Customer Analytics and Customer Insights: Conjoint Analysis on Preferences and Segments in the Portable Bluetooth Speaker Market.

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1 Market Relevance and Methology

The market of portable bluetooth speakers has been rapidly growing within the last years. Since 2014, when the GfK introduced "connected audio" as a category of itself within the home audio market, the revenue with portable audio devices in Germany has almost doubled to 384 million Euro in the year 2017.[1] The purpose of this paper is to provide insights on customer preferences and to identify relevant customer segments within this important category. To achieve this goal a choice based conjoint analysis will be conducted. The necessary data has been collected through an online survey by the Institute of Marketing of the Humboldt University. The survey consisted of two parts. The first one contained personal questions towards category knowledge and socio-demographics, the second one contained responses to the product choice sets. I am going to start the data analysis by introducing the choice data set and the mixed logit model, which is used to estimate customers preferences. The resulting estimates on the individual respondent level will be used to cluster the respondents into homogeneous segment. I will proceed to analyse the segment specific preferences and propose example products to target each identified segments. Subsequently the individual data set is going to be introduced and I will analyse how the segments differ in their characteristics. A decision tree will be used to find out which features are the best predictors for segment membership. Finally the analysis results will be summarized.

2 Customer Preferences and Segments

The survey respondents were presented with different product profiles (stimuli) out of the bluetooth speaker category. For each such choice set they had to select their favourite. Each profile combined a certain price, ranging from 70 to 150 Dollar and different realizations from the attributes battery power, weight and sound quality. The attribute

[1] de.statista.com/statistik/daten/studie/20221/umfrage/umsatz-im-bereich-home-audio-seit-2005/

battery power is measured in hours ranging from 8 - 16 hours. The weight of the speakers is defined in gram and includes four levels from 400 to 700 gram. Sound quality was presented on a rating scale, as it is commonly used for product reviews. The attribute also contains four different levels from 3.5 to 5 stars. Each respondent was presented with 12 choice sets containing three different stimuli and a 'None' option to choose from. The analysis is based on survey data from 300 respondents containing 14400 rows. The data is effect coded and contains 17 columns: A respondent id, a choice set id, a choice variable indicating the selected stimuli, a dummy coded variable for the 'None' option and 12 dummy variables representing the attribute levels of the stimuli. Within each attribute the highest attribute level is omitted.

A mixed logit model is used to estimate aggregated and individual preference parameters. One advantage of a mixed over a simple multinomial logit model is, that it allows for person specific preferences. Not only does it seem more intuitive that individuals differ in their preferences, but this also allows to identify clusters of customers with similar preferences. I estimate the mixed logit model under the assumption of normal distributed preference parameters. Thus the model returns estimates the parameter means and their standard deviations. Subsequently the analysis focuses exclusively on the parameter means. After model estimation I extract the estimates for each individual respondent, resulting in a data set with 300 rows and 15 parameter columns. Since positive price parameters seem implausible and might disturb further analysis, such respondents are removed from the data set and the model is re-estimated for the remaining 289 respondents. Since the input data is effect coded, the resulting attribute parameters represent part worths. They tell us how much the utility of a stimuli changes for a given attribute level compared to the attributes average utility. I use the estimated part worths to calculate the part worths for the omitted attribute levels, the relative attribute importance and the willingness to pay per attribute level. All these measures are calculated for every respondent.

