref. = > 1000]	0			0				
	[Purchasing time= Quart 1]	.148	.023	40.942	1	.000	1.160	1.108	1.213
	[Purchasing time= Quart 2]	.096	.023	17.881	1	.000	1.100	1.053	1.150
	[Purchasing time= Quart 3]	.129	.022	33.549	1	.000	1.138	1.089	1.189
	[Purchasing time= Quart 4]	0			0				
	[Pax Nationality = North America]	-.250	.077	10.610	1	.001	.778	.670	.905
	[Pax Nationality = Europe and Aus.]	-.458	.032	199.446	1	.000	.633	.594	.674
	[Pax Nationality = East Asia]	-.934	.031	898.012	1	.000	.393	.370	.418
	[Pax Nationality = South Asia]	-.548	.020	730.962	1	.000	.578	.556	.601
	[Pax Nationality = Other Origin]	0			0				
	[Promo Pref.= 2+1]	.706	.022	1069.560	1	.000	2.026	1.942	2.114
	[Promo Pref.= 3+1]	1.004	.028	1316.958	1	.000	2.730	2.586	2.882
	[Promo Pref.= Save Dollar]	-.579	.027	451.280	1	.000	.560	.531	.591
	[Promo Pref.= Mix n match]	-17.421	1.831	.003	1	.957	2.716E-08	3.095E-282	2.384E+266
	[Promo Pref.= No Promo]	0			0				

4.4 Probability of Brand Selection

As per the above sections, multinomial logistic regression model for brand choice is tested and approved, thus it can be used for the prediction of brand wise purchasing probabilities subjected to different levels in Nationality (X_1), Time of Purchase (X_2), Preference for promotions (X_3), and preference for weights (X_4).

Multinomial Logistic Regression model equation which was discussed under Materials and Methods (Equation 3.6) is used to calculate the log of probability of selecting particular brand of chocolate (i.e.: Mars, Mondelez, Nestle) over the log of probability of selecting other brands. Below mentioned equations of 4.1, 4.2 and 4.3 are shown Multinomial Logistic Regression of selecting Mars, Mondelez and Nestle over other brands respectively.

Once the Multinomial Logistic Regression model for each brand is derived with respect to the other brands, Multinomial Logistic Transformation equation which was discussed under Materials and Methods (Equation 3.7) is used to calculate the probability of selecting particular brand name of chocolate (i.e.: Mars, Mondelez, Nestle). Below mentioned equations of 4.4, 4.5, 4.6 and 4.7 are shown Multinomial Logistic Regression of selecting Mars, Mondelez, Nestle and other brands respectively.

$$
\begin{aligned}
\ln\left(\frac{\mathrm{Prob(brand = Mars)}}{\mathrm{prob(brand = Other)}}\right)
&= \beta_{\mathrm{Mars},0} + \beta_{\mathrm{Mars},1}(\mathrm{nationality} = 1) + \beta_{\mathrm{Mars},2}(\mathrm{nationality} = 2) \\
&+ \beta_{\mathrm{Mars},3}\ (\mathrm{nationality} = 3) + \beta_{\mathrm{Mars},4}(\mathrm{nationality} = 4) \\
&+ \beta_{\mathrm{Mars},5}(\mathrm{nationality} = 5) + \beta_{\mathrm{Mars},6}(\mathrm{time\ of\ purchase} = 1) \\
&+ \beta_{\mathrm{Mars},7}(\mathrm{time\ of\ purchase} = 2) + \beta_{\mathrm{Mars},8}(\mathrm{time\ of\ purchose} = 3) \\
&+ \beta_{\mathrm{Mars},9}(\mathrm{time\ of\ purchase} = 4) + \beta_{\mathrm{Mars},10}(\mathrm{promo\ pref.} = 1) \\
&+ \beta_{\mathrm{Mars},11}(\mathrm{promo\ pref.} = 2) + \beta_{\mathrm{Mars},12}(\mathrm{promo\ pref.} = 3) \\
&+ \beta_{\mathrm{Mars},13}(\mathrm{promo\ pref.} = 4) + \beta_{\mathrm{Mars},14}(\mathrm{promo\ pref.} = 5) \\
&+ \beta_{\mathrm{Mars},15}(\mathrm{weight\ pref.} = 1) + \beta_{\mathrm{Mars},16}(\mathrm{weight\ pref.} = 2) \\
&+ \beta_{\mathrm{Mars},17}(\mathrm{weight\ pref.} = 3) + \beta_{\mathrm{Mars},18}(\mathrm{weight\ pref.} = 4) \\
&+ \beta_{\mathrm{Mars},19}(\mathrm{weight\ pref.} = 5) = (\beta'_{\mathrm{Mars}}\mathrm{X_i})\ (4.1)
\end{aligned}
$$

