30-10-2015

A Comparison of Segmentation Based on Relevant Attributes and Segmentation Based on Determinant Attributes

Kayleigh Meister
WAGENINGEN UR

A Comparison of Segmentation Based on Relevant Attributes and Segmentation Based on Determinant Attributes

Kayleigh Meister
Student number: 920330555040
Specialization: Management Studies – 33 credits
Wageningen University, Wageningen
First supervisor: Dr.ir. F.J.H.M. Verhees
Second supervisor: Dr. I.A.C.M. van der Lans
Department of Social Science, Marketing and Consumer Behaviour
October 2015

Preface

This research is part of my master thesis for the master Management, Economics and Consumer Behavior at Wageningen University. I have chosen for the specialization in Marketing and Consumer Behavior. My thesis subject gave me the opportunity to further develop my knowledge of Marketing, in particular in market segmentation. I expect that this thesis has a great contribution to my future career.

I am very thankful that I got the opportunity to do this research project. I would like to express my gratitude to my first supervisor Frans Verhees and my second supervisor Ivo van der Lans. I learned a lot from them during the past half year. Thanks to them I have the feeling that I am well prepared to start my internship.

Table of contents

Preface.....ii

Summary.....iv

1. Introduction.....1

2. Literature.....3

   2.1 Market segmentation.....3

      2.1.1 Four types of segmentation bases.....3

      2.1.2 Six criteria.....3

   2.2 Attribute importance.....4

3. Hypotheses.....5

4. Method.....7

   4.1 Sample.....7

   4.2 Measuring Relevance.....7

   4.3 Measuring Determinance.....7

   4.4 Factor Analysis.....7

   4.5 Latent class analysis (Relevance).....8

   4.6 Cluster analysis (Relevance).....8

   4.7 Latent class regression (Determinance).....9

   4.8 Comparing latent class analysis and cluster analysis (Relevance).....9

   4.9 Comparing segmentation based on relevance and segmentation based determinance.....9

5. Results.....11

   5.1 Factor analysis.....11

   5.2 Segmentation based on relevance: Latent class model.....12

   5.3 Segmentation based on relevance: Two-stage clustering procedure.....13

   5.4 Segmentation based on determinance: Latent class regression.....13

   5.5 Comparison segmentation based on relevance: LCA and two-stage clustering procedure.....14

      5.5.1 Comparison of factor means per segment.....15

   5.6 Comparison segmentation based on relevance(LCA) and determinance (LCA).....17

6. Conclusions.....18

7. Discussion.....20

References.....22

Appendices.....24

   Appendix I: Questionnaire.....24

Summary

Market segmentation is one of the fundamental principles of marketing (Kotler & Armstrong, 2010). Market segmentation can be used by management when developing a marketing strategy (Green, 1977). Future buying behavior is of central interest to marketers (Haley, 1968). Different variables can serve as a base for segmentation. When different segmentation bases are evaluated based on the six criteria for segmentation (identifiability, substantiality, accessibility, responsiveness, and actionability), unobservable product specific bases are recommended. Product benefit perceptions and importances is one of the variables in this category (Wedel & Kamakura, 2000).

When using importances as a base for segmentation, the different dimensions of attribute importance are not taken into account. However, three dimensions of attribute importance can be distinguished; salience, relevance and determinance. “*Salience reflects the degree of ease with which attributes come to mind or are recognized when thinking about or seeing a certain object. The relevance of attributes is largely determined by personal values and desires and reflects the importance of attributes for individuals. The determinance of attributes reflects the importance of an attribute in judgement and choice”* . Attributes that are considered relevant by consumers, are not by definition determinant for buying behavior (Van Ittersum, Pennings, Wansink, & Van Trijp, 2007).

In this research segmentation based on relevant attributes and segmentation based on determinant attributes is compared using latent class analysis. In addition, latent class analysis is compared with cluster analysis for segmentation based on relevant attributes. The research question and the corresponding hypotheses are as follows:

Question 1: “*Does segmentation based on relevant attributes have a relation with segmentation based on determinant attributes?”.*

Based on the multi-dimensionality of attribute importance the following hypothesis is formulated:

Hypothesis 1: Segmentation based on relevant attributes is independent of segmentation based on determinant attributes.

Question 2: *"Does segmentation based on relevant attributes using cluster analysis have a relationship with segmentation based on relevant attributes using latent class analysis?”.*

Since the two methods use the same input data, the output of the two segmentation methods is expected to have a strong relationship. The following hypothesis is formulated:

Hypothesis 2: Segmentation based on relevant attributes using a two-stage clustering procedure is dependent of segmentation based on relevant attributes using latent class analysis.

In order to do this, data regarding 4 different smartphones and 12 product attributes were used. As input for the segmentation based on relevant attributes, the importance scores of the 12 different attributes were used. For segmentation based on determinant attributes, the perception scores of 4 different smartphones based on the same 12 attributes were used. Also the intention to buy was measures for the 4 smartphones. To reduce the number of variables, factor analysis was performed. Factors for relevance were formed by calculating the average of the importance scores standardized per respondent. Factors for determinance were formed by calculating the average of the perceptions standardized per respondent across the 4 smartphones. For segmentation based on determinance also buying intentions were standardized and factors were centered so that the intercept for all segments is set to 0.

To test if segmentation using latent class analysis allocated the same respondents to the same segments as segmentation using cluster analysis, a chi-square test for independence was used. The chi-square test of independence results in a chi-square value of 223.98 with a significant P-value of 0.000 (<0.05). To test the strength of the relation, a Cramer's V test was performed. The Cramer's V value is 0.85 with a significant p-value of 0.000 (<0.05). This Cramer's V association indicates, as expected, a very strong association between segmentation based on relevance using the two stage clustering procedure and latent class analysis (Rea & Parker, 1992 as cited in Kotrlik, Williams, & Jabor, 2011).

A chi-square test of independence was also performed to compare segmentation based on relevant attributes and segmentation based on determinant attributes. This resulted in a chi-square value of 7.424 with a p-value of 0.060 (<0.2). This indicates, in contrast to hypothesis 1 that segmentation based on relevant attributes is dependent of segmentation based on determinant attributes. The Cramer's V coefficient of 0.219 indicates a moderate association (Rea & Parker, 1992 as cited in Kotrlik et al., 2011). Though for marketing purposes the results from segmentation based on relevant attributes and segmentation based on determinant attributes cannot be substituted with each other. For developing a marketing strategy the moderate association that is found is too weak.

The difference in results between segmentation based on relevant attributes and segmentation based on determinant attributes could be explained by a conflict in valued goals, as can be found in the literature of sustainable food consumption. Knowing which attributes are relevant but are not determinant for buying behavior is essential since marketers should ensure a market-typical level of performance for these relevant attributes, under-performance may result in a competitive disadvantage (Mikulić & Prebežac, 2012).