To identify homogeneous customer segments one has to define, how similarity between customers should be measured, e.g. which measurements should be included to calculate distances between them. While part worths are on an interval scale, the price parameters used here corresponds to the utility change per 10 Dollar difference and the 'None' parameter describes the absolute utility when the 'None' option is selected. To make these scales comparable I normalize each parameters by subtracting its mean and dividing it through its variance. While this makes the scales comparable, it also means that differences within every each feature are weighted equally, e.g. differences within the price parameter have the same influence on respondents similarities as differences in one of the weight parameters. To account for the fact that features may differ within their absolute impact on a customers utility I also include the normalized importance measurements in the cluster data set. Based on this measurements I calculate euclidean distances between the respondents. Several clustering methods (kmeans, hierarchical) and linkage criteria (single, complete, Wards) are tested. The selection criteria for the most appropriate method was a high decrease of between cluster distance at a low cluster count and the interpretability of the resulting segments. The later was assessed by analysing the relative importance and willingness to pay of the clusters. Hierarchical clustering with Ward's method has shown to produce the best results. The "elbow plot" of the between cluster distance decreases between two and four cluster almost similar and becomes then flatter. The visual analysis on the importance measures have been conducted on the segment means and on a 2-dimensional visualization of the importance measures (see Figure 1). For the later multidimensional scaling and property fitting of the importance parameters was used. The two dimensional importance map with four clusters shows a clear separation of three main clusters between the fitted importance vectors. The members of the forth clusters are mainly defined by a common preference for weight and battery power, while they are otherwise spread along the other dimensions. This property and the small cluster size could imply that three clusters a favourable. However, without a fourth cluster the over all cluster mixture is significantly higher. It is notable, that three of the four importance dimensions are clearly separated. Yet the direction of the weight and the battery importance are almost identical. One can conclude that people who value a light speaker also care about battery power.

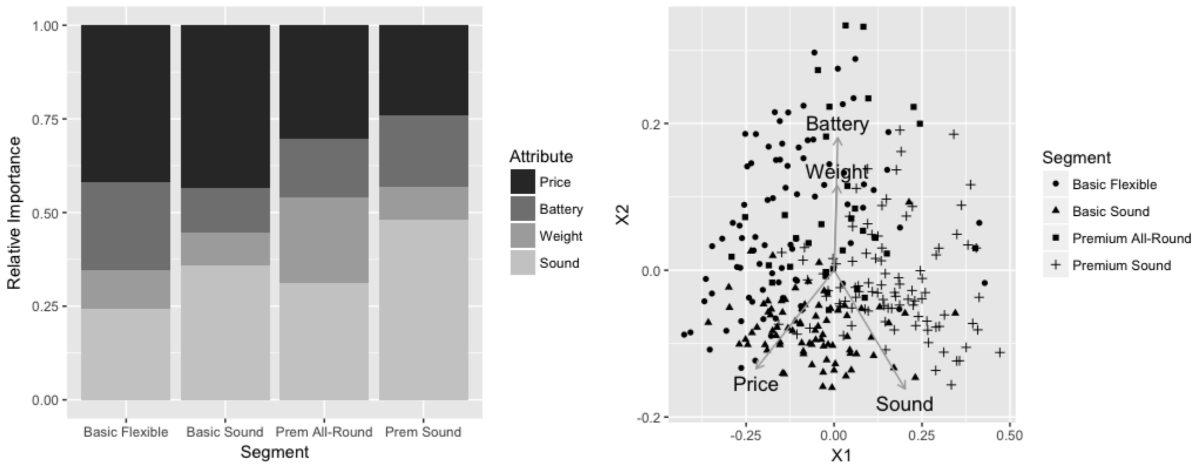

Figure 1: Relative Importance Means (a) and 2D Visualisation (b) per Segment

The names of the identified segments are based on their relative attribute importances as Premium Sound Enthusiasts, Basic Sound Enthusiasts, Premium All-Round Users and Basic Flexibility Fans. Premium Sound Enthusiasts show the smallest price sensitivity and value sound quality the most. Battery is almost as important for them as price. Base Sound Enthusiasts care a lot about sound quality, too. However they are quite price sensitive and weight and battery do not matter for them. The Premium All-Round Users value sound quality a little less and have the second lowest price sensitivity. The importance of weight is clearly bigger compared to all other segments. The Flexibility Fans are quite price sensitive and care most of all segments about battery duration. The Premium Sound Segment is with 91 members the biggest one, followed with little difference by the Basic Sound and the Basic Flexibility segment. The Premium All-Round segment has with 32 members only about one third of their size.

