

Product Design using Conjoint and Principal Component Analyses

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1.0 Introduction

Product design is an important concept in different fields such as Industrial Engineering, Marketing, just to mention a few. It has become crucial for companies to consider customers' need in its design processes. In the era of big data and technological innovation, customers are well informed about product offerings and as such, their taste and preference continue to change, giving rise to various service and product design problems that tries to find a balance of meeting customer needs in the area of preference, form, features, as well as lowering cost of production in order to be profitable and gain a significant market share (Matthyssens and Vandenbempt, 2008).

In solving this problem, analytics such as conjoint analysis can be of help. Green et al. (2001, p. S57) defined conjoint analysis 'as a technique for measuring trade-offs for analysing survey responses concerning preferences and intentions to buy, and it is a method for simulating how consumers might react to changes in current products or to new products introduced into an existing competitive array'. Additionally, Gensler et al., (2012) opine that conjoint analysis cannot be complete until customers' willingness to pay(WTP) is estimated, which is the insignificant price difference when a customer decides to buy a product or not.

Product and service design problems are multi-layered and complicated in nature, which requires the understanding of the needs of customers such as, financial considerations, preference and technical requirements. Matthyssens and Vandenbempt (2008) identified numerous challenges in new product and service design, where customers may not always be aware of what they want or may have difficulty articulating their needs. It can be suggested that conjoint analysis can be helpful, in providing data insights into the behaviour and preferences of customers, which Green et al. (2001) opine to be the method of choice by researchers when identifying the preferences of customers. They further analysed how conjoint analysis gotten from fractional factorial design experiment to create models that deduce customer's part-worth for different levels of attributes in making predictions on how customers make decisions among product and services.

The purpose of this paper is to proffer solutions to service and product design problems of a multi-channel retailer planning to expand new product offerings in the laptop product line. It will involve the use of conjoint analysis to obtain the best optimal combination of attributes that determine customer's purchasing decision. The paper has been organised as follows: Session 2 will discuss the methods for carrying out the task. The interpretation of results and findings will be discussed in session 3. The paper concludes in session 4 by identifying the main implication of the task in practice and theory, including the limitations associated with it.

2.0 Methodology

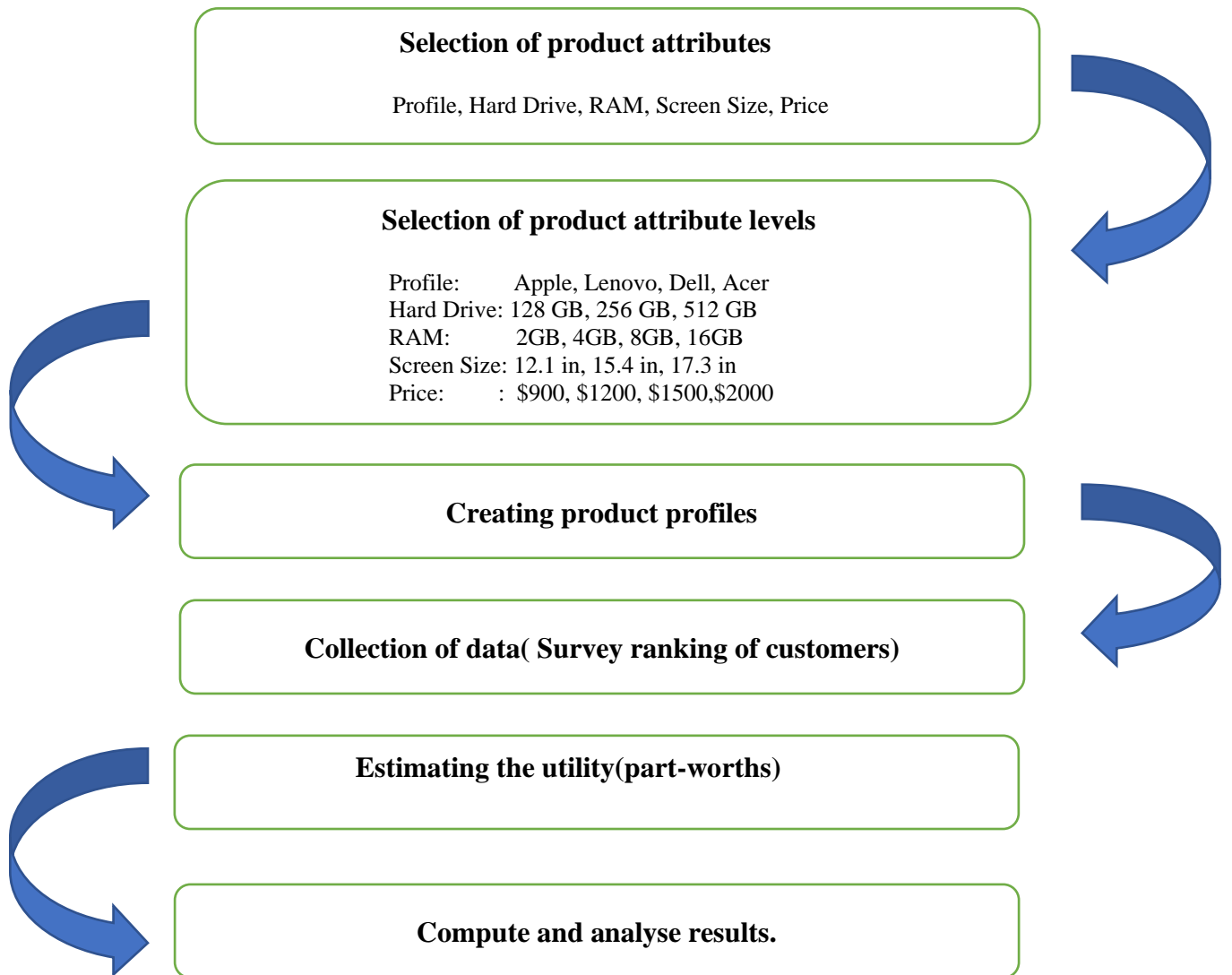


Chart 1: Conjoint analysis flow chart

The conjoint analysis followed a six-step process as can be seen in Chart 1. It began by importing 20 selected optimal profiles into R after the first and second stages had already taken place by choosing the five most important attributes that customers are willing to see in order to make buying decision on a new laptop in the next three months. The product attribute levels was set at $4 \times 3 \times 4 \times 3 \times 4 = 576$ possible attribute combinations. Due to the large number of the possible attribute combinations, a fractional factorial experimental design method was used to select 20 optimal product profiles (McCullough, 2002), in order to reduce the size of the experiment and at the same time limiting the trade off of critical information that might be lost by not conducting a full experiment of all the possible combinations of the levels (Maldonado, 2015). Though there are other experimental design methods such as full factorial design. Fractional factorial design was preferred because it identifies the most important factors and interactions for optimal settings, including the scientific based knowledge that it allows to make informed decisions on the consequences of reducing the size of an experiment (Gunst and Mason, 2009). Additionally, fractional factorial design was adopted because it is more practical and economical and requires less time and resources than full factorial design approach, particularly in estimating the lower-order effects (Jaynes et al., 2012). This was followed by running a correlation matrix on the dummy variables to test for the appropriateness of the selected 20 subset profile to ensure the variables in the analysis are uncorrelated. This was satisfied as the result of the correlation matrix show that the orthogonal values of the correlation matrix are closer to zero, hence reducing the possibility of multicollinearity from affecting the regression model.

