EBA5005 – Practice Module in Specialized Predictive Modelling and Forecasting

Project Report for EBA5005

A study on Customer Preferences for Smartphone Features applying Conjoint Analysis

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Analytics Arena

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Introduction

In the highly competitive world of Smartphones, where giants are falling and new companies and technologies are usurping the top sellers in the market, it has become vital for every company, existing and newcomers, to learn the preference of consumers. Smart Tech is an internationally established Smart Phone manufacturer and is looking to expand into the Indian Market. Smart Tech is exploring ins to the new market, the mode of entry and the product to introduce. The Data Analytics wing of Smart Tech will explore these and present to the stakeholders with actionable Business Insights.

Industry Overview

Smart Phone industry is a very thriving industry but a risky one at that due to the continuous shift of Market, based on consumers choice. As per the report by Indian council for research on consumer electronics industry: With the mobile as the future of everything, it is estimated that smart phone users alone will touch 442.5 million by 2022 making India a very seductive smartphone market (Asher, 2020). India, a country with large population, and a large population of people able to afford Smart Phones, is a lucrative market to venture into.

Business Problem and Objective

Smart Tech wants to test waters in the new market, laced with the insights, backed by Data, to minimise risks. Deciding which models of phones to launch is a crucial element of this endeavour. However, the analytics on customer preferences on smartphone specifications could be easier if all the consumers had a common preference. There are customer satisfaction/feedback agencies that have traditionally been playing catch-up with adversaries when it comes to technology. Our team hopes to help bridge that gap.

As the Analytics team in Smart Tech, our focus is on developing Conjoint Analysis solution that will allow people from various demographics to have a say on their preferences, reliably and without bias, helping Smart Tech to launch Consumer preferred option in the Market.

Given the volume of smartphone specifications and variants, it is also not practical to try and include all the factors that could influence the people’s preferences. That could give too many levels and complexity in analysis. Thus, there is a need for a solution that can effectively and efficiently disseminate the most influential factors in the smartphone specifications for any kind of analysis. Smart Tech plans to conduct Choice Based Conjoint analysis to gauge present consumer’s preference. The resulting utility score can be used to identify the attributes that have the least preference and the most preferences. Such insights could support the management in its design decision making.

The other goal that Conjoint analysis can help to achieve is to predict the market shares or shares of preference by using probabilistic models. Various 'Probabilistic Models' to predict Market Share will be explored in order to support this study.

1. Design of Experiment

To determine the factors, the decision variables, which impacts the user's decision most, study of various Tech Review and Rating websites was done. As there are many specifications, but for an average user, only a number of factors matter, these most common, most relevant and most frequently occurring Factors, among all the Tech review websites were gathered to base the design of experiment on.

These Factors (and selected attribute levels) were:

- Price (INR 17999, INR 19999 & INR 22999)
- RAM (4GB, 6GB & 8GB)
- Internal Memory (64GB, 128GB, 264GB)
- Screen Size (5 inches, 6 inches, 7 inches)
- Display Type (IPS LCD & AMOLED)
- Presence of Audio Jack (Yes, No)

There may have been multiple combinations of Attributes and levels, Attributes and their levels were kept homogeneous to prevent noisier outputs or "Number of Level Effect".

Once the Attributes were selected, Sawtooth and JMP were used to design the experiment.

JMP Output:

After preparing orthogonal design JMP gave 3 surveys with 15 tasks and each having 3 choices. But there were obvious choices, for example 256 GB at Price Rs17999 will be an obvious choice and customer will choose that only.

We found that such choices cannot be removed too as the design won't remain orthogonal. We concluded the JMP design is not much helpful when there are unrealistic choices in the design which will affect the outcome greatly.

Sawtooth :

Sawtooth gives the option to restrict combinations based on rules. Design still remains orthogonal and useful for the survey. Sawtooth gave 1 set of 16 questions, where all combinations were feasible (in terms of production). So we used sawtooth for designing choices which reduced the task from 45 earlier (15 tasks per survey) to 16 tasks only in total.

As we could not afford only the demo version of software, these 16 cards are attached as images at the end of this document (Google Drive Link).

2. Survey Data Analysis

Businesses frequently make the mistake of assuming that customers make decisions based on the same criteria that they usually do -Cost. Customers make decisions based on value- a complex interplay of sociological and psychological factors.

Conjoint analysis is a survey-based statistical technique used in market research that helps determine how people value different attributes (feature, function, benefits) that make up an individual product or service.