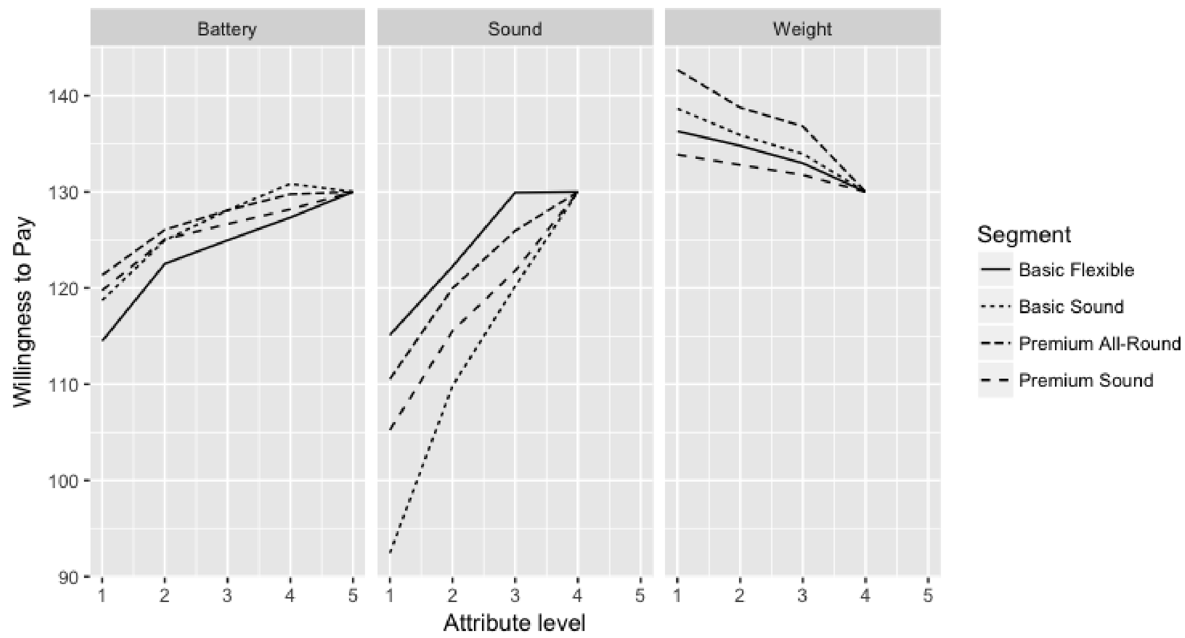

Figure 2: Willingness to Pay per Segment

Figure 2 shows the willingness to pay (WTP) for different attribute levels and market segments. It is defined as deviation from the product profile containing the omitted attribute levels. It shows how much more or less a customer (segment) would pay for a certain attribute level in comparison to the omitted one. The omitted profile has 16 hours of battery duration, a 5 star sound rating and weights 800 gram. By default its WTP is defined as zero. Since negative monetary values seem counter intuitive, I shifted its WTP for illustrative reasons to 130 Dollar. This value was choosen ad hoc because 130 Dollar correspond to the third quartile of the price range and the omitted profile has quite favourable attributes. The different attribute levels in Figure 2 are decoded from one to five (or four) on the x-axis and represent the lowest to the highest attribute level. Obviously speakers with a higher battery duration, a higher sound rating and a lower weight are generally preferred. In consistence with the importance analysis, the potential for price increases through a better sound quality is about twice as high as for the other two attributes. When comparing a stimuli with the lowest attribute levels against against the highest ones the maximum WTP difference lies roughly between 30 and 40 Dollar, depending on the segments. This seems rather low considering that the price range in the survey was 80 Dollar. Depending on improvement costs between the different attribute levels, this could imply that producing lower quality speakers might be more economic for a company. Especially when looking at the battery attribute, the WTP increase from a 8 hour battery to a 10 hours is clearly higher than between the higher attribute levels. The active base users are not even willing to pay more for a battery that lasts 12 hours than for one that lasts 10 hours and the base sound enthusiasts even prefer the 10 hour battery. While this implausibility is similar to positive price coefficients I refrain from removing the corresponding respondents from the dataset because the effect is rather small and real world choices could show such inconsistencies as well.

