Development of Utility Function for Vehicle Insurance: Comparison of Logarithmic Goal Programming Method and Conjoint Analysis Method

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W. P. No. 2020-02-01

February 2020

INDIAN INSTITUTE OF MANAGEMENT

AHMEDABAD-380 015

INDIA

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Abstract

The increase in competition among the vehicle insurance sectors has increased the number of policy options available in the market. This study focuses on the development of a utility function for these policies that will aid policy holders and potential investors in comparing them based on various attributes. A comparison of various vehicle insurance policies can help the customers to compare and choose a vehicle insurance that is suitable to them. Although there are several methods for developing a utility function, in this study, we intend to develop a linear utility model for vehicle insurance policies using two approaches: Logarithmic Goal Programming Model (LGPM) and Conjoint Analysis Method (CAM). We propose to compare the similarities and differences between the results obtained from LGPM and CAM approaches, used for developing the utility function for vehicle insurance policies. We also derive a choice probability of the vehicles insurance policies available in market by developing a multinomial logit choice model. We also study the consistency indicators of the respondents. We will provide useful insights for the use both approaches as research tools.

Keywords: utility function, vehicle insurance policy, logarithmic goal programming, conjoint analysis.

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1. Introduction

An important aspect to understand the customer behavior is to generate a utility function. The utility function is defined as a linear combination of multiple attributes that are considered by the customers in choosing a product/service. Several methodologies have been proposed to develop a utility function. In this paper, we use two approaches viz: Logarithmic Goal Programming Model (LGPM) and Conjoint Analysis Method (CAM) to develop the utility scores of the attributes/factors that affects the customers' decision making process towards a product/service. We intend to compare the two approaches, LGPM and CAM, under a common context by analysing the similarities and differences between them.

The rapid growth of urbanization gave rise to an increase in demand for motor vehicles. The widespread use of motor vehicles has made it mandatory for the customers to buy a vehicle insurance policy that provides financial protection against any damage/ loss caused to the vehicle and against any physical damage or injury. Vehicle insurance sector is one of the rapidly growing sectors giving rise to an increase in the competition among various insurance companies, offering number of policy options in the market. Vehicle insurance provides insurance covers for the loss or any damages that are caused to the vehicle or its parts owing to man-made or natural calamities. Accident cover is also provided by these insurances, for individual owners of the vehicle while driving and also for other passengers in the vehicle along with an inclusion of third party legal liability. The customers have ample choices to choose the right kind of vehicle insurance policy for their vehicle. A comparative study of the competing insurance companies helps the customers to choose the policies suited to them. One cannot directly measure benefit, satisfaction or happiness from a product or service, so one can represent and measure utility in terms of customer choices that can be counted. We intend to study the customer preferences to choose a vehicle insurance policy by developing a utility function for a small section of these policies. The development of utility function will aid both policy holders and potential investors in differentiating them based on various attributes.

In a competitive framework it becomes critical for the insurance companies to understand the preference of customers choices based on multiple attributes/factors that makes an impact on the decision of the customers. As customer choice includes multiple factors, we address the problem by applying a Multi Criterion Decision-making Approach (MCDA). We estimate the importance of each of the multiple decision making factors that affects the customers' decision, by developing a utility function using two approaches viz: Logarithmic Goal Programming Model (LGPM) and Conjoint Analysis Method (CAM). LGPM approach determines the utility scores of each of the attributes independently while CAM approach determines the utility scores by considering all feasible combinations of each attribute levels. As both approaches evaluate the utility (importance) scores of the various attributes of the vehicle insurance policies, we consider a comparison of the analysis results obtained from both LGPM and conjoint analysis method. The comparison study of these two research tools will provide useful insights in using one or either or both the methods to arrive at a market analysis. Although couple of research studies are available that presents the comparison of Analytic Hierarchy Process (AHP) and Conjoint Analysis Method (CAM) used for studying the customer behavior towards a particular product or service, we propose the comparison of LGPM and CAM by applying it to study the customer decision process while buying a vehicle insurance policy.

This research study contributes to the following:

1) To study the key factors or attributes that affects the customers' preference choice while purchasing a vehicle insurance policy.
2) To develop the utility scores or the relative importance of the various attributes, using two approaches viz: LGPM and CAM.
3) To present the choice probability of the competing insurance companies.
4) To compare LGPM and CAM analytically and empirically on the attributes affecting the purchase of vehicle insurance policies.
5) To compare the similarities and differences between LGPM and CAM.

The paper is organized as follows.

2. Literature Survey

Multiple factors affect the decision of a customer choice while purchasing a vehicle/automobile insurance policy. While studying the consumer behavior towards their preference choices for any product or service, consisting of multiple criteria decision making, we consider Analytic Hierarchy Process (AHP) that was proposed and developed by Satty (1980) as the basic methodology to address such problems. This process was further improvised by and Aczel and Satty (1983). A critical survey was done by Stewart (1992) on the practical and theoretical use of multiple criteria decision making. Further Velasquez and Hester (2013) analyzed various multi-criteria decision making methods by examining their advantages and disadvantages. Researchers apply various methods like multinomial logit choice model, regression analysis, and neural network, to estimate the importance of each of the attributes that influences the customer choices. Yeo et al. (2001), described a neural network modeling approach to study the consequences and outcome of premium price changes on the vehicle insurance policy holders. Wang et al. (2010) proposed two modeling systems: a paired combinatorial logit (PCL) and multinomial logit (MNL) models, to describe the choice behaviors of automobile insurance policy alternatives, in case of Taiwanese non-life insurance company. Later, Bowne et al. (2013) discussed the methods and techniques used to determine a vehicle insurance policy premium, being one of the major attributes to purchase a vehicle insurance policy, on the basis of vehicle operated data. In this paper, we intend to study the importance of various factors affecting the customer preference choices for buying a vehicle insurance policy, by developing a utility function using two research methodologies viz: Logarithmic Goal Programming Model (LGPM) approach and Conjoint Analysis Method (CAM).

The primary work of inventing Logarithmic Goal Programming Model (LGPM) was initiated by Bryson and Joseph (1999). While reviewing the application of LGPM in the process of developing a utility function, a considerable amount of literature was available. Dutta et al. (2010) demonstrated the application of LGPM to develop a utility function that determines the behaviour of life insurance policy buyers in India. Further, the same concept of LGPM was used by Dutta &

Ghosh (2011) and Dutta & Ghosh (2015), to develop a utility function to study the passenger preferences for domestic airline travel and railway travel in India respectively. As an extension to the paper by Dutta & Ghosh (2011), Natesan et al. (2019), developed a utility function to study the passengers choice for domestic airline travel in Nepal using LGPM, along with its comparison to the airline travel in India.

Conjoint Analysis Method (CAM) is another research tool primarily used in market research to study the customer choices towards a product or service. An initial research to quantify data using conjoint measurement was presented by Green and Rao (1971). Further study discussed by Green and Srinivasan (1978) lead to the application of conjoint analysis in consumer research. Acito and Jain (1980) described and compared three methods for evaluating the results using conjoint analysis. A lot of approaches to evaluate conjoint analysis were developed causing the creation of new branches of research. Cattin and Wittink (1982) presented a detailed survey on the commercial usage of conjoint analysis approach. The commercialized use of conjoint analysis approach in consumer research gave rise to hybrid models described by Green (1984). The increase in the application of conjoint analysis as a research tool in marketing study, gave rise to new developments and new methods to evaluate CAM. Green and Srinivasan (1990) compiled and presented these new developments in conjoint analysis with implications for research and practice. A survey study by Rao (2008, 2014) explains about all the developments in the field of applied conjoint analysis and its developments in marketing research. Both in marketing practice and research, CAM is a commercially successful and one of the most popular methodologies for measuring customer preferences.

AHP is also another popular methodology used in evaluating product tasks that consists of multiple attributes. Several studies have shown that AHP also has potential to give promising results in a marketing practices and research. Later studies show that both AHP and CAM approaches can be used to get desirable results and provides a comparison of the two approaches. We find a considerable amount of research in the comparison of AHP and CAM. Mulye (1998) provided with an empirical comparison of the two attribute valuation methods: AHP and CAM, by examining variants within each approach. Chee (2004) analyzed the training factors/attributes for the gaming industry in Macau by using AHP and CAM and empirically compared the similarities and differences between AHP and CAM. A similar study by Scholl et al. (2005) considered the empirical comparison of AHP and CAM by applying them to solve multi-attribute design problems. Meißner and Decker (2009) increased the practical relevance of comparison studies by conducting a comparison of AHP and Choice-Based Conjoint Analysis (CBC) approaches and showed that AHP outperforms CBC in market share predictions. Ijzerman et al. (2012) compared the two approaches: AHP and CAM in assessing the attributes for stroke rehabilitation treatment while Lee (2014) also presented a detailed comparison of AHP and CAM by applying them to measure the brand equity in the hotel industry. In most comparative studies we observe that the preference/utility measure obtained using AHP approach, has better accurate predictions of the market.

As we see there is not much literature available on the application of LGPM, in this paper we consider the application of LGPM along with CAM, to study the attributes that affect the purchase of vehicle insurance policies and attempt to compare these two approaches empirically. The existing literature shows several studies using AHP and CAM approaches to measure consumer preferences and the comparison between them. In the context of comparative study between two approaches, we extend research by discussing the comparative study between the two approaches: LGPM and CAM, to develop the utility function for vehicle insurance policy.