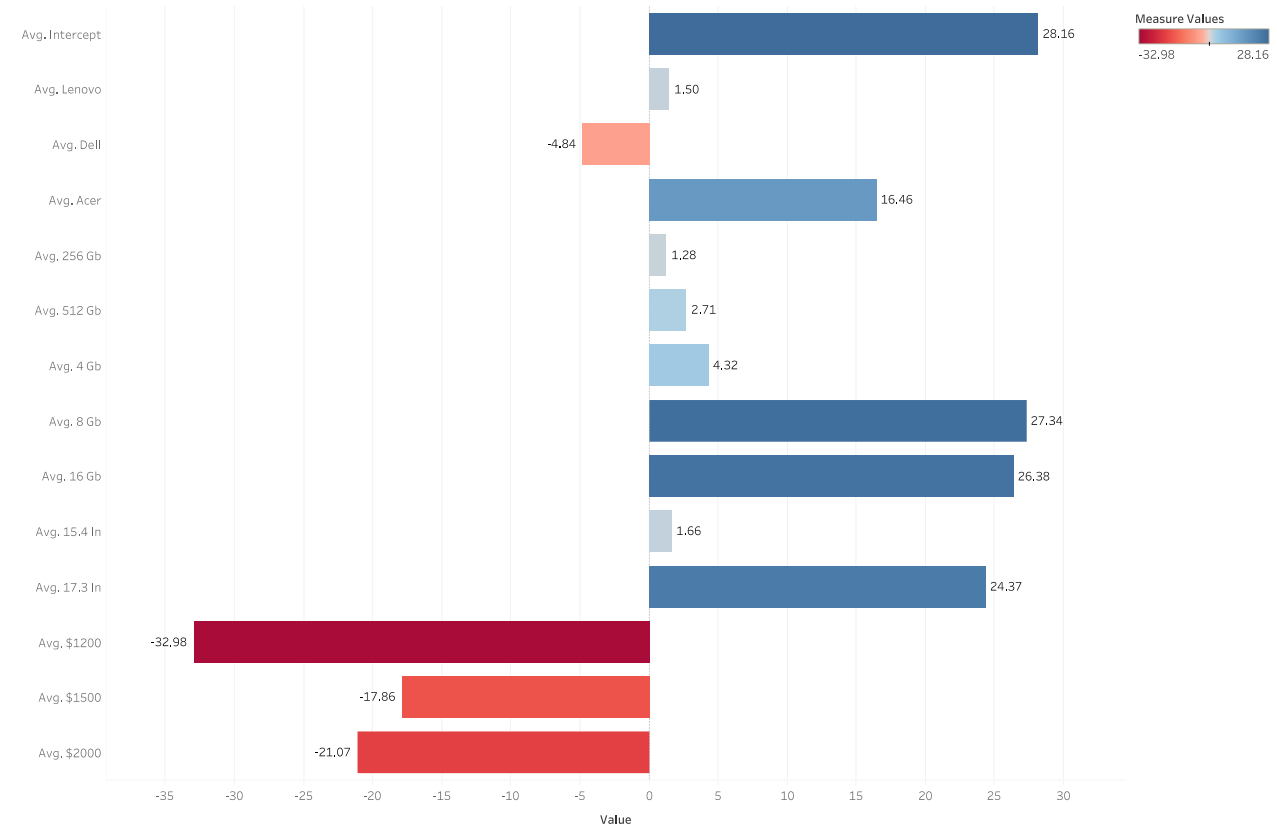
The data collection process used a survey design method. Data from 132 respondents were used to rank the product profiles on a scale of 1-20, where 1 is the best preferred product profile and 20 the worst preferred product profile. Thereafter, the utility was calculated for the 132 respondent. Furthermore, principal component analysis was used to compute an already eight existing profile in the market to determine the most important attributes that customers consider when buying a laptop. Singular values, loading factors and proportional value explained were computed in order to know which attributes are most important (Hastie *et al.*, 2021). Tableau was used to compute and visualize the conjoint part-worth profiles, and the perceptual map.

3.0 Results and Discussions

3.1 Conjoint Analysis Results

3.1.1 Average Attribute Part-Worth

Average Attribute Part-worth



Avg. Intercept, Avg. Lenovo, Avg. Dell, Avg. Acer, Avg. 256 Gb, Avg. 512 Gb, Avg. 4 Gb, Avg. 8 Gb, Avg. 16 Gb, Avg. 15.4 In, Avg. 17.3 In, Avg. \$1200, Avg. \$1500 and Avg. \$2000. Color shows Avg. Intercept, Avg. Lenovo, Avg. Dell, Avg. Acer, Avg. 256 Gb, Avg. 512 Gb, Avg. 4 Gb, Avg. 8 Gb, Avg. 16 Gb, Avg. 15.4 In, Avg. 17.3 In, Avg. \$1200, Avg. \$1500 and Avg. \$2000. The marks are labeled by Avg. Intercept, Avg. Lenovo, Avg. Dell, Avg. Acer, Avg. 256 Gb, Avg. 512 Gb, Avg. 4 Gb, Avg. 8 Gb, Avg. 16 Gb, Avg. 15.4 In, Avg. 17.3 In, Avg. \$1200, Avg. \$1500 and Avg. \$2000. Details are shown for Avg. Intercept, Avg. Lenovo, Avg. Dell, Avg. Acer, Avg. 256 Gb, Avg. 512 Gb, Avg. 4 Gb, Avg. 8 Gb, Avg. 16 Gb, Avg. 15.4 In, Avg. 17.3 In, Avg. \$1200, Avg. \$1500 and Avg. \$2000.

Chart 2: Average Attribute Part-Worth

The above chart show the average attribute part-worths of the entire 132 respondents. Result show a strong preference for Acer laptop than Apple, and Lenovo, and not interested in Dell. Additionally, All respondent prefer large hard drive of 512GB(util= 2.71) than that of 256GB(util=1.28) and 128GB(util=0). This suggests that the average value of the respondent prefer large Hard drive. Similarly, the average respondents prefer RAM of 8GB(util=27.34) to that of 16GB(26.38). This can be claimed that the respondents do not mind either going for a 8GB RAM or 16GB RAM since the difference in utility is small.