Due to the phenomenon of selective perception, knowing which attributes are considered relevant by a consumer might be useful in advertising, but this requires further research. Also the relationship between segmentation based on relevance and segmentation based on determinance should be further researched. A recommendation is to do this for specialty goods. Due to the difference in decision making resulting from a different level of involvement, a stronger relationship might be found between segmentation based on relevant attributes and segmentation based on determinant attributes.

1. Introduction

Since the introduction of market segmentation by Wendell Smith in 1956, market segmentation is one of the most researched concepts in marketing research (Green, 1977; Peltier & Schribrowsky, 1997; Wind, 1978). *“Market segmentation consists of viewing a heterogeneous market as a number of smaller homogeneous markets in response to differing product preferences among important market segments”* (Smith, 1956).

Market segmentation can be used by management when developing a marketing strategy (Green, 1977). Future buying behavior is of central interest to marketers (Haley, 1968). When management understands the factors that motivate behavior and the evaluative criteria influencing decision making, segment-specific marketing strategies can be improved (Peltier & Schribrowsky, 1997). Many different variables are used for segmentation studies. When trying to predict buying behavior, geographic, demographic and volume segmentation are not efficient, since they rely on descriptive factors rather than causal factors. An approach that uses causal factors is called benefit segmentation (Haley, 1968). The underlying belief about benefit segmentation is that *“the benefits which people are seeking in consuming a given product are the basic reasoning for the existence of true market segments” (Haley, 1968).*

To identify buying motives and benefits sought, different question techniques are proposed by Peltier and Schribrowsky (1997). If consumers are able to express their motives, the focus of the question techniques is on the identification of attribute **importance** (Peltier & Schribrowsky, 1997). When measuring attribute importance, the different dimensions of attribute importance are not taken into account. However, three dimensions of attribute importance can be distinguished; salience, relevance and determinance. “*Salience reflects the degree of ease with which attributes come to mind or are recognized when thinking about or seeing a certain object. The relevance of attributes is largely determined by personal values and desires and reflects the importance of attributes for individuals. The determinance of attributes reflects the importance of an attribute in judgement and choice”* . Attributes that are considered relevant by consumers, are not by definition determinant for buying behavior (Van Ittersum et al., 2007). When asking for the importance of an attribute to identify buying motives the relevance of attributes is measured. It is not clear if these relevant attributes are also determinant for buying behavior.

A previous segmentation study on apples (a fast moving consumer good) shows that even though attributes are considered relevant by consumers, they are not determinant for the consumer’s intention to buy (Rodenburg, 2015). As a result, the question arises if the same applies for durable goods. This research aims to answer “*Does segmentation based on relevant attributes have a relation with segmentation based on determinant attributes?”.* This segmentation study on smartphones compares segmentation based on relevant attributes and segmentation based on determinant attributes using latent class analysis. In addition, cluster analysis and latent class analysis are compared for the segmentation based on relevance. This leads to the question *"Does segmentation based on relevant attributes using cluster analysis have a relationship with segmentation based on relevant attributes using latent class analysis?”* In order to answer these questions, first more information about market segmentation will be discussed. Furthermore, the concept of attribute importance will be discussed. Based on this review of the literature, hypotheses will be formulated. Then the methods used, which are factor analysis, the two-stage clustering procedure, and latent class analysis, will be explained. The results for each individual segmentation will be provided followed by a comparison of segmentation based on relevant attributes using cluster analysis and latent class analysis using a chi-square test of independence. Finally, segmentation based on relevant attributes will be compared with segmentation based on determinant attributes using a chi-square test of independence and a conclusion will be drawn.

2. Literature

2.1 Market segmentation

Market segmentation is one of the fundamental principles of marketing (Kotler & Armstrong, 2010). Organizations can normally not serve the entire market, which is one of the reasons why market segmentation is widely accepted (Dibb, Stern, & Wensley, 2002). When developing a marketing strategy, market segmentation can be useful (Green, 1977). When consumers are segmented based on buying needs and behavior, a more homogeneous response to a marketing strategy can be expected. Segmentation can help to better understand the market, for positioning studies, for new product concepts and new product introduction, pricing decisions, advertising decisions and distribution decisions (Wind, 1978).

2.1.1 Four types of segmentation bases

Segmentation bases should depend on the purpose of the study, the market in question (Wedel & Kamakura, 2000), and the current state of marketing and consumer behavior knowledge about variables as bases for market segments (Wind, 1978). Many different variables can be used as a base for segmentation, these variables can be classified into four categories. First a segmentation base can be classified into general or product-specific. A general segmentation base is independent of the product, a product-specific segmentation base is related to both the product and the consumer (Wedel & Kamakura, 2000). Second, a segmentation base can be classified into observable or unobservable (Frank, Massy, & Wind, 1972). Observable segmentation bases are measured directly, in contrast to unobservable segmentation bases which are inferred (Wedel & Kamakura, 2000). In order to identify the most effective class of segmentation, six criteria can be used.

2.1.2 Six criteria

Six criteria are used to determine the effectiveness and profitability of a market segment. The criteria are: identifiability, substantiality, accessibility, stability, responsiveness and actionability (Frank et al., 1972).

Identifiability stands for the degree to which managers are able to recognize distinct groups of consumers in the market using the variables used for segmentation. If it is not possible to identify the consumers in a segment, the segment cannot be targeted. A market segment is substantial when it represents a large enough proportion of the market to ensure profitability of targeted marketing programs. Accessibility stands for the extent to which managers are able to access the segment through promotion or distribution. A market segment will not be effective and profitable if it cannot be reached. A market segment is responsive, when the segment responds uniquely to marketing efforts targeted at the segment. Differentiated marketing mixes are only effective if different segments do have a unique response to them. Stability stands for the extent to which a segment is stable over time. If a segment has changed by the time a marketing strategy is ready for implementation, it is very likely that the strategy will not be successful. The identification of a segment is actionable if it provides guidance for decision making about the effective specification of marketing instruments. A strategy necessary to target a segment should be in line with the goals or core competencies of the company in order to be actionable (Wedel & Kamakura, 2000).

When the four types of segmentation bases are evaluated based on the six criteria of effective segmentation mentioned above, the most effective bases are found in the unobservable product-specific class. This class consists of product specific psychographics, product benefit perceptions and importances, brand attitudes and behavioral intentions (Wedel & Kamakura, 2000).