3. Research Methodology

The initial stage of research methodology consists of data collection for both approaches: LGPM and CAM. The data collection is done using a questionnaire. The respondents for this study belonged to a particular city in Gujarat, India. The responses for both the approaches were collected from all the 202 respondents using the same questionnaire. These 202 respondents are separated according to socio-demographic factors viz: gender, age, occupation and annual income. We segregate these 202 respondents into homogenous clusters in each of the factors (gender, age, occupation and annual income) as shown in table 1 below, which also represents the number of respondents (frequencies) belonging to each of the categories.

Table 1: Segregation of the respondents into clusters

Groups	**Clusters in each group**	**Frequency**
Gender	Male	157
	Female	45
Age	20 – 30	33
	30 – 40	73
	40 – 50	51
	50 – 60	44
	60 – 70	1
Occupation	Private Sector	124
	Government Sector	49
	Self Employed	17
	Student	7
	Retired	2
	Others	3
Monthly Income	10000 – 20000	18
	20000 – 30000	25
	30000 – 40000	16
	40000 – 50000	20
	50000 and above	123

The detailed research methodology for each approach is discussed in the following sections.

4. Logarithmic Goal Programming Model (LGPM)

An important step to a research design is to identify the key attributes that affects the customer choices while purchasing a vehicle insurance policy. In order to aid the customers to select the right kind of vehicle insurance policy, we develop a utility model using Logarithmic Goal Programming Model (LGPM). We assume a linear utility function that measures the utilities of each of the key attributes independently. The linear form of the utility function $U(X)$ is described as shown below:

$$U(X) = \sum_{i} w_i x_i + \varepsilon$$

where,

x_i = level of the i^{th} factor/attribute significant for selection of vehicle insurance policy

w_i = the relative weights or importance score allocated to the i^{th} factor/attribute.

ε = random error term.

The main objective of LGPM approach (Bryson and Joseph (1999)) is to determine the utility scores or weights associated to each of the key attributes independently. A goal programming model minimizes the over fulfilment and under fulfilment from the desired goal. In LGPM, we minimize the logarithm of a linear objective function consisting of two variables that are multiplied over indices, which is equivalent to minimizing the linear objective function summed over the same above mentioned indices. Therefore, the LGPM approach minimizes the logarithms of the product of over fulfilment and under fulfilment (Dutta & Ghosh (2012) and Dutta *et al.* (2010)).

The parameters, sets and indices of the model are defined as follows:

J = set of criteria1 such that $J = (1,2,3, i \ldots .Jmax)$ indexed by i

K = set of criteria 2 such that K= (1,2,3 ..j..Kmax) indexed by j

P = paired set of criteria (i,j) where i ∈ J, j ∈ K such that i ≠ j

Q = set of respondents indexed by q, Q = (1,2,…q….Qmax)

r^q_{ij} = denotes the value specified by the respondent q for a paired combination of attribute (i,j) where $q \in Q$ and $(i,j) \in P$

s^q_{ij} = denotes the process generated value for the q^{th} respondent corresponding to the pair of attribute (i,j) where $q \in Q$ and $(i,j) \in P$

t^q_{ij} = denotes another process generated value for the q^{th} respondent corresponding to the pair of attribute (i,j) where $q \in Q$ and $(i,j) \in P$

u_i denotes the decision variables of the model that are un-normalized and

v_i denotes the decision variables of the model that are normalized, which actually denotes the weights of the factors/attributes.

The objective of the LGPM model is to determine a grouped mean priority vector point $v = (v_1, v_2, \ldots, v_N)$ in such a way that the absolute difference between the value r^q_{ij} specified by the respondents and the value of the ratio (v_i/v_j), while comparing each paired combination of criteria 'i' and 'j', is minimized.

We now establish two real numbers $s^q_{ij} \geq 1$ and $t^q_{ij} \geq 1$ with the condition that $(v_i/v_j)*(s^q_{ij} / t^q_{ij}) = r^q_{ij}$, where the value of both s^q_{ij} and t^q_{ij} are not greater than 1.

This implies the following cases:

1) if $s^q_{ij} = t^q_{ij} = 1$ then $(v_i/v_j) = r^q_{ij}$
2) if $s^q_{ij} > 1$ then $(v_i/v_j) < r^q_{ij}$, and
3) if $t^q_{ij} > 1$ then $(v_i/v_j) > r^q_{ij}$.

Then the set of responses or point estimates given by the respondents 'q' will be consistent only if $s^q_{ij} = t^q_{ij} = 1$ for each paired combination of criteria 'i' and 'j'; else the data set of responses will be inconsistent. Now our focus is to minimize the product $\prod_{i\epsilon J}\prod_{j\epsilon K} s^q_{ij}t^q_{ij},$ corresponding to one respondent but according to Aczel & Saaty, 1983, we need to consider the complete set of pairwise comparison values. Therefore, the above product needs to be minimized for all the responses given by the respondents $q \in Q$ and each value of the paired combination $(i,j) \in P$.

Thus the product $\prod_{q\epsilon Q}\prod_{i\epsilon J}\prod_{j\epsilon(i,j)\in P} s^q_{ij}t^q_{ij}$ is to be minimized, that represents a linear goal programming problem with un-normalized decision variables vector $(u_1, u_2, \ldots, u_N)$.

The objective of LGPM model is to minimize the logarithm of the product $\prod_{q\epsilon Q}\prod_{i\epsilon J}\prod_{j\epsilon(i,j)\in P} s^q_{ij}t^q_{ij}$

Thus the LGPM model is:

Minimize $Z = \left(\frac{1}{T}\right) \sum_{i \in J} \sum_{j \in K} \left(\left(ln\left(s_{ij}^{q}\right) + ln\left(t_{ij}^{q}\right) \right) - ln(\Theta^{q}) \right) = 0 \ \forall \ q \in Q$

subject to $\ln(u_i) - \ln(u_j) + \ln(s^q_{ij}) - \ln(t^q_{ij}) = \ln(r^q_{ij}) \ \forall \ q \in Q; \ (i, j) \in P$

where, all decision variables are non-negative, J = {1,2,….N} and T = N*(N-1).

The results of this problem is the un-normalized vector $u = (u_1, u_2, \ldots, u_N)$. The normalized vector $v = (v_1, v_2, \ldots, v_N)$ such that $(u_i/u_j) = (v_i/v_j)$ for each pair of (i,j), which forms priority point vector is the optimal solution of this LGPM model.

The optimal solution of this model denotes the weights of each of the attributes.

Further we multiply the weights of the corresponding attributes with the particular levels of the attribute to obtain the weighted score of the attributes. We then determine the scores of each of the competing vehicle insurance policies available in the market by applying a linear additive model.

5. Research Methodology for LGPM

The research methodology for LGPM firstly consists of the survey design used to collect data and then the implementation of LGPM approach to the collected data to develop the utility function. Finally we analyze the data and validate the results.

5.1. Survey Design for LGPM

We have considered the study for five popular vehicle insurance policies. The important attributes that affect the customer's preference to choose among these five vehicle insurance policies that best suit them is as shown in the figure 1 below.

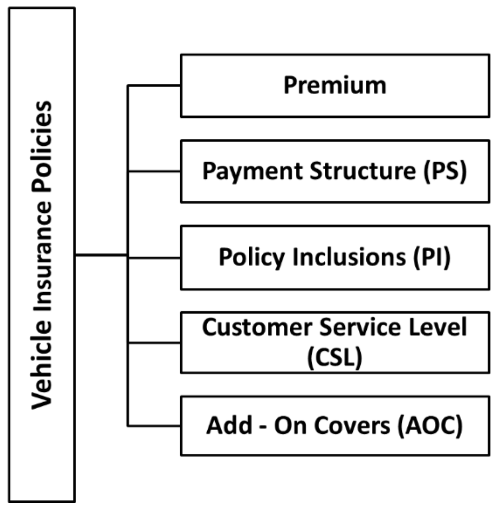

Figure 1: Important Attributes for application of LGPM

A total of 202 respondents were interviewed through a questionnaire. The respondents were asked to evaluate each of the above attributes on a scale of 1 to 100 with the score of 1 being least important attribute and 100 being the most attribute for them while purchasing vehicle insurance policies. The respondents were also asked to rate each of the five competing vehicle insurance policies across each of the five attributes on a scale of 1 to 10 with 1 being least suitable and 10 being most suitable to the respondent.

5.2. LGPM Model Implementation with a Small Data Set

In order to present a simpler explanation of the LGPM model, we implement it to a small data set consisting of 10 responses across 5 attributes, using MS Excel Solver. We consider the responses of the first 10 respondents across 5 attributes (as shown in Table 2). We run this LGPM for a data set of 10 responses using MS Excel.

Table 2: Sample Data Set of 10 responses					
Respondent	**Premium**	**PS**	**PI**	**CSL**	**AOC**
1	90	70	80	70	50
2	50	50	60	70	70
3	60	10	30	60	45
4	95	98	80	100	50
5	78	95	90	100	50
6	70	90	100	100	80
7	30	60	50	70	30
8	60	80	50	90	70
9	80	85	66	76	65
10	25	25	80	80	25

We now follow the steps below to implement the LGPM model and use MS Excel Solver to determine the utility scores of each of the attributes and rank the 5 competing policies across these attributes.