3.1.2 Average Attribute Importance

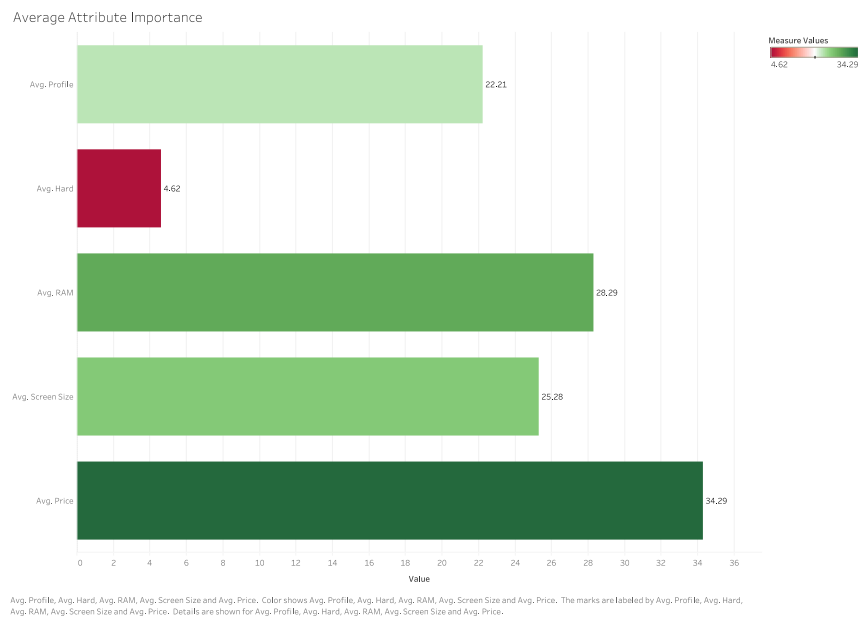


Chart 3: Average attribute importance

The average attribute importance for the 132 respondent can be seen in Chart 3. The average part-worth for

Profile: Range of average part-worth from 0 to 22.21 = 22.21

HardDrive: Range of average part-worth from 0 to 4.62= 4.62

RAM: Range of average part-worth from 0 to 28.29= 28.29

Screen Size: Range of average part-worth from 0 to 25.28= 25.28

Price: Range of average part-worth from 0 to 34.29 =34.29

Comparing the above ranges, it can be concluded that price is the most important attribute to the 132 respondents, which is then followed by RAM type, then the screen size, the type of profile and finally the HardDrive is the least preferred.

3.1.3 Average Percentage Attribute Importance

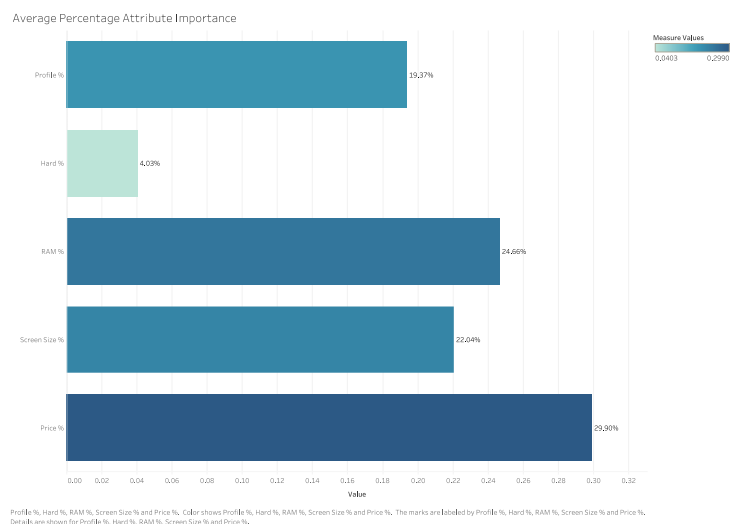


Chart 4: Average percentage attribute importance

Chart 4 show the average percentage attribute importance. It can be seen that price has the highest average percentage attribute importance with 29.90%, followed by RAM at 24.66%, Screen size at 22.04%, profile at 19.37% and hard drive at 4.03%. It can be claimed that since price has the determinant factor, it is important that the various profiles should be strategic in their pricing policy because profile is the least importance to lure customers into buying their products. The RAM size which follows pricing should be considered since customers are not particular about 8GB or 16GB as shown in the average attribute part-worth in Chart 2.

3.1.4 Average Willingness to Pay for a Feature

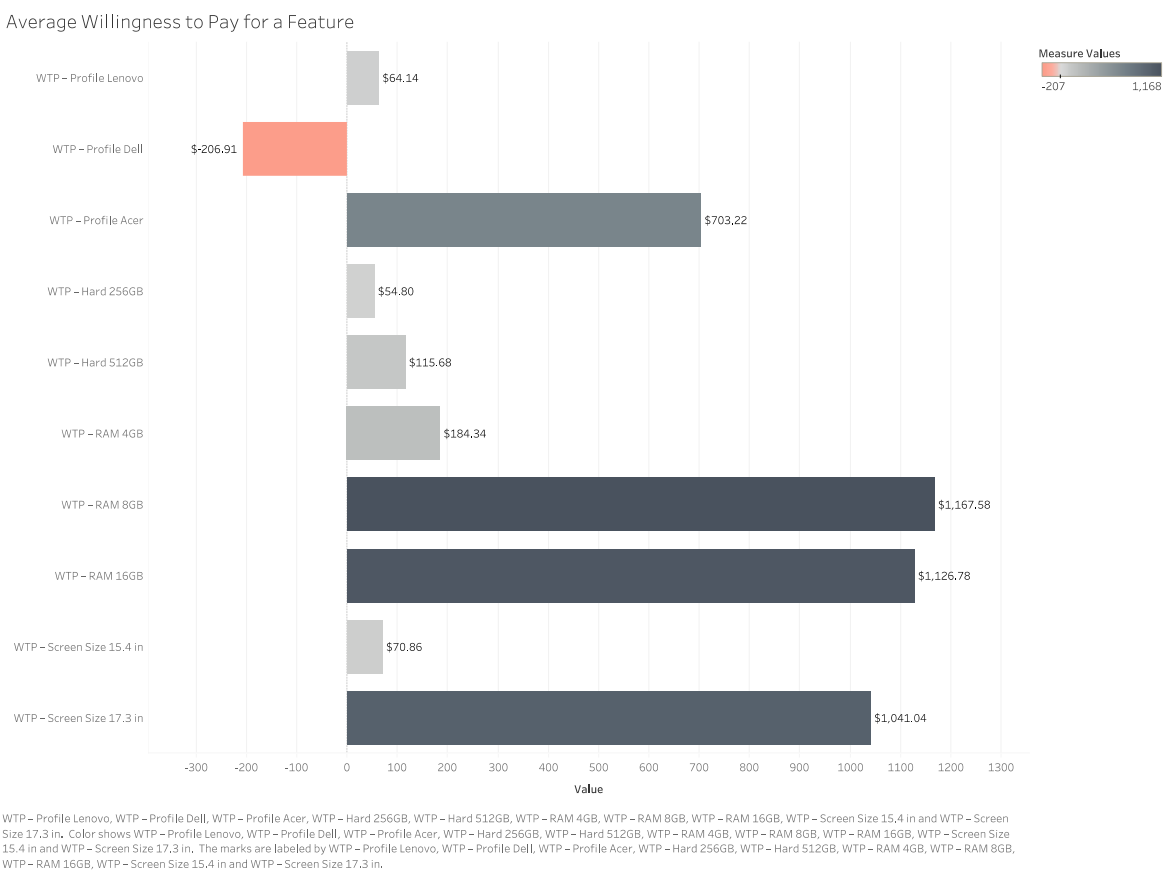
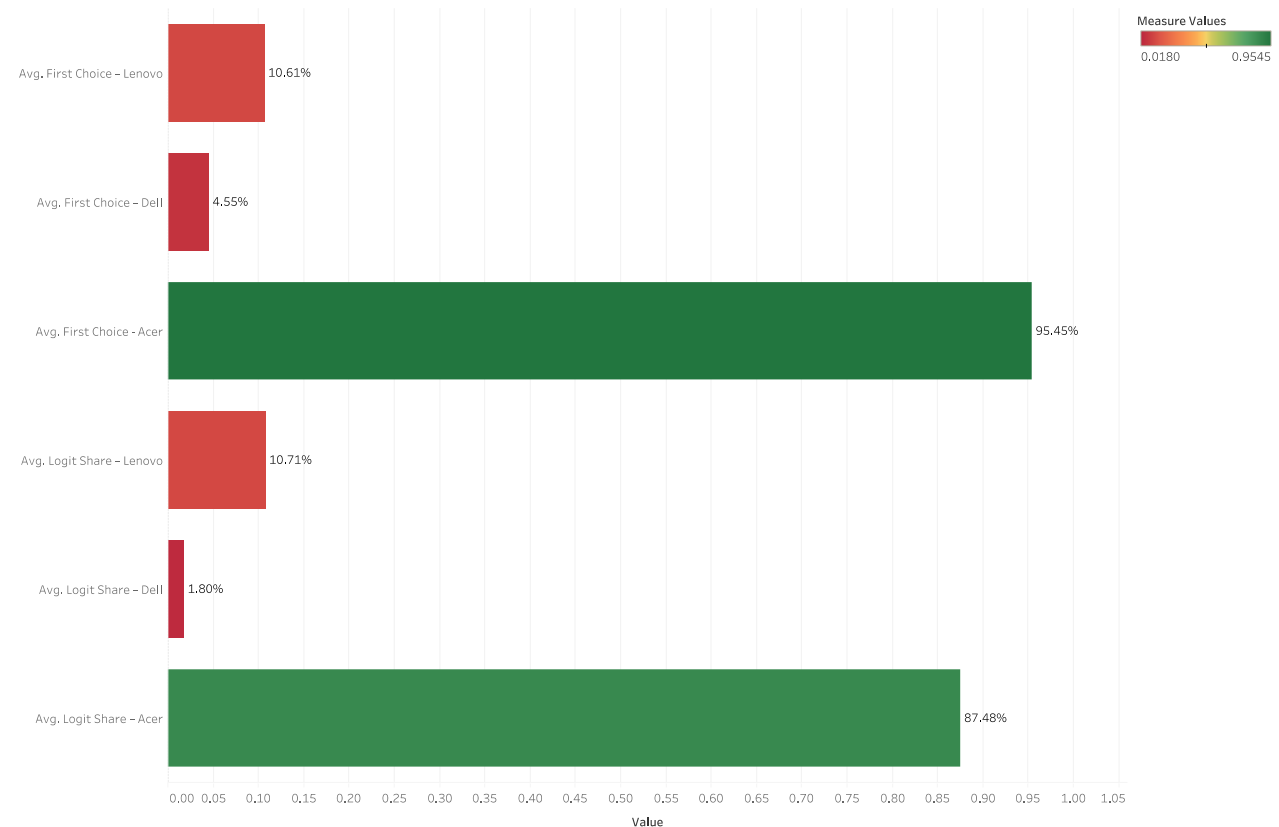