Product	Price	Battery	Sound	Weight	1	2	3	4	5
A	150.00	12 h	5.00	700 g	30.23%	90.00%	2.89%	3.35%	3.81%
B	100.00	8 h	4.50	700 g	37.03%	7.40%	66.75%	5.39%	9.90%
C	130.00	10 h	4.00	400 g	17.56%	2.13%	2.77%	83.98%	8.50%
D	80.00	12 h	3.50	700 g	12.18%	0.39%	2.44%	2.11%	76.01%
E	-	-	0.00	-	3.00%	0.08%	25.15%	5.17%	1.79%

Table 1: Example Products and Market Shares

In order to give an inspiration on how this results can be used for new product development, I create four example product profiles tailored to the preferences of each segments. Since no production costs are known the underlying assumption is a simple trade off between attribute quality and prices. The example profiles are used to calculate the utility for every customer segment and for the full market. These utilities are subsequently used to predict market shares with a logit model. Table 1 gives an overview of the stimuli derived from the prior analysis and the market share estimations. The fact that each product clearly dominates the corresponding segment points out, that the clustering approach was successful. Moreover the low share of the 'None" option in all but the Basic Sound segment is promising for the industry. However one should notice that stated preference data tends to be overly optimistic. Interestingly product B has with 66,76 % the smallest value in its own segment. Yet it has the highest market share in the full sample (37,03 %). This implies the stimuli itself has a favourable price - quality ratio. Considering this and the outstanding share of the 'None' option, the Basic Sound Enthusiasts might not be the best targeting choice.

3 Segment Characteristics and Predictors

After identifying relevant customer segments the analysis of the individual customer data focuses on the question, how these segments can be described using customer characteristics and which characteristics can be used to predict a certain segment membership. The individual data set contains, after removing additional label decoding, 32 columns per respondent. Apart from the respondent id and two dummy variables stating whether the respondent owns or plans to buy a bluetooth speaker the remaining columns can be categorized like this: five features each on subjective domain knowledge and product category involvement (PII) both on a scale from one to seven, four features with stated relative attribute importances in percentage and five socio-demographic features on a categorical scale.

Table 2 shows the most frequent levels for the socio-demographic features. Clearly the sample is not independent identically distributed from the full German bluetooth speaker market: About half of the respondents do not live in Germany, yet on an international scale German residents are over represented. Since statistical interference becomes impossible for very small observation counts, I assign all residence level with less than five occurrences with a name called 'other'. Similar biases occur in the other socio-demographic variables, except for the gender variable. However, this was foreseeable since respondents were non randomly selected by students of a German masters course. Thus students are as well over represented as the higher educational levels, younger age groups and low income classes. It is hard to predict how this affects the analysis results. If preference parameters are fairly independent from social-demographics the sample results might still be a good estimation for population preferences.

GenderLabel	AgeLabel	Residence	OccupationLabel	EducationLabel	IncomeLabel
female: 127	25-29: 117	Germany: 167	Employed: 94	Graduate: 124	501-1000 $: 95
male: 156	18-24: 115	Turkey: 21	Retired: 2	High school: 61	<500 $: 52
unknown: 6	30-34: 20	Belgium: 11	Self-employed: 21	Less than high school: 4	1001-1500 $: 42
	>=50 : 19	France: 11	Student: 163	Other: 4	unknown: 39
	35-39 : 8	United States: 8	Unemployed: 9	Undergraduate: 96	>=3001 $: 24
	<18 : 4	Saudi Arabia: 7			1501-2000: $ 17
	(Other): 6	(Other): 64			(Other): 20

