MGT7215: Marketing Analytics
Assignment 2

Title : Integrating Conjoint Analysis and PCA for Enhanced Market Insight

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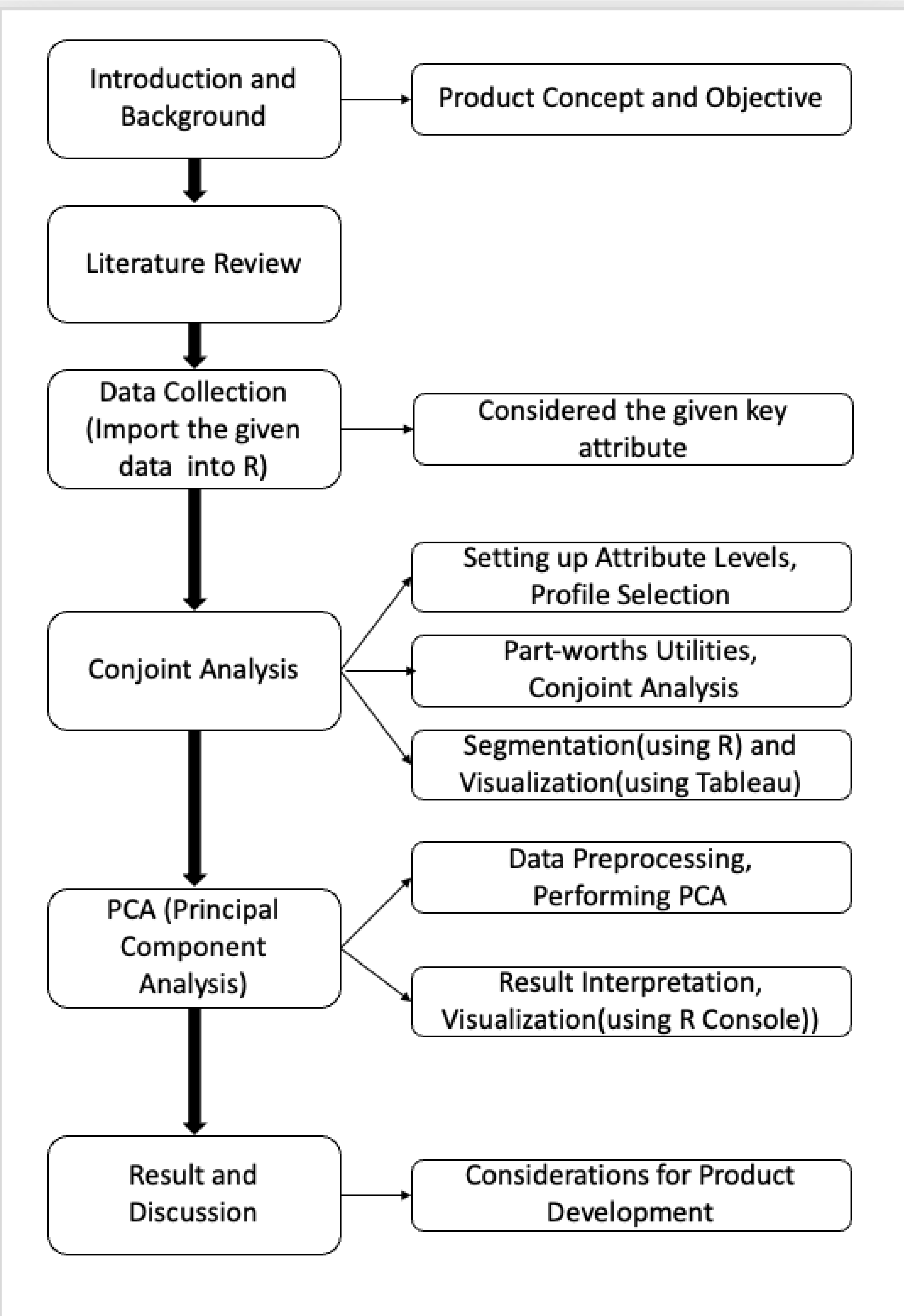

1.0 Introduction and Background

Consumer preferences must be integrated into product design to attain a competitive edge and achieve success in the market. This report analyses a novel circular product by employing sophisticated analytical techniques, namely conjoint analysis, and principal component analysis (PCA), to collect and leverage consumer data efficiently. These procedures are crucial for ensuring that the product meets both functional requirements and environmental sustainability goals.

The study is motivated by the growing consumer demand for environmentally friendly products. Conjoint analysis examines six key attributes: Environmental Friendliness, Delivery Time, Service Level, Price, Quality of Material, and Marketing Proficiency. This approach facilitates the identification of attribute combinations that are highly valued by customers, hence uncovering crucial trade-offs that they are ready to accept. PCA is used concurrently to evaluate consumer impressions across different models using 11 variables. This analysis identifies the essential characteristics that impact purchasing decisions, which are vital for improving the product design. (Allenby, Arora & Ginter 1995).

The goal is to utilise these analytical methods to gain a comprehensive understanding of the target market, which will then inform the creation of a product that meets customer expectations and encourages sustainable consumption. The knowledge acquired from these assessments will be used to develop strategic recommendations that will help achieve a balance between desirability and ecological responsibility. This will contribute to the successful introduction of the new product. (Kuhfeld 2005)

2.0 Literature Review

Title of the paper	Year of Publication	Author	Conclusion
An exploration of the strategic implementation of marketing planning: strategic alignment and firm performance	2002	Hooley, Graham J., Greenley, Gordon E., Cadogan, John W., and Fahy, John	The paper concludes that strategic alignment between market orientation, marketing planning, and implementation influences the effectiveness and financial performance of firms. Specifically, it emphasizes that well-aligned marketing strategies that are executed with clear, coordinated implementation across the firm lead to better performance outcomes and competitive advantages. The study underlines the importance of integrating marketing planning and implementation processes as a unified whole, rather than isolated tasks, to enhance firm success in dynamic markets.
Influences on the Organisational Implementation of Marketing Planning	2002	Susan Bridgewater and Ian E. Taplin	The paper discusses the various influences on the organizational implementation of marketing planning, highlighting how internal and external factors shape marketing strategy execution. It emphasizes the role of organizational structure, leadership, and market dynamics in impacting the effectiveness of marketing plans. The study provides insights into the complexities of implementing marketing strategies within organizations, suggesting that successful marketing planning requires not only strategic alignment but also adaptability to changing market conditions and internal capabilities.

Choice-Based Conjoint Analysis	2022	Felix Eggers, Henrik Sattler, Thorsten Teichert, Franziska Völckner	The paper provides a comprehensive overview of choice-based conjoint analysis, a popular method for preference measurement that simulates real-world decision-making scenarios. It outlines the process of conducting discrete choice experiments, from identifying attributes and levels, to creating experimental designs, and implementing these into surveys. The chapter highlights the method's flexibility in measuring preferences across various contexts beyond traditional marketing applications, such as transportation and health economics, demonstrating its utility in predicting consumer choices and informing strategic decisions in product development and marketing.
Conjoint Analysis: A Useful Tool in the Design Process	1999	Anders Gustafsson, Fredrik Ekdahl, Bo Bergman	The paper explores the application of conjoint analysis in enhancing product design through a better understanding of customer preferences, specifically within educational program design. The research outlines a methodological framework for conjoint analysis, emphasizing its strategic importance in identifying key attributes that satisfy customer demands. By integrating conjoint analysis into the Quality Function Deployment (QFD) process, the study demonstrates how this approach can effectively prioritize product features based on customer

			preferences, thus guiding strategic decisions in product development and design processes.
Conjoint Analysis	2010	Vithala R. Rao	The paper discusses the application of conjoint analysis as a robust methodology for understanding consumer decision-making processes. It emphasizes how this analysis helps in quantifying how consumers value different attributes of a product or service, which assists in marketing strategy development including product design, pricing, and targeting. The article details various types of conjoint analysis methods, such as traditional, choice-based, and adaptive conjoint analysis, explaining their uses and benefits in market research. Significant advancements in conjoint analysis methodologies are also highlighted, showcasing the adaptability and depth of conjoint analysis in addressing complex marketing challenges.
PCA in Studying Coordination and Variability: A Tutorial	2004	Andreas Daffertshofer, Claudine J.C. Lamoth, Onno G. Meijer, Peter J. Beek	This paper provides a detailed tutorial on the use of Principal Component Analysis (PCA) in clinical biomechanics for studying coordination and variability. It discusses how PCA serves as an efficient, unbiased method for reducing complex, high-dimensional data into simpler, understandable components. This reduction helps in distinguishing invariant (structural) and variable components in data sets, which