Chart 5: Average willingness to pay

Chart 5 above contains results of the 132 respondents’ average willingness to pay for a feature. These values are calculated with respect to the base value of each attribute. It can be observed for the profile attribute that Lenovo is worth \$64.14 more than the Apple laptop. Dell is worth \$206.91 less than an Apple laptop, while Acer is worth \$703.22 more than an Apple laptop. Similarly, a screen size of 17.3 inches is worth \$1,041.04 more than a screen size of 15.4 inches that is worth \$70.86. This suggests that customers are willing to pay more when the screen size in increased from 12.1 inches to 17.3 inches. Also, customers are WTP more for a 512GB of hard drive at \$115.68 compared to 128GB, as well as WTP more for a 256GB of hard drive than 128GB. It can be suggested that customers are WTP more for larger hard drive. Finally, customers are WTP more for a 16GB of RAM at \$1,126.78 more than 2GB, as well as WTP more for 8GB of RAM at \$1,167.58 more than 2GB. This can also suggest that customers may be willing to pay for either 8GB or 16GB of RAM since the difference between the values of WTP is small.

3.1.5 Market Share – Current Product

Market Share - Current Products



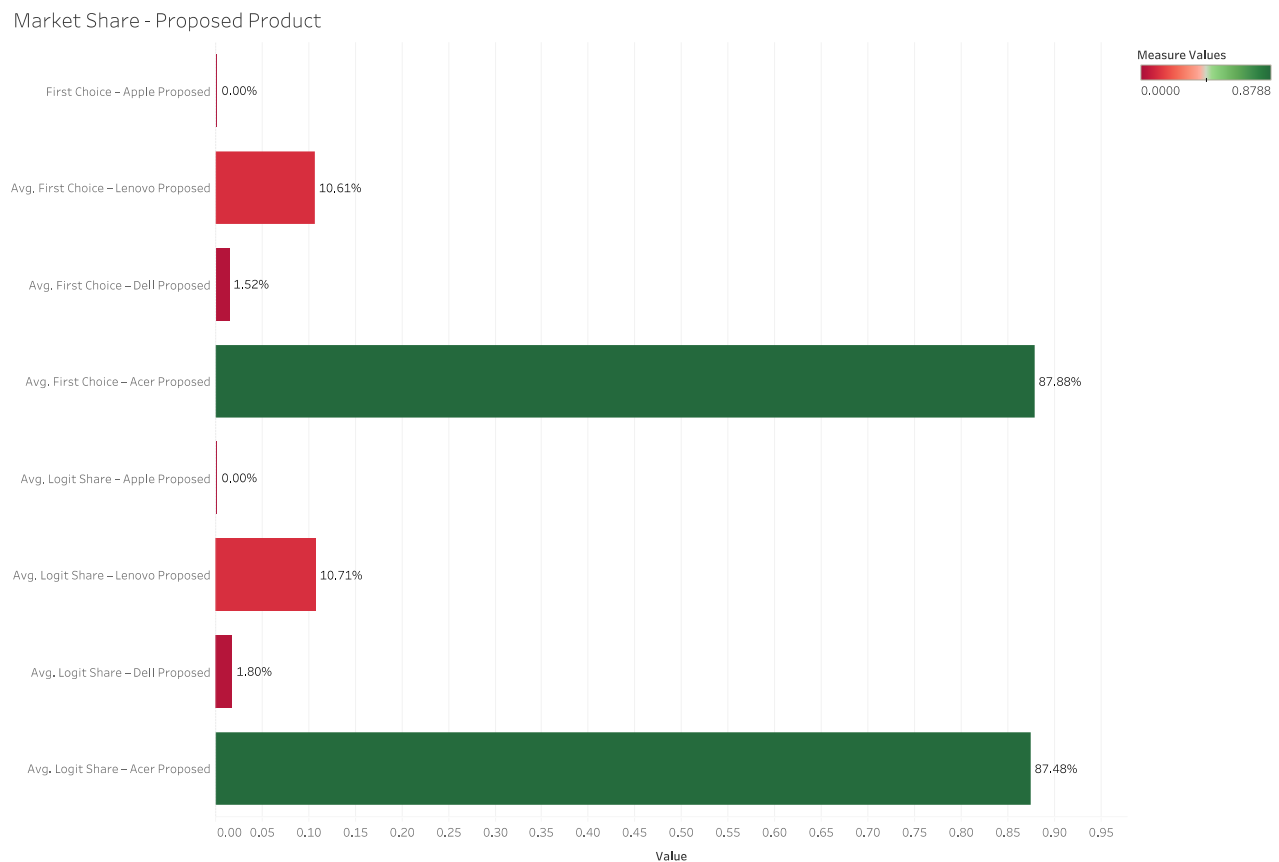
Avg. First Choice – Lenovo, Avg. First Choice – Dell, Avg. First Choice – Acer, Avg. Logit Share – Lenovo, Avg. Logit Share – Dell and Avg. Logit Share – Acer. Color shows Avg. First Choice – Lenovo, Avg. First Choice – Dell, Avg. First Choice – Acer, Avg. Logit Share – Lenovo, Avg. Logit Share – Dell and Avg. Logit Share – Acer. Details are shown for Avg. First Choice – Lenovo, Avg. First Choice – Dell, Avg. First Choice – Acer, Avg. Logit Share – Lenovo, Avg. Logit Share – Dell and Avg. Logit Share – Acer.