After rolling out the survey, the collected results were as shown below.

Name	Gender	Age Group	Which Brand of phone	On a scale of 5 to 1, hc	How would you prefer b	If these were your only	If these were your only	If these were your only	If these were your only	If
Raju Pandey	Male	Above 36	Oppo	4	Retail Store	A3	B2	C1	D3	E
Rahul M	Male	Above 36	Samsung	3	Retail Store	A3	B3	C3	D3	E
P Dhandapani	Male	Above 36	Apple	5	Online	A2	B2	C1	D1	E
Dilip K Mallik	Male	Above 36	Apple	3	Retail Store	A2	B3	C2	D2	E
Sanchita Mallik	Female	Above 36	Samsung	3	Retail Store	A3	B2	C1	D1	E
Sahil Arora	Male	Above 36	Apple	4	Online	A1	B3	C2	D3	E
Roshan Aryan	Male	Above 36	Xiaomi	3	Online	A1	B3	C2	D3	E
Ankur Modi	Male	Above 36	Oppo/Vivo	2	Retail Store	A1	B3	C2	D3	E
Rajeshwar Singha	Male	Above 36	Xiaomi	3	Retail Store	A2	B3	C2	D3	E
Ravi Pratap Sisodia	Male	Above 36	Xiaomi	4	Online	A1	B3	C2	D3	E
Srijita Mukherjee	Female	Above 36	Samsung	4	Online	A1	B3	C2	D3	E

Analysis:

After this for analysis purpose transformed the data .

rep	Set_id	Alt_id	Price	RAM	Screen siz	Display ty	Audio jack	Internal m	Selected
1	1	1	22999	8GB	6"	AMOLED	No	64GB	0
1	1	2	19999	4GB	7"	IPS LCD	Yes	128GB	1
1	1	3	17999	4GB	5"	IPS LCD	Yes	64GB	0
1	2	1	17999	4GB	5"	IPS LCD	Yes	64GB	0
1	2	2	17999	6GB	6"	IPS LCD	No	64GB	1
1	2	3	19999	8GB	5"	IPS LCD	Yes	128GB	0
1	3	1	17999	4GB	5"	IPS LCD	Yes	64GB	0
1	3	2	22999	6GB	6"	AMOLED	No	128GB	0
1	3	3	19999	4GB	7"	IPS LCD	Yes	64GB	1
1	4	1	17999	4GB	5"	IPS LCD	Yes	64GB	0
1	4	2	19999	8GB	5"	AMOLED	No	64GB	0
1	4	3	22999	8GB	7"	IPS LCD	No	256GB	1

Our data

Response variable: Selected

Explanatory variable: Attributes of Price, RAM ,Screen_size, Display_type, Audio_jack, Internal Memory

The aim of our analysis is that we predict choice probabilities based on the Choice profiles.

After collection of results to estimate Utilities and choice probabilities, Multinomial Logistic Regression is used.

Multinomial Logistic Regression: Assumes that the probability that an individual will choose one of the m alternatives i from the choice set C is:

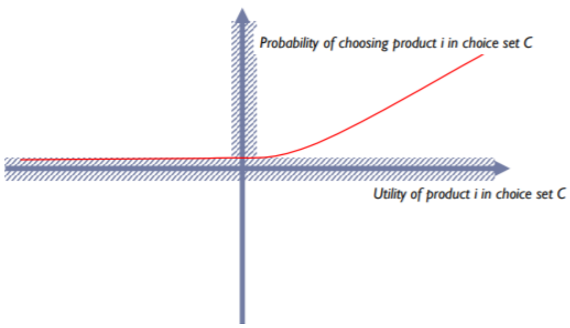
$$p(i|C) = \frac{exp(U_i)}{\sum_{j=1}^{m} exp(U_j)} = \frac{exp(x_i\beta)}{\sum_{j=1}^{m} exp(x_j\beta)}$$

where

U_i = the utility of alternative *i*,

x_i = a vector of attribute level dummies for alternative *i*,

β = a vector with unknown part-worth utilities [to be estimated]



The probability of choosing a product in choice set C increases as Utility of product in choice set C.