Step 1: Priority Matrix 'r^q_{ij}' for each Individual

We evaluate the r^q_{ij} matrix for each of the 10 respondents across each of the attributes where r^q_{ij} denotes the ratio of response values of the i^{th} attribute with respect to that of the j^{th} attribute specified by the q^{th} respondent. Therefore, we obtain a 10 X 10 matrix (Number of Respondents x Number of Comparison Ratios values for each attribute= 10 x ${}^5C_2$ = 10 rows X 10 Columns).

Now we have $r^q_{ij} = r^q_i/r^q_j$, for each q = 1 to 10, j = (i+1) to 5 for all i = 1 to 5

For example, the first respondent (t=1) rates the attribute Premium (i=1) at 90 and PS (j=2) at 70. So a^1_{12} = 90/70 = 1.286. Table 3 below represents the a^t_{ij} matrix for 10 respondents.

Table 3: Individual Priority Matrix ‘r_{ij}^{q}’										
Respondent	**r_{12}**	**r_{13}**	**r_{14}**	**r_{15}**	**r_{23}**	**r_{24}**	**r_{25}**	**r_{34}**	**r_{35}**	**r_{45}**
1	1.286	1.125	1.286	1.800	0.875	1.000	1.400	1.143	1.600	1.400
2	1.000	0.833	0.714	0.714	0.833	0.714	0.714	0.857	0.857	1.000
3	6.000	2.000	1.000	1.333	0.333	0.167	0.222	0.500	0.667	1.333
4	0.969	1.188	0.950	1.900	1.225	0.980	1.960	0.800	1.600	2.000
5	0.821	0.867	0.780	1.560	1.056	0.950	1.900	0.900	1.800	2.000
6	0.778	0.700	0.700	0.875	0.900	0.900	1.125	1.000	1.250	1.250
7	0.500	0.600	0.429	1.000	1.200	0.857	2.000	0.714	1.667	2.333
8	0.750	1.200	0.667	0.857	1.600	0.889	1.143	0.556	0.714	1.286
9	0.941	1.212	1.053	1.231	1.288	1.118	1.308	0.868	1.015	1.169
10	1.000	0.313	0.313	1.000	0.313	0.313	1.000	1.000	3.200	3.200

Step 2: Group Priority Vector ‘v_i’ obtained from the Individual Priority Matrix r^q_{ij}

The objective of LGPM approach is to create a group mean priority point vector v = (v_1, v_2, …, v_N) in such way that the difference between the ratio (v_i/v_j) and the individual priority matrix r^q_{ij} is minimized while we compare each paired combination of criteria ‘i’ and ‘j’.

A: Computation of r^q_{ij}*(v_j/v_i) Matrix

We establish two real numbers s^q_{ij} and $t^q_{ij} \geq 1$ such that $(v_i/v_j) * (s^q_{ij} / t^q_{ij}) = r^q_{ij}$

Now, the ‘v_i’ vector is unknown, so we obtain the optimal values of v_i. We then calculate the r^q_{ij}*(v_j/v_i) matrix to estimate the values of s^q_{ij} and t^q_{ij}. Table 4 represents the r^q_{ij}*(v_j/v_i) matrix for 10 respondent, after evaluating the optimal values of v_i.

Table 4: r^q_{ij}*(v_j/v_i) Matrix										
Respondent	**r_{12}**	**r_{13}**	**r_{14}**	**r_{15}**	**r_{23}**	**r_{24}**	**r_{25}**	**r_{34}**	**r_{35}**	**r_{45}**
1	1.380	1.205	1.577	1.568	0.873	1.142	1.136	1.308	1.301	0.995
2	1.073	0.893	0.876	0.622	0.832	0.816	0.580	0.981	0.697	0.711
3	6.441	2.143	1.226	1.162	0.333	0.190	0.180	0.572	0.542	0.947
4	1.041	1.272	1.165	1.656	1.223	1.119	1.591	0.916	1.301	1.421
5	0.881	0.929	0.956	1.359	1.053	1.085	1.542	1.030	1.464	1.421
6	0.835	0.750	0.858	0.762	0.898	1.028	0.913	1.145	1.017	0.888
7	0.537	0.643	0.526	0.871	1.198	0.979	1.623	0.818	1.355	1.658
8	0.805	1.286	0.817	0.747	1.597	1.015	0.928	0.636	0.581	0.914
9	1.010	1.299	1.291	1.072	1.285	1.278	1.061	0.994	0.826	0.831
10	1.073	0.335	0.383	0.871	0.312	0.357	0.812	1.145	2.602	2.274

B: Computation of s^q_{ij} & t^q_{ij} matrix:

We need to determine the real numbers s^q_{ij} and $t^q_{ij} \geq 1$ such that

$$(v_i/v_j) * (s^q_{ij} / t^q_{ij}) = r^q_{ij} \text{ -------------(1)}$$

Both the real numbers s^q_{ij} and t^q_{ij} should not be greater than 1 for the same pair of criteria (i,j).

Now $(v_i/v_j) = r_{ij}$ is ideally not possible. Therefor we look at two cases which are as follows:

1) **$(v_i/v_j) > r_{ij}$:** This case implies $(s^q_{ij} / t^q_{ij}) < 1$ in order to satisfy equation (1), hence $t^q_{ij} > s^q_{ij} \geq 1$ or $t^q_{ij} > 1$. The equation $(s^q_{ij} / t^q_{ij}) < 1$ is valid only if we obtain the value of $s^q_{ij} = 1$. Thus, if r^q_{ij}* $(v_j/v_i) < 1$ then $s^q_{ij} = 1$ and $1/t^q_{ij} = r^q_{ij}$* (v_j/v_i).
2) **$(v_i/v_j) < r_{ij}$:** This case implies $(s^q_{ij} / t^q_{ij}) > 1$ in order to satisfy equation (1), hence $s^q_{ij} > t^q_{ij} \geq 1$ or $s^q_{ij} > 1$. The equation $(s^q_{ij} / t^q_{ij}) > 1$ is valid only if we obtain the value of $t^q_{ij} = 1$. Thus, if r^q_{ij}* $(v_j/v_i) > 1$ then $1/t^q_{ij} = 1$ and $s^q_{ij} = r^q_{ij}$* (v_j/v_i).

So, either p^t_{ij} is a variable with $q^t_{ij} = 1$ or q^t_{ij} is a variable with $p^t_{ij} = 1$.

We compute the values of p^t_{ij} and q^t_{ij} separately as follows:

The matrix s^q_{ij} is determined by considering the fact that if r^q_{ij}* $(v_j/v_i) > 1$ then $s^q_{ij} = r^q_{ij}$* (v_j/v_i) else $s^q_{ij} = 1$, as shown in table 5.

Table 5: s^q_{ij} Matrix										
Respondent	r_{12}	r_{13}	r_{14}	r_{15}	r_{23}	r_{24}	r_{25}	r_{34}	r_{35}	r_{45}
1	1.380	1.205	1.577	1.568	1.000	1.142	1.136	1.308	1.301	1.000
2	1.073	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3	6.441	2.143	1.226	1.162	1.000	1.000	1.000	1.000	1.000	1.000
4	1.041	1.272	1.165	1.656	1.223	1.119	1.591	1.000	1.301	1.421
5	1.000	1.000	1.000	1.359	1.053	1.085	1.542	1.030	1.464	1.421
6	1.000	1.000	1.000	1.000	1.000	1.028	1.000	1.145	1.017	1.000
7	1.000	1.000	1.000	1.000	1.198	1.000	1.623	1.000	1.355	1.658
8	1.000	1.286	1.000	1.000	1.597	1.015	1.000	1.000	1.000	1.000
9	1.010	1.299	1.291	1.072	1.285	1.278	1.061	1.000	1.000	1.000
10	1.073	1.000	1.000	1.000	1.000	1.000	1.000	1.145	2.602	2.274

Similarly, the matrix t^q_{ij} is determined by considering the fact that if $r^q_{ij}* (v_j/v_i) < 1$ then $1/t^q_{ij} = r^q_{ij}* (v_j/v_i)$ else $1/t^q_{ij} = 1$, shown in table 6.

Table 6: t^q_{ij} Matrix										
Respondent	r_{12}	r_{13}	r_{14}	r_{15}	r_{23}	r_{24}	r_{25}	r_{34}	r_{35}	r_{45}
1	1.000	1.000	1.000	1.000	1.145	1.000	1.000	1.000	1.000	1.005
2	1.000	1.120	1.142	1.607	1.202	1.226	1.725	1.019	1.435	1.407
3	1.000	1.000	1.000	1.000	3.006	5.253	5.544	1.747	1.844	1.055
4	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.092	1.000	1.000
5	1.135	1.077	1.046	1.000	1.000	1.000	1.000	1.000	1.000	1.000
6	1.198	1.333	1.165	1.312	1.113	1.000	1.095	1.000	1.000	1.126
7	1.863	1.556	1.903	1.148	1.000	1.021	1.000	1.223	1.000	1.000
8	1.242	1.000	1.223	1.339	1.000	1.000	1.078	1.573	1.721	1.095
9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.006	1.211	1.204
10	1.000	2.987	2.610	1.148	3.206	2.801	1.232	1.000	1.000	1.000

We then evaluate the logarithmic value of s^q_{ij} and t^q_{ij} matrices. Therefore, our objective is to minimize $\ln(s^q_{ij} * t^q_{ij}) = \ln(s^q_{ij}) + \ln(t^q_{ij})$, over all q's, for all pair of criteria i and j.