2.2 Attribute importance

The identification of important product attributes is of central interest in marketing research (Van Ittersum et al., 2007). When consumers make a purchase decision, they compare important product attributes (Häubl & Trifts, 2000). Importance of attributes can be used for identifying consumers' buying motives and benefits sought (Peltier & Schribrowsky, 1997). The importance of product attributes is one of the most effective bases for segmentation (Wedel & Kamakura, 2000).

However, when measuring attribute importance, a lack of convergent and nomological validity exists. The lack of validity can be explained by the multi-dimensionality of attribute importance (Van Ittersum et al., 2007). Three dimensions of attribute importance can be distinguished: salience, relevance and determinance (Myers & Alpert, 1968). *Salience reflects the ease with which attributes come to mind or are recognized when thinking about or seeing a certain object. The relevance of attributes reflects the importance of attributes for individuals. Determinance reflects the importance of an attribute in judgement and choice* (Van Ittersum et al., 2007).

When a consumer is asked to assign importance weights to product attributes for the same product of different brands, it is possible that a certain product attribute is very important to the consumer. However, if the product attribute is perceived to be equal for all the competing products it is not determinant. So, if an attribute is relevant to a consumer, it is not by definition determinant in judgement and choice (Myers & Alpert, 1977). Not only the difference between the attribute levels of competing products influences the determinance of an attribute, the determinance of an attribute also depends on the reference point of a consumer (Van Ittersum, Pennings, Wansink, & Van Trijp, 2004). A reference point is a stimulus to which other stimuli are seen in relation to (Rosch, 1975). If consumers perceive the attribute levels as losses relative to their reference point, the determinance of an attribute is larger than when attribute levels are perceived as gains (Van Ittersum et al., 2004). The determinance of an attribute also depends on the performance of other attributes of a certain product. Attribute determinance is a complex and dynamic concept (Mikulić & Prebežac, 2012).

Beside relevance and determinance, another distinction of attribute importance is made in literature: the global and local interpretation of importance. Global interpretations of importance are considered to be independent of the stimuli. When subjects use a global interpretation of attribute importance, importance ratings should remain constant. Local interpretations of importance are considered to depend on the stimulus set. When subjects use a local interpretation of attribute importance, importance ratings should differ in different stimulus sets (Goldstein, 1990). Differentiation between the global and local interpretation of attribute importance, helps to reduce the lack of validity when measuring attribute importance (van Ittersum & Pennings, 2012).

3. Hypotheses

In this research, segmentation based on relevant attributes will be compared with segmentation based on determinant attributes using latent class analysis. Also two methods for segmentation based on relevance, which are cluster analysis and latent class analysis, will be compared with each other.

Latent class analysis is used, since this method is able to perform a segmentation based on relevant attributes and a segmentation based on determinant attributes. Latent class analysis is compared with cluster analysis since cluster analysis is often used in segmentation research (Wedel & Kamakura, 2000). Cluster analysis is not suitable for segmentation based on determinant attributes. The methods are summarized in figure 1.

Figure 1: Overview of the methods used for segmentation based on relevant attributes and determinant attributes

	Relevance	Determinance
Cluster analysis		x
Latent class analysis		

As mentioned in the literature overview, different ways of measuring importance can lead to different outcomes due to the multi-dimensionality of attribute importance. Therefore, it is expected to find a different outcome for segmentation based on relevant attributes and segmentation based on determinant attributes.

The first research question is "*Does segmentation based on relevant attributes have a relation with segmentation based on determinant attributes?*" . Figure 2 shows the part that this research question assesses.

Figure 2: Segmentation based on relevant attributes and segmentation based on determinant attributes using latent class analysis

	Relevance	Determinance
Cluster analysis		x
Latent class analysis		

The following hypothesis is formulated:

Hypothesis 1: Segmentation based on relevant attributes is independent of segmentation based on determinant attributes.

Since this hypothesis tests a type-2 error, a significance level of 0.20 is used.

For the question *"Does segmentation based on relevant attributes using cluster analysis have a relationship with segmentation based on relevant attributes using latent class analysis?",* it is expected that there is a strong relationship between the two segmentation methods, since both methods use the same input variables. Figure 3 shows the part that this research question assesses.

Figure 3: Segmentation based on relevant attributes using cluster analysis and latent class analysis

	Relevance	Determinance
Cluster analysis		x
Latent class analysis		

The following hypothesis is formulated:

Hypothesis 2: Segmentation based on relevant attributes using a two-stage clustering procedure is dependent of segmentation based on relevant attributes using latent class analysis.

This hypothesis tests a type-1 error, for this hypothesis a significance level of 0.05 is used.

4. Method

4.1 Sample

For this study, an existing data source was used. Data was gathered from students following the course "Advanced Management and Marketing" at Wageningen University in January 2014 . The sample consists of 155 respondents, of which 76 are male and 79 are female. The year of birth varies from 1981 till 1995, which means respondents were between 18 and 33 years old. The average year of birth is 1991 which corresponds to an age of 22 or 23 years old. The standard deviation is 2.889.

4.2 Measuring Relevance

Relevance was measured with importance scores of 12 attributes. The following question was used:

- *"When you buy a smart phone, how important is it for you that the smart phone …"*

Subsequently, respondents needed to answer this question on a 5 point scale, in which 1= not important at all and 5= very important for the following 12 attributes:

- *Has a beautiful style*
- *Is reliable*
- *Is durable*
- *Does what it is supposed to do*
- *Is expensive*
- *Is cheap*
- *Offers excellent value for money*
- *Is widely available*
- *Is easy to use*
- *Comes with a lot of service support*
- *Has many uses*
- *Can use most applications*

4.3 Measuring Determinance

Determinance was measured using perception scores of 4 different smartphones. The perception was based on the same 12 attributes as the importance scores. The questions used to measure the perceptions were:

- *Do you think that smart phones of Apple iPhone…*
- *Do you think that smart phones of Nokia Lumia…*
- *Do you think that smart phones of LG Optimus…*
- *Do you think that smart phones of Samsung Galaxy…*

Perceptions were measured on a 5 point scale (1=Strongly Disagree, 5=Strongly agree). Furthermore, the intention to buy for the 4 different smartphones was measured on a 7 point scale (1=Very Unlikely, 7=Very Likely). The complete questionnaire can be found in appendix 1.

4.4 Factor Analysis

To reduce the amount of data, factors were formed by grouping attributes. To decide which attributes should be grouped together, a principle component analysis and a factor analysis were performed using the importance scores that are measuring relevance as input data. For factor analysis, principle axis factoring was used, since this is the preferred method when data are not normally distributed (Costello & Osborne, 2011). In order to assess if factor analysis is suitable for the data, the KMO measure of sampling adequacy and Bartlett's test of Sphericity were used. The number of factors were determined based on the criteria that the eigenvalue should be larger than 1 and that at least 50% of the variance should be explained.