R is used to run logistic model on the collected results:

```
cbc.mlogit <- mlogit.data(data=cbc, choice="Selected", shape="long",alt.var = 'Alt_id', id.var="i..rep")
cbc.ml <- mlogit(Selected ~ 0 + Price + RAM + Screen_size + Display_type+RAM+Audio_jack+Internal_memory, data = cbc.mlogit)
names(summary(cbc.ml))
```

And the parameter estimates can be seen in table :

Levels	Estimate	Std.Error	z-value	Pr(>|z|)
Price19999	-0.129	0.064	-1.99	0.044*
Price22999	-0.426	0.08	-5.023	4.33e-07***
RAM6GB	0.6244	0.07	7.9838	1.332e-15***
RAM8GB	0.74	0.08	8.9012	<2.2e-16***
Screen_size6"	0.138	0.07	1.8576	0.0632
Screen_size7"	-0.334	0.06	-5.4588	4.794e-08***
Display_typeIPS	-0.245	0.055	-4.4061	1.053e-05***
Audio_jackYes	0.302	0.076	3.9414	8.102e-05***
Internal_memory256	0.189	0.069	2.743	0.006088**
Internal_memory64	-0.353	0.053	-6.6716	2.530e-11***

Parameter estimates

Summary of model fit	Log Likelihood:-3069.1

The parameter estimates shows that Price Rs 19999 is more popular than 22999, RAM 8GB is more popular than 6GB, Screen size 7” is less popular ,Display type IPS LCD is less preferred, Audio Jack is popular, Internal memory 256 GB is more popular.

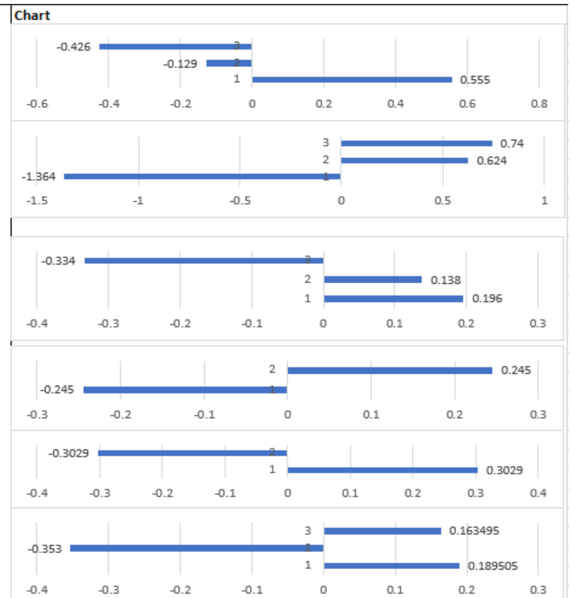
In multinomial logistic one level in any attribute is considered as reference level. The parameter for this level is held constant. In order to estimate the parameter of the other levels, we use dummy variable for attribute levels and then used Effect coding which takes value -1 for the reference level. Finally, to evaluate the last level we estimate it as minus the sum of all other levels of that attribute.

The utility range is difference of maximum utility of level of attribute and minimum utility of level of attribute, this is used to evaluate how much difference each attribute could make in total utility of a product, while the importance is a relative measure it is calculated using:

$$\text{Importance of attribute } m = |\text{Range}_m|/(|\text{Range}_1|+|\text{Range}_2|+\ldots+|\text{Range}_K|)$$

Attribute	Importance	Level	Effect	Utility_Range
Price	**18.67%**	Price17999	**0.555**	
		Price19999	-0.129	
		Price22999	-0.426	0.981
		RAM4GB	-1.364	
		RAM6GB	0.624	
RAM	**40.05%**	RAM8GB	**0.74**	2.104
		Screen_size5"	**0.196**	
		Screen_size6"	0.138	
Screen_size	10.08%	Screen_size7"	-0.334	0.53
Display_type	9.32%	Display_typeIPSLCD	-0.245	0.49
		Display_typeAMOLED	**0.245**	
		Audio_jackYes	**0.3029**	
Audio_Jack	11.53%	Audio_jackNo	-0.3029	0.6058
Internal_memory	10.32%	Internal_memory256GB	**0.18951**	0.542505
		Internal_memory64GB	-0.353	
		Internal_memory128GB	0.1635	

Chart



Looking at the table RAM is having a relative importance of 40% and a utility range value of 2.104 which shows people preferred performance in their mobile, the next best attribute is Price which has an importance of 18%.

Willingness to Pay-This is the maximum price a customer is willing to pay for a product. It is a crucial factor to find the best price to sell a product at, for both seller and buyer.

$$\mathrm{MWTP}_j = V_j / V_p$$

where:

- MWTP_j is the standard marginal willingness to pay of feature j,
- V_j is the value (mean coefficient) of feature j,
- V_p is the value (mean coefficient) of price.