With these formulations and with the objective function

Z = Minimize ($\ln(s^q_{ij} * t^q_{ij})$) for all values of i, j and q.

We obtain the normalized values of the consensus priority vector v_i where $(v_i/v_j) = (u_i/u_j)$ for each paired combination of (i,j), as shown in table 7. These values of v_i's represents the weights of each attribute for a sample of 10 respondents.

Table 7: Consensus Priority Vector for a Sample Data Set of 10 respondents

Premium	PS	PI	CSL	AOC
0.190753	0.204772	0.204367	0.233902	0.166206

5.3. LGPM Model to develop the utility function

We can implement LGPM for a small data set using MS Excel Solver. But using Excel Solver becomes difficult for the implementation of LGPM approach to a large data set that requires large scale optimization. Since our data set consists of 202 data points, it requires a large optimization model and hence Microsoft Excel Solver is not the right choice. We carry out the implementation of our LGPM approach for a sample size of 202 data points using AMPL with CPLEX solver, to obtain the weights of all attributes. The decision variables of the LGPM model represent the weights (importance scores) of each of the attributes. We obtain the weights (v_i) of the attributes by normalizing the un-normalized weights (u_i). The weights (importance scores) of each of the attributes are as shown in table 8.

Table 8: Weights of the attributes using LGPM approach

Attributes	Weights (in percent)
Premium	21.41
Payment Structure (PS)	17.84
Policy Inclusions (PI)	21.92
Customer Service Level (CSL)	21.92
Add - On Covers (AOC)	16.90

The utility function for purchasing vehicle insurance policies using LGPM approach is given as follows:

$$\mathbf{U(X) = 21.41 * Premium + 17.84 * PS\ + 21.92 * PI\ + 21.92 * CSL\ + 16.9 * AOC +\ \varepsilon}$$

We observe that using LGPM approach wherein the attributes are treated independently, the utility scores of the attributes, reflects that 'policy inclusions' (PI) and 'customer service level' (CSL) are the two most important attributes that affects the decision of the customers while purchasing a vehicle insurance policy. The top two attributes are followed by 'premium' and then 'payment structure' (PS) in list of importance. The least important attribute is 'add-on covers' (AOC).

The correlation co-efficient between estimated and observed preferences are as given in table 9.

Table 9: Correlation co-efficient between estimated and observed values

	Values	Significance
Pearson's R	0.9842	0.000
Spearman's rho	0.8721	0.000

The correlation co-efficient measure, suggests that there is good correlation between the estimated and the observed preferences.

5.4. Results obtained from LGPM approach

The utility scores of the attributes form a basis to obtain the importance scores of each of the competing vehicle insurance policies which are as shown in table 10.

Table 10: Utility Scores of the competing policies

Attributes	**Premium**	**PS**	**PI**	**CSL**	**AOC**	**Score**
Weights	**0.2141**	**0.1784**	**0.2192**	**0.2192**	**0.1690**	
Policy 1	1.4318	1.3475	1.3582	1.3950	1.2376	**1.35973**
Policy 2	1.4291	1.3733	1.3505	1.4018	1.2767	**1.37017**
Policy 3	1.4075	1.3814	1.3361	1.3889	1.2628	**1.35866**
Policy 4	1.4336	1.3834	1.3229	1.4082	1.2297	**1.36033**
Policy 5	1.3015	1.2676	1.2354	1.2377	1.1609	**1.24322**

We observe that when attributes are treated independently, the utility scores of the competing policies indicate that Policy 2 is the most preferred policy by the customers followed by Policy 4, Policy 1 and Policy 3. As Policy 5 corresponds to lowest utility value, it is the least preferred choice of the customers.

As the policy options are mutually exclusive for the choice preference of the policies, we compute the choice probability using the multinomial logit choice model. The choice probabilities of the competing policy brands are as shown in table 11.

Table 11: Choice probabilities of the competing policy brands

Policy Brands	Choice Probability
Policy 1	0.2032
Policy 2	**0.2047**
Policy 3	0.2030
Policy 4	0.2033
Policy 5	0.1858

The choice probability for almost all the competing vehicle insurance policies is the same at approximately 20% each but among these Policy 2 has the highest choice probability closely followed by other choices. Policy 5 is a less preferred policy as it has the least choice probability, compared to others. This reflects that Policy 4, Policy 1 and Policy 3 closely compete with each other. Thus when we consider the attributes independently we observe that the most preferred choice of policy is Policy 2 with rank 1, followed by Policy 4, Policy 1, Policy 3 and Policy 5 with rank 2, 3, 4 and 5 respectively.

We now apply LGPM model to various clusters formed by segregating the respondents according to various factors like gender, age, income, occupation, and then we estimate the consistency indicator, $\ln(\theta)$ for each of the clusters. The estimated consistency indicators of the respondents when separated into various clusters (table1) according to their socio-demographic factors, is listed in table 12.

Table 12: Consistency Indicators for different clusters		
Clusters	**Number of Respondents**	**Consistency Indicators**
Gender		
Male	157	0.8640
Female	45	0.6073
Age		
20 – 30	33	0.9018
30 – 40	73	0.7693
40 – 50	51	0.8342
50 – 60	44	0.7606
60 – 70	1	0.0000
Occupation		
Private sector	124	0.8296
Government sector	49	0.8221
Self employed	17	0.6924
Student	7	0.7530
Retired	2	0.1941
Others	3	0.6243
Income		
10000 – 20000	18	0.6001
20000 – 30000	25	0.5760
30000 – 40000	16	0.5822
40000 – 50000	20	0.4982
50000 and above	123	0.9280

We observe there are significant differences between the consistency indicators of the clusters. In case of the age and gender factor, the consistency among the clusters do not differ much except for the age group above 60 but in case of factors like occupation and income the consistency indicators differ significantly among the clusters. So, we can argue that weights should be applied in an aggregative manner, rather than in socio- demographic clusters.

6. Conjoint Analysis Method (CAM)

Conjoint Analysis Method (CAM) is another advanced market research analysis method that mathematically analyzes consumer preference choices in a purchasing process that involves multiple attributes, to formulate a purchasing decision. CAM helps in developing business strategies by determining pricing, product features and configurations and bundling them as packages. This helps to cater to the consumer needs in order to create a competitive edge. It is an effective model that measures the trade-offs concerning preferences and buying options. CAM considers the whole range of product attributes in totality instead of treating each attribute independently and the studies the joint effect of multiple product attribute on product choice. The most widely used approaches for the survey design are: two-factor conjoint approach, choice-based conjoint (CBC) approach, adaptive conjoint analysis (ACA) approach and full-profile conjoint (FPC) approach. There are other approaches such as self-explicated, hybrid conjoint, adaptive CBC and max-diff conjoint analysis, which are also considered for survey design.

7. Research methodology for CAM

This research uses CAM to measure the part-worth utilities of the profile cards and the importance scores of each attribute that affects the decision of the consumers while purchasing a vehicle insurance policy when the attributes are considered in a certain combination.

The steps in conducting a conjoint analysis study are elaborated as follows:

1) The initial step for applying CAM is to estimate the most relevant product/service attributes along with the examinable performance levels for each and every attribute.
2) To determine the orthogonal design by developing stimuli for the product/service as a combination of the levels of a set of attributes called as ‘choice cards’ or ‘hypothetical profiles’.
3) To prepare the questionnaire for data collection consisting of the profile/choice cards.

4) To administer the survey by presenting the questionnaire with stimuli (choice cards/hypothetical profiles) to a sample of appropriate respondents. Data collection is done by asking the respondents to rank the choice cards/profiles relative to other choice cards/profiles or choose among the alternative profiles in a choice, according to their purchasing preferences.
5) To estimate the part-worth utility scores and importance scores of each of the attributes.
6) Study individual conjoint effects by computing each person's utility scores and also to study the combined effects by considering one value for each attribute level.
7) Simulation or sensitivity analysis for optimization of single product or product line

There are different types of response scales that are used to collect responses from the respondents viz: rating-based (ranking), and choice-based. The data is analysed differently and accordingly for each type of response scales to estimate the part-worth utilities for each of the profiles/choice cards and importance for each of the attributes considered for the study.

7.1. Survey Design for CAM

For application of CAM, we consider the study for the same five popular brands of vehicle insurance policies as mentioned in section 4.1. and the same five attributes affecting the customers' choice preferences, as that considered for the application of LGPM. The attribute 'Premium' consists of three levels i.e. **high, medium and low** premium rates. The attribute 'Payment Structure' is further divided into three levels consisting of various payment modes viz: **yearly, half yearly, quarterly** payments modes for the premium. The attribute 'Policy Inclusions' is further divided into two levels that covers **only own damage costs (OD only)** and the one that covers **own damage cost as well as third party damage costs (OD + TP)**. The attribute 'Customer Service Level' is further divided into two levels that consist of **low quality service level** and **high quality service level**. The attribute 'Add – On Covers' is further divided into five levels viz: extra cover for **engine protection**, **Return to invoice (RTI)** that fetches the total loss amount (the on-road price paid for the vehicle) that is incurred because of losing it, extra cover for **consumables**, **zero depreciation** cover that omits the depreciation factor from the coverage, thus giving complete cover and **no claim bonus (NCB) protection** that is an extra cover on car insurance policies, which means the no claims bonus will not be affected by one claim in the insurance year. Details of some of the terms are provided in Appendix 1. Each of the above mentioned attributes are further broken down into certain levels that specify each of the attributes as shown in figure 2.