Equation 4-1: Multinomial Logistic Regression for selection of Mars

$$\ln(\frac{\text{Prob(brand = Mondelez)}}{\text{prob(brand = Other)}})$$
$$= \beta_{Mondelez,0} + \beta_{Mondelez,1}(\text{nationality} = 1)$$
$$+ \beta_{Mondelez,2}(\text{nationality} = 2) + \beta_{Mondelez,3}(\text{nationality} = 3)$$
$$+ \beta_{Mondelez,4}(\text{nationality} = 4) + \beta_{Mondelez,5}(\text{nationality} = 5)$$
$$+ \beta_{Mondelez,6}(\text{time of purchase} = 1)$$
$$+ \beta_{Mondelez,7}(\text{time of purchase} = 2)$$
$$+ \beta_{Mondelez,8}(\text{time of purchose} = 3)$$
$$+ \beta_{Mondelez,9}(\text{time of purchase} = 4) + \beta_{Mondelez,10}(\text{promo pref.} = 1)$$
$$+ \beta_{Mondelez,11}(\text{promo pref.} = 2) + \beta_{Mondelez,12}(\text{promo pref.} = 3)$$
$$+ \beta_{Mondelez,13}(\text{promo pref.} = 4) + \beta_{Mondelez,14}(\text{promo pref.} = 5)$$
$$+ \beta_{Mondelez,15}(\text{weight pref.} = 1) + \beta_{Mondelez,16}(\text{weight pref.} = 2)$$
$$+ \beta_{Mondelez,17}(\text{weight pref.} = 3) + \beta_{Mondelez,18}(\text{weight pref.} = 4)$$
$$+ \beta_{Mondelez,19}(\text{weight pref.} = 5) = (\beta'_{Mondelez}X_i)(4.2)$$

Equation 4-2: Multinomial Logistic Regression for selection of Mondelez

$$\ln(\frac{\text{Prob(brand = Nestle)}}{\text{prob(brand = Other)}})$$
$$= \beta_{Nestle,0} + \beta_{Nestle,1}(\text{nationality} = 1) + \beta_{Nestle,2}(\text{nationality} = 2)$$
$$+ \beta_{Nestle,3}(\text{nationality} = 3) + \beta_{Nestle,4}(\text{nationality} = 4)$$
$$+ \beta_{Nestle,5}(\text{nationality} = 5) + \beta_{Nestle,6}(\text{time of purchase} = 1)$$
$$+ \beta_{Nestle,7}(\text{time of purchase} = 2) + \beta_{Nestle,8}(\text{time of purchose} = 3)$$
$$+ \beta_{Nestle,9}(\text{time of purchase} = 4) + \beta_{Nestle,10}(\text{promo pref.} = 1)$$
$$+ \beta_{Nestle,11}(\text{promo pref.} = 2) + \beta_{Nestle,12}(\text{promo pref.} = 3)$$
$$+ \beta_{Nestle,13}(\text{promo pref.} = 4) + \beta_{Nestle,14}(\text{promo pref.} = 5)$$
$$+ \beta_{Nestle,15}(\text{weight pref.} = 1) + \beta_{Nestle,16}(\text{weight pref.} = 2)$$
$$+ \beta_{Nestle,17}(\text{weight pref.} = 3) + \beta_{Nestle,18}(\text{weight pref.} = 4)$$
$$+ \beta_{Nestle,19}(\text{weight pref.} = 5) = (\beta'_{Nestle}X_i)\ (4.3)$$