The actual factor loadings resulting from the analysis were only used to decide which attributes could be grouped together. The actual factors were formed by calculating the average of attributes that belonged to the same factor according to the factor analysis. Factor analysis based on the importance scores leads to different factors than a factor analysis based on the perceptions. Since in the end segmentation based on relevant attributes and determinant attributes will be compared, the build op of the factors have to be the same. Therefore only the importance scores were used to decide which attributes should be grouped together and factors were formed based on averages. In this manner, factors were forced to be equal for both segmentation based on relevant attributes and segmentation based on determinant attributes. Before forming factors by calculating the average, importance scores were standardized per respondent and perceptions were standardized per respondent across the four smartphones. This was done to correct for differences in response styles of respondents. Also the intention to buy was standardized per respondent.

4.5 Latent class analysis (Relevance)

Latent class models are statistical-model-based approaches to clustering. They connect classical clustering to conventional statistical estimation methods (Wedel & Kamakura, 2000). The factors calculated based on the average of standardized importance scores were used as input for the analysis. The analysis was performed using the computer program GLIMMIX. The best cluster solution was determined based on the corrected CAIC score. Due to standardization of the input data, the degrees of freedom in the CAIC should be corrected by at least one time the number of respondents (n=155). This should be done since the average of the attributes is set to 0 due to the standardization. Also, the standard deviation is known, this is set to 1 due to standardization. Therefore the degrees of freedom in the CAIC could be corrected by two times the number of respondents, once for knowing the average is 0 and once for knowing the standard deviation is 1. To find the best cluster solution, the degrees if freedom in the CAIC were corrected by one and two times the number of respondents to check if this would lead to a difference in which model is preferred based on the lowest CAIC score. The formula of the CAIC is:

$$CAIC= -2l + d(\ln n + 1)$$

In which l is de log likelihood, d is the dimension of the model, and n reflects the size of the data.

The final cluster solution consists of probabilities for a respondent to belong to a certain cluster. A respondent was allocated to the segment with the highest probability.

4.6 Cluster analysis (Relevance)

To perform the cluster analysis, a two stage clustering procedure was used. A two stage clustering procedure starts with an hierarchical clustering method followed by a non-hierarchical procedure to form the final clusters (Punj & Stewart, 1983). In this study, Ward's method was used as the hierarchical clustering method. The hierarchical cluster procedure was performed 10 times with a different input order of the data, since the input order of the data could influence the outcome of hierarchical clustering procedures (Van Der Kloot, Spaans, & Heiser, 2005). Based on the hierarchical cluster solution, the number of clusters and the starting points were determined. The number of clusters were based on the dissimilarity coefficient, which is a subjective method for determining the number of clusters. The point where the percentage increase in dissimilarity becomes too high was used as a cut-off point to determine the number of clusters. As a starting point, the cluster-means were used. Then, K-means clustering was used as the non-hierarchical method of the two stage clustering procedure.

4.7 Latent class regression (Determinance)

To be able to perform a segmentation based on determinant attributes, latent class regression was used. A latent class regression model identifies segments by simultaneously grouping subjects into unobserved segments. Within each segment, a regression model is estimated in which a dependent variable is related to a set of independent variables. When using latent class regression models, clusters can be formed that are homogeneous in terms of responsiveness. The clusters are formed based on the inferred relationship between the dependent variable and a set of independent variables (Wedel & Kamakura, 2000). The factors calculated based on the average of standardized perception scores per respondent across the four smartphones were used as the independent variables. The standardized buying intention per respondent is set as the dependent variable.

The average of the factor scores was set to 0 by calculating the average of a factor and subtracting it from the factor score for all 4 smartphones. The average of the intention to buy was already zero as a result of the standardization process. By doing this, all the estimated regressions have an intercept of 0. In this way, only the difference between the regression coefficients will remain. To perform the latent class regression, GLIMMIX was used. The procedure was done 10 times, to prevent for local optima. To determine the number of clusters, GLIMMIX was asked to find solutions ranging from 1 cluster to 9 clusters. To determine the best solution, the CAIC score was used. The lower the CAIC, the better the solution. The degrees of freedom in the CAIC score was corrected by 155, since there are 155 respondents in this research. The corrected CAIC score should be used since the intercept was estimated 155 times already. The solution with the lowest corrected CAIC score was used as the final cluster solution. The formula of the CAIC is:

$$CAIC = -2l + d(\ln n + 1)$$

In which l is de log likelihood, d is the dimension of the model, and n reflects the size of the data.

The final cluster solution consists of probabilities for a respondent to belong to a certain cluster. A respondent was allocated to the segment with the highest probability.

4.8 Comparing latent class analysis and cluster analysis (Relevance)

To test if segmentation using latent class analysis allocated the same respondents to the same segments as segmentation using cluster analysis, a chi-square test for independence was used. To test the strength of the relation, a Cramer's V test was performed.

Also the cluster centers were compared for each segment using an independent samples t-test.

4.9 Comparing segmentation based on relevance and segmentation based determinance

The cluster solution resulting from the latent class analysis based on relevance and the cluster solution resulting from the latent class regression based on determinance were compared. A chi-square test for independence was performed to test if there is a relation between segmentation based on relevance and segmentation based on determinance. To test the strength of the relation, a Cramer's V test was performed.

5. Results

In this section, the results of the research are provided. First the factors resulting from the analysis are described. Then for every segmentation method, the resulting segments are described. Secondly the results of the comparison of the two-stage clustering procedure and latent class analysis are described. Finally, the results of the comparison of the segmentation based on relevance and the segmentation based on determinance are discussed.

5.1 Factor analysis

In order to assess if factor analysis is suitable for the data, the KMO measure of sampling adequacy and Bartlett's test of Sphericity is used. The KMO measure of sampling adequacy equals 0.581 which is larger than 0.5 which means that factor analysis is suitable for the data. The Bartlett's test of Sphericity is 0.00 which is smaller than 0.05, so there is significant correlation between the variables.

The factor analysis results in four different factors. Four components have an initial eigenvalue larger than 1. Furthermore 52.5% of the variance is explained with four factors.

Both principle axis factoring and principal component analysis result in the same composition of factors. Also no difference in composition of factors is found when using a orthogonal or non-orthogonal rotation. An overview of the factors can be found in table 1.