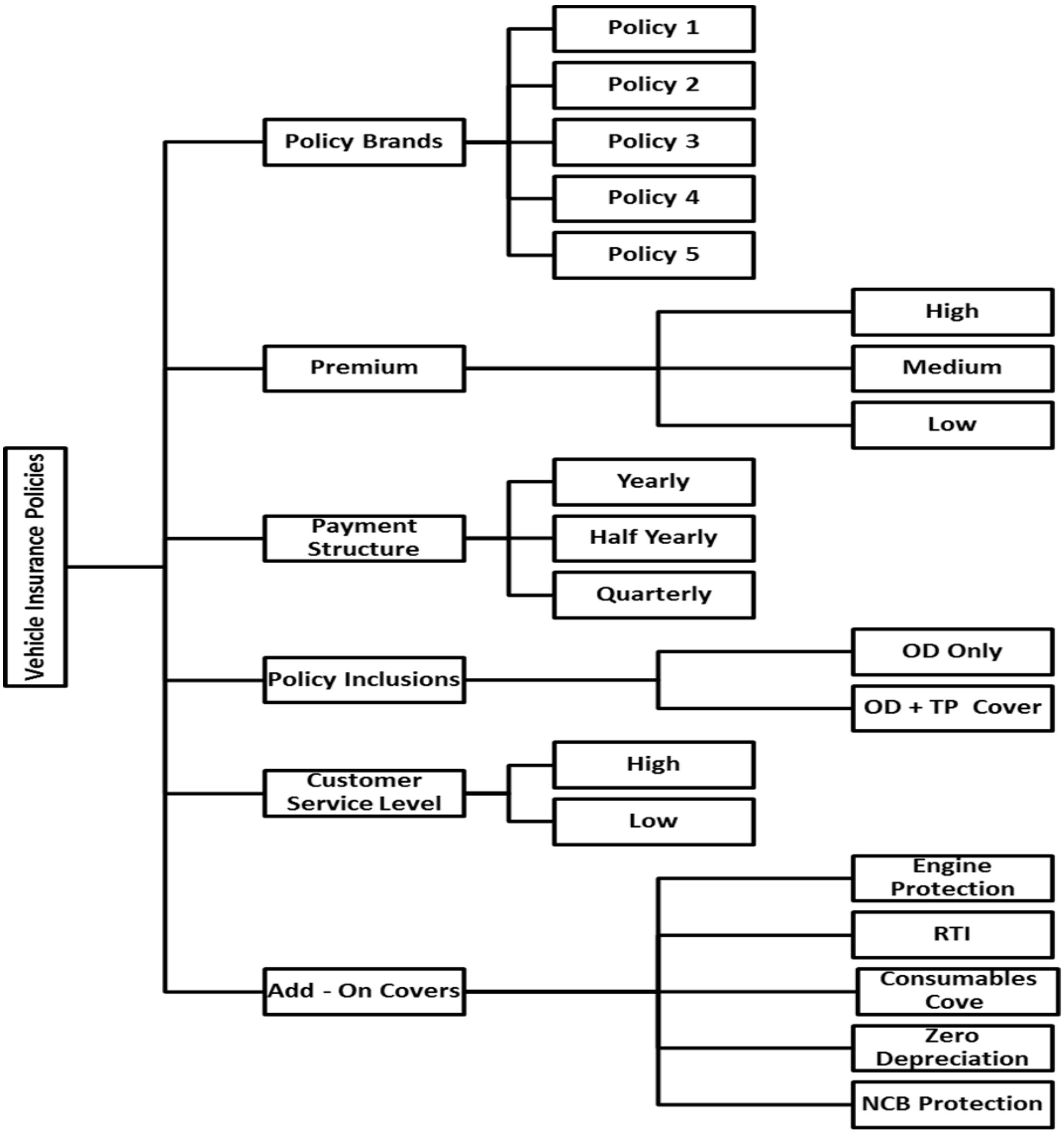

Figure 2: Attributes and its corresponding levels for application of CAM

We consider full profile approach for data collection as it considers all the attributes and evaluates them at the same time. The full design consists of 5 x 3 x 3 x 2 x 2 x 5 = 900 possible combinations of profiles or choice cards. Since all the possible combinations of the attribute levels are too large for the respondents to rank them, we use SPSS to produce an orthogonal array with 25 profiles or choice cards. The reduced design consisting of 25 profiles or choice cards were presented to the respondents and they were asked to rank all the 25 profiles or choice cards from 1 to 25 without assigning the same rank for 2 or more options, according to their choice preferences. The respondent had to rank starting with rank 1 assigned to the most preferred profile option, rank 2 to the next preferred option and so on, until rank 25 assigned to the least preferred profile option.

7.2. CAM approach to develop the utility function

The basic estimation process for full-profile conjoint (FPC) analysis is the effects of analysis of variance (ANOVA). This procedure estimates the utility of each attribute level such that the sum of the utilities of all the levels in a particular profile/choice card is equal to the total utility of that profile. The mathematical form of the part-worth (additive) model of conjoint analysis that estimates the total utility value of each profile/choice cards and partial utility value of each level of each and every attribute is given as follows:

Total Utility = Sum of all partial utilities

$$y_k = \beta_0 + \sum_{j=1}^{J} \sum_{m=1}^{M_j} \beta_{jm} x_{jm} + \varepsilon_k$$

where,

$j = 1,2,\ldots\ldots,J =$ no. of attributes important for selection of vehicle insurance policy

$m = 1,2,\ldots\ldots M_j =$ no. of levels assigned to the j^{th} attribute

$y_k =$ the estimated total utility value for profile/choice card k

$\beta_{jm} =$ the partial utility value assigned to the m^{th} level of the j^{th} attribute.

$$x_{jm} = \begin{cases} 1, & if\ profile/choice\ card\ k\ consists\ of\ the\ m^{th}\ level\ of\ the\ j^{th}\ attribute \\ 0, & else \end{cases}$$

$\beta_0 =$ utility constant term

$\varepsilon_k =$ random error

The utility of attribute is the value of an attribute level, representing the relative worth of the attribute. High utility score indicates more value and low utility score indicates less value. The part-worth utility or the utility estimates of all the levels are estimated, such that the sum of the utility estimate of all the levels of a particular attribute is zero.

We examine the difference between the lowest and the highest utility scores across the levels of attributes and determine the importance of each attribute. The relative importance of each attribute compared to other attributes can be estimated by taking the ratio of the difference between the highest and lowest partial utilities of the levels of that attribute to the sum of all attribute utility range, as shown below:

$$RI_j = \frac{\left(\max \beta_{jm} - \min \beta_{jm}\right)}{\sum_{j=1}^{j=J}\left(max\, \beta_{jm} - min\, \beta_{jm}\right)}$$

where,

$RI_j =$ relative importance of the j^{th} attribute, $j = 1,2, \ldots\ldots, J$

We carry out the implementation of CAM approach for a sample size of 202 data points using SPSS software, to obtain the part-worth utilities of all attribute levels.

7.3. Results obtained from CAM Approach

The part-worth utility estimates or the partial value estimates of all the levels of each attribute and the constant term obtained after running the conjoint analysis in SPSS is as given in the table 13. The relationship between all the attributes and the ranks given by the respondents is assumed to be discrete.

Table 13: Part-worth utilities of each attribute levels			
Attributes	**Level Notation**	**Attribute Levels**	**Part-worth Utility Estimate**
	CONSTANT	Constant	13.020
Policy Brands	PB1	Policy 1	1.623
	PB2	Policy 2	1.358
	PB3	Policy 3	0.459
	PB4	Policy 4	-1.223
	PB5	Policy 5	-2.218
Premium	Premium1	Low	-0.101
	Premium2	Medium	0.003
	Premium3	High	0.097
Payment Structure	PS1	Quarterly	0.147
	PS2	Half Yearly	-0.082
	PS3	Yearly	-0.065
Policy Inclusions	PI1	OD Only Cover	-0.134
	PI2	OD + TP Cover`	0.134
Customer Service Level	CSL1	Low	0.068
	CSL2	High	-0.068
Add-On Covers	AOC1	Zero Depreciation	0.22
	AOC2	Engine Protection	-0.113
	AOC3	RTI	0.146
	AOC4	Consumables Cover	0.07
	AOC5	NCB Protection	-0.323

We observe that when the policy brands are bundled with one level of each attribute, the most preferred policy brand according to the customer choices is Policy 1, having the highest utility estimate as compared to other policy brands. Next most preferred is Policy 2, followed by Policy 3 and Policy 4 and the least preferred brand is Policy 5, having the least utility estimate. Similarly from the above table 10, we obtain the utility estimate for each of the levels of each attribute based on the customer preferences for the 25 profiles/choice cards.

The correlation co-efficient between estimated and observed preferences is as given in table 14.

Table 14: Correlation co-efficient between estimated and observed values		
	Values	Significance
Pearson's R	0.987	0.000
Kendall's tau	0.833	0.000
Spearman’s rho	0.720	0.001

The correlation co-efficient measure, suggests that there is good correlation between the estimated and the observed preferences.

The average importance scores taken by considering all the 202 respondents, gives the measure (in percent) of the relative importance of the 5 single attributes for the determination of the utilities of the individual attributes. The importance scores are as given in table 15 below.