			is crucial for studying motor variability and developing clinical diagnostics. The tutorial includes both theoretical explanations and practical applications, demonstrating PCA’s potential to enhance the understanding of coordinated movement and its variability in clinical settings.
The use of principal component analysis (PCA) to characterize beef	2000	G. Destefanis, M.T. Barge, A. Brugiapaglia, S. Tassone	The paper discusses the application of principal component analysis (PCA) in analyzing chemical, physical, and sensory data from beef of various cattle breeds to characterize meat quality. The study shows that PCA effectively summarized the major variations in the data into three principal components, which explained about 63% of the total variability. The results provided clear groupings of meat characteristics by breed, illustrating PCA's utility in yielding synthetic judgments about meat quality and highlighting relationships between different meat attributes. The paper concludes that PCA is a valuable tool in meat science for simplifying complex datasets and identifying key variables that influence meat quality.
Multivariate Statistical Data Analysis- Principal Component Analysis (PCA)	2017	Sidharth Prasad Mishra, Uttam Sarkar, Subhash Taraphder, Sanjay Datta, Devi Prasanna	The paper provides a comprehensive overview of Principal Component Analysis (PCA), a multivariate technique used to reduce the dimensionality of large datasets while retaining most of the

		Swain, Reshma Saikhom, Sasmita Panda, Menalsh Laishram	variation present in the data. It explains the mathematical basis of PCA, including eigenvalues and eigenvectors, and highlights its applications in various fields such as image compression and data analysis. The authors detail the process of conducting PCA, from data preparation to the extraction of principal components, emphasizing PCA's utility in simplifying data analysis and enhancing interpretability.
PCA versus LDA	2001	Aleix M. Martínez, Member, IEEE, and Avinash C. Kak	This paper examines the effectiveness of Principal Component Analysis (PCA) versus Linear Discriminant Analysis (LDA) within the realm of appearance-based object recognition, particularly focusing on small training data sets. The authors challenge the prevailing belief that LDA is superior to PCA, demonstrating through experiments on a face database that PCA can outperform LDA when the training dataset is small. PCA is also shown to be less sensitive to variations in training datasets compared to LDA. The paper concludes that while LDA may perform better with large, representative datasets, PCA is more reliable with limited or non-uniform data, providing an important nuance to the application of these techniques in object recognition.
Principal Component Analysis	2010	Hervé Abdi and Lynne J. Williams	This paper offers a comprehensive overview of Principal Component Analysis (PCA), describing it as a

			multivariate statistical technique used to analyze data where observations are described by inter-correlated quantitative variables. It details the mathematical basis of PCA, including its reliance on eigen-decomposition and singular value decomposition, and explores its application across different types of data to extract significant patterns and reduce dimensionality. The paper emphasizes the versatility of PCA in simplifying complex datasets and revealing underlying structures in the data, which are valuable for further analysis and interpretation.

3.0 Methodology

This study utilised two separate analytical methods, **Conjoint Analysis** and **Principal Component Analysis (PCA)**, to obtain a deeper understanding of consumer preferences and perceptions for a novel circular product.

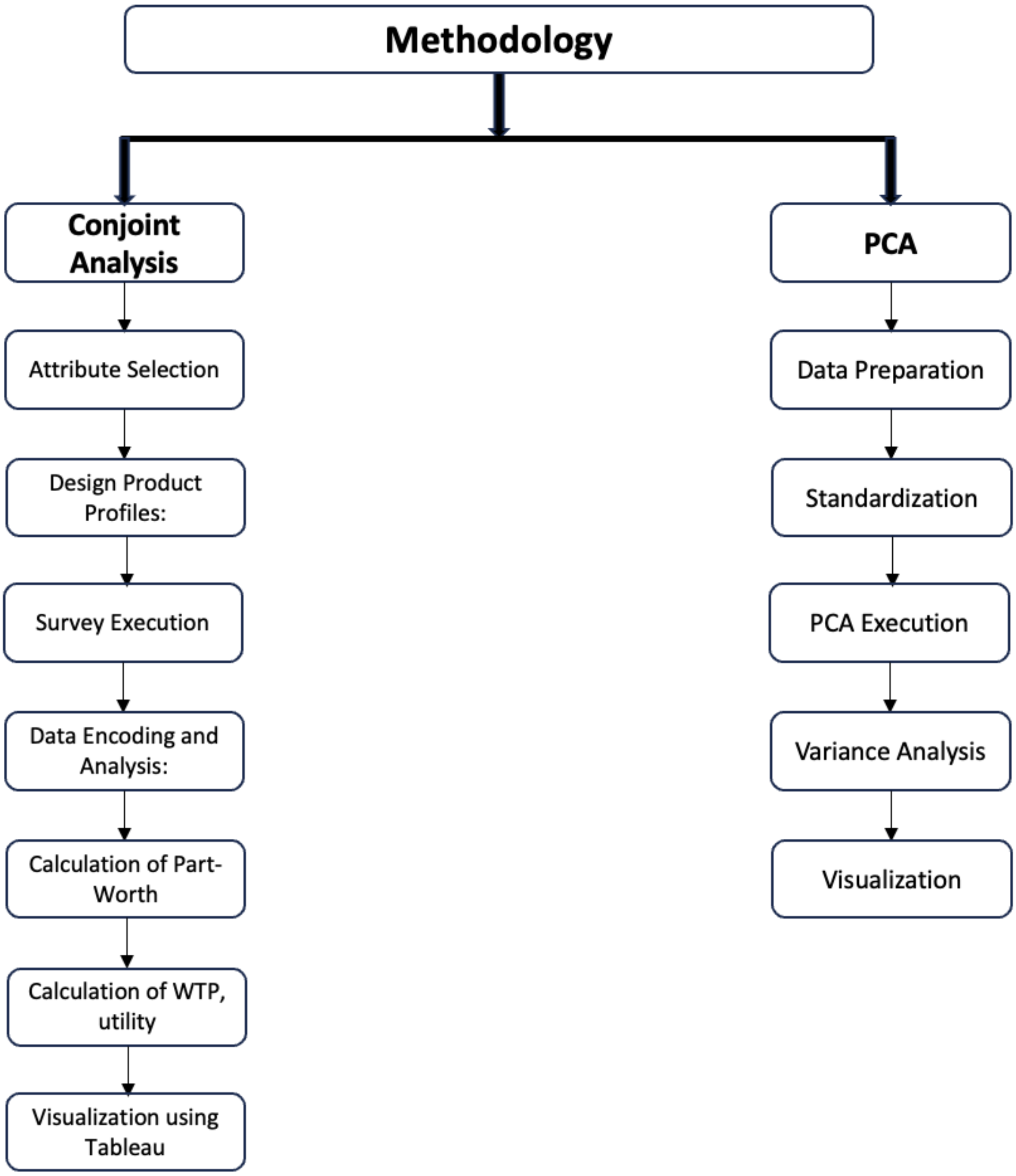

Fig 3.0: Flow of the methodology used.

3.1 Conjoint analysis

Conjoint analysis is a statistical method employed in market research to ascertain the relative importance that individuals assign to several attributes of a specific product or service. The primary goal of conjoint analysis is to discern consumer preferences by soliciting their evaluations of various product aspects, thereby enabling researchers to pinpoint the combinations of features that exert the most influence on consumer choices (Green & Srinivasan, 1990).

A Conjoint Analysis was performed to ascertain the relative importance that consumers place on different features of the product. In order to accomplish this, we employed a fractional factorial design to choose 18 product profiles from a broader pool of potential combinations. The selection of this style was made to guarantee a streamlined examination of the attribute space while effectively portraying the notable interconnections among various attribute levels. The profiles were based on six key attributes and their levels :

Attributes	Level
1. Environmental Friendliness	• 0% CO_2 reduction • 30% CO_2 reduction • 50% CO_2 reduction
2. Delivery time (order fulfilment time)	• days • days • 30 days
3. Service level	• 5-year warranty • 5-year warranty& free maintenance • 5-year warranty, free maintenance and installation, & upgradeability
4. Price	• 1000 GBP • 1200 GBP • 1500 GBP
5. Quality of material	• Market average • A bit higher than market average
6. Marketing proficiency	• Not very proficient and poor communication • Very proficient and have good communication skills.

each calibrated at varying levels to represent diverse market offerings.