Attribute	Variable	Effect	WTP	WTP*1000
RAM	RAM4GB	-1.364	-6.7861	-6786.07
	RAM6GB	0.624	3.10448	3104.48
	RAM8GB	0.74	3.68159	3681.59
Screen_size	Screen_size5"	0.196	0.97512	975.12
	Screen_size6"	0.138	0.68657	686.57
	Screen_size7"	-0.334	-1.6617	-1661.69
Display_type	Display_typeIPSLCD	-0.245	-1.2189	-1218.91
	Display_typeAMOLED	0.245	1.21891	1218.91
Audio_Jack	Audio_jackYes	0.3029	1.50697	1506.97
	Audio_jackNo	-0.3029	-1.507	-1506.97
Internal_memory	Internal_memory256GB	0.18951	0.94281	942.81
	Internal_memory64GB	-0.353	-1.7562	-1756.22
	Internal_memory128GB	0.1635	0.81341	813.41

To_upgrade	Price in Rs
4GB to 6GB	989.05
6GB to 8GB	57.71
4GB to 8GB	1046.77
IPS to AMOLED	243.78
Audio Jack	301.39
64GB to 128GB	256.96
64GB to 256GB	289.9

It can be concluded that people are willing to pay Rs 3681 more for 8GB RAM .

1. For screen size 5”, they are willing to pay Rs 975.12 more.
2. For Display type AMOLED, they are willing to pay Rs 1218.91 more.
3. For a mobile with audio jack, they are willing to pay Rs 1506.91 more.
4. For a mobile with internal memory 256 GB they are ready to pay Rs 942.81 more.

To calculate how much people are willing to pay for an upgrade, we took the difference of coefficients of levels divided by the price coefficient and populated the table: Table No:3

Referring the table we can conclude, people are willing to pay Rs 989.05 more for an upgrade from 4GB to 8GB, while for an upgrade to 8GB from 4GB ,people are ready to pay Rs 1046.77.People are ready to pay higher to upgrade for a better performance mobile.

To check trade-off between price and performance, we can see there is a utility loss to go from Price Rs 19999 to Rs 17999 and to go from Rs 22999 to Rs 17999 while there is a utility gain while changing from RAM 6GB to 8GB.The utility loss and gain are calculated simply by taking a difference of effects column which is essentially utility values.

Share of preference:

Share of preference does not equal market share. It is very powerful .They help us understand what a product's potential is ,how well it is liked versus competitive products and what aspects of the product are most contributing to preference. After careful analysis of the results collected and running a basic regression on profiles. It was found that the top profiles were as highlighted in the Table below.