Equation 4-3: Multinomial Logistic Regression for selection of Nestle

$$p\ (Y_i = \text{Mars}) = \frac{\exp(\beta'_{Mars}X_i)}{1 + \sum_{J=1}^{j-1} \beta'_j X_i}\ \ (4.4)$$

Equation 4-4: Multinomial Logistic Transformation of selection of Mars

$$p\ (Y_i = \text{Mondelez}) = \frac{\exp(\beta'_{Mondelez}X_i)}{1 + \sum_{J=1}^{j-1} \beta'_j X_i}\ (4.5)$$

Equation 4-5: Multinomial Logistic Transformation of selection of Mondelez

$$p\ (Y_i = \text{Nestle}) = \frac{\exp(\beta'_{\text{Nestle}} X_i)}{1 + \sum_{J=1}^{j-1} \beta'_j X_i} \quad (4.6)$$

Equation 4-6: Multinomial Logistic Transformation of selection of Nestle

$$p\ (Y_i = \text{Other}) = \frac{1}{1 + \sum_{J=1}^{j-1} \beta'_j X_i} \quad (4.7)$$

Equation 4-7: Multinomial Logistic Transformation of selection of Other brands

Where,

Nationality 1 = North America
Nationality 2 = Europe and Australia
Nationality 3 = East and South East Asia
Nationality 4 = South Asia
Nationality 5 = Other origin
Time of purchase 1 = quarter 1
Time of purchase 2 = quarter 2
Time of purchase 3 = quarter 3
Time of purchase 4 = quarter 4
Promo pref. 1 = 2 + 1
Promo pref. 2 = 3 + 1
Promo pref. 3 = dollar off
Promo pref. 4 = mix and match
Promo pref. 5 = no promotions
Weight pref. 1 = 0 – 290g
Weight pref. 2 = 291g – 490g
Weight pref. 3 = 491g – 710g
Weight pref. 4 = 711g – 1000g
Weight pref. 5 => 1000g

4.4.1 Calculate the Brand Choice Probabilities

Probabilities of selecting a chocolate brand which was under the weight category of 0 grams to 290 grams were calculated by using the multinomial logistic transformation. They were calculated under different states of the factors; Nationality (X_1), Time of Purchase (X_2), promotional preference (X_3) and preference of weight category (X_4). In a particular table, it is shown the fixed status of preference of weight category (X_4) and Preference for promotional category (X_3) in the given weight category of 0 grams to 290 grams. The relative probabilities of selecting a given brand is grouped considering the all levels of nationalities to compare easily the nationality wise brand selection probabilities under fixed Time of Purchase (X_2) and promotional preference (X_3).

Below mentioned tables 4.20, 4.21, 4.22, 4.23 and 4.24 show the respective nationality wise probabilities of selecting a chocolate brand of weight category of 0 grams to 290 grams under different states of promotional preference; buy 2 get 1 free, buy 3 get 1 free, cash discounts, mix and match and no promotions respectively.

Table 4-20: Brand Preference Probability - fixed Weight Category 1 and promo category 1