Data collecting entailed conducting a survey in which ten prospective consumers evaluated the profiles on a scale ranging from 1 to 10. The conjoint analysis was conducted using the R 'conjoint' package. This package allowed for the conversion of attribute levels into dummy variables, regression analysis to calculate part-worth utilities for each attribute level, and changes of utilities in relation to baseline levels. By conducting this analysis, we were able to ascertain the additional worth of each attribute level and effectively discern consumer preferences.

3.1.1 Steps to perform conjoint analysis

1. Set up attribute levels, create a fractional factorial design, check for correlation, and load data.
2. Calculate part-worth utilities based on consumer preferences and product profiles.
3. Adjust utilities relative to a baseline case for simplified interpretation.
4. Visualize results using Conjoint Analysis and segmentation analysis.
5. Interpret findings, analyzing the impact of attributes on consumer preferences and discussing implications for product development, pricing, and marketing strategies.
6. Calculate Willingness to Pay (WTP) for each attribute level and average WTP for a feature, alongside computing average attribute part-worths for further analysis and visualization using Tableau.

3.1.2 Rationale for choosing 18 product profiles as the most Optimal

There are six qualities, each with sixteen levels. This results in a total of 324 distinct product profiles, which are formed by combining all possible combinations of attribute levels. This full factorial approach enables thorough testing of consumer responses to every variety. Collecting input on all 324 profiles is not feasible; instead, a smaller sample, chosen using a fractional factorial design, is commonly employed in conjoint analysis to simplify the study.

3 (Environmental Friendliness) X 3 (Delivery Time) X 3 (Service Level) X 3 (Price) X 2 (Quality of Material) X 2 (Marketing Proficiency) = 324

In addition, we utilise a correlation matrix to determine why the product profile with a value of 18 is considered optimum.

Based on my investigation, choosing 18 product profiles instead of other configurations (50, 25, 22 profiles) provides the best statistical efficiency and the least attribute correlation. When configurations become larger, they sometimes bring about complexities and correlations among attributes such as Delivery_time, Service_level, and Price. These correlations can make it difficult to determine the individual effects of each attribute and complicate the interpretation of data.

The 18-profile approach achieves an optimal equilibrium between extensive attribute coverage and survey manageability, thereby reducing respondent fatigue and enhancing data quality. This option prevents the additional workload on participants that may arise from using more complex setups, which could potentially make the results less evident. Therefore, the choice to employ 18 profiles guarantees a targeted and effective investigation of consumer preferences, making it very suitable for in-depth market research within the context of my academic project.

<table>
<tr><th>Image</th><th>Cards Num</th></tr>
<tr><td>
> print(cor(caEncodedDesign(design)))
Environmental_friendliness Delivery_time Service_level Price Quality_of_material Marketing_proficiency
Environmental_friendliness 1 0.0000000 0.00000000 0.00000000 0.0000000 0.0000000
Delivery_time 0 1.0000000 0.00000000 0.00000000 0.0000000 -0.1360828
Service_level 0 0.0000000 1.00000000 0.08333333 0.0000000 0.0000000
Price 0 0.0000000 0.08333333 1.00000000 0.0000000 0.0000000
Quality_of_material 0 0.0000000 0.00000000 0.00000000 1.0000000 -0.1111111
Marketing_proficiency 0 -0.1360828 0.00000000 0.00000000 -0.1111111 1.0000000
>
</td><td>18</td></tr>
<tr><td>
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Environmental_friendliness 1.00000000 0 -0.03183962 0.03183962 0.00 0.00
Delivery_time 0.00000000 1 0.00000000 0.00000000 0.00 0.00
Service_level -0.03183962 0 1.00000000 -0.02712264 0.00 0.00
Price 0.03183962 0 -0.02712264 1.00000000 0.00 0.00
Quality_of_material 0.00000000 0 0.00000000 0.00000000 1.00 0.04
Marketing_proficiency 0.00000000 0 0.00000000 0.00000000 0.04 1.00
>
</td><td>50</td></tr>
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Delivery_time 0.065892084 1.00000000 0.00000000 0.065892084 0.10460765 -0.10460765
Service_level -0.060705366 0.00000000 1.00000000 -0.060705366 0.00000000 0.00000000
Price -0.002358491 0.06589208 -0.06070537 1.000000000 0.04665906 -0.04665906
Quality_of_material 0.046659064 0.10460765 0.00000000 0.046659064 1.00000000 -0.03846154
Marketing_proficiency -0.046659064 -0.10460765 0.00000000 -0.046659064 -0.03846154 1.00000000
>
</td><td>25</td></tr>
<tr><td>
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Environmental_friendliness Delivery_time Service_level Price Quality_of_material Marketing_proficiency
Environmental_friendliness 1.000000000 0.06464775 -0.006324049 -0.06324049 -0.05513178 0.05513178
Delivery_time 0.064647748 1.00000000 0.000000000 0.00000000 0.00000000 0.00000000
Service_level -0.006324049 0.00000000 1.000000000 -0.05921053 0.00000000 0.00000000
Price -0.063240494 0.00000000 -0.059210526 1.00000000 0.00000000 0.00000000
Quality_of_material -0.055131785 0.00000000 0.000000000 0.00000000 1.00000000 -0.09090909
Marketing_proficiency 0.055131785 0.00000000 0.000000000 0.00000000 -0.09090909 1.00000000
>
</td><td>22</td></tr>
</table>

Fig 3.1.2: Figures of Correlation Matrix

3.1.3 Calculation Of Part – Worth

The process of determining part-worth utilities in conjoint analysis entails generating attribute vectors from specified product profiles and subsequently utilising the caPartUtilities function to calculate the utilities for each respondent based on their preferences. The intercept is adjusted by subtracting the baseline level of each characteristic from its coefficients. This ensures that the utility values reflect deviations from a base scenario, making it easier to analyse and compare different product configurations.

	OP1	OP2	OP3	OP4	OP5	OP6	OP7	OP8	OP9	OP10
Profile 1	9	8	10	5	8	7	9	8	7	7
Profile 2	6	10	10	8	10	7	10	10	10	10
Profile 3	10	10	10	10	8	10	8	10	10	9
Profile 4	4	8	4	6	5	5	5	6	6	2
Profile 5	5	8	7	6	4	5	5	3	3	2
Profile 6	2	2	1	4	1	3	3	1	2	1
Profile 7	6	2	2	5	1	7	1	8	8	6
Profile 8	2	1	4	1	7	4	1	2	1	3
Profile 9	6	3	4	3	5	7	5	6	7	1
Profile 10	3	5	3	8	4	8	5	7	3	4
Profile 11	4	8	6	2	3	8	8	3	4	6
Profile 12	3	5	6	4	7	4	7	7	7	2
Profile 13	5	3	5	4	5	5	6	9	6	6
Profile 14	4	4	1	3	1	5	2	3	3	7
Profile 15	5	1	1	3	2	1	2	3	1	3
Profile 16	1	1	2	1	2	3	2	2	1	1
Profile 17	7	7	5	5	4	4	2	1	3	3
Profile 18	5	6	7	1	5	6	6	7	4	2

Fig 3.1.3: Conjoint Preferences

The presented results reveal a Tibble with conjoint preference ratings. The Tibble consists of 18 rows and 10 columns, with each column indicating ratings for different product profiles evaluated by the customers. Columns OP1 through OP10 may represent individual responses to each profile or ratings for certain features within those profiles. This data will enable the calculation of part-worth utilities in a conjoint analysis, which will uncover the impact of different product features on consumer preferences.

Individual Part-Worths for Respondents

Following an analysis of customer ratings, we determined the individual part-worth utilities by establishing a baseline with particular attribute levels. We were able to determine how variations from these initial standards affected customer preferences for all product characteristics by employing this methodology.