S.no	Share	Price	RAM	Screen_siz	Display_ty	Audio_jac	Internal_r	Set_id	Alt_id
1	0.427452	22999	8GB	6"	AMOLED	No	64GB	1	1
2	0.270548	19999	4GB	7"	IPS LCD	Yes	128GB	1	2
3	0.302	17999	4GB	5"	IPS LCD	Yes	64GB	1	3
4	0.187432	17999	4GB	5"	IPS LCD	Yes	64GB	2	1
5	0.337118	17999	6GB	6"	IPS LCD	No	64GB	2	2
6	0.47545	19999	8GB	5"	IPS LCD	Yes	128GB	2	3
7	0.282074	17999	4GB	5"	IPS LCD	Yes	64GB	3	1
8	0.542354	22999	6GB	6"	AMOLED	No	128GB	3	2
9	0.175572	19999	4GB	7"	IPS LCD	Yes	64GB	3	3
10	0.219017	17999	4GB	5"	IPS LCD	Yes	64GB	4	1
11	0.500316	19999	8GB	5"	AMOLED	No	64GB	4	2
12	0.280667	22999	8GB	7"	IPS LCD	No	256GB	4	3
13	0.188304	17999	4GB	5"	IPS LCD	Yes	64GB	5	1
14	0.584338	19999	6GB	5"	AMOLED	Yes	128GB	5	2
15	0.227358	19999	8GB	7"	IPS LCD	No	64GB	5	3
16	0.196639	17999	4GB	5"	IPS LCD	Yes	64GB	6	1
17	0.48876	19999	6GB	7"	AMOLED	Yes	256GB	6	2
18	0.314601	22999	8GB	5"	IPS LCD	No	128GB	6	3
19	0.342178	17999	6GB	7"	IPS LCD	Yes	128GB	7	1
20	0.303256	22999	8GB	5"	IPS LCD	Yes	128GB	7	2
21	0.354565	22999	8GB	5"	IPS LCD	No	256GB	7	3
22	0.181987	17999	4GB	5"	IPS LCD	Yes	64GB	8	1
23	0.20739	19999	6GB	7"	IPS LCD	Yes	64GB	8	2
24	0.610623	17999	6GB	6"	AMOLED	Yes	128GB	8	3
25	0.376915	17999	4GB	5"	IPS LCD	Yes	64GB	9	1
26	0.234604	19999	4GB	7"	IPS LCD	Yes	64GB	9	2
27	0.388481	22999	6GB	6"	IPS LCD	No	64GB	9	3
28	0.197735	17999	4GB	6"	IPS LCD	Yes	64GB	10	1
29	0.34978	19999	8GB	7"	IPS LCD	Yes	128GB	10	2
30	0.452486	22999	6GB	6"	AMOLED	No	256GB	10	3
31	0.319237	17999	4GB	5"	IPS LCD	Yes	64GB	11	1
32	0.198704	19999	4GB	7"	IPS LCD	Yes	64GB	11	2
33	0.482059	22999	6GB	5"	IPS LCD	Yes	128GB	11	3
34	0.281409	17999	4GB	5"	IPS LCD	Yes	64GB	12	1
35	0.251177	19999	4GB	6"	IPS LCD	Yes	64GB	12	2
36	0.467414	22999	8GB	7"	AMOLED	No	256GB	12	3
37	0.217395	17999	4GB	5"	IPS LCD	Yes	64GB	13	1
38	0.377056	22999	6GB	6"	IPS LCD	No	256GB	13	2
39	0.405549	17999	4GB	5"	AMOLED	Yes	128GB	13	3
40	0.286364	17999	4GB	5"	IPS LCD	Yes	64GB	14	1
41	0.345757	19999	8GB	7"	IPS LCD	Yes	64GB	14	2
42	0.367879	19999	4GB	6"	IPS LCD	No	128GB	14	3
43	0.197372	17999	4GB	6"	IPS LCD	Yes	64GB	15	1
44	0.52942	17999	6GB	5"	IPS LCD	Yes	128GB	15	2
45	0.273207	22999	6GB	5"	AMOLED	Yes	64GB	15	3
46	0.170108	17999	4GB	5"	IPS LCD	Yes	64GB	16	1
47	0.653918	19999	8GB	5"	AMOLED	Yes	256GB	16	2
48	0.175974	22999	6GB	7"	IPS LCD	No	128GB	16	3

Further scope of analysis:

RFC-BOLSE can be further explored to analyse market share prediction.

3. Segmentation

Every business wants to identify customer groups who will be more willing to buy their product in the targeted market. Along with that they also want to know which features of their product are preferred by which group of the population. Thereby they can have a better understanding of their potential customers, their behaviors, and their preferences. These insights will help them in designing the product and also marketing it in their target country.

This is where segmentation plays a crucial role as it helps to identify groups among survey respondents based on their preferences and their demographics data.

In this project segmentation of the respondents have been done based on their preference of features, age group, gender, mode of purchase and satisfaction level with current product.

Data Preparation-

The survey data collected needed pre-processing before it could be used for Clustering.

Profiles Selected by respondents- The profiles of smart-phone features were used; they are represented as A1, A2, A3, B1, B2 and so on till P3. They were taken as input in form of dummy Variables 0 and 1 where 0 represents profile not selected and 1 represents profile selected.

Age Group- for the group below age 22 years the value 1 was assigned, for group 22 to 36 years value 2 was assigned and for above 36 years age value 3 was assigned

Gender- To represent Female the value 1 was used and for male value 2 was used.

Satisfaction Level bracket- The satisfaction levels of the respondents were grouped in two brackets; bracket with value 1 represents level 1 to 3 and bracket with value represents level 4 and 5.

Mode of Purchase- Online purchase is represented by 0, Retail purchase is represented by 1
Software JMP and Python has been used for clustering.
K means clustering algorithm has been used for clustering.
JMP uses Cubic Clustering Criterion metrics to decide the optimal number of cluster whereas in Python Elbow method has been used to get the optimal number.

Based on Elbow method, Figure 3.1, we got 3 as optimal number of cluster whereas in JMP it is 4, Figure 3.2.