				Time of Purchase (X2)			
Weight Category (X4)	**Promo Category (X3)**	**Nationality Group (X1)**	**Brand Preference (Yi)**	**Q1**	**Q2**	**Q3**	**Q4**
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = North America (1)	Y(i) = Mars (1)	0.034	0.033	0.024	0.057
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Europe + Australia (2)	Y(i) = Mars (1)	0.035	0.035	0.025	0.060
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = East and South East Asia (3)	Y(i) = Mars (1)	0.034	0.034	0.024	0.059
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = South Asia (4)	Y(i) = Mars (1)	0.048	0.049	0.034	0.083
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Other (5)	Y(i) = Mars (1)	0.049	0.048	0.035	0.082
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = North America (1)	Y(i) = Mondelez (2)	0.756	0.586	0.761	0.621
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Europe + Australia (2)	Y(i) = Mondelez (2)	0.753	0.582	0.758	0.615
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = East and South East Asia (3)	Y(i) = Mondelez (2)	0.789	0.632	0.794	0.660
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = South Asia (4)	Y(i) = Mondelez (2)	0.779	0.626	0.788	0.648
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Other (5)	Y(i) = Mondelez (2)	0.741	0.573	0.749	0.601
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = North America (1)	Y(i) = Nestle (3)	0.168	0.301	0.171	0.249
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Europe + Australia (2)	Y(i) = Nestle (3)	0.162	0.289	0.165	0.239
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = East and South East Asia (3)	Y(i) = Nestle (3)	0.118	0.218	0.120	0.178
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = South Asia (4)	Y(i) = Nestle (3)	0.129	0.240	0.132	0.193
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Other (5)	Y(i) = Nestle (3)	0.176	0.315	0.180	0.258
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = North America (1)	Y (i) = Others (4)	0.042	0.044	0.044	0.073
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Europe + Australia (2)	Y (i) = Others (4)	0.050	0.052	0.052	0.086
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = East and South East Asia (3)	Y (i) = Others (4)	0.059	0.061	0.061	0.103
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = South Asia (4)	Y (i) = Others (4)	0.044	0.046	0.046	0.076
X4 = 0g - 290g (1)	X3 = 2+1 (1)	X1 = Other (5)	Y (i) = Others (4)	0.035	0.036	0.036	0.059

Table 4-21: Brand Preference Probability - fixed Weight Category 1 and promo category 2

				Time of Purchase (X2)			
Weight Category (X4)	**Promo Category (X3)**	**Nationality Group (X1)**	**Brand Preference (Y)**	**Q1**	**Q2**	**Q3**	**Q4**
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = North America (1)	Y(i) = Mars (1)	0.079	0.096	0.089	0.136
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Europe + Australia (2)	Y(i) = Mars (1)	0.084	0.096	0.094	0.143
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = East and South East Asia (3)	Y(i) = Mars (1)	0.080	0.096	0.090	0.139
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = South Asia (4)	Y(i) = Mars (1)	0.110	0.096	0.124	0.188
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Other (5)	Y(i) = Mars (1)	0.113	0.096	0.126	0.188
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = North America (1)	Y(i) = Mondelez (2)	0.768	0.627	0.708	0.632
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Europe + Australia (2)	Y(i) = Mondelez (2)	0.764	0.622	0.704	0.626
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = East and South East Asia (3)	Y(i) = Mondelez (2)	0.798	0.668	0.744	0.668
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = South Asia (4)	Y(i) = Mondelez (2)	0.770	0.637	0.715	0.630
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Other (5)	Y(i) = Mondelez (2)	0.736	0.592	0.675	0.590
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = North America (1)	Y(i) = Nestle (3)	0.128	0.224	0.170	0.190
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Europe + Australia (2)	Y(i) = Nestle (3)	0.123	0.215	0.164	0.182
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = East and South East Asia (3)	Y(i) = Nestle (3)	0.090	0.161	0.120	0.135
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = South Asia (4)	Y(i) = Nestle (3)	0.096	0.170	0.128	0.141
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Other (5)	Y(i) = Nestle (3)	0.132	0.226	0.174	0.190
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = North America (1)	Y (i) = Others (4)	0.024	0.032	0.032	0.041
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Europe + Australia (2)	Y (i) = Others (4)	0.028	0.038	0.038	0.049
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = East and South East Asia (3)	Y (i) = Others (4)	0.033	0.045	0.045	0.058
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = South Asia (4)	Y (i) = Others (4)	0.024	0.033	0.033	0.041
X4 = 0g - 290g (1)	X3 = 3+1 (2)	X1 = Other (5)	Y (i) = Others (4)	0.019	0.026	0.026	0.032

Table 4-22: Brand Preference Probability - fixed Weight Category 1 and promo category 3