Table 1: The composition of the four factors from the rotated component matrix

	Luxury	Ease/Service	Price	Dependability
When you buy a smart phone, how important is it for you that the smart phone-has a beautiful style	**.456**	.092	-.370	-.074
When you buy a smart phone, how important is it for you that the smart phone-is reliable	.035	-.130	.131	**.722**
When you buy a smart phone, how important is it for you that the smart phone-is durable	.065	-.029	.549	**.428**
When you buy a smart phone, how important is it for you that the smart phone-does what it is supposed to do	.015	.232	-.125	**.719**
When you buy a smart phone, how important is it for you that the smart phone-is expensive	**.555**	.135	-.053	-.206
When you buy a smart phone, how important is it for you that the smart phone-is cheap	-.258	.150	**.669**	-.170
When you buy a smart phone, how important is it for you that the smart phone-offers excellent value for money	.140	-.009	**.706**	.045
When you buy a smart phone, how important is it for you that the smart phone-is widely available	.087	**.595**	.251	-.113
When you buy a smart phone, how important is it for you that the smart phone-is easy to use	-.065	**.795**	-.150	.218
When you buy a smart phone, how important is it for you that the smart phone-comes with a lot of service support	.229	**.662**	-.006	-.013
When you buy a smart phone, how important is it for you that the smart phone-has many uses	**.793**	-.036	.026	.205
When you buy a smart phone, how important is it for you that the smart phone-can use most applications	**.586**	.190	.276	.289

The variable "is durable" has the highest loading on the third factor, but based on subjective judgement it is placed in the factor with the second highest loading which is factor 4 Dependability.

5.2 Segmentation based on relevance: Latent class model

From the 90 different outcomes, the best model is chosen based on the lowest corrected CAIC score. Since the input data are standardized data, the degrees of freedom in the CAIC should be corrected by one or two times the number of respondents. Both corrections result in the lowest CAIC score for the same model which is the model with 4 segments from the sixth iteration. Also before correction this model had the lowest CAIC score. Before correction the CAIC score was 709.8, after the correction with one time the number of respondents the CAIC score was 1861.4 and after the correction with two times the number of respondents the CAIC score was 3013.0.

The best model is a model with four segments. The following division of respondents is found:

Segment 1 21 respondents
Segment 2 59 respondents
Segment 3 33 respondents
Segment 4 42 respondents

All four segments score high on Dependability. For the other three factors, the order of importance for the factors differs. In table 2 an overview per segment is provided with the average scores from a segment on a factor. The number in parentheses represent the order of importance of the factors describing the segments.

Table 2: Overview of the factors describing the segments resulting from the latent class analysis

	Segment 1	Segment 2	Segment 3	Segment 4
Luxury	-0.432 (4)	-0.492 (4)	-0.028 (3)	-0.083 (3)
Ease/Service	-0.160 (2)	-0.322 (3)	-0.824 (4)	-0.062 (2)
Price	-0.285 (3)	0.516 (2)	0.083 (2)	-0.671 (4)
Dependability	0.926 (1)	0.633 (1)	0.806 (1)	0.620 (1)

When trying to describe the segments with the descriptor variables age and gender, no significant difference is found. Gender results in a chi-square value of 4.390 with a p-value of 0.222 (>0.05). For age, F=0.086 with a p-value of 0.968 (>0.05).

5.3 Segmentation based on relevance: Two-stage clustering procedure

Performing the hierarchical clustering procedures 10 times, results in the same outcome 10 times. Based on subjective interpretation of the agglomeration coefficient, the number of clusters is set to 3. The point where the percentage increase in dissimilarity becomes too high was used as a cut-off point to determine the number of clusters. The following division of respondents is found:

Segment 1 55 respondents
Segment 2 59 respondents
Segment 3 41 respondents

The one-way ANOVA table shows that the three clusters are significantly different from each other when looking at the cluster means for the factor luxury, ease/service, and price. The clusters are not significantly different looking at the cluster means of the factor dependability. When looking at the cluster means, all three segments score high on dependability. For the other three factors, the order of importance for the factors differs. In table 3 an overview per segment is provided with the average scores from a segment on a factor. The number in parentheses represent the order of importance of the factors describing the segments.

Table 3: Overview of the factors describing the segments resulting from the cluster analysis

	Segment 1	Segment 2	Segment 3
Luxury	-0.239 (3)	-0.501 (4)	0.018 (2)
Ease/Service	-0.002 (2)	-0.337 (3)	-0.785 (4)
Price	-0.586 (4)	0.541 (2)	-0.012 (3)
Dependability	0.711 (1)	0.645 (1)	0.769 (1)

When trying to describe the segments with the descriptor variables age and gender, no significant difference is found. Gender results in a chi-square value of 2.628 with a p-value of 0.269 (>0.05). For age, F=0.129 with a p-value of 0.879 (>0.05).

5.4 Segmentation based on determinance: Latent class regression

From the 90 different outcomes, the best model is chosen based on the lowest corrected CAIC score. The best model is a model with 2 segments. Before correction the lowest CAIC score was 1151.8 for the model with 2 segments from the third iteration. After correction the lowest CAIC score was

2303.5, this score also indicates that the best model was a the model with 2 segments resulting from the third iteration.

The following division of respondents is found:

Segment 1 76 respondents
Segment 2 79 respondents

The t-values of the regression coefficient should be larger than 1.960 to be significant at an α=0.05 level. For the factor ease/service of segment 2, t=1.020 which is smaller than 1.960 so it is not significant. This means that changes in ease/service are not associated with changes in intention to buy for segment 2. All the other regression coefficient are significant.

In table 4 an overview per segment is provided with the average scores from a segment on a factor. The number in parentheses represent the order of importance of the factors describing the segments.

Table 4: Overview of the factors describing the segments resulting from latent class regression

	Segment 1	Segment 2
Luxury	0.715 (1)	0.406 (3)
Ease/Service	0.385 (2)	0.081 (4) - not significant
Price	-0.142 (4)	0.624 (1)
Dependability	0.149 (3)	0.533 (2)

When trying to describe the segments with the descriptor variables age and gender, no significant difference is found. Gender results in a chi-square value of 0.311 with a p-value of 0.577 (>0.05). For age, F=0.160 with a p-value of 0.689 (>0.05).

5.5 Comparison segmentation based on relevance: LCA and two-stage clustering procedure

The chi-square test of independence results in a chi-square value of 223.98 with a significant P-value of 0.000 (<0.05). This means that there is a relation between segmentation based on relevance using the two-stage clustering procedure and the latent class analysis method. To indicate the strength of the relationship, Cramer's V is used. The Cramer's V value is 0.85 with a significant p-value of 0.000 (<0.05). This Cramer's V association indicates, as expected, a very strong association between segmentation based on relevance using the two stage clustering procedure and latent class analysis (Rea & Parker, 1992 as cited in Kotrlik et al., 2011).