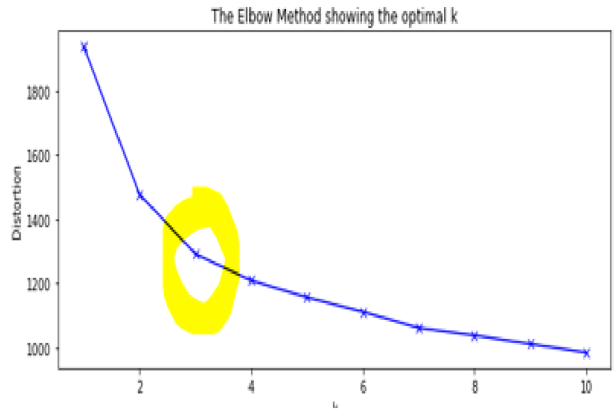


Fig 3.1: The Elbow Chart as obtained in Python

Cluster Comparison

Method	NCluster	CCC	Best
K Means Cluster	2	1.39362	
K Means Cluster	3	3.62025	
K Means Cluster	4	3.73464	Optimal CCC
K Means Cluster	5	2.33674	
K Means Cluster	6	3.3148	
K Means Cluster	7	1.63793	
K Means Cluster	8	2.06625	
K Means Cluster	9	3.48239	
K Means Cluster	10	2.21398	

Fig 3.2: Cluster Comparison Chart of JMP

Investigation of results from model with 4 cluster-

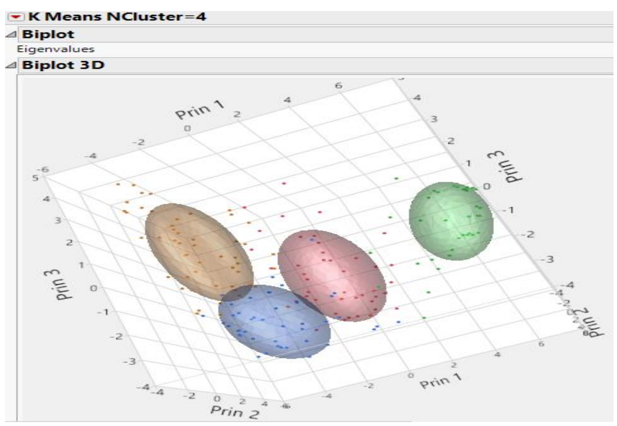


Fig 3.3: The 4 clusters of the model in 3D Plot with 4 clusters

K Means NCluster=4

Columns Scaled Individually

Cluster Summary

Cluster	Count
1	43
2	41
3	48
4	53

Step	Criterion
6	0

Fig 3.4: Cluster Summary for model

It can be observed from Figure 3.3, that there are certain overlapping clusters in the model with 4 clusters even though from Figure 3.4, we can say that the cluster elements are well distributed.

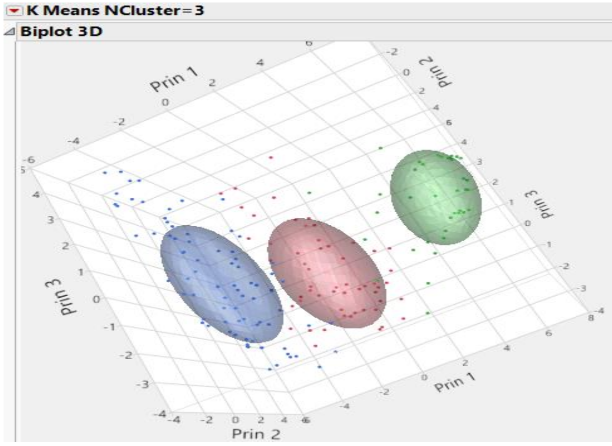


Fig 3.5: The 3 clusters of the model in 3D Plot

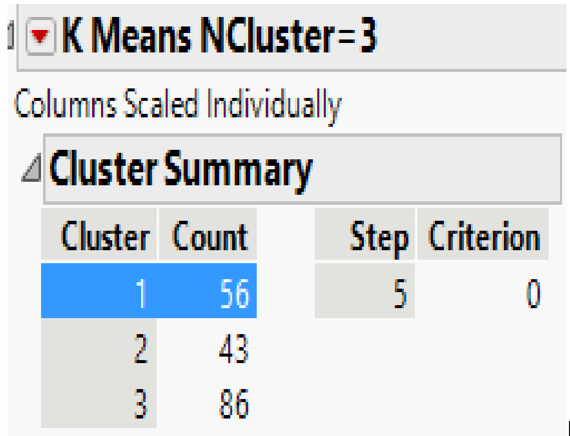


Fig 3.6: Cluster Summary for model with 3 clusters

Observing Figure 3.5, we can say that there is no visible overlapping of clusters for model with 3 clusters and the number of elements are well distributed among the clusters as per Figure 3.6 .