				Time of Purchase (X2)			
Weight Category (X4)	**Promo Category (X3)**	**Nationality Group (X1)**	**Brand Preference (Y)**	**Q1**	**Q2**	**Q3**	**Q4**
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = North America (1)	Y(i) = Mars (1)	0.043	0.046	0.043	0.062
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Europe + Australia (2)	Y(i) = Mars (1)	0.044	0.046	0.044	0.063
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = East and South East Asia (3)	Y(i) = Mars (1)	0.041	0.044	0.042	0.060
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = South Asia (4)	Y(i) = Mars (1)	0.061	0.067	0.063	0.090
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Other (5)	Y(i) = Mars (1)	0.063	0.068	0.064	0.092
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = North America (1)	Y(i) = Mondelez (2)	0.552	0.365	0.462	0.387
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Europe + Australia (2)	Y(i) = Mondelez (2)	0.535	0.348	0.445	0.369
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = East and South East Asia (3)	Y(i) = Mondelez (2)	0.556	0.367	0.465	0.385
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = South Asia (4)	Y(i) = Mondelez (2)	0.573	0.388	0.486	0.404
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Other (5)	Y(i) = Mondelez (2)	0.550	0.367	0.463	0.386
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = North America (1)	Y(i) = Nestle (3)	0.212	0.301	0.256	0.268
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Europe + Australia (2)	Y(i) = Nestle (3)	0.199	0.278	0.239	0.247
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = East and South East Asia (3)	Y(i) = Nestle (3)	0.144	0.203	0.174	0.180
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = South Asia (4)	Y(i) = Nestle (3)	0.164	0.238	0.201	0.209
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Other (5)	Y(i) = Nestle (3)	0.226	0.323	0.275	0.286
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = North America (1)	Y (i) = Others (4)	0.193	0.238	0.238	0.283
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Europe + Australia (2)	Y (i) = Others (4)	0.223	0.272	0.272	0.321
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = East and South East Asia (3)	Y (i) = Others (4)	0.259	0.319	0.319	0.376
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = South Asia (4)	Y (i) = Others (4)	0.201	0.251	0.251	0.297
X4 = 0g - 290g (1)	X3 = dollar off (3)	X1 = Other (5)	Y (i) = Others (4)	0.160	0.198	0.198	0.236

Table 4-23: Brand Preference Probability - fixed Weight Category 1 and promo category 4

				Time of Purchase (X2)			
Weight Category (X4)	**Promo Category (X3)**	**Nationality Group (X1)**	**Brand Preference (Y)**	**Q1**	**Q2**	**Q3**	**Q4**
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = North America (1)	Y(i) = Mars (1)	0.249	0.344	0.286	0.403
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Europe + Australia (2)	Y(i) = Mars (1)	0.260	0.355	0.297	0.415
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = East and South East Asia (3)	Y(i) = Mars (1)	0.241	0.332	0.276	0.390
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = South Asia (4)	Y(i) = Mars (1)	0.315	0.420	0.356	0.483
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Other (5)	Y(i) = Mars (1)	0.331	0.439	0.373	0.502
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = North America (1)	Y(i) = Mondelez (2)	0.733	0.623	0.690	0.569
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Europe + Australia (2)	Y(i) = Mondelez (2)	0.720	0.606	0.675	0.552
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = East and South East Asia (3)	Y(i) = Mondelez (2)	0.736	0.624	0.692	0.572
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = South Asia (4)	Y(i) = Mondelez (2)	0.669	0.550	0.622	0.493
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Other (5)	Y(i) = Mondelez (2)	0.656	0.537	0.609	0.478
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = North America (1)	Y(i) = Nestle (3)	0.000	0.000	0.000	0.000
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Europe + Australia (2)	Y(i) = Nestle (3)	0.000	0.000	0.000	0.000
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = East and South East Asia (3)	Y(i) = Nestle (3)	0.000	0.000	0.000	0.000
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = South Asia (4)	Y(i) = Nestle (3)	0.000	0.000	0.000	0.000
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Other (5)	Y(i) = Nestle (3)	0.000	0.000	0.000	0.000
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = North America (1)	Y (i) = Others (4)	0.017	0.024	0.024	0.028
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Europe + Australia (2)	Y (i) = Others (4)	0.020	0.028	0.028	0.033
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = East and South East Asia (3)	Y (i) = Others (4)	0.023	0.032	0.032	0.038
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = South Asia (4)	Y (i) = Others (4)	0.016	0.022	0.022	0.025
X4 = 0g - 290g (1)	X3 = mix and match (4)	X1 = Other (5)	Y (i) = Others (4)	0.013	0.018	0.018	0.020