It can been seen from table 5 that the respondents in segment 1 from the clustering procedure corresponds with segment 1 and 4 from the latent class analysis. The respondents of segment 2 of the clustering procedure corresponds with segment 2 of the latent class analysis and segment 3 from the clustering procedure corresponds with segment 3 of the latent class analysis.

Table 5: Crosstab segments resulting from the latent class analysis and segments resulting from the cluster analysis

		Segments resulting from cluster analysis			Total
		1	2	3	
Segments resulting from the latent class analysis	1	16	3	2	21
	2	3	55	1	59
	3	0	1	32	33
	4	36	0	6	42
Total		55	59	41	155

In table 6, a comparison of the importance of factors for the different segments is made. The similarities are marked green.

Table 6: A comparison of the factors describing the segments resulting from the latent class analysis and the segments resulting from the cluster analysis.

Segments latent class analysis	Factors describing the segment		Segments cluster analysis	Factors describing the segment	
1	Luxury	-0.432 (4)	1	Luxury	-0.239 (3)
	Ease/Service	-0.160 (2)		Ease/Service	-0.002 (2)
	Price	-0.285 (3)			
	Dependability	0.926 (1)			
4	Luxury	-0.083 (3)		Price	-0.586 (4)
	Ease/Service	-0.062 (2)			
	Price	-0.671 (4)		Dependability	0.711 (1)
	Dependability	0.620 (1)			
2	Luxury	-0.492 (4)	2	Luxury	-0.501 (4)
	Ease/Service	-0.322 (3)		Ease/Service	-0.337 (3)
	Price	0.516 (2)		Price	0.541 (2)
	Dependability	0.633 (1)		Dependability	0.645 (1)
3	Luxury	-0.028 (3)	3	Luxury	0.018 (2)
	Ease/Service	-0.824 (4)		Ease/Service	-0.785 (4)
	Price	0.083 (2)		Price	-0.012 (3)
	Dependability	0.806 (1)		Dependability	0.769 (1)

From table 6 it is clear that there are some similarities and some differences between the description of the segments based on the factors. In order to test if the factor means are equal for a segments resulting from the latent class analysis and a segment resulting from the cluster analysis, independent t-test are used. The mean for each factor is calculated in SPSS. Factor means calculated for segments formed by latent class analysis are different in SPSS than in the original GLIMMIX output. GLIMMIX uses probabilities that a respondent belongs to a certain segment. In SPSS a respondent only belongs to one segment. This difference leads to different factor means for the segments resulting from latent class analysis.

5.5.1 Comparison of factor means per segment

Segment 1 latent class analysis versus segment 1 cluster analysis

Levene's test for equality of variance results in F=12,295 with p=0.001 for factor 1, F=21,025 with p=0.000 for factor 2, F=11,617 with p=0.001 for factor 3, and F=9.633 and p=0.003 for factor 4. All p-values are <0.05 which means they are significant. For the t-tests, equal variance is not assumed. In table 7 the t-values and p-values for all the factors are provided.

Table 7: T-value and corresponding P-value independent samples t-test

Factor	Factor means latent class analysis	Factor means cluster analysis	T-value	P-value
Luxury	-0.438	-0.239	3.858	0.000
Ease/Service	-0.174	-0.002	3.320	0.001
Price	-0.258	-0.586	-5.384	0.000
Dependability	0.931	0.711	-4.374	0.000

All p-values are <0.05 so significant. This means that the factor means of segment 1 resulting from the latent class analysis are significantly different from the factor means of segment 1 resulting from the cluster analysis.

Segment 4 latent class analysis versus segment 1 cluster analysis

Levene's test for equality of variance results in F=0.343 with p=0.559 for factor 1, F=6.580 with p=0.012 for factor 2, F=0.628 with p=0.430 for factor 3, and F=0.391 and p=0.533 for factor 4. Only the p-value of factor 2 is <0.05, so for this factor equal variance is not assumed. In table 8 the t-values and p-values for all the factors are provided.

Table 8: T-value and corresponding P-value independent samples t-test

Factor	Factor means latent class analysis	Factor means cluster analysis	T-value	P-value
Luxury	-0.071	-0.239	-2.589	0.011
Ease/Service	-0.048	-0.002	0.583	0.562
Price	-0.709	-0.586	1.718	0.089
Dependability	0.615	0.711	1.450	0.150

The p-value of factor 1 is <0.05 which means that for factor 1 the means resulting from latent class analysis and the cluster analysis are significantly different. For the other three factors, the p-value is >0.05 so the means of the clusters are not significantly different.

Segment 2 latent class analysis versus segment 2 cluster analysis

Levene's test for equality of variance results in F=0.105 with p=0.747 for factor 1, F=0.191 with p=0.663 for factor 2, F=0.007 with p=0.934 for factor 3, and F=0.178 and p=0.674 for factor 4. All p-values are >0.05, which means that equal variance is assumed. In table 9 the t-values and p-values for all the factors are provided.

Table 9: T-value and corresponding P-value independent samples t-test

Factor	Factor means latent class analysis	Factor means cluster analysis	T-value	P-value
Luxury	-0.499	-0.501	-0.051	0.959
Ease/Service	-0.312	-0.337	-0.383	0.702
Price	0.538	0.541	0.053	0.958
Dependability	0.618	0.645	0.431	0.667

All p-values are >0.05 which means that the factor means resulting from latent class analysis are not significantly different from the factor means resulting from the cluster analysis.

Segment 3 latent class analysis versus segment 3 cluster analysis

Levene's test for equality of variance results in F=0.087 with p=0.769 for factor 1, F=1.017 with p=0.317 for factor 2, F=0.706 with p=0.404 for factor 3, and F=0.730 and p=0.396 for factor 4. All p-values are >0.05, which means that equal variance is assumed. In table 10 the t-values and p-values for all the factors are provided.

Table 10: T-value and corresponding P-value independent samples t-test

Factor	Factor means latent class analysis	Factor means cluster analysis	T-value	P-value
Luxury	-0.012	0.018	0.528	0.599
Ease/Service	-0.852	-0.785	1.272	0.207
Price	0.080	-0.012	-1.319	0.191
Dependability	0.814	0.769	-0.785	0.435

All p-values are >0.05 which means that the factor means resulting from latent class analysis are not significantly different from the factor means resulting from the cluster analysis.

5.6 Comparison segmentation based on relevance(LCA) and determinance (LCA)

The chi-square test of independence results in a chi-square value of 7,424 with a p-value of 0.060 (<0.2), so it is significant. This means that a relation is found between segmentation based on relevance attributes and segmentation based on determinant attributes. The Cramer's V value of 0.219 indicates a moderate association (Rea & Parker, 1992 as cited in Kotrlik et al., 2011). Looking at the crosstab in table 11, no clear relation between the two segmentations can be seen. In order to predict future buying behavior, still segmentation based on determinant attributes has to be performed by marketers.