Chart 6: Market Share-Current products

The current market share of current product can be seen in Chart 6. Considering the first choice method, it can be seen that Lenovo current market share stands at 10.61%, Dell at 4.55% and Acer at 95.45%. Logit share of preference, the second method for calculating the market share, show that Lenovo is expected to get a market share of 10.71%, Dell at 1.80% and Acer at 87.48%.

Additionally, in order to maximize profit and production resources, as well as gain market share for a new product, the Apple laptop can be introduced to the market to see how it will perform among other types (Lenovo, Dell and Acer) that are already in the market.

3.1.6 Market Share – Proposed Product



First Choice – Apple Proposed, Avg, First Choice – Lenovo Proposed, Avg, First Choice – Dell Proposed, Avg, First Choice – Acer Proposed, Avg, Logit Share – Apple Proposed, Avg, Logit Share – Lenovo Proposed, Avg, Logit Share – Dell Proposed and Avg, Logit Share – Acer Proposed. Color shows First Choice – Apple Proposed, Avg, First Choice – Lenovo Proposed, Avg, First Choice – Dell Proposed, Avg, First Choice – Acer Proposed, Avg, Logit Share – Apple Proposed, Avg, Logit Share – Lenovo Proposed, Avg, Logit Share – Dell Proposed and Avg, Logit Share – Acer Proposed. Details are shown for First Choice – Apple Proposed, Avg, First Choice – Lenovo Proposed, Avg, First Choice – Dell Proposed, Avg, First Choice – Acer Proposed, Avg, Logit Share – Apple Proposed, Avg, Logit Share – Lenovo Proposed, Avg, Logit Share – Dell Proposed and Avg, Logit Share – Acer Proposed.

Chart 7: Market share – Proposed product

Chart 7 show the result of the market share of the new product(Apple) when introduced to compete with other profiles(Lenovo, Dell, and Acer). For the first choice method, it can be seen that the proposed Apple laptop has no market share at 0.00%., Lenovo at 10.61%, Dell at 1.52%, and Acer at 87.88%. Also, the logit share preference value has it that, Apple has 0.00% share if it is to be introduced to the market, Lenovo at 10.17%, Dell at 1.80% and Acer at 87.48%. It can be claimed that the insight from the result above show that there is no opportunity to sell the Apple laptop because it is not going to get a market share in the industry. Furthermore, comparing the result from Chart 6 and Chart 7 shore that there are no changes to the market share of other laptop since the introduction of the new Apple laptop does not control any market share, meaning there is no opportunity for customers to leave their previous choice of laptops(Lenovo, Dell, and Acer) to purchase the new Apple laptop.

3.2 Perceptual Map

Perceptual Map of Retailers and Attributes

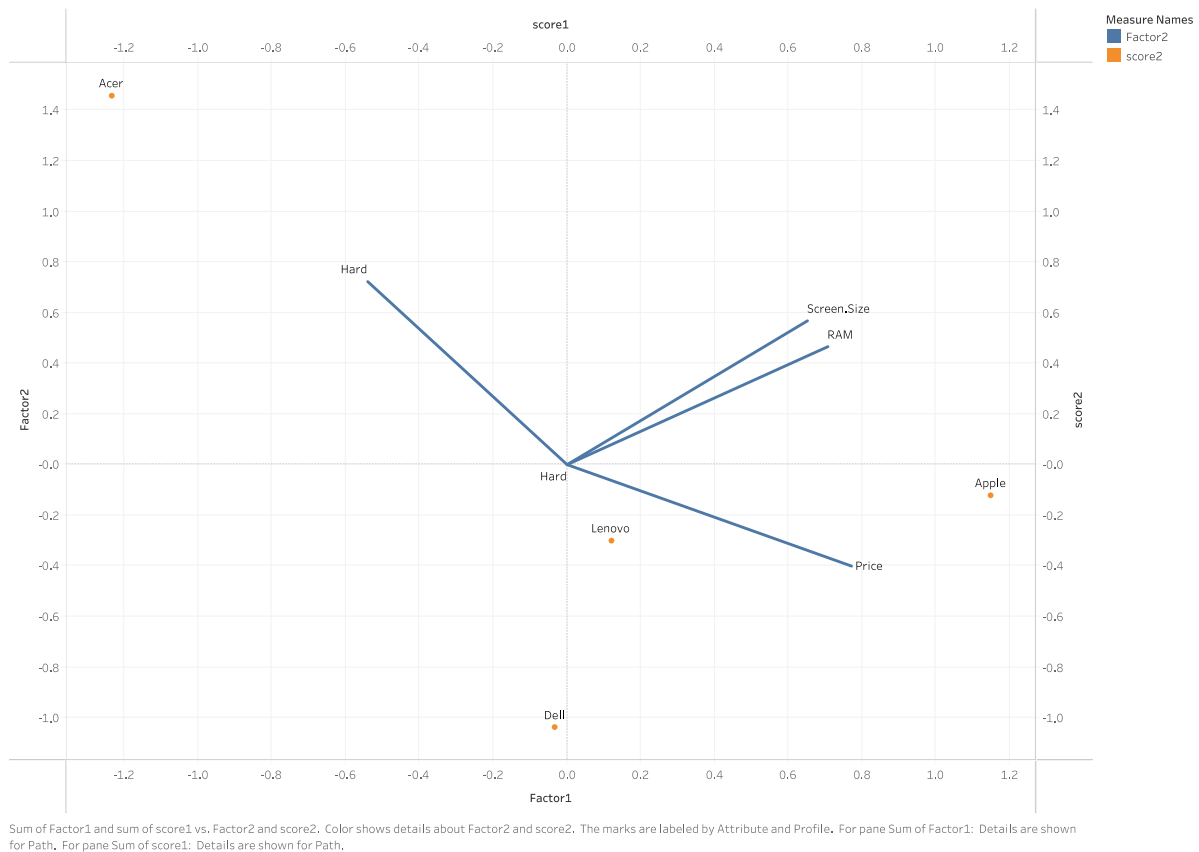


Chart 8: Perceptual Map

According to Ayaz et al. (2012) ‘perceptual maps is used in new product design, advertising, retail location, and many other marketing applications where a manager wants to know the basic cognitive dimensions of the product being evaluated and more importantly the relative positioning of the product relative to the ones present in the market’. The perception map in Chart 8 show that Acer has a very strong edge over its competitors because it is located at the extreme top left of the quadrant away from its competitors. Screen size and RAM can be said to have similar attributes from the customers’ perspective because they are close to each other in the map (Gigauri, 2019).