Sl. No	Attribute	Base Attribute Level
1.	Environmental Friendliness	0% CO2 reduction
2.	2 Delivery Time	14 Days
3.	Service Level	5 – Year Warranty
4.	Price	1000 GBP
5.	Quality of Material	Market Average
6.	Marketing Proficiency	Not Very proficient and poor communication

3.1.4 Interpretation of Part-worth

intercept	0% CO2 r	30% CO2	50% CO2	14 d	21 day	30 days	5-y	5-ye	5-year w	1000 (	1200 G	1500 (	Marke	A bit hig	Not	Very proficient and have good communication skills
1.798	0	-1.5	-2	0	-1	-0.5	0	0.3	-0.834	0	0.5	-0.5	0	-1.076	0	-1.33
1.723	0	-1.666	-2	0	0.834	0	0	1.5	-1.667	0	1	-0.67	0	-4.124	0	-0.87
0.611	0	-2.167	-3.167	0	1	0.667	0	-1	-2.833	0	0.5	1.17	0	-3.626	0	-1.38
0.078	0	-0.667	-0.167	0	-2	-1.33	0	0.2	0	0	-0.33	-2	0	-2.824	0	-1.58
0.51	0	-1.667	-2.167	0	1	-0.33	0	-1	-2.167	0	-0.5	1.17	0	-2.726	0	-1.48
1.834	0	0	-1	0	-1.67	-2.33	0	-0	-2.166	0	1	0	0	-2	0	-1
1.034	0	-1.167	-1.833	0	0.667	-0.17	0	0.2	-1.166	0	-0.83	-0.17	0	-4.3	0	-0.3
-0.435	0	-2.167	-2.333	0	-1.67	-2.83	0	-2	-0.334	0	-0.33	0.33	0	-3.226	0	-0.98
-0.012	0	-2.166	-3	0	-2	-2.67	0	0.7	0.666	0	1	0.33	0	-2.65	0	-2.15
-0.067	0	0.334	-2.833	0	-0.5	-1.5	0	0.5	-1	0	-0.83	-2.67	0	-2.276	0	-0.52

Fig 3.1.4: Figure of part-Worth Csv

The first line of data regarding environmental friendliness suggests how respondents value different levels of CO2 reduction. The part-worth utility for 0% CO2 reduction is 0, indicating this level serves as the base level or point of comparison. A 30% CO2 reduction is associated with a part-worth of -1.5, suggesting that respondents have a negative preference for this level compared to the base level. Conversely, a 50% CO2 reduction has a part-worth of -2, which indicates an even stronger negative preference compared to the base level. These negative values suggest that, in this context, respondents might prefer less or no reduction in CO2, or that there are trade-offs involved with higher levels of CO2 reduction (e.g., higher costs or other negative attributes associated with greater CO2 reduction efforts).

3.2 Principal Component Analysis

Principal Components Analysis (PCA) is a statistical technique employed to decrease the number of variables in a dataset by converting the original variables into a fresh set of uncorrelated variables known as principal components. The components are arranged in such a way that the initial ones capture the majority of the variability present in the data. Principal Component Analysis (PCA) is advantageous for streamlining data, diminishing noise, and discerning novel significant factors (Maćkiewicz & Ratajczak, 1993). It is commonly used in disciplines such as neuroscience, economics, and marketing to reveal the internal organisation of data in a manner that optimally elucidates its variability. This technique is crucial for data analysis when there is a need to reduce complex data sets without sacrificing important information.

Principal Component Analysis (PCA) was employed to decrease the number of dimensions in a dataset that included evaluations for 32 product models across 11 qualities, which were assessed according to consumer perceptions. The first phase was eliminating non-numeric columns and standardising the data, guaranteeing that each attribute had an equal impact on the analysis and avoiding any dominance caused by disparities in magnitude. The **prcomp** function in R was used to do PCA, with the variables centred and scaled. The analysis facilitated the identification of the primary factors that accounted for the most variation, and the loadings of these factors were investigated to determine which traits had the most significant impact.

3.2.1 Steps in PCA

1. Set seed for consistency in results.
2. Load the dataset and pre-process it by removing identifier columns.
3. Standardize the data for equal scale comparison.
4. Perform PCA to reduce dimensions.
5. Extract loading factors to understand variable contributions.
6. Calculate the proportion of variance explained by each principal component.
7. Generate perceptual maps and other visualizations for interpretation.

3.2.2 Singular values

```
> print(singular_values)
 [1] 2.5706809 1.6280258 0.7919579 0.5192277 0.4727061 0.4599958 0.3677798 0.3505730 0.2775728 0.2281128 0.1484736
```

Fig 3.2.2: Figure of Singular Values

The singular values indicate the importance of each principal component, with the first one explaining the most variance in the dataset. Subsequent values decrease, showing that they account for less variance, which guides the selection of components in PCA.

3.2.3 Loading Factors

```
> # Calculate and view loading factors
> loadings <- pca$rotation
> print(loadings)
                 PC1         PC2         PC3
Feature1  -0.3625305 -0.01612440  0.22574419
Feature2   0.3739160 -0.04374371  0.17531118
Feature3   0.3681852  0.04932413  0.06148414
Feature4   0.3300569 -0.24878402 -0.14001476
Feature5  -0.2941514 -0.27469408 -0.16118879
Feature6   0.3461033  0.14303825 -0.34181851
Feature7  -0.2004563  0.46337482 -0.40316904
Feature8  -0.3065113  0.23164699 -0.42881517
Feature9  -0.2349429 -0.42941765  0.20576657
Feature10 -0.2069162 -0.46234863 -0.28977993
Feature11  0.2140177 -0.41357106 -0.52854459
```

Fig 3.2.3: Figure of Loading Values

The loading factors reveal the impact of each feature on the principal components: negative values indicate an inverse relationship with the component, and positive values indicate a direct relationship. Feature1, for example, is strongly inversely related to PC1, while Feature7 is strongly directly related to PC2, suggesting that as Feature7 increases, so does its influence on PC2.

3.2.4 Proportion of variance Explained (PVE's)

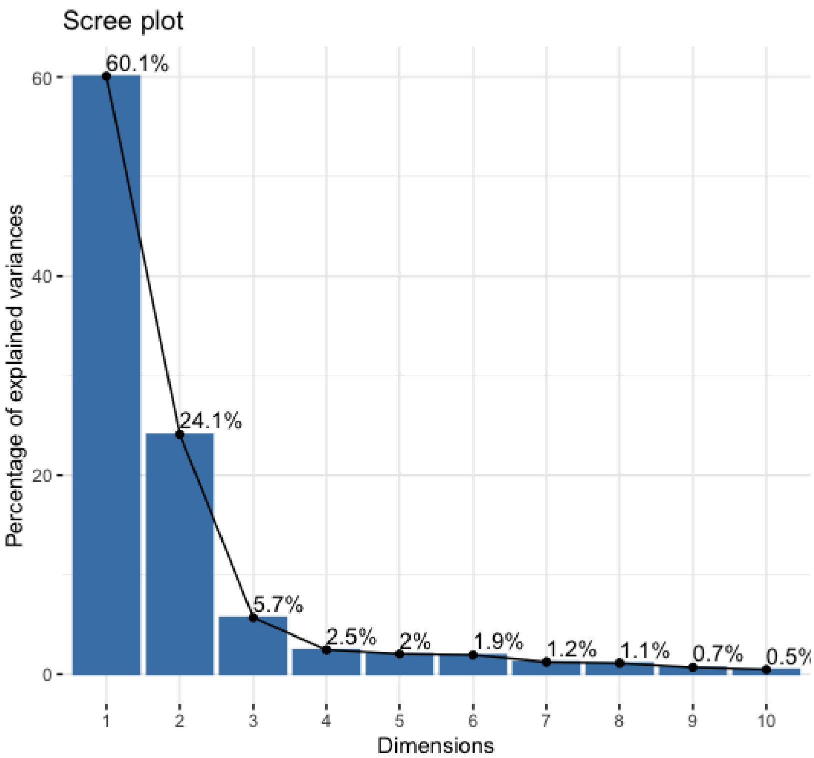

Fig 3.3.4: Scree plot

The scree plot indicates that the first principal component accounts for 60.1% of the variance, dominating the data's structure. The second component explains 24.1%, and subsequent components contribute much less, each below 6%. The steep drop after the second component suggests that these two components capture the most significant structure of the data, and further dimensions may contribute diminishingly to explaining variability.

3.2.5 Analysis Attribute importance

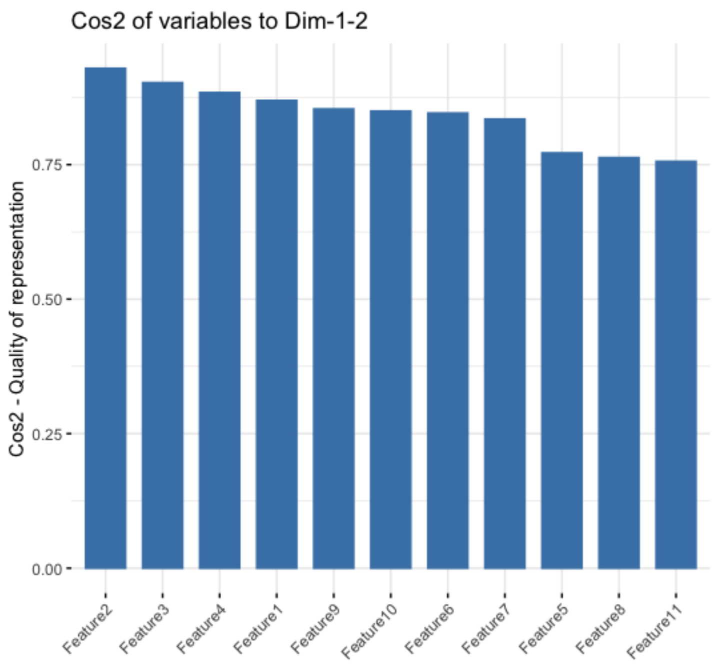

Fig 3.2.5: Analysis of Important Attributes

The bar chart shows the squared cosine values of variables to the first two principal components. The variables with higher values, such as Feature2, are better represented by these components, indicating that Feature2 plays a vital role in explaining the variability within the data. This suggests that Feature2's characteristics should be considered carefully in decision-making as it likely has a significant influence on the principal components' direction and magnitude.