Ncluster \ Metrics	Sillhouette Score	Calinski Harabasz Score	Davies-Bouldin Score
NCluster=3	0.193	42.995	2.143
NCluster=4	0.156	34.276	2.202
NCluster=5	0.158	28.595	2.213

Table 3.1: Comparing the models based on various metrics.

To select the best model out of the models developed in this project, the models were evaluated based on certain well-known metrics for clustering algorithm. The evaluation metrics used in the project are Silhouette Score, Calinski Harabasz Score and the Davies Bouldin Score. From the Table 3.1, it can be observed that the Silhouette Score for 3 cluster containing model is the highest compared to other clusters and is positive, so it tells us that our clustering is correct. However, since the value is close to Zero, we can infer that there is some overlapping of clusters, even though we did not observe any visible overlapping in JMP Software's output. We know that higher Silhouette Score means more dense clustering so based on this metric the model with 3 clusters is preferable as it got the highest silhouette score among the 3 models.

It can be observed from Table 3.1, that the Calinski Harabasz Score for model with 3 clusters is highest compared to others. Higher Calinski Harabasz score means more, and this also indicates that model with 3 clusters is the best performer in this case.

Davies Bouldin Score for 3 cluster containing model is the lowest as observed from Table 3.1, and again this indicates that for the model containing 3 cluster, separation between the cluster is better compared to others.

Therefore, in this project the model with 3 clusters will be considered and will used for further analysis.

Observation –

On analyzing the 3 clustered model it was found that-

Cluster 1 represents group whose predominant features are presence of 3.5 mm Audio Jack , IPS LCD Screen, almost equally divided between price of INR 19,999 and INR 22,999 and corresponds to age group 22-36. **30.3%** of total respondents belong to this cluster.

Cluster 2 consists of profile whose pre dominant features are 4GB RAM, Screen Size 5", presence of 3.5mm Jack, Internal Memory 64 GB, IPS LCD, below 22 age group and corresponding to price of INR 17,999. **23.24%** of the total respondents belongs to this group.

Cluster 3 represents the group pre-dominated by the features like 6GB RAM, Screen Size 6", No audio jack, age group above 36 and price of INR 22,999. **46.5%** of total respondents falls in this group.

64.3% of the respondents want to buy their next phone online and 35.7% of the respondents prefer buying their next smartphone from retail stores.

30.3% of the respondents are not satisfied with their current phone whereas 69.7% of the respondents are satisfied with their current phone.

The means for the variables gender, satisfaction level and the mode of purchase were found to be similar in each cluster and hence were not discriminating factors in the segmentation.

Insights gained-

Based on the observations from the cluster the following insights can be gained-

Cluster 3 representing the highest age group people also corresponds to the highest price group. This is logical as people above 36 years old generally has more purchasing power than others and they are not concerned by the budget in context of the Indian market.

Cluster 2 representing the youngest respondents also corresponds to the lowest price range, this is also in line to the logic that generally younger people have lower purchasing power besides in Indian context a very small population below 22 years old has income sources.

Cluster 1 represents the young adults of India and they are comprised of people going for the costliest option and many opting the mid option as well.

Gender is not a factor in preferences among the respondents of the survey based on the features analyzed in the survey.