Table 2: Socio-Demographic Frequencies

Analysing every variable within the dataset individually would exceed the scope of this paper. However it also promises little informational gain, because the variables within each category are strongly related. All product category involvement variables rate the subjective importance of bluetooth speakers. They only differ within their wording. For people unfamiliar with scales of customer involvement they seem synonymous. In fact all five variables are strongly correlated. The same is true for the subjective knowledge variables, even though they do put the subjective knowledge on bluetooth speakers in different contexts. If the stated relative importance measures are related to the revealed importances, comparing them between segments becomes redundant: The clustering was based on revealed importance similarities. In fact all four importances show a moderate correlation between 0.43 and 0.59. One can therefore expect to observe a similar importance distribution based on the stated data as shown in Figure 1. Interestingly the correlation of the battery and price importances are higher than for weight and battery. This means that people are worse at assessing attribute importances which matter less for them. Table 3 contains summary statistics for the individual variables and segments. For categorical data the modus is used, variables which had the same modus in all segments such as occupation have been omitted. Binary variables present the rate of "true" responses. Brand awareness is the rate of known brands out of eight in the survey. Subjective knowledge and category involvement are averaged over the respective five ratings. Average incomes have been estimated by assigning the category mean to each category observation and averaging over the segments. The highest income group has been assumed to have an average income of 4000 Dollar, respondents without reply have been omitted.

Within the two premium segments more people own a speaker than in the basic segments. This shows that first time customers are less willing to spent a lot of money. The rates of people who plan to buy a speaker are similar in all but the Premium All-Round segment. Due to this small rate and its overall small size I'd advise practitioners against targeting it. Brand awareness subject knowledge and category involvement all show the

	Own	PlanToBuy	BrandAw	SubjKn	PII	Female	AgeGr	Education	Income
Prem Sound	0.56	0.34	0.39	3.96	4.52	0.36	25-29	Graduate	1494 $
Basic Sound	0.37	0.33	0.38	3.68	4.21	0.42	18-24	Undergrad	859 $
Prem Allround	0.44	0.16	0.35	3.68	4.29	0.44	18-24	Undergrad	1388 $
Basic Flexible	0.35	0.36	0.33	3.61	3.98	0.56	25-29	Graduate	1275 $

Table 3: Summary Statistics on Respondent Characteristics

same pattern. The Premium Sound Enthusiasts show the highest values, Basic Sound Enthusiasts and Premium All-Round User are in the middle, and Basic Flexible Users show the smallest values. The "Is female" variable has the opposite pattern indicating that man are generally more interested and educated in the field and willing to spent more money on speakers. The modi of age group and education yield little insight because they are simply the most common levels in the sample. As one would expect the premium segments have the highest impact and Basic Sound Enthusiasts have the smallest.