3.2.6 Perceptual Map analysis

The biplot reveals the relationships between features and the principal components (PC1 and PC2) that explain the most variance. Feature7 exhibits a strong positive relationship with PC2, while Feature2 is positively aligned with PC1, indicating that they have a significant influence on these respective dimensions. The spread of data points across the biplot illustrates the variance in the dataset, with clusters near Feature2 and Feature6 indicating groups of similar characteristics, while the negative correlation of Feature5 with both components suggests it contributes differently to the dataset's variance.

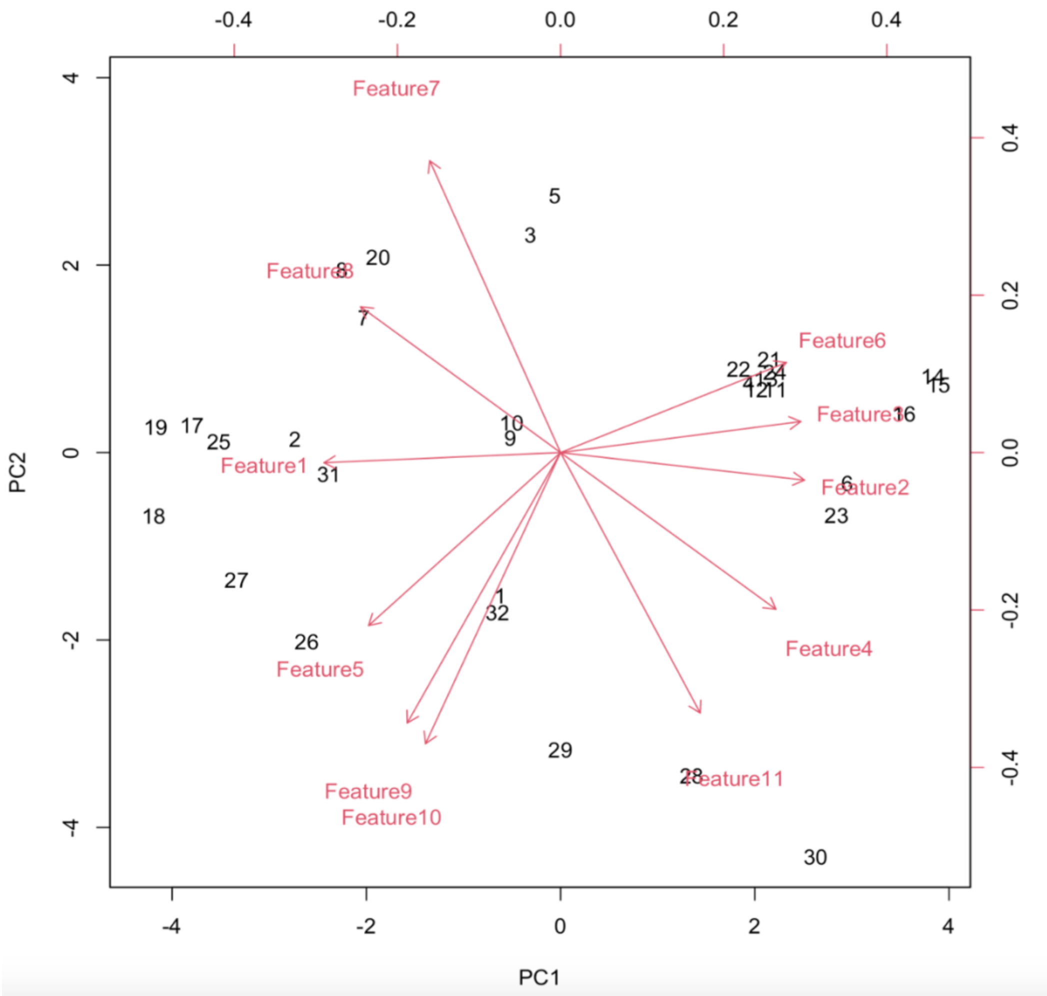

Fig 3.2.6: Analysis of Important Attributes

4.0 Results and discussion

4.1 Conjoint Analysis Results

4.1.1 Willingness To Pay(WTP)

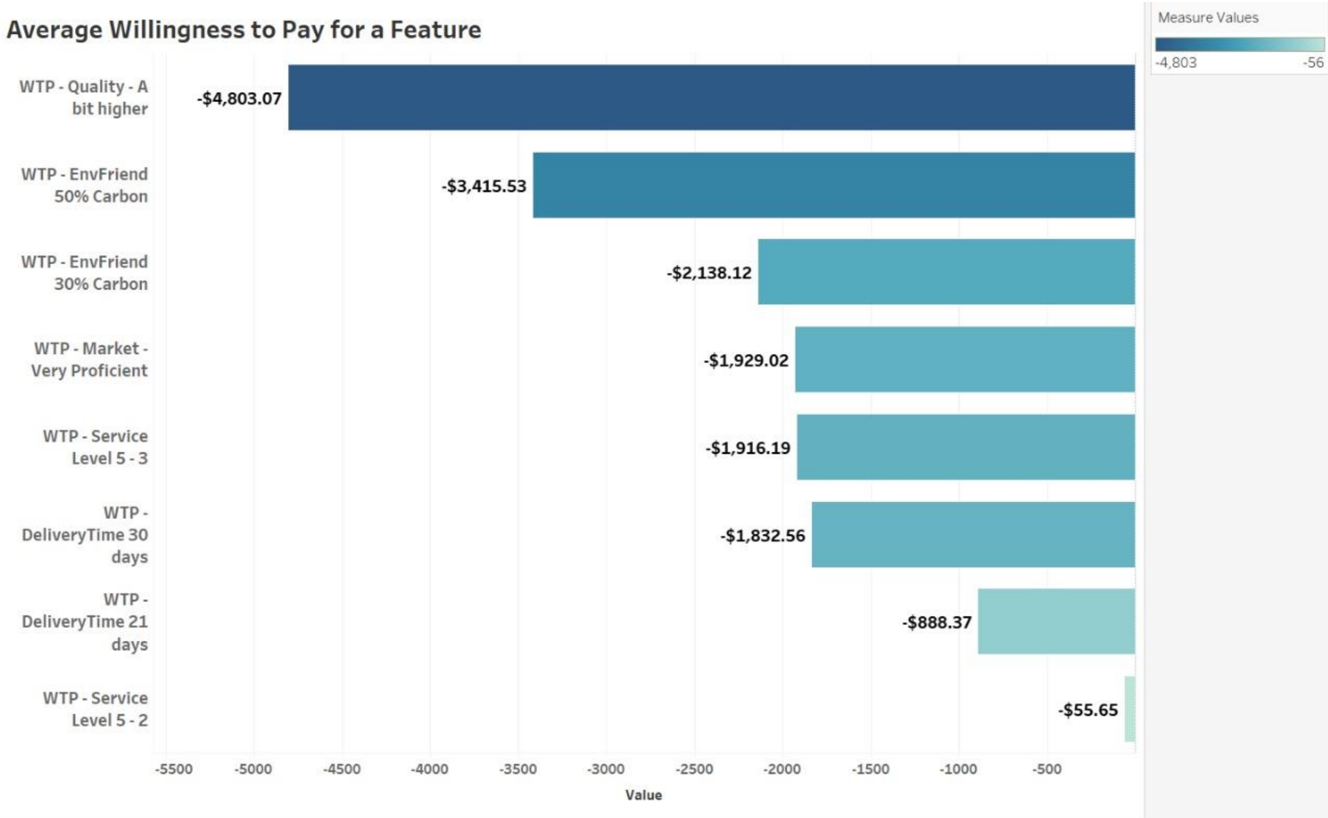

Fig 4.1.1: Graph of willingness to pay.