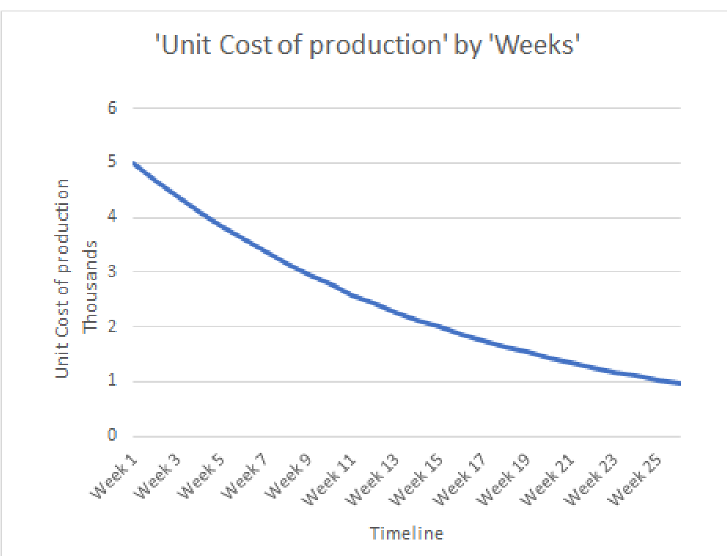
4. Learning Rate

We use the term "Learning Rate", to refer to the relationship between volume of production (i.e., Cumulative Output) and unit costs. Cumulative output is a measure of experience gained in production. Just as individuals have been found to benefit from their experience, groups and organizations have also been found to benefit from the experience they acquire. The Learning can reflect efficiencies gained in production processes, improvements in tooling and in the design of the manufactured components, increased proficiency of individual employees, and improvements in the organization's structure or some combination of these factors. There are vast majority of studies that conclude that cost of reductions through learning do, in fact, occur.

The management approached the analytics team to support in their decision of Outsourcing the assembly and packaging of the new smartphones in a local facility based in SIPCOT area Chennai. The team needs to perform POC and analysis at the site and derive the attributes that can allow them to make calculated decision using statistical analysis.

For our analysis, we sought the assistance of a Subject Matter Expert who had extensive field of mobile device manufacturing and assembling learning curves. Based on our review of literature, we expect an 84% progress ration in mobile manufacturing industries. If the progress ratio(p) is 84%, the learning rate(b) would be equal to -.25. The information about cumulative output and forecasts of the number of units to be produced can be obtained from industry sources, but for academic and project purposes we have made assumptions on few of the variables.

The number of units to be produced by the firm is assigned to be 130000 units. The initial unit cost of production is derived to be 4999.75(INR), with a learning rate of 84% the observation of the learning curve tends to follow a negative exponential distribution as depicted below.



At the end of the POC, the analysis team provided its feedback to the management that its more profitable to go ahead with outsourcing to the local facility for the time being at least until the model starts appealing to the masses.

5. Applied Linear Programming for Operations in manufacturing facility.

Linear Programming is a widely used mathematical technique designed to help in the planning and allocation of key organizational resources. We design our problem equation in such a way that all the equations and inequalities would have linear relationships. The end goal is to achieve the objective function, which is the maximum Profit contribution in retrospect to the following constraints specified in the production facility.

Equipment and respective model	**Time required to assemble respective models of phone(hours)**	**Maximum operational time in week (hours)**	**Profit Return**
E1 _1st Model	0.32	110	15004
E2 _2nd Model	0.43	124	13604

There are two different equipment (E1 and E2) to assemble 5-inch phones and 6-inch phones. The respective equipment has constraint on the maximum operational time in a week as mentioned. The profit return calculated from each model is in INR. Our decision variable that can be optimized would be the number of units that can be assembled. On applying the solver function in Excel, we can obtain that in order to achieve our objective function i.e., maximized profit contribution we can assemble 344 number of 5-inch phones and 288 numbers of 6-inch phones respectively. This is achieved with maximum utilization of the operational hours for each equipment. Note that the Profit return cost split up is sourced from Tech Walls portal.

6. Business Insights and Conclusion

The main objectives of the exercise were to:

a. Select the best Phone Model/Models to launch: Going through the Conjoint Survey, 2 clear winners, for different demographics emerged.
   Model 1: RAM - 8GB, Internal Memory - 256GB, Screen Size - 5 inches, Display Type - AMOLED, Audio Jack - Yes, Price INR 19999
   Model 2: RAM - 6GB, Internal Memory - 128GB, Screen Size - 6 inches, Display Type - AMOLED, Audio Jack - Yes, Price INR 17999

   These two models, being vastly popular give a good willingness to pay for upgrade of over 23.2% and 25.8% of the current prices of the two models, making them very attractive to the Budget Smartphone segment.

b. Identify the Customer Segments: Two segments, with large base in India in terms of prospective customers, i.e.
   i. Students below 22, looking for bigger, flashier mobiles, can compromise on performance and
   ii. People in Jobs, higher income, high performing phones were identified to offer Model 2 and Model 1 respectively.

c. Select the Mode of Entry: It would be prudent to take the route of hiring a third party for assembly and distribution, as this will offer company instant monetary benefits through "Make in India" and "Special Economic Zone" schemes of the government through taxes reliefs and grants. Additionally, through learning rates analysis, we established base line prices to offer to the third party. We also established the share of manufacturing through Linear programming for maximum profit by hiring least resources.

With the right Model identified, Customers Segmented and Modes of Entry with production planning strategy defined, Smart Tech is equipped to venture into the new Market.

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Images of Sawtooth Choices:

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