Table 15: Importance scores of the attributes using CAM approach	
Attributes	**Average Importance Scores**
Premium	23.63
Payment Structure (PS)	18.95
Policy Inclusions (PI)	10.67
Customer Service Level (CSL)	10.59
Add - On Covers (AOC)	36.15

When we consider a combination of all attributes in our study, the importance scores estimated for each attribute individually based on customer choices, suggests that ‘Add – On Covers’ is the attribute that is most important, followed by ‘Premium’ being the second important and ‘Payment Structure’ the third important attribute. ‘Policy Inclusions’ and ‘Customer Service Level’ are both the least important attribute.

We can compute the total utility values for all the profiles or choice cards based on the partial utility values achieved as in table 13. For eg. total utility value for the profile or choice card 1 (Policy 1 + High Premium + Half – Yearly Payment Structure + OD + TP Cover + Low CSL + Engine Protection AOC) is given as follows:

Profile / Choice Card 1						
Attributes	PB	Premium	PS	PI	CSL	AOC
Level Combination	Policy 1	High	Half-Yearly	OD + TP Cover	Low	Engine Protection
Part-worth Utility Score	1.623	0.097	-0.082	0.134	0.068	-0.113

Total Utility of profile 1= Constant + Sum of partial utilities of choice card 1

= 13.020 + 1.623 + 0.097 - 0.082 + 0.134 + 0.068 - 0.113

= 14.75

The total utility of all the 25 profiles or choice cards considered in this study is as given in table 16 below.

Table 16: Total Utility Scores of all the 25 profiles

Choice cards	Policy Brand	Premium	Payment Structure	Policy Inclusions	Customer Service	Add - On Covers	Total Utility Scores
1	Policy 1	High	Half Yearly	OD + TP Cover	Low	Engine Protection	14.75
2	Policy 1	Medium	Yearly	OD + TP Cover	Low	RTI	14.93
3	Policy 1	Medium	Quarterly	OD Only Cover	High	Consumables Cover	14.66
4	Policy 1	Low	Quarterly	OD Only Cover	Low	Zero Depreciation	14.84
5	Policy 1	Low	Half Yearly	OD Only Cover	High	NCB Protection	13.94
6	Policy 2	High	Quarterly	OD + TP Cover	Low	NCB Protection	14.50
7	Policy 2	Medium	Half Yearly	OD Only Cover	Low	Zero Depreciation	14.45
8	Policy 2	Medium	Quarterly	OD Only Cover	Low	Engine Protection	14.35
9	Policy 2	Low	Yearly	OD + TP Cover	High	Consumables Cover	14.35
10	Policy 2	Low	Half Yearly	OD Only Cover	High	RTI	14.14
11	Policy 3	High	Quarterly	OD Only Cover	High	RTI	13.67

12	Policy 3	Medium	Half Yearly	OD Only Cover	Low	Consumables Cover	13.41
13	Policy 3	Medium	Yearly	OD Only Cover	Low	NCB Protection	13.03
14	Policy 3	Low	Quarterly	OD + TP Cover	Low	Zero Depreciation	13.95
15	Policy 3	Low	Half Yearly	OD + TP Cover	High	Engine Protection	13.25
16	Policy 4	High	Yearly	OD Only Cover	High	Zero Depreciation	11.85
17	Policy 4	Medium	Half Yearly	OD + TP Cover	Low	RTI	12.07
18	Policy 4	Medium	Quarterly	OD Only Cover	High	Engine Protection	11.63
19	Policy 4	Low	Half Yearly	OD Only Cover	Low	NCB Protection	11.23
20	Policy 4	Low	Quarterly	OD + TP Cover	Low	Consumables Cover	12.11
21	Policy 5	High	Half Yearly	OD Only Cover	Low	Consumables Cover	10.82
22	Policy 5	Medium	Quarterly	OD + TP Cover	High	NCB Protection	10.70
23	Policy 5	Medium	Half Yearly	OD + TP Cover	High	Zero Depreciation	11.01
24	Policy 5	Low	Quarterly	OD Only Cover	Low	RTI	10.93
25	Policy 5	Low	Yearly	OD Only Cover	Low	Engine Protection	10.46

The total utility scores of all the 25 profiles, computed based on all the 202 responses, suggests that the most preferred combination of the levels of all the attributes is profile/choice card 2 (Policy 1 + Medium Premium + Yearly PS + OD+TP Cover + Low CSL + RTI AOC) with the highest total utility value of 14.93.

The total utility scores for each of the 25 profiles are used to compute the choice probability of the customer preferences for each of the competing policies as shown in table 17.

Table 17: Choice probability of the competing policies	
Policy Brands	**Probability**
Policy 1	**0.2250**
Policy 2	0.2209
Policy 3	0.2071
Policy 4	0.1812
Policy 5	0.1659

In case of CAM also we observe that the choice probability of all the competing vehicle insurance policies is the same at approximately 20% each. When the policies are bundled with other attributes we observe that the most preferred policy is Policy 1 as it has the highest probability score, closely followed by other choices and Policy 5 being the least preferred policy. Thus when each of the attribute levels are bundled with the policy brands as a single combination, the policy with rank 1 is Policy 1, followed by Policy 2, Policy 3, Policy 4 and Policy 5 with rank 2, 3, 4 and 5 respectively.

We now apply CAM model to obtain the utility scores of each attribute in various clusters formed by segregating the respondents according to different socio-demographic factors such as gender, age, income, and occupation. Unlike the LGPM approach where we compute the consistency indicators for clusters in each factor, in case of CAM approach we consider the consistency among the respondents when separated into clusters (table 1) in each factor, by estimating the correlation among them as shown in table 18.

Table 18: Correlation among the Utility Scores of the attributes in various clusters of each factor						
Gender						
	Male	**Female**				
Male	1					
Female	0.932422757	1				
Age						
	20-30	**30-40**	**40-50**	**50-60**	**60-70**	
20-30	1					
30-40	0.730478066	1				
40-50	0.581194358	0.906806791	1			
50-60	0.66188447	0.730342061	0.719390169	1		
60-70	0.330322715	0.798465346	0.873205119	0.620603476	1	
Occupation						
	Student	**Government**	**Private**	**Self-Employed**	**Retired**	**Others**
Student	1					
Government	0.729405956	1				
Private	0.841987042	0.846722462	1			
Self-Employed	0.058995277	0.272364172	0.331070243	1		
Retired	0.429502412	0.686684626	0.500097423	0.419657624	1	
Others	0.61458964	0.842237126	0.742042941	0.196928786	0.421302082	1
Income						
	10000-20000	**20000-30000**	**30000-40000**	**40000-50000**	**50000 & above**	
10000-20000	1					
20000-30000	0.67067715	1				
30000-40000	0.692201432	0.499325927	1			
40000-50000	0.52412283	0.854668586	0.395133507	1		
50000 & above	0.689994123	0.907442483	0.542596096	0.777922305	1	

The correlation table of the clusters suggests that there is consistency among the clusters in each socio-demographic factor: gender, age, occupation, income. Except for some cases where the correlation is low, in most cases the correlation is high which means the respondents' behaviour when clustered (table 1) is almost similar while rating the attributes, in each factor.

8. Conceptual Comparison of LGPM and CAM Approaches

Theoretically and conceptually the two approaches: LGPM and CAM differ in many ways. The conceptual comparison of the two approaches is listed in table 19.

Table 19: Conceptual comparison of LGPM and CAM approach

Sr. No.	LGPM	CAM
1.	It is based on multi-attribute value theory.	It is based on random utility theory.
2.	Compositional approach: It considers the independent attributes that describes the product.	De-compositional approach: It considers possible combinations of each attribute/factor levels that form a product/service bundle.
3.	Many attributes can be considered.	Less number of attributes with many stimuli can be considered.
3.	Data collection is easy, as the respondents are required to rate each attribute independently.	Data collection is difficult, as the respondents are required to rate each combination (product bundle) of attribute levels.
4.	It measures the consumer preferences towards a list of attributes.	It measures how consumers value or rate the combination of attributes that forms a product/ service bundle.
5.	Based on the respondents' evaluations of a list of attributes, we determine the utility score that each attribute holds.	Based on the respondents' ranking of the bundled profiles of a product, we determine the utility value that each attribute adds to the product.
6.	It yields utility values for each attribute	It yields utility values for each level of the attributes
7.	It is an additive model, where the value of the overall product is equivalent to the sum of its utilities (weights) of the attributes.	It is an additive model, where the value of the overall product concept/profile is equivalent to the sum of its part-worth utilities of the attribute levels.
9.	The weights or utility score of the attributes explains the importance of each of the attributes.	The importance of each of the attributes can be computed using the part-worth utility scores of the attribute levels.

10.	One can directly compare the utilities of attributes among themselves as they are independent of each other.	One can only directly compare the utilities within each attribute. Direct comparisons of a level from one attribute to another from a separate attribute may not be proper.

As CAM approach yields the utility values for each attribute levels, it can be used to perform a trade-off analysis by varying the attribute levels for different customer segments. This information can be helpful to the consumers to determine the best product attribute combination and perform a cost benefit analysis. Thus, theoretically CAM approach yields added information as compared to LGPM approach that helps to enhance or improve the product mix.

9. Empirical Comparison of LGPM and CAM Approaches

The comparison of the importance scores/weights of the five attributes calculated using LGPM and CAM for all 202 respondents is compared as below in table 20. The sum of all the average estimates of the importance of each attribute for all respondents is equal to 100.