The WTP visualisation demonstrates a significant aversion to paying additional amounts for marginal enhancements in quality, as evidenced by a decrease in willingness to pay to -4803.07 GBP for minor gains in quality. Nevertheless, a slight reduction in willingness to pay (WTP) for enhanced service levels (-1916.19 GBP) indicates a potential market opportunity. This implies that customers might be more willing to invest in services that improve their user experience, even if they hesitate to pay for minor product modifications.

4.1.2 Average Attribute Part-Worth Visualization:

This graphic demonstrates that customers assign a small positive value (+0.12) to marketing proficiency, with a particular emphasis on the influence of communication on their purchase decisions. Nevertheless, the presence of a 50% decrease in CO_2 emissions indicates a significant unfavourable part-worth (-2.05), suggesting that environmental promises of this nature may not be as convincing as previously thought, either due to perceived expenses or practicality. Significantly, as prices rise to 1500 GBP, consumer satisfaction declines significantly (-0.53), indicating a crucial susceptibility to price that should guide pricing strategies.

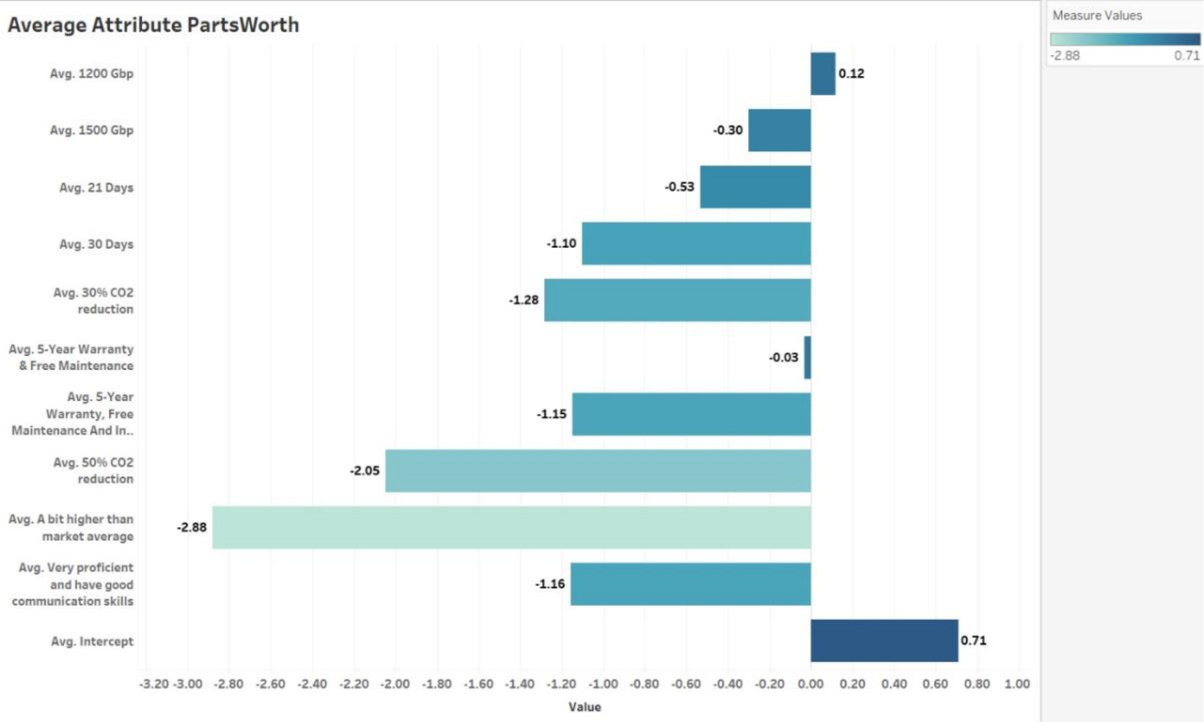

Fig 4.1.2: Graph of Average Attribute part-Worth.

4.1.3 Average Attribute Importance Graph:

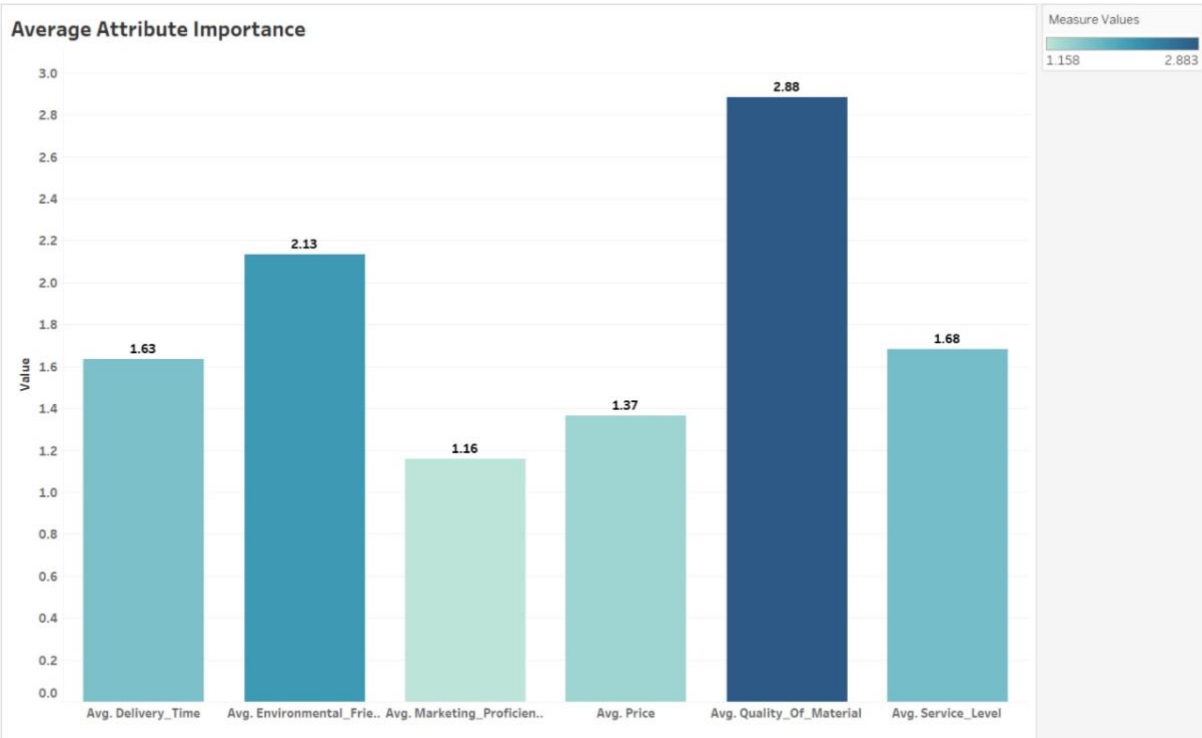

Fig 4.1.3: Graph of Average Attribute Importance Graph.

The graph indicates that the characteristic of 'Quality of Material' holds the highest level of significance among customers, as evidenced by its importance score of 2.88. This suggests that durability and material quality are key factors that greatly influence consumers' purchasing decisions. The 'Service Level' is highly evaluated at 1.68, suggesting that warranty and service options are significant factors taken into account. Although the trait of 'Environmental Friendliness' is considered vital with a score of 2.13, its relatively lower negative part-worth indicates that there may be other attributes that have a greater impact on adding value.