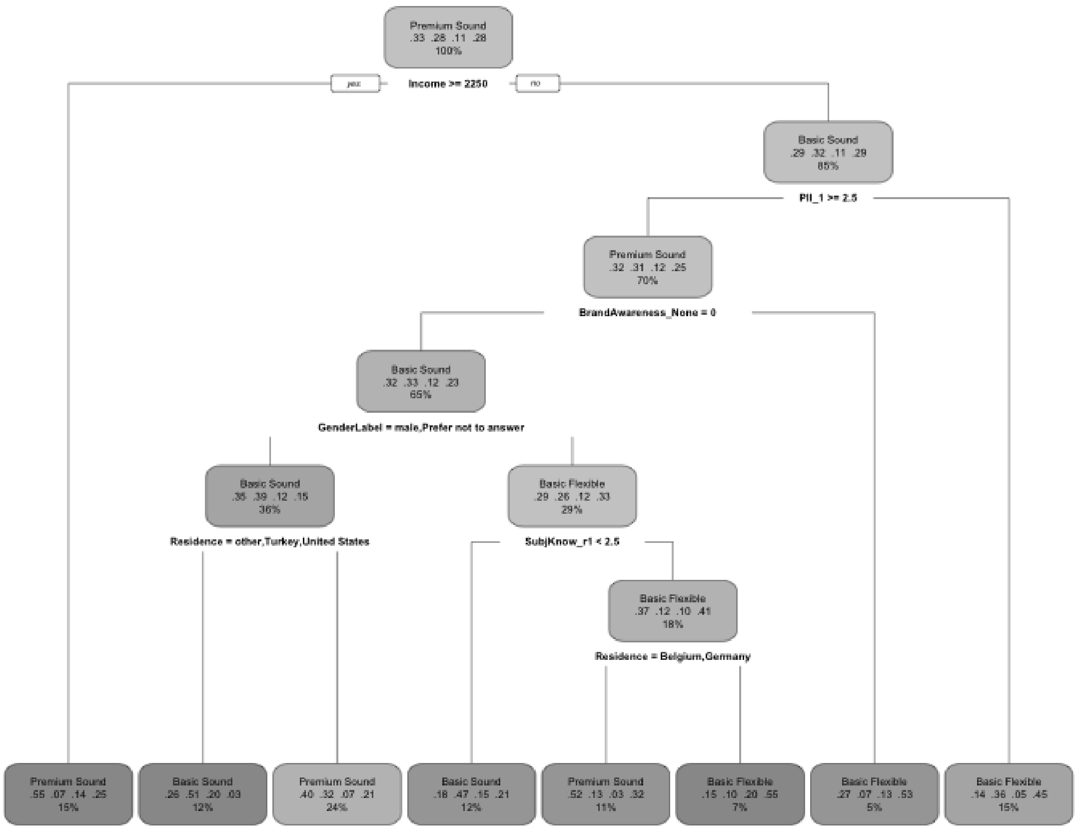

Figure 3: Decision Tree for Segment Classification

In order to find out which customer characteristics are the best predictors for segment membership a decision tree is used. A decision tree splits the data starting from the full data set in the initial node iteratively into two child nodes. It selects the feature which maximizes the heterogeneity between the resulting nodes as split criterion. In our case the heterogeneity refers to differences to occurrence rates of the four segments. The algorithm could be continued until perfect classification is achieved or no splitting criteria remain. However the given tree was pruned to seven splits to keep it interpretable. If a individual variable has a major impact on class membership which has been concealed through aggregation in Table 3, the variable would be selected as a early splitting criterion on the tree. When building a tree on the full individual data set the first five splits occur on different thresholds of the stated importances for sound quality, price and battery power. Thus stated importances are the best predictors for class segment membership. Since this result seems obvious a new tree without importance variables is built. The results can be seen in Figure 3. As assumed before a high income is the best predictor for the Premium Sound segment. For customers with a lower income a agreement with the statement "bluetooth speakers are unimportant" was the best predictor for the Basic Flexible Segment, followed by the feature for zero known brands. Further socio-demographic predictors for segment membership are gender and residence. Probably due to its small since, none of the end nodes is classified as Premium All-Round.

4 Conclusion

Four customer segments with clearly distinguishable preferences have been identified. They mainly differ in their price sensitivity and in the extent to which they value sound quality. Based on these results four products, one targeted to each customer segment, where proposed. The estimation of market shares has shown, that they all clearly outperformed the alternatives products in their respective segment. The product targeted at the Basic Sound Segment showed a very high none purchase rate even though it performed best in the full market. The segment does therefore not seem like a favourable target choice. Further analysis of customer characteristics has shown, that the Premium All-Round segment has a very low rate of people with intent to buy a speaker. Therefore and due to its small size the Premium Sound segment and the Basic Flexible segment are recommended as target groups for practitioners. The first of which can be characterized by a relative high income, a higher probability of owning a bluetooth speaker and a high domain knowledge. Also its members are more likely to be male. The Basic Flexible segment shows the opposite characteristics. A decision tree has shown that stated importances are the best predictors for segment membership in the available data set. If no stated importance data is available income a importance rating on the product category, residence might be used to predict segment memberships. Due to biases in the demographics of the selected respondents this results only apply for the social circle of German students. The fact that income and residence are relative good segment predictors implies, they might not generalize well on the full market population.