Table 4-24: Brand Preference Probability - fixed Weight Category 1 and promo category 5

				Time of Purchase (X2)			
Weight Category (X4)	**Promo Category (X3)**	**Nationality Group (X1)**	**Brand Preference (Y)**	**Q1**	**Q2**	**Q3**	**Q4**
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = North America (1)	Y(i) = Mars (1)	0.128	0.108	0.038	0.150
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Europe + Australia (2)	Y(i) = Mars (1)	0.131	0.110	0.038	0.152
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = East and South East Asia (3)	Y(i) = Mars (1)	0.134	0.114	0.038	0.155
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = South Asia (4)	Y(i) = Mars (1)	0.190	0.165	0.038	0.221
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Other (5)	Y(i) = Mars (1)	0.179	0.154	0.038	0.210
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = North America (1)	Y(i) = Mondelez (2)	0.166	0.087	0.124	0.094
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Europe + Australia (2)	Y(i) = Mondelez (2)	0.160	0.083	0.119	0.090
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = East and South East Asia (3)	Y(i) = Mondelez (2)	0.181	0.095	0.135	0.101
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = South Asia (4)	Y(i) = Mondelez (2)	0.179	0.096	0.135	0.100
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Other (5)	Y(i) = Mondelez (2)	0.158	0.084	0.118	0.089
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = North America (1)	Y(i) = Nestle (3)	0.467	0.523	0.501	0.475
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Europe + Australia (2)	Y(i) = Nestle (3)	0.436	0.485	0.466	0.439
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = East and South East Asia (3)	Y(i) = Nestle (3)	0.341	0.383	0.367	0.343
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = South Asia (4)	Y(i) = Nestle (3)	0.374	0.429	0.407	0.378
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Other (5)	Y(i) = Nestle (3)	0.474	0.538	0.512	0.480
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = North America (1)	Y (i) = Others (4)	0.239	0.260	0.260	0.281
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Europe + Australia (2)	Y (i) = Others (4)	0.274	0.298	0.298	0.320
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = East and South East Asia (3)	Y (i) = Others (4)	0.345	0.378	0.378	0.402
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = South Asia (4)	Y (i) = Others (4)	0.257	0.285	0.285	0.301
X4 = 0g - 290g (1)	X3 = Other (5)	X1 = Other (5)	Y (i) = Others (4)	0.188	0.207	0.207	0.221

4.4.2 Nationality Impact on Brand Choice Probability

In order to test whether there are nationality wise differences for the mean probability of selecting a particular brand, one – way ANOVA was used among the nationality groups for each brand preference.

The null hypothesis would be that there are no differences in the mean probability of selecting a particular brand of chocolate by consumers from a particular nationality in a given state of promotional preference and weight group preference.

$$H_0: \mu_{\text{Prob. North Americans}} = \mu_{\text{Prob. Europeans}} = \mu_{\text{Prob. East Asians}} = \mu_{\text{Prob.South Asians}} = \mu_{\text{Prob. Others}}$$

Vs.

$H_1 =$ at least one $\mu_{\text{Prob.Nationality i}}$ is different

Results are tested in 0.05 significance level.

Below tables shows the summary of the conclusions according to each level in the promotional preference.

Table 4-25: Nationality impact on Brand Selection Probabilities – 2+1 Promotion activated

Weight Preference	Promotion Preference	Brand Preference	Null Hypothesis	F value	Sig.	Conclusion
X4 = 0g - 290g (1)	X3 = 2+1 (1)	Y(i) = Mars (1)	no impact from nationality on Mars brand chocolate selection probabilities	0.978	0.449	no impact from nationality on Mars brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = 2+1 (1)	Y(i) = Mondelez (2)	no impact from nationality on Mondelez brand chocolate selection probabilities	0.261	0.899	no impact from nationality on Mondelez brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = 2+1 (1)	Y(i) = Nestle (3)	no impact from nationality on Nestle brand chocolate selection probabilities	1.179	0.36	no impact from nationality on Nestle brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = 2+1 (1)	Y (i) = Others (4)	no impact from nationality on Other brand chocolate selection probabilities	1.1796	0.182	no impact from nationality on Other brand chocolate selection probabilities

As per the results shown in the above table 5.26, when 2+1 promotion is activated for all the brands, nationality impact does not exist for the brand wise mean selection probabilities of chocolate of the 0g – 290g chocolate category.