Table 20: Comparison of LGPM and CAM Importance Scores/Weights

Weights	Attributes	LGPM Scores	Conjoint Scores
1	Premium	21.41	23.63
2	Payment Structure (PS)	17.84	18.95
3	Policy Inclusions (PI)	21.92	10.67
4	Customer Service Level (CSL)	21.92	10.59
5	Add - On Covers (AOC)	16.90	36.15

We observe that in case of LGPM approach, the most important attribute is ‘PI’ and ‘CSL’. In case of CAM approach, the most important attribute is ‘AOC’. The above table suggests that the importance scores computed using LGPM and CAM approaches are almost similar for the attributes ‘Premium’ and ‘Payment Structure’ but the mean importance scores between LGPM and CAM approaches differ significantly in case of the attributes ‘Policy Inclusions’, ‘CSL’ and ‘AOC’. We statistically prove the hypothesis for difference or similarity between the importance scores computed from LGPM and CAM, under paired sample t-test. The results of the paired samples t-test is presented in table 21 below.

Table 21: Paired samples test for importance scores calculated from LGPM and CAM

		Paired Differences					$t_{0.025}$	$t_{0.05}$	df	p value (2-tailed)		Significant Diff.
		Mean	Std. Dev.	Std. Error	95% CI of the difference							
Pairs	Attributes for LGPM & CAM				Lower	Upper						
1	Premium	-2.12	16.66	1.17	-4.44	0.19	1.97	-1.81	201	0.07	$p > 0.05$	No
2	Payment Structure	-3.08	12.00	0.84	-4.74	-1.41	1.97	-3.64	201	0.00	$p < 0.05$	Yes
3	Policy Inclusions	12.40	9.66	0.68	11.06	13.74	1.97	18.26	201	0.00	$p < 0.05$	Yes
4	Customer Service Level	12.84	9.57	0.67	11.51	14.17	1.97	19.07	201	0.00	$p < 0.05$	Yes
5	Add-On-Covers	-20.04	14.74	1.04	-22.09	-18.00	1.97	-19.32	201	0.00	$p < 0.05$	Yes

The above table suggests that the importance scores between LGPM and CAM approaches under paired samples t-test, differ significantly in ‘PS’, ‘PI’, ‘CSL’ and ‘AOC’ attributes that describes the vehicle insurance policies. We also perform a bivariate correlation analysis among the importance scores computed using LGPM and CAM. The Person’s correlation as well as the Spearman’s rank correlation between the respective importance scores of each of the attributes, computed using LGPM and CAM. Table 22 shows the computation of the Pearson’s correlation of the respective importance scores of the attributes.

Table 22: Pearson's Correlation of the importance scores of the attributes using LGPM and CAM

		Premium-LGPM	PS-LGPM	PI-LGPM	CSL-LGPM	AOC-LGPM
Premium-CAM	Correlation Coefficient	-0.134	-0.025	.217**	-0.028	-0.01
	Significance (2-tailed)	0.058	0.724	0.002	0.69	0.891
PS-CAM	Correlation Coefficient	-0.03	0.048	-0.037	0.047	-0.03

	Significance (2-tailed)	0.672	0.495	0.602	0.51	0.67
PI-CAM	Correlation Coefficient	0.083	0.105	-.164*	-0.056	-0.006
	Significance (2-tailed)	0.238	0.138	0.02	0.427	0.933
CSL-CAM	Correlation Coefficient	0.019	0.037	-.147*	-0.004	0.067
	Significance (2-tailed)	0.793	0.598	0.037	0.956	0.342
AOC-CAM	Correlation Coefficient	0.116	-0.091	-0.033	0.029	-0.004
	Significance (2-tailed)	0.101	0.198	0.644	0.681	0.959

The Pearson's correlation of the importance scores of the respective attributes computed from LGPM and CAM observed along the diagonal of the above table, suggests no significant correlation (linear relationship) between the respective attributes importance scores except for the importance score of the 'policy inclusions' (PS) attribute obtained from LGPM and CAM, that shows correlation is 2-tailed significant at the alpha level of 0.05.

We now consider the monotonic relationship of the respective importance scores of the attributes computed using LGPM and CAM. The monotonic relationship is studied by computing the Spearman's rank correlation of the respective importance scores of the attributes as shown in table 23 below.

Table 23: Spearman's Rank Correlation of the importance scores of the attributes using LGPM and CAM

		Premium-LGPM	PS-LGPM	PI-LGPM	CSL-LGPM	AOC-LGPM
Premium-CAM	Correlation Coefficient	-0.064	-0.056	.182**	0.006	-0.008
	Significance (2-tailed)	0.369	0.432	0.01	0.937	0.908
PS-CAM	Correlation Coefficient	-0.057	0.045	-0.047	0.031	0.015
	Significance (2-tailed)	0.418	0.526	0.509	0.664	0.837

PI-CAM	Correlation Coefficient	0.042	0.089	-0.105	-0.051	-0.045
	Significance (2-tailed)	0.556	0.205	0.136	0.472	0.521
CSL-CAM	Correlation Coefficient	0.09	0.09	-0.138	-0.025	0.042
	Significance (2-tailed)	0.203	0.203	0.05	0.723	0.557
AOC-CAM	Correlation Coefficient	0.117	-0.082	-0.045	0.03	-0.021
	Significance (2-tailed)	0.096	0.244	0.525	0.673	0.764

The Spearman's rank correlation of the importance scores of the respective attributes computed from LGPM and CAM observed along the diagonal of the above table, suggests no significant correlation (monotonic relationship) between any of the respective attribute's importance scores. Thus, we can conclude that customer choices change when they choose between individual policies and bundled policies.

Similarly, we consider the correlation of the respondents' choice for a policy brand in LGPM and CAM approach. Table 24 and table 25 show the results for Pearson's correlation co-efficient values and Spearman's rank correlation co-efficient values respectively.

Table 24: Pearson's Correlation between choice of respective policy brands in LGPM and CAM approaches

		Policy 1-LGPM	**Policy 2-LGPM**	**Policy 3-LGPM**	**Policy 4-LGPM**	**Policy 5-LGPM**
Policy 1-CAM	Correlation Coefficient	**0.375****				
	Significance (2-tailed)	**0.000**				
Policy 2-CAM	Correlation Coefficient		**0.199****			
	Significance (2-tailed)		**0.005**			
Policy 3-CAM	Correlation Coefficient			**-0.034**		
	Significance (2-tailed)			**0.635**		

Policy 4-CAM	Correlation Coefficient				**-0.023**	
	Significance (2-tailed)				**0.747**	
Policy 5-CAM	Correlation Coefficient					**0.267****
	Significance (2-tailed)					**0.00**

In case of Pearson's correlation co-efficient we observe that there exists a linear relationship in the respondents' choice of brands like Policy 1, Policy 2 and Policy 5 in case of LGPM and CAM approach but no correlation exists between Policy 3 and Policy 4, amongst the two approaches. This suggests that the respondents' behavior towards choice of policies in both the approaches is similar for Policy 1, Policy 2 and Policy 5 but not in case of Policy 3 and Policy 4. In both approaches the most preferred choice of the customers in Policy 1, Policy 2 and Policy 5.

Now we consider the monotonic relationship of the respondents' choices of policy brands in LGPM and CAM approaches by computing the Spearman's rank correlation between them as shown in table 25 below.

Table 25: Spearman's Rank Correlation between choice of respective policy brands in LGPM and CAM approaches

		Policy 1-LGPM	**Policy 2-LGPM**	**Policy 3-LGPM**	**Policy 4-LGPM**	**Policy 5-LGPM**
Policy 1-CAM	Correlation Coefficient	**0.427****				
	Significance (2-tailed)	**0.000**				
Policy 2-CAM	Correlation Coefficient		**0.163***			
	Significance (2-tailed)		**0.020**			
Policy 3-CAM	Correlation Coefficient			**-0.038**		
	Significance (2-tailed)			**0.589**		
Policy 4-CAM	Correlation Coefficient				**0.239****	

	Significance (2-tailed)				**0.001**	
Policy 5-CAM	Correlation Coefficient					**0.321****
	Significance (2-tailed)					**0.000**

Similar to the case of Pearson's correlation, in case of computing Spearman's rank correlation we observe that there exists a monotonic relationship in the respondents' choice of brands like Policy 1, Policy 2, Policy 4 and Policy 5 in case of LGPM and CAM approach except for the policy brand Policy 3. This suggests that the respondents' behavior towards choice of policies in both the approaches is similar for Policy 1, Policy 2, Policy 4 and Policy 5 but not in case of Policy 3. In both approaches the most preferred choice of the customers in Policy 1, Policy 2, Policy 4 and Policy 5.