Table 11: Crosstab segments resulting from segmentation based on relevant attributes and segmentation based on determinant attributes.

		Segments latent class analysis (Determinance)		Total
		1	2	
Segments latent class analysis (Relevance)	1	12	9	21
	2	23	36	59
	3	14	19	33
	4	27	15	42
Total		76	79	155

6. Conclusions

This research aims to answer two questions. The first research question refers to the relation between segmentation based on relevance and segmentation based on determinance. “*Does segmentation based on relevant attributes have a relation with segmentation based on determinant attributes?”*. As stated in hypothesis 1 *“Segmentation based on relevant attributes is independent of segmentation based on determinant attributes”.* In contrast with hypothesis 1, a moderate association is found between segmentation based on relevant attributes and segmentation based on determinant attributes. Though, the moderate association is insufficient for marketers to predict future buying behavior using segmentation based on relevant attributes.

The second question refers to the relation between two segmentation methods that are used for segmentation based on relevant attributes: latent class analysis and cluster analysis. *"Does segmentation based on relevant attributes using cluster analysis have a relationship with segmentation based on relevant attributes using latent class analysis?”.* As stated in hypothesis 2: *“Segmentation based on relevant attributes using a two-stage clustering procedure is dependent of segmentation based on relevant attributes using latent class analysis”* a relationship was expected to be found. The results from this research support the hypothesis. A very strong relation is found between outcomes of the two segmentation methods. Although the outcomes are not exactly the same. The cluster analysis found three segments. In latent class analysis segment 1 from the cluster analysis is divided into two separate segments, namely segment 1 and segment 4. After performing the independent t-test, it is shown that the factor means from segment 1 from the cluster analysis and segment 4 from the latent class analysis are not significantly different except for the mean of factor 1. When comparing segment 1 from the cluster analysis with segment 1 of the latent class analysis, all factor means are significantly different. This could indicate that the outcome from the cluster analysis with three segments is not optimal. Furthermore, the number of clusters in cluster analysis is based on a subjective interpretation of the results. An advantage of using latent class analysis is that the CAIC score can be used to determine the number of clusters.

Recalling the six criteria to determine the effectiveness and profitability of segmentation, the difference in segmentation based on relevance and segmentation based on determinance can be explained:

1. Identifiability: both segmentation based on relevance and segmentation based on determinance resulted in distinct groups based on the variables used for segmentation.
2. Substantiality: both segmentation based on relevance and segmentation based on determinance resulted in segments that represented a large enough proportion of the market.
3. Accessibility: based on the data both segmentation based on relevance and segmentation based on determinance did not result in segments that were accessible. Not enough descriptor variables were asked, though for the goal of this research descriptor variables were not necessary.
4. Stability: for segmentation based on relevance and segmentation based on determinance the stability over time was not tested.
5. Responsiveness: segmentation based on relevance and segmentation based on determinance do differ in terms of responsiveness. When responsiveness is seen as buying behavior and segmentation is based on relevant attributes, expected buying behavior differs from actual buying behavior. Attributes that are relevant by consumers are not per definition determinant for buying behavior. Therefore when a segment is targeted and a certain

response, in this case buying behavior, is expected, segmentation based on determinance would score better in terms of responsiveness.

6. Actionability: for segmentation based on relevance and segmentation based on determinance the actionability was not tested.

7. Discussion

Results of this research should be interpreted with caution. The results are based on data gathered at Wageningen University, the sample consists of students only. This means that it is not representative for the whole of the Netherlands. It could be possible that for students price is more determinant, since in general students have less to spend. Furthermore, intention to buy is used instead of actual buying behavior. The assumption is made that people that intend to buy will actually buy. Intention to buy is the single best predictor for buying behavior (Fishbein and Ajzen in Morwitz and Schmittlein 1992). A review of the literature shows that the intention to buy is a powerful but imperfect predictor for actual buying behavior (Morwitz & Schmittlein, 1992). Also, when performing the t-tests the factor means for the segments resulting from the latent class analysis were calculated by SPSS. In SPSS the respondents were placed in one segment only, in contrast to GLIMMIX that attaches a probability of belonging in a certain segments to respondents.

In sustainable food consumption a difference between attitude and behavior is noticed (Stewart & Craig, 2000 as cited in van Dam & van Trijp, 2013). Consumers indicate that sustainability is important, though this is not reflected in the actual food choice. Sustainability is an example of an attribute that is considered relevant by consumers but not determinant for buying behavior. An explanation is sought in a conflict in valued goals. A conflict that may occur, is a conflict between desirability goals and feasibility goals. This type of conflict implies a conflict between more general relevance, which is context independent and the actual determinance which is context dependent (van Dam & van Trijp, 2013).

For a marketer, it is important to know which attributes are considered relevant and which attributes are considered determinant by consumers. When developing a marketing strategy, segmentation based on relevant product attributes is not useful for predicting future buying behavior according to the results of this research. This does not mean that segmentation based on relevant product attributes is useless in developing a marketing strategy. Attributes that are not determinant for buying behavior but that are considered as very relevant should ensure a market-typical level of performance, under-performance may result in a competitive disadvantage (Mikulić & Prebežac, 2012). Therefore it is important to know which attributes are considered relevant as well.

Knowing which attributes are considered relevant but not determinant by consumers might be useful for another reason. In attitude research selective perception is explained as the phenomenon that people perceive and evaluate information more positively when it corresponds with their attitude compared to information that is inconsistent with a person's attitude (Eagly & Chaiken, 1993 as cited in Hwang, 2010). Due to the phenomenon of selective perception, knowing which attributes are considered relevant by a consumer might be useful in advertising. If a marketer wants to target a certain segment by advertising, the advertisement might be perceived and evaluated more positively when it corresponds with the attributes that are considered relevant by consumers. Whether this is the case needs to be examined.

A moderate association is found between segmentation based on relevant attributes and segmentation based on determinance attributes for smartphones, a durable good. Also, as mentioned in the introduction, no relation was found for apples which is a fast moving consumer good. Besides fast moving consumer goods and durable goods, another distinction is made in literature; convenience goods, shopping goods and specialty goods. Whether a product is a convenience, shopping or specialty good depends on the individual consumer. Specialty goods require consumers to make a special purchasing effort (Holton, 1958). The possibility exists that both apples and smartphones are in general not considered as specialty goods by consumers. A question that arises is if for specialty goods a relation can be found between relevance and determinance due to higher involvement in the purchase process. Involvement can be described as a person's perceived relevance of the object based in inherent needs, values and interests (Zaichkowsky, 1985). When a consumer is involved in the purchase decision, more information will be searched and more time is spend searching for the right selection (Clarke & Belk, 1979). The decision making process and the information search differs depending on the level of involvement of a consumer (Laurent & Kapferer, 1985). A relation between relevance and determinance might be found for specialty goods since they require higher involvement in the decision making process. This needs to be further researched.