Table 4-26: Nationality impact on Brand Selection Probabilities – 3+1 Promotion activated

Weight Preference	Promotion Preference	Brand Preference	Null Hypothesis	F value	Sig.	Conclusion
X4 = 0g - 290g (1)	X3 = 3+1 (2)	Y(i) = Mars (1)	no impact from nationality on Mars brand chocolate selection probabilities	0.925	0.475	no impact from nationality on Mars brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = 3+1 (2)	Y(i) = Mondelez (2)	no impact from nationality on Mondelez brand chocolate selection probabilities	0.569	0.689	no impact from nationality on Mondelez brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = 3+1 (2)	Y(i) = Nestle (3)	no impact from nationality on Nestle brand chocolate selection probabilities	0.2072	0.135	no impact from nationality on Nestle brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = 3+1 (2)	Y (i) = Others (4)	no impact from nationality on Other brand chocolate selection probabilities	0.3698	0.027	no impact from nationality on Other brand chocolate selection probabilities

As per the results shown in the above table 5.26, when 3+1 promotion is activated for all the brands, nationality impact does not exist for the brand wise mean selection probabilities of chocolate of the 0g – 290g chocolate category.

Table 4-27: Nationality impact on Brand Selection Probabilities – Dollar off Promotion activated

Weight Preference	Promotion Preference	Brand Preference	Null Hypothesis	F value	Sig.	Conclusion
X4 = 0g - 290g (1)	X3 = dollar off (3)	Y(i) = Mars (1)	no impact from nationality on Mars brand chocolate selection probabilities	0.5248	0.008	impact from nationality on Mars brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = dollar off (3)	Y(i) = Mondelez (2)	no impact from nationality on Mondelez brand chocolate selection probabilities	0.105	0.979	no impact from nationality on Mondelez brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = dollar off (3)	Y(i) = Nestle (3)	no impact from nationality on Nestle brand chocolate selection probabilities	0.6349	0.003	impact from nationality on Nestle brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = dollar off (3)	Y (i) = Others (4)	no impact from nationality on Other brand chocolate selection probabilities	0.5092	0.009	impact from nationality on Other brand chocolate selection probabilities

As per the results shown in the table 5.27, when dollar off promotion is activated for all the brands, nationality impact on mean brand selection probability does not exist for Mondelez brand chocolates while others have nationality impact on the customers' mean probability of brand selection of the 0g – 290g chocolate category.

Table 4-28: Nationality impact on Brand Selection Probabilities – Mix and Match Promotion activated

Weight Preference	Promotion Preference	Brand Preference	Null Hypothesis	F value	Sig.	Conclusion
X4 = 0g - 290g (1)	X3 = mix and match (4)	Y(i) = Mars (1)	no impact from nationality on Mars brand chocolate selection probabilities	0.1717	0.199	no impact from nationality on Mars brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = mix and match (4)	Y(i) = Mondelez (2)	no impact from nationality on Mondelez brand chocolate selection probabilities	1.165	0.365	no impact from nationality on Mondelez brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = mix and match (4)	Y(i) = Nestle (3)	no impact from nationality on Nestle brand chocolate selection probabilities	0.2546	0.83	no impact from nationality on Nestle brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = mix and match (4)	Y (i) = Others (4)	no impact from nationality on Other brand chocolate selection probabilities	0.5895	0.005	impact from nationality on Other brand chocolate selection probabilities

As per the results shown in the table 5.28, when mix and match promotion is activated for all the brands, nationality impact mean brand selection probability exist only for Other brand chocolates while the rest of the brands (i.e.: Mars, Mondelez, Nestle) do not have nationality impact of the customers on brand selection probability of the 0g – 290g chocolate category.