4.0 Conclusions

This paper present the study of a new product design for a new laptop profile to gain entrance into the market. The first choice and logit share preference indicate that the Apple laptop profile will have no market share if it is rolled out into the market. Also it was observed that price is a highly significant attribute that determines customers’ WTP. Price was also considered as the attribute that customers considers before purchasing a laptop. Therefore companies should design an appropriate pricing strategy that will win the heart of customers. The limitation of this task is in the calculate conjoint part-worth because the average value may not necessarily give the actual preference of the different customer profile selected for the survey. Clearly, the implication of this task in practice is adhering to what data insight has shown in order not to run at a loss when the product is introduced in the market.

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Appendix 1: R Code

```
#####  
## Conjoint Analysis in R #  
#####  
  
# Load library and Set Seed to an integer  
library(conjoint)  
set.seed(1845)  
  
## Set up attributes and levels as a list from the data given  
attrib.level <- list(Profile = c("Apple", "Lenovo", "Dell", "Acer"),  
                     HardDrive = c("128 GB", "256 GB", "512 GB"),  
                     RAM = c("2 GB", "4 GB", "8 GB", "16 GB"),  
                     Screensize = c("12.1 in", "15.4 in", "17.3 in"),  
                     Price = c("$900", "$1200", "$1500", "$2000"))  
  
####import already generated product profiles  
design <- read.csv(file.choose())  
  
preff <- read.csv(file.choose()) ## Choose the file named conjoint_preferences.csv  
  
#transpose survey data  
pref <- t(preff)  
  
attrib.vector <- data.frame(unlist(attrib.level,use.names=FALSE))  
colnames(attrib.vector) <- c("levels")  
part.worths <- NULL  
for (i in 1:ncol(pref)){  
  temp <- caPartUtilities(pref[,i], design, attrib.vector)  
  Base_Profile <- temp[,"Apple"]; Base_HardDrive <- temp[,"128 GB"]; Base_RAM <- temp[,"2  
GB"]  
  Base_Screensize <- temp[,"12.1 in"]; Base_Price <- temp[,"$900"]  
  temp[,"intercept"] <- temp[,"intercept"] - Base_Brand - Base_HardDrive - Base_RAM -  
  Base_Screensize - Base_Price  
  L1 <- length(attrib.level$Brand) + 1 ## Add 1 for the intercept  
  for (j in 2:L1){ temp[,j] <- temp[,j] - Base_Brand}  
  L2 <- length(attrib.level$HardDrive) + L1  
  for (k in (L1+1):L2){ temp[,k] <- temp[,k] - Base_HardDrive}  
  L3 <- length(attrib.level$RAM) + L2  
  for (l in (L2+1):L3){ temp[,l] <- temp[,l] - Base_RAM}  
  L4 <- length(attrib.level$Screensize) + L3  
  for (m in (L3+1):L4){ temp[,m] <- temp[,m] - Base_Screensize}  
  L5 <- length(attrib.level$Price) + L4  
  for (n in (L4+1):L5){ temp[,n] <- temp[,n] - Base_Price}  
  part.worths <- rbind.data.frame(part.worths,temp)  
}
```

```

rownames(part.worths) <- colnames(pref)
## Export part-worths from analysis
write.csv(part.worths, file.choose(new=TRUE), row.names = FALSE) ## Name the file
conjoint_partworths.csv

## Principal Component Analysis in R #

install.packages("data.table")

## Load Packages and Set Seed
library(data.table)
set.seed(1845)

## Read in perception and preference data
perc <- read.csv(file.choose()) ## Choose perceptions.csv file
prefc <- read.csv(file.choose()) ## Choose preferences.csv file

## Run Principle Components Analysis on Perceptions
pca <- prcomp(perc[,2:length(perc)], retx=TRUE, scale=TRUE)

## Perceptual Map Data - Attribute Factors and CSV File
attribute <- as.data.table(colnames(perc[,2:length(perc)])); setnames(attribute, 1, "Attribute")
factor1 <- pca$rotation[,1]*pca$sdev[1]; factor2 <- pca$rotation[,2]*pca$sdev[2]; path <- rep(1,
nrow(attribute))
pca_factors <- subset(cbind(attribute, factor1, factor2, path), select = c(Attribute, factor1, factor2,
path))
pca_origin <- cbind(attribute, factor1 = rep(0,nrow(attribute)), factor2 = rep(0,nrow(attribute)), path
= rep(0,nrow(attribute)))
pca_attributes1 <- rbind(pca_factors, pca_origin)
write.csv(pca_attributes1, file = file.choose(new=TRUE), row.names = FALSE) ## Name file
perceptions_attributes1.csv

## Perceptual and Preference Mapping #

## Perceptual Map Data - Brand Factors and CSV File
score1 <- (pca$x[,1]/apply(abs(pca$x),2,max)[1])
score2 <- (pca$x[,2]/apply(abs(pca$x),2,max)[2])
pca_scores1 <- subset(cbind(perc, score1, score2), select = c(Profile, score1, score2))
write.csv(pca_scores1, file = file.choose(new=TRUE), row.names = FALSE) ## Name file
perceptions_scores1.csv

## Preference Map Data - Respondent Preferences and CSV File
prefa <- data.matrix(prefc[,2:ncol(prefc)])%*% (cbind(score1,score2))

prefa[,1] <- (prefa[,1]/max(abs(prefa[,1])))
prefa[,2] <- (prefa[,2]/max(abs(prefa[,2])))
preferences1 <- subset(cbind(prefc, prefa, preference = rep(1,nrow(prefc))), select = c(Customer,
score1, score2))
write.csv(preferences1, file = file.choose(new=TRUE), row.names = FALSE) ## Name file
preference_scores1.csv

```

Appendix 2: Calculated Conjoint Part-worth for the 132 respondents.