4.1.4 Percentage Average Attribute Importance Chart:

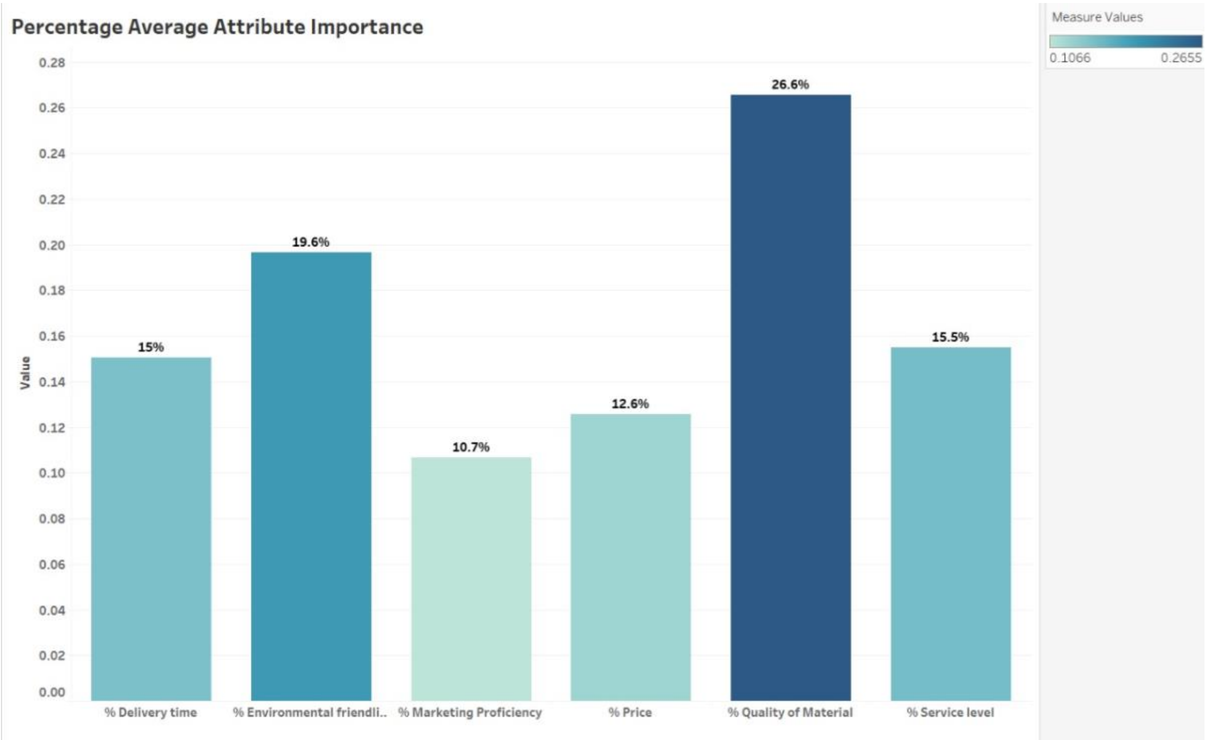

Fig 4.1.4: Graph of Percentage Average Attribute Importance .

The percentage breakdown reveals that 'Quality of Material' is the primary factor (26.6%) that influences purchasing decisions, indicating that buyers may give this component greater importance when distinguishing between products. The factor of 'Service Level' also carries significant influence (15.5%), suggesting that a considerable portion of the market highly values customer service. While 'Environmental Friendliness' (19.6%) does have an impact, it faces competition from more immediate benefits related to product quality and service.

4.1.5 Cluster analysis using Conjoint analysis

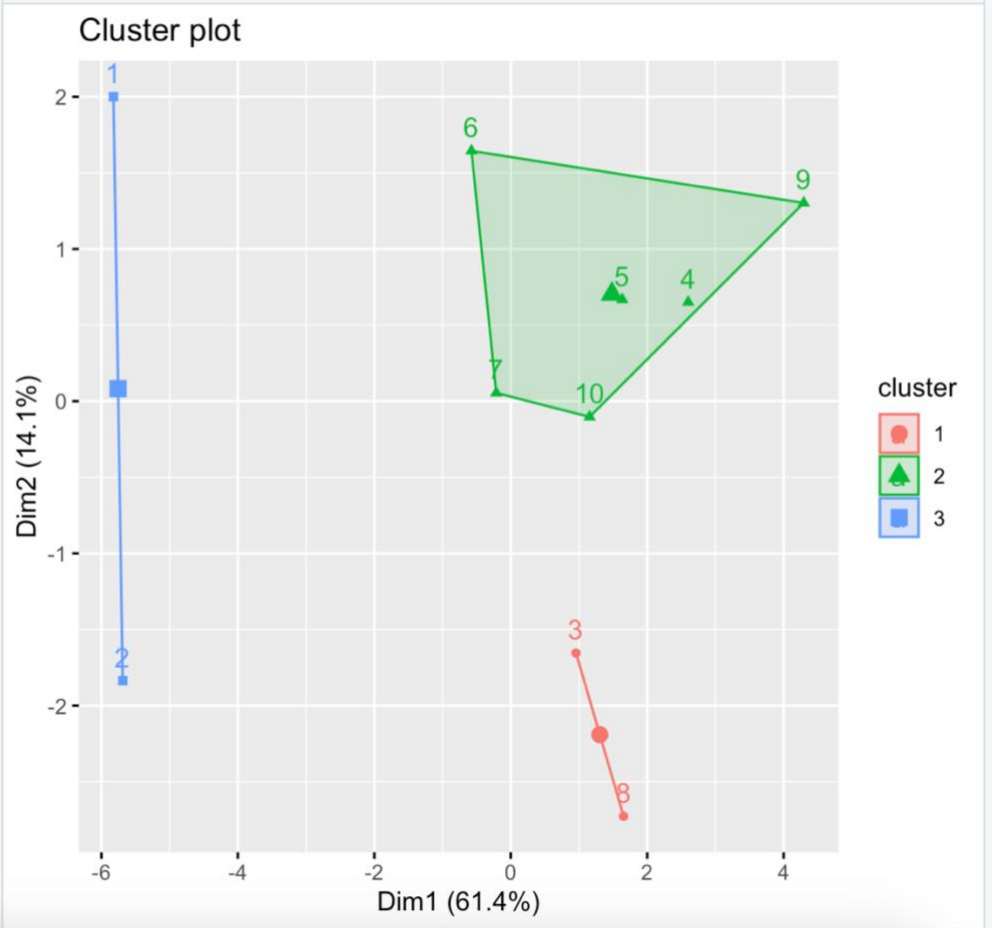

Fig 4.1.5: Cluster Plot.

The conjoint analysis segmentation cluster map shows three distinct consumer preference clusters with symbols and colours. The first cluster (red circles) is highly cohesive, suggesting common preferences. Green triangles form the second cluster, which is larger and suggests more tastes. The blue squares in the third cluster represent outliers, indicating rare tastes. Dimension 1 has the most variation (61.4%), indicating that it is the main factor separating consumer groups.

5.0 Conclusion and Recommendations

5.1 Conclusion

The study leveraged conjoint analysis and principal component analysis (PCA) to explore consumer preferences for a new circular product, identifying key attributes that influence purchasing decisions. Conjoint analysis revealed significant consumer valuation of environmental features, service levels, and price sensitivity. PCA efficiently reduced data complexity, highlighting critical consumer preference factors, enabling a holistic understanding of market needs.

5.2 Recommendations

1. **Enhance Environmental Sustainability:** Strengthen the product's environmental attributes to appeal to eco-conscious consumers, potentially increasing CO2 reduction levels and using sustainable materials (Allenby, Arora & Ginter, 1995).
2. **Balance Price and Quality:** Set a competitive price without compromising quality to align with consumer price sensitivity (Kuhfeld, 2005).
3. **Improve Service Offerings:** Enhance service packages to include extended warranties and maintenance, adding value and differentiating the product in the market.
4. **Emphasize Quality Materials:** Ensure high-quality, durable materials are used, enhancing consumer trust and satisfaction.
5. **Effective Marketing Strategies:** Develop targeted marketing campaigns that clearly communicate the product's unique features and environmental benefits.
6. **Utilize Ongoing Analytics:** Continue employing analytical tools like conjoint analysis and PCA for ongoing product and strategy refinement based on real-time data and consumer feedback.