Table 4-29: Nationality impact on Brand Selection Probabilities – No Promotions activated

Weight Preference	Promotion Preference	Brand Preference	Null Hypothesis	F value	Sig.	Conclusion
X4 = 0g - 290g (1)	X3 = Other (5)	Y(i) = Mars (1)	no impact from nationality on Mars brand chocolate selection probabilities	0.541	0.708	no impact from nationality on Mars brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = Other (5)	Y(i) = Mondelez (2)	no impact from nationality on Mondelez brand chocolate selection probabilities	0.17	0.951	no impact from nationality on Mondelez brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = Other (5)	Y(i) = Nestle (3)	no impact from nationality on Nestle brand chocolate selection probabilities	24.118	0	impact from nationality on Nestle brand chocolate selection probabilities
X4 = 0g - 290g (1)	X3 = Other (5)	Y (i) = Others (4)	no impact from nationality on Other brand chocolate selection probabilities	44.185	0	impact from nationality on Other brand chocolate selection probabilities

As per the results shown in the table 5.29, when no promotions are activated for all the brands, nationality impact on mean brand selection probability exists only for Mars and Mondelez brand chocolates while the rest two brand categories (i.e.: Nestle and others) do not have nationality impact of the customers on brand selection probability of the 0g – 290g chocolate category.

4.5 Summary of the Results

Nationality of the consumers, quarter of the year which the purchase is occurred, consumers' preference for promotional activities and consumers' preference for weight category were identified as the influential factors for the chocolate brand choice with the likelihood ratio tests of the multinomial logistic regression model. The Nagelkerke R – Square indicates that 44.9% of the total variation in the brand choice was explained by the model. The overall classification accuracy was 52.4%. The values of the odds of selecting particular brands of chocolate were derived from the parameter estimates of the different levels of the categorical response variables. The different levels of the nationalities do not have significant impact over the brand selection probabilities when the consumers are preferring buy 2 get 1 free or buy 3 get 1 free promotion.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Based on the inferences derived on data analyses in the chapter 4, the following conclusions and recommendations are given,

5.1 Conclusions

1. Nationality of the consumers, time (quarter) of the year which the purchase is occurred, consumers' preference for promotional activities and consumers' preference for weight categories are significant factors on the chocolate brand choice.
2. The relative preference for purchasing any chocolate brand increases during the 1st quarter of the year irrespectively to the brand of chocolates.
3. Buying preference is maximized for Mars and Nestle brand chocolates when there is a mix and match promotion activated.
4. Buying preference for Nestle is maximized for buy 3 and get 1 free promotion.
5. Preference for weight category is variant for the 3 brands.
6. The 291g to 490g category become the most preferred weight category for Mars chocolates, while 0g to 290g and 710g to 1000g would be the respective weight categories for Mondelez and Nestle brand chocolates.
7. There is no impact from the different levels of the nationalities on the purchasing probabilities when the consumers are preferring buy 2 get 1 free or buy 3 get 1 free promotion.
8. Multinomial regression can be effectively used in such studies to derive more useful inferences.

5.2 Recommendations

1. In the study, it is only considered the nationality of the consumers as a demographic characteristic of the consumers due to the unavailability of the secondary data. As per the previous studies related to buying behavior analysis, it has been identified income level, gender, age, life style, family size and presence of children and acculturation level as some of the factors which influence for the buying behaviors. Therefore, if the above mentioned demographic information can be gathered pertaining to each sales entry, that

would help to improve the percentage of variance which is explained by the model.

2. Calculated estimates for the odds and odd ratios can be used to quantify the effect of a factor over selecting a particular chocolate brand when all other factors are controlled as constant.
3. This information can be effectively utilized to determine the relative level of preference to be changed for a particular brand over the reference brand when the explanatory factors are fixed. Therefore, the sales and marketing team can use the information qualitatively to plan the promotional activities accordingly to target the correct group of consumers.
4. The calculated nationality wise probabilities of selecting a chocolate brand for fixed levels of time of purchase, preference for promotion and preference for product weight can be used to estimate the number of potential consumers to select a brand of chocolate when the explanatory variables are known.
5. In the study, the multinomial logistic model was developed to identify the factors influence for the selection of chocolate brands considering the segment which the chocolate brand is belonged to. This model can be further extended to each stock keeping unit level (SKU) by identifying the factors which influence for the selection of each product.
6. Similar studies can be extended for other brands as well.

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