conjoint_pathworths																			
	Intercept	Apple	Lenovo	Dell	Acer	128 GB	256 GB	512 GB	2 GB	4 GB	8 GB	16 GB	12.1 in	15.4 in	17.3 in	\$900	\$1200	\$1500	\$2000
1	16.561	0	4.971	6.563	7.422	0	-3.104	-1.363	0	-1.187	1.018	1.897	0	-6.07	4.54	0	3.022	8.511	4.289
2	24.424	0	13.469	5.861	12.17	0	-2.785	6.412	0	-1.912	-0.851	2.419	0	-0.175	5.056	0	6.35	4.777	5.199
3	19.106	0	11.402	2.918	6.931	0	-1.221	6.758	0	-2.279	-4.847	-1.335	0	2.818	-0.712	0	7.697	2.159	4.292
4	19.631	0	7.19	6.502	7.497	0	-3.246	1.686	0	0.431	0.4	-0.207	0	0.216	4.142	0	0.173	10.124	4.214
5	19.358	0	11.154	2.615	7.174	0	-1.108	6.721	0	-2.095	-3.965	-0.556	0	2.901	-0.066	0	6.507	1.455	3.495
6	15.941	0	3.595	5.15	7.312	0	-2.383	-1.364	0	-1.432	2.83	3.662	0	-7.035	5.707	0	0.931	5.608	1.968
7	21.369	0	11.912	3.403	9.289	0	-1.543	6.797	0	-1.703	-2.165	1.312	0	2.376	1.9	0	4.615	1.752	2.915
8	20.37	0	7.726	1.693	9.341	0	-1.328	3.833	0	-1.414	3.328	6.842	0	-2.314	7.188	0	3.907	-3.232	1.968
9	18.291	0	9.283	1.778	6.263	0	-0.526	6.067	0	-1.323	-3.167	-0.813	0	3.55	-0.101	0	3.386	1.367	1.813
10	24.384	0	11.115	5.546	13.34	0	-2.822	4.402	0	-1.079	3.905	6.174	0	-1.631	8.972	0	-0.321	3.761	1.744
11	22.707	0	9.488	1.99	10.84	0	-1.465	5.245	0	-1.508	4.236	8.116	0	-0.979	8.584	0	2.268	-4.065	1.144
12	17.51	0	8.212	1.18	5.356	0	-0.134	6.086	0	-1.269	-2.565	-0.766	0	3.877	-0.085	0	1.643	0.511	0.447
13	25.117	0	10.619	5.08	13.83	0	-2.739	4.152	0	-0.912	5.333	7.583	0	-1.997	10.093	0	-1.73	2.501	0.671
14	23.449	0	8.529	5.475	10.93	0	-3.577	2.416	0	0.649	5.821	5.723	0	0.666	9.175	0	-4.808	5.569	0.475
15	20.579	0	7.024	4.074	7.47	0	-2.323	3.016	0	0.736	3.167	2.489	0	3.01	5.811	0	-5.104	5.32	-0.007
16	19.942	0	4.99	4.805	8.373	0	-2.772	0.951	0	1.207	5.278	3.715	0	0.716	8.096	0	-7.274	5.951	-0.88
17	22.804	0	6.858	5.115	10.27	0	-2.92	1.827	0	1.313	6.941	6.238	0	0.422	9.581	0	-7.318	5.204	-0.799
18	21.176	0	9.698	0.369	8.629	0	0.021	6.826	0	-0.991	1.606	4.865	0	3.753	4.261	0	-0.988	-4.166	-1.593
19	26.579	0	11.359	3.285	14.24	0	-1.82	6.106	0	-0.349	6.644	9.041	0	0.542	10.557	0	-3.762	-1.2	-1.575
20	23.701	0	9.136	-0.14	11.26	0	-0.251	6.206	0	-0.988	6.3	10.01	0	1.065	10.106	0	-2.34	-7.474	-2.213
21	26.796	0	10.567	2.608	15.05	0	-1.644	5.451	0	-0.492	8.938	11.61	0	-0.528	12.533	0	-5.27	-3.584	-2.615
22	21.643	0	8.657	0.728	9.239	0	-0.152	5.881	0	0.295	3.555	5.305	0	3.688	5.081	0	-4.767	-2.221	-3.128
23	26.137	0	9.688	2.871	15.31	0	-1.969	4.585	0	-0.066	9.949	12.11	0	-1.355	13.376	0	-7.049	-2.748	-3.592
24	23.691	0	5.99	4.055	11.12	0	-2.523	1.701	0	1.956	10.03	8.965	0	0.716	11.846	0	-11.48	2.743	-3.588
25	22.211	0	6.201	-1.243	11.25	0	-0.21	4.71	0	-0.509	9.653	12.48	0	0.038	12.095	0	-5.947	-10.48	-5.05
26	21.216	0	4.986	-1.963	10.43	0	0.045	4.143	0	-0.362	9.704	12.39	0	-0.538	11.855	0	-6.317	-10.74	-5.391
27	22.549	0	4.335	3.016	10.29	0	-1.941	1.272	0	2.546	10.54	8.752	0	1.187	11.586	0	-13.51	2.037	-4.95
28	24.035	0	6.038	2.668	10.94	0	-1.865	2.537	0	2.283	10.37	9.28	0	2.846	11.97	0	-13.3	0.707	-5.024
29	23.501	0	6.73	-1.836	11.45	0	0.094	5.492	0	-0.24	10.69	13.64	0	0.998	12.909	0	-7.675	-11.59	-6.194
30	25.115	0	7.129	-0.89	13.15	0	-0.387	4.903	0	0.24	12.61	15.52	0	-0.177	14.733	0	-9.034	-10.75	-6.427
31	23.539	0	6.018	-1.962	11.87	0	0.034	4.838	0	-0.091	12.06	14.85	0	0.275	14.081	0	-9.208	-12.08	-7.064
32	27.604	0	9.312	1.857	15.67	0	-1.226	5.243	0	1.012	12.61	13.87	0	0.912	15.04	0	-12.72	-4.39	-6.874
33	22.105	0	4.117	-3.024	11.28	0	0.443	4.018	0	0.282	12.79	15.12	0	-0.242	14.12	0	-10.48	-13.2	-8.18
34	22.491	0	3.232	1.635	9.692	0	-1.147	1.838	0	3.001	12.41	9.918	0	2.491	12.371	0	-17.28	-0.433	-7.835
35	24.923	0	5.17	1.607	11.79	0	-1.468	2.41	0	2.928	13.46	12.01	0	3.141	14.235	0	-17.46	-1.754	-7.813
36	25.876	0	6.385	-1.799	13.87	0	-0.046	4.795	0	0.791	15.26	17.85	0	0.076	16.674	0	-12.6	-12.86	-8.818
37	21.505	0	0.996	1.444	12.74	0	-1.03	-1.673	0	2.028	17.88	16.81	0	-4.576	17.546	0	-18.57	-5.588	-10.603
38	24.641	0	5.613	-3.201	12.54	0	0.604	5.33	0	0.587	14.65	17.14	0	1.378	15.821	0	-13.03	-14.75	-9.78
39	26.256	0	6.013	-2.254	14.24	0	0.124	4.741	0	1.068	16.58	19.02	0	0.202	17.645	0	-14.39	-13.91	-10.014
40	24.583	0	5.242	-3.515	12.91	0	0.632	5.098	0	0.663	15.64	18.16	0	0.969	16.619	0	-14.17	-14.99	-10.787
41	28.833	0	7.515	1.011	16.86	0	-1.032	4.059	0	1.788	17.03	17.62	0	0.128	18.53	0	-18.54	-6.583	-10.333
42	24.665	0	2.938	0.565	11.93	0	-0.916	1.621	0	3.959	16.66	14.16	0	2.627	15.914	0	-22.09	-3.446	-10.853
43	29.458	0	8.011	-0.527	17.51	0	-0.574	5.265	0	1.733	17.88	19.26	0	0.61	18.948	0	-17.88	-10.4	-11.29
44	26.228	0	3.508	1.024	13.55	0	-1.387	1.342	0	3.796	18.85	16.76	0	1.561	18.318	0	-23.38	-4.29	-11.557
45	26.19	0	3.126	0.173	15.53	0	-0.448	0.253	0	2.643	20.88	20.9	0	-3.279	20.267	0	-21.65	-8.558	-12.697
46	21.014	0	-1.389	-0.912	12.16	0	-0.111	-2.082	0	2.247	20.47	19.24	0	-5.347	18.652	0	-22.86	-8.457	-13.97
47	24.436	0	1.121	-0.355	14.61	0	-0.295	-0.89	0	3.052	21.63	20.93	0	-4.302	19.854	0	-23.23	-8.441	-13.81
48	24.939	0	5.431	-3.211	12.39	0	1.324	5.414	0	2.686	15.02	15.43	0	4.784	13.494	0	-20.23	-11.36	-13.488
49	28.867	0	6.061	-3.436	16.35	0	0.858	5.115	0	2.067	20.58	22.8	0	1.07	20.991	0	-20.35	-16.48	-13.602
50	21.52	0	-1.865	-1.518	12.65	0	0.115	-2.155	0	2.614	22.23	20.8	0	-5.179	19.946	0	-25.24	-9.863	-15.564
51	30.255	0	6.554	-1.562	18.65	0	-0.294	4.503	0	2.435	21.9	22.81	0	0.14	22.062	0	-22.98	-13.01	-14.552
52	27.741	0	4.945	-5.004	15.15	0	1.293	5.415	0	2.222	20.89	22.84	0	2.71	20.681	0	-21.55	-19.11	-15.035
53	30.726	0	6.77	-2.042	18.73	0	-0.006	5.085	0	2.653	22.29	23.16	0	1.032	22.184	0	-23.83	-13.92	-15.275
54	22.028	0	-2.362	-2.125	13.13	0	0.342	-2.226	0	2.983	24	22.36	0	-5.009	21.241	0	-27.62	-11.27	-17.157
55	20.518	0	-4.045	-3.388	12.61	0	0.751	-2.821	0	3.172	24.44	22.67	0	-5.706	21.055	0	-27.79	-13	-17.953
56	23.427	0	2.738	-6.208	11.47	0	2.584	5.593	0	3.24	17.49	17.35	0	5.256	14.194	0	-23.68	-16.54	-17.246
57	31.016	0	5.81	-2.471	19.38	0	0.047	4.396	0	2.987	24.55	25.15	0	0.393	24.003	0	-26.55	-15.12	-16.943
58	28.519	0	4.421	-5.898	15.87	0	1.905	5.523	0	2.507	23.06	24.81	0	2.667	22.403	0	-24.94	-20.84	-17.354
59	27.306	0	3.008	-6.383	15.09	0	1.797	4.953	0	2.519	23.91	25.32	0	2.264	22.617	0	-25.52	-22.13	-18.147
60	31.458	0	5.622	-2.045	18.99	0	0.219	4.335	0	3.569	24.91	24.58	0	1.736	24.153	0	-29.5	-13.47	-17.829
61	31.74	0	5.777	-3.255	19.69	0	0.448	4.942	0	3.389	25.82	26.27	0	1.37	24.773	0	-28.59	-16.73	-18.463
62	23.802	0	-2.52	-2.825	14.95	0	0.456	-2.016	0	3.757	27.76	25.77	0	-4.417	24.449	0	-32.26	-14.23	-20.423
63	31.993	0	5.529	-3.558	19.94	0	0.561	4.905	0	3.572	26.7	27.05	0	1.453	25.42	0	-29.78	-17.43	-19.259
64	25.316	0	2.551	-6.91	13.13	0	2.653	5.287	0	3.645	21.24	21.04	0	5.732	17.795	0	-28.83	-18.94	-20.18
65	29.39	0	3.333	-6.973	16.72	0	2.03	5.181	0	3.417	26.62	27.91	0	3.259	24.888	0	-29.29	-23.68	-20.215
66	27.274	0	3.216	-5.769	15.05	0	2.16												