6.0 Appendix

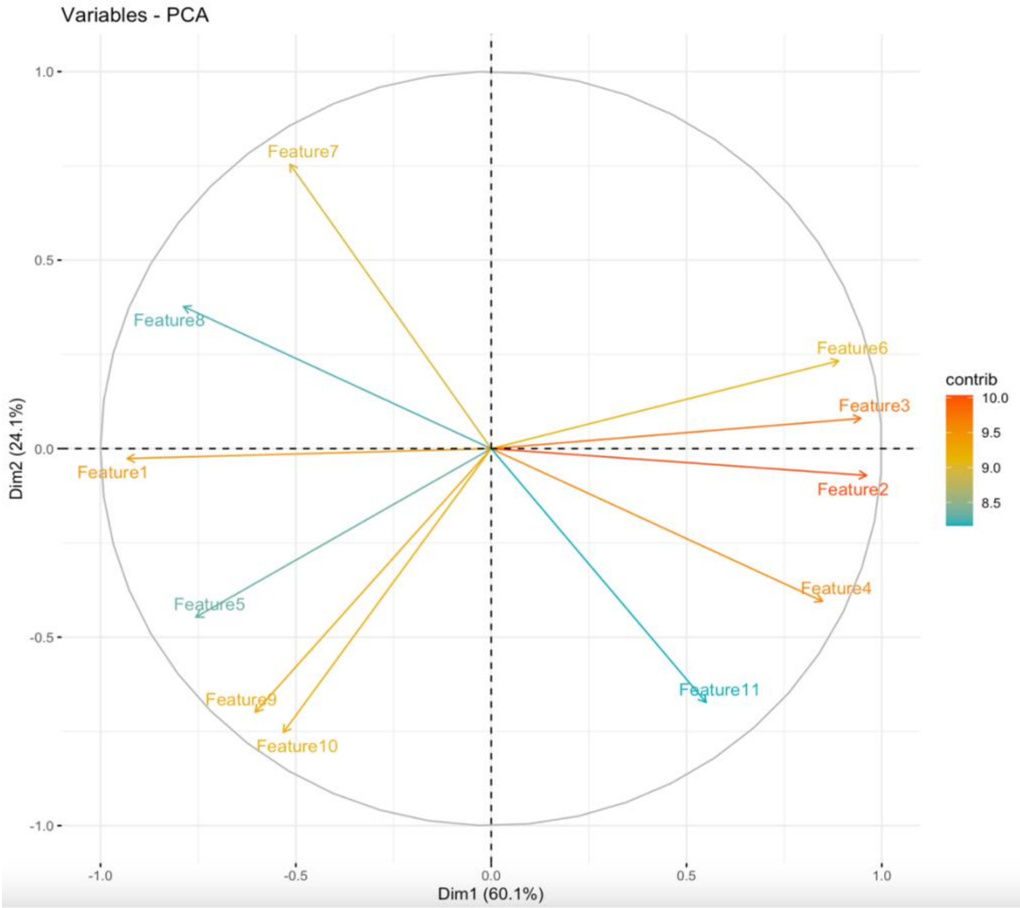

Fig 6.0: Feature Co-relation plot.

This PCA variables plot illustrates the contribution of each feature to the first two principal components. Features that are further from the centre have a greater influence on the dataset's variability along these components. Feature2 stands out with a strong positive correlation on Dimension 1, indicating it's a significant driver of variance. Feature7 shows considerable influence on Dimension 2. The vectors' directions and lengths indicate how these features are correlated with each other; for instance, Feature2 and Feature3 point in similar directions, suggesting a positive correlation between them.

6.1 R Code

Code for PCA

Marketing analysis

#PCA (Principal Componenet Analysis)

#loading librarires

```
library(tidyverse)
library(data.table)

#set seed
set.seed(40412492)

#set working directory
getwd()
setwd('/Users/dhanush/Desktop/Bussiness analytics /Sem 2/Marketing Analytics/Assigment_2')

#load the pca dataset
pca_data <- read_csv('PCA data.csv')

#Remove column one i.e model
pca_data <- pca_data[,-1]

# Standardize the data
data_scaled <- scale(pca_data)

# Perform PCA
pca <- prcomp(data_scaled, retx = TRUE, scale. = TRUE)

# Summary of PCA to see the proportion of variance explained
print(summary(pca))

# Calculate and view loading factors
loadings <- pca$rotation
print(loadings)

# Calculate singular values
singular_values <- pca$sdev
print(singular_values)

# Proportion of Variance Explained
var_explained <- pca$sdev^2 / sum(pca$sdev^2)
print(var_explained)

# Plotting a perceptual map
perceptual_map_data <- as.data.frame(pca$x[, 1:2])
colnames(perceptual_map_data) <- c("PC1", "PC2")
ggplot(perceptual_map_data, aes(x = PC1, y = PC2)) +
  geom_point() +
  xlab("Principal Component 1") +
  ylab("Principal Component 2") +
  ggtitle("Perceptual Map") +
  theme_minimal()
```

```
#Important Feature selection
fviz_cos2(pca,choice = "var",axes = 1:2)


fviz_eig(pca, addlabels = TRUE)
#or

# Adding a biplot to visualize both scores and loadings
biplot(pca, scale = 0)  # scale = 0 to keep arrows and points in proportion

# Using fviz_pca_var to visualize variables' contribution
fviz_pca_var(pca, col.var = "contrib",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE)  # Avoid text overlapping
```

Code for Conjoint Analysis

```
#Conjoint analysis

#setting up the attrib level

#setting seed

set.seed(40412492)

#loading library conjonint
library(conjoint)

#creating list of attributes and list

attrib.level <- list(
  Environmental_friendliness = c("0% CO2 reduction", "30% CO2 reduction", "50% CO2 reduction"),
  Delivery_time = c("14 days", "21 days", "30 days"),
  Service_level = c("5-year warranty", "5-year warranty & free maintenance",
                    "5-year warranty, free maintenance and installation, & upgradeability"),
  Price = c("1000 GBP", "1200 GBP", "1500 GBP"),
  Quality_of_material = c("Market average", "A bit higher than market average"),
  Marketing_proficiency = c("Not very proficient and poor communication", "Very proficient and have good communication skills")
)

## Create the fractional factorial design
#Top 18 product profiles
experiment <- expand.grid(attrib.level)
```

```
design <- caFactorialDesign(data=experiment, type="fractional", cards=22, seed=40412492) #(optimal)

## Check for correlation in fractional factorial design
#Answers the first question
print(cor(caEncodedDesign(design)))
print(experiment)

#uploading data for pref and profiles
attrib.vector <- data.frame(unlist(attrib.level,use.names=FALSE))

#Load Conjoint Preferncces.xlsx
pref <- readxl::read_excel("/Users/dhanush/Desktop/Bussiness analytics /Sem 2/Marketing Analytics/Assigment_2/Conjoint Preferncces.xlsx")
pref <- pref[,2:11]

# Design - Load Product Profiles.csv
design <- read.csv("/Users/dhanush/Desktop/Bussiness analytics /Sem 2/Marketing Analytics/Assigment_2/Product Profiles.csv")
design <- design[,2:7]

#Calculation of part-worths
caPartUtilities(y = pref, x = design, z = unlist(attrib.level))
part_worths <- caPartUtilities(y = pref, x = design, z = unlist(attrib.level))

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)
  ## Pick the baseline case
  ## Adjust coding as needed based on number of attributes and levels
  ## Base Case: Environmental friendliness - 0% CO2 reduction; Delivery time (order fulfilment time) - 14 days;
  ## Service level - 5-year warranty ; Price - 1000 GBP ; Quality of material -  Market average; Marketing proficiency - Not very proficient and poor communication

  Base_Enviromental <- temp[,"0% CO2 reduction"]; Base_Delivery <- temp[,"14 days"]; Base_Service <- temp[,"5-year warranty"]
  Base_Price <- temp[,"1000 GBP"]; Base_Quality <- temp[,"Market average"]; Base_Marketing <- temp[,"Not very proficient and poor communication"]
  ## Adjust Intercept
  temp[,"intercept"] <- temp[,"intercept"] - Base_Enviromental - Base_Marketing - Base_Quality - Base_Price - Base_Service - Base_Delivery
  ## Adjust Coefficients
  ## Envirnomental
  L1 <- length(attrib.level$Environmental_friendliness) + 1 ## Add 1 for the intercept
```

```
  for (j in 2:L1){temp[,j] <- temp[,j] - Base_Enviromental}
  ## Delivery
  L2 <- length(attrib.level$Delivery_time) + L1
  for (k in (L1+1):L2){temp[,k] <- temp[,k] - Base_Delivery}
  ## Service
  L3 <- length(attrib.level$Service_level) + L2
  for (l in (L2+1):L3){temp[,l] <- temp[,l] - Base_Service}
  ## Price
  L4 <- length(attrib.level$Price) + L3
  for (m in (L3+1):L4){temp[,m] <- temp[,m] - Base_Price}
  ## Quality
  L5 <- length(attrib.level$Quality_of_material) + L4
  for (n in (L4+1):L5){temp[,n] <- temp[,n] - Base_Quality}
  ## Marketing
  L6 <- length(attrib.level$Marketing_proficiency) + L5
  for (n in (L5+1):L6){temp[,n] <- temp[,n] - Base_Marketing}

  part.worths <- rbind(part.worths, temp)
}

rownames(part.worths) <- colnames(pref)

write.csv(part.worths, file.choose(new=TRUE), row.names = FALSE)

#Do cojoint analysis on given files
Conjoint(pref, design, attrib.vector)

cluster <- caSegmentation(y=pref, x=design, c=3)
plot(fviz_cluster(cluster$segm, scale(cluster$util)))


###########or##################################
```

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