10. Clustered Comparison of LGPM and CAM approaches

We now compare the utilities computed from LGPM and CAM in each of the above mentioned socio-demographic factors as shown in table 1. We perform Anova test to check for significant difference among the utilities in each of the above mentioned clusters. The results are represented in table 26 below

Table 26: Anova Results for each attribute in each of the clusters

Attributes	***Source of Variation***	***SS***	***df***	***MS***	***F***	***P-value***	***F crit***	***Significant Difference***
Premium	**Gender**	0.004549	1	0.004549	0.916251	0.513916	161.4476	No
	Approach (LGPM/CAM)	0.018038	1	0.018038	3.63297	0.307597	161.4476	No
	Age	161.7483	4	40.43706	1.032773	0.487909	6.388233	No
	Approach (LGPM/CAM)	94.37354	1	94.37354	2.410325	0.195492	7.708647	No
	Occupation	512.8035	5	102.5607	1.027817	0.488357	5.050329	No
	Approach (LGPM/CAM)	187.3497	1	187.3497	1.877534	0.228935	6.607891	No
	Income	109.0334	4	27.25835	0.891294	0.54306	6.388233	No
	Approach (LGPM/CAM)	47.03311	1	47.03311	1.53789	0.282708	7.708647	No
PS	**Gender**	15.30198	1	15.30198	6.167996	0.243691	161.4476	No
	Approach (LGPM/CAM)	15.13053	1	15.13053	6.098886	0.244936	161.4476	No
	Age	119.6293	4	29.90731	1.415372	0.372294	6.388233	No

	Approach (LGPM/CAM)	35.72046	1	35.72046	1.690481	0.263394	7.708647	No
	Occupation	304.2859	5	60.85718	1.316092	0.385231	5.050329	No
	Approach (LGPM/CAM)	25.38243	1	25.38243	0.548918	0.492066	6.607891	No
	Income	205.5127	4	51.37817	1.277081	0.409189	6.388233	No
	Approach (LGPM/CAM)	1.698037	1	1.698037	0.042207	0.847257	7.708647	No
PI	**Gender**	4.403351	1	4.403351	3.547649	0.31072	161.4476	No
	Approach (LGPM/CAM)	39.31135	1	39.31135	31.67199	0.111952	161.4476	No
	Age	123.9419	4	30.98549	1.164897	0.442984	6.388233	No
	Approach (LGPM/CAM)	240.3506	1	240.3506	9.035961	0.039707	7.708647	Yes
	Occupation	111.5718	5	22.31437	1.129074	0.448635	5.050329	No
	Approach (LGPM/CAM)	352.7747	1	352.7747	17.84988	0.008289	6.607891	Yes
	Income	221.0506	4	55.26265	1.532097	0.344714	6.388233	No
	Approach (LGPM/CAM)	266.9206	1	266.9206	7.400086	0.05297	7.708647	Yes
CSL	**Gender**	26.39397	1	26.39397	1.53018	0.432803	161.4476	No
	Approach (LGPM/CAM)	261.3431	1	261.3431	15.15127	0.16009	161.4476	No
	Age	121.6784	4	30.41959	1.010025	0.496259	6.388233	No
	Approach (LGPM/CAM)	367.8804	1	367.8804	12.21477	0.02501	7.708647	Yes
	Occupation	60.65168	5	12.13034	1.296508	0.391317	5.050329	No
	Approach (LGPM/CAM)	804.6353	1	804.6353	86.00062	0.000245	6.607891	Yes
	Income	46.95005	4	11.73751	0.690118	0.635971	6.388233	No
	Approach (LGPM/CAM)	361.7643	1	361.7643	21.27026	0.009941	7.708647	Yes
AOC	**Gender**	11.70064	1	11.70064	1.040072	0.493747	161.4476	No
	Approach (LGPM/CAM)	166.2896	1	166.2896	14.78151	0.161995	161.4476	No
	Age	217.5629	4	54.39073	1.310039	0.399944	6.388233	No
	Approach (LGPM/CAM)	957.6244	1	957.6244	23.06505	0.008632	7.708647	Yes
	Occupation	277.2089	5	55.44178	0.953757	0.520085	5.050329	No
	Approach (LGPM/CAM)	807.851	1	807.851	13.89734	0.0136	6.607891	Yes
	Income	243.0821	4	60.77053	0.99272	0.50274	6.388233	No
	Approach (LGPM/CAM)	888.2083	1	888.2083	14.50938	0.018955	7.708647	Yes

The two-way Anova for each of the clusters and approaches (LGPM and CAM) we observe that there is no significant differences among the both clusters (in all factors) and approaches for the attributes ‘Premium’ and ‘PS’. There is no significant difference among the clusters (in all factors) for the attributes ‘PI’ , ‘CSL’, and ‘AOC’ but when we consider the approaches applied to these clusters (in all factors) for the attributes ‘PI’ , ‘CSL’, and ‘AOC’, we observe significant difference in them with an alpha level of 0.05.

11. Conclusion

A linear utility function that represents the customer choice preference while purchasing a vehicle insurance policy is developed in this paper, using two approaches viz: LGPM and CAM. Both the approaches are based on the five attributes that are important to consumers while choosing a suitable policy. This study yields a scheme for competing policies to recognize and comprehend the customer preferences in order to align the product offerings to make more profit and also compare themselves with their competitors. This study also provides a comparative study of the two approaches: LGPM and CAM, as a research tool for market analysis.

In a broad context, when the attributes are considered independently in case of LGPM approach, the attributes like ‘Policy Inclusions’ and ‘Customer Service Level’, have more weightage to the consumers’ selection of a policy but when all the five attribute levels are bundled as packages or combination of attribute levels, the attributes ‘Add-On Covers’ has more weightage to the consumer choices. The empirical results conclude that the two approaches LGPM and CAM yield similar score fluctuation patterns in terms of the attributes ‘Premium’ and ‘PS’ but we can observe significant differences in the scores of the attributes ‘PI’, ‘CSL’, and ‘AOC’. The two research approaches bear some degree of similarity and some degree of differences depending upon the attributes. Based on these findings, we can further strengthen our argument by concluding that the respondent behavior in terms of rating the attributes and in terms of choosing a policy brands in the case of both approaches are different. In other words, a respondent’s rating change when the attributes are considered independently and when each of the attribute levels are bundled as a combination in the form of a packaged product. The correlation of the observed and the estimated values is strong in both approaches as seen in table 9 and table 14. So both approaches are similar in some sense. Further, when the respondents are clustered into groups in each of the socio-demographic factors like gender, age, occupation and income we conclude that the respondents scaling of the attributes are fairly similar but are they differ in their scaling of attributes like ‘Policy Inclusions’, ‘Customer Service Level’ and ‘Add-On Covers’ in the two approaches: LGPM and CAM.

The application of LGPM is an easier as compared to CAM. Although there is certain amount of similarity in the two approaches, the weights of the utilities of the attributes in LGPM approach are considered independently and in case of CAM approach the weights of the utilities is based on all attributes taken together, which resembles reality. However, CAM approach provides other useful information that LGPM approach cannot produce. In case of CAM the utility value for each of the attribute level is obtained unlike LGPM approach where we get the utility scores or weights of the attributes alone. The utility scores of each attribute level can help the policy makers to determine the best product attribute combination and perform cost benefit analysis. CAM also helps in conducting trade-off analysis by varying the attribute levels and their combinations. In this research study, we have generated the utility function for vehicle insurance policy and we have exhibited the efficacy of the LGPM and CAM approaches as useful research tools for market analysis.

12. Scope for Future Research

1) This study considers only five attributes to demonstrate the utility of vehicle insurance policies as a limitation of survey design in case of conjoint analysis. We can extend this study by considering more number of attributes that describes the product and apply other approaches like adaptive or hybrid conjoint analysis. We can also consider this study applying choice based conjoint analysis.
2) This study can be extended further to various other products.
3) We can also study the comparison of other marketing research tools that are used to study the customer behavior.

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Appendix - 1

Following are some of the terminologies used in the above study:

Own Damage (OD) Cover – The Own Damage (OD) cover includes losses incurred due to accidents, theft, fire, strikes, terrorist activities, landsides, floods, earthquakes, riots etc. Losses incurred to the vehicle while in transit via road, waterways, airways or elevators are also covered.

Third – Party (TD) Liability Cover: The third-party (TD) liability cover offers protection to third-party property damages. It also offers protection for the life and property of the third party. In short, this plan provides insurance cover against legal liability to a third party in an accident.

Return to Invoice (RTI): RTI is an add-on option that covers the gap between the insured declared value and the invoice value of the car. This option fetches the total loss amount (the on-road price you paid for your car) that is incurred from losing it. In the event of a theft or total damage of the vehicle, you can raise a claim under the car insurance. In this case, the insurance company will offer you an amount equal to the Insured Declared Value (IDV) of the vehicle. But if your vehicle was protected with the RTI cover, you can get the actual invoice price, i.e., the on-road price that you paid for the vehicle at the time of purchase.

No Claim Bonus Protection Cover: No claims (NC) bonus protection is an extra option available on car insurance policies, that does not affect the no claims bonus at all for one claim in the insured year. After more than one claim, step back no claims protection will apply. In order to prevent current claims (other than total loss claims) from nullifying no claim benefits accrued on the policy, this cover ensures payment of the no claim bonus as specified in the contract upon renewal.

Zero Depreciation: Zero depreciation also known as Nil depreciation or Bumper to Bumper car insurance is a policy that omits the depreciation factor from the coverage, thus giving you complete cover. It means that if the car gets damaged due to a collision, no depreciation is subtracted from the coverage of wearing out of any body parts of car excluding tyres and batteries. This insurance policy will pay out the entire cost of the body part for replacement.

Consumables Cover: At the time of claims, usually consumables like bolts, nuts, oil etc. are not covered under the insurance. The policy holder can save on consumables like bolt and nut, washers, screw, etc. when he is making a claim. This add-on covers those expenses towards consumables that are not fit for further use, arising out of damage due to an accident or any such event.