Appendix 3a: Perceptions Scores

AutoSave OFF

perceptions_scores1

Helvetica Neue 10

General

Condition Formatting

D4

perceptions_scores1		
Profile	score1	score2
Acer	-0.233786505	1
Apple	0.900102915	0.296725222
Dell	-0.006893835	-0.61539098
Lenovo	-0.358292325	-0.783927745
Acer	-1	0.457832721
Dell	-0.026777272	-0.42130887
Lenovo	0.478392544	0.48369693
Apple	0.247254478	-0.417627279

Appendix 3b: Perceptions Attributes

AutoSave OFF

perceptions_attributes1

Home Insert Draw Page Layout Formulas Data Review View Tell me

Helvetica Neue 10

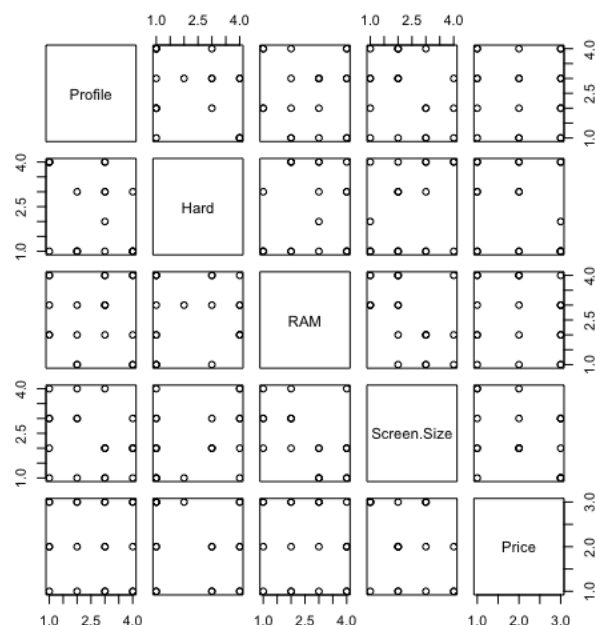
General

Condition Formatting

E9

perceptions_attributes1			
Attribute	factor1	factor2	path
Hard	-0.540192377	0.723159183	1
RAM	0.706588424	0.466205325	1
Screen.Size	0.65127933	0.568148714	1
Price	0.770506354	-0.400767262	1
Hard	0	0	0
RAM	0	0	0
Screen.Size	0	0	0
Price	0	0	0

Appendix 4: Correlation Matrix and Dummy variables for subset of selected profile



```
> # Check for correlation among attributes
> print(cor(caEncodedDesign(design)))
```

	Profile	Hard	RAM	Screen.Size	Price
Profile	1.00000000	-0.4382478	-0.04646616	-0.2806271	-0.1131734
Hard	-0.43824776	1.00000000	0.10317569	0.2858176	-0.1905429
RAM	-0.04646616	0.1031757	1.00000000	-0.4894689	-0.1249576
Screen.Size	-0.28062709	0.2858176	-0.48946886	1.00000000	-0.3354075
Price	-0.11317343	-0.1905429	-0.12495756	-0.3354075	1.00000000

```
>
> caEncodedDesign(design)
```

	Profile	Hard	RAM	Screen.Size	Price
1	1	3	4	4	2
2	2	2	1	3	2
3	3	1	4	2	2
4	4	1	2	2	2
5	1	3	3	2	2
6	3	2	4	2	2
7	4	1	1	3	3
8	2	1	2	3	3
9	3	3	3	1	3
10	3	2	3	1	3
11	1	1	4	1	3
12	1	3	2	3	3
13	2	1	3	1	3
14	4	1	1	2	3
15	3	3	2	4	1
16	3	2	3	2	1
17	4	1	4	1	1
18	4	2	4	2	1
19	2	1	1	4	1
20	1	3	2	3	1

```
>
```