References

Clarke, K., & Belk, R. W. (1979). The effects of product involvement and task definition on anticipated consumer effort. *Advances in consumer research, 6*(1).

Costello, A., & Osborne, J. (2011). Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. Practical Assessment Research & Evaluation 2005; 10. *URL http://pareonline. net/getvn. asp, 10*, 7.

Dibb, S., Stern, P., & Wensley, R. (2002). Marketing knowledge and the value of segmentation. *Marketing Intelligence & Planning, 20*(2), 113-119.

Frank, R. E., Massy, W. F., & Wind, Y. (1972). *Market segmentation*: Prentice-Hall Englewood Cliffs, NJ.

Goldstein, W. M. (1990). Judgments of relative importance in decision making: Global vs local interpretations of subjective weight. *Organizational Behavior and Human Decision Processes, 47*(2), 313-336.

Green, P. E. (1977). A new approach to market segmentation. *Business Horizons, 20*(1), 61-73.

Haley, R. I. (1968). Benefit segmentation: a decision-oriented research tool. *The Journal of Marketing*, 30-35.

Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing science, 19*(1), 4-21.

Holton, R. H. (1958). The distinction between convenience goods, shopping goods, and specialty goods. *The Journal of Marketing*, 53-56.

Hwang, Y. (2010). Selective exposure and selective perception of anti-tobacco campaign messages: The impacts of campaign exposure on selective perception. *Health Communication, 25*(2), 182-190.

Kotler, P., & Armstrong, G. (2010). *Principles of marketing*: Pearson Education.

Kotrlik, J. W., Williams, H. A., & Jabor, M. K. (2011). Reporting and Interpreting Effect Size in Quantitative Agricultural Education Research. *Journal of Agricultural Education, 52*(1), 132-142.

Laurent, G., & Kapferer, J.-N. (1985). Measuring consumer involvement profiles. *Journal of Marketing Research*, 41-53.

Mikulić, J., & Prebežac, D. (2012). Accounting for dynamics in attribute-importance and for competitor performance to enhance reliability of BPNN-based importance–performance analysis. *Expert systems with applications, 39*(5), 5144-5153.

Morwitz, V. G., & Schmittlein, D. (1992). Using segmentation to improve sales forecasts based on purchase intent: Which" intenders" actually buy? *Journal of Marketing Research*, 391-405.

Myers, J. H., & Alpert, M. I. (1968). Determinant buying attitudes: meaning and measurement. *The Journal of Marketing*, 13-20.

Myers, J. H., & Alpert, M. I. (1977). Semantic confusion in attitude research: salience vs. importance vs. determinance. *Advances in consumer research, 4*(1), 106-110.

Peltier, J. W., & Schribrowsky, J. A. (1997). The use of need-based segmentation for developing segment-specific direct marketing strategies. *Journal of Direct Marketing, 11*(4), 53-62.

Punj, G., & Stewart, D. W. (1983). Cluster analysis in marketing research: review and suggestions for application. *Journal of Marketing Research*, 134-148.

Rodenburg, D. (2015). *The impact of fluctuating quality*. [S.l.: s.n.].

Rosch, E. (1975). Cognitive reference points. *Cognitive psychology, 7*(4), 532-547.

Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *The Journal of Marketing*, 3-8.

van Dam, Y. K., & van Trijp, H. C. (2013). Relevant or determinant: Importance in certified sustainable food consumption. *Food Quality and Preference, 30*(2), 93-101.

Van Der Kloot, W. A., Spaans, A. M., & Heiser, W. J. (2005). Instability of hierarchical cluster analysis due to input order of the data: the PermuCLUSTER solution. *Psychological methods, 10*(4), 468.

van Ittersum, K., & Pennings, J. M. (2012). Attribute-value functions as global interpretations of attribute importance. *Organizational Behavior and Human Decision Processes, 119*(1), 89-102.

Van Ittersum, K., Pennings, J. M., Wansink, B., & Van Trijp, H. (2004). Improving attribute-importance measurement: A reference-point approach. *Advances in consumer research, 31*(2004), 84-85.

Van Ittersum, K., Pennings, J. M., Wansink, B., & Van Trijp, H. C. (2007). The validity of attribute-importance measurement: A review. *Journal of Business Research, 60*(11), 1177-1190.

Wedel, M., & Kamakura, W. A. (2000). *Market segmentation: Conceptual and methodological foundations*: Springer Science & Business Media.

Wind, Y. (1978). Issues and advances in segmentation research. *Journal of Marketing Research*, 317-337.

Zaichkowsky, J. L. (1985). Measuring the involvement construct. *Journal of Consumer Research*, 341-352.

Appendices

Appendix I: Questionnaire

Questionnaire_MST21306_2014 - Copy

Q3 What is your family name?

Q4 What is your first name?

Q5 What is your registration number?

Q32 When you buy a smart phone, how important is it for you that the smart phone

	Not important at all (1)	Not important (2)	Important nor unimportant (3)	Important (4)	Very important (5)
has a beautiful style (1)	❍	❍	❍	❍	❍
is reliable (2)	❍	❍	❍	❍	❍
is durable (3)	❍	❍	❍	❍	❍
does what it is supposed to do (4)	❍	❍	❍	❍	❍
is expensive (5)	❍	❍	❍	❍	❍
is cheap (6)	❍	❍	❍	❍	❍
offers excellent value for money (7)	❍	❍	❍	❍	❍
is widely available (8)	❍	❍	❍	❍	❍
is easy to use (9)	❍	❍	❍	❍	❍
comes with a lot of service support (10)	❍	❍	❍	❍	❍
has many uses (11)	❍	❍	❍	❍	❍
can use most applications (12)	❍	❍	❍	❍	❍

Q35 Read the following list of smart phones. As you read the list try to imagine each phone. Think about what you like and dislike about it. Think about how these phones are similar or how they are different. Apple iPhone (5c, for example)Nokia Lumia (900, for example)LG Optimus (P970 for example)Samsung Galaxy (S4 for example)

Q36 Please indicate how familiar you are with each phone

	never heard of it (1)	have heard of it (2)	have seen it (3)	have used it (4)
Apple iPhone (1)	❍	❍	❍	❍
Nokia Lumia (2)	❍	❍	❍	❍
LG Optimus (3)	❍	❍	❍	❍
Samsung Galaxy (4)	❍	❍	❍	❍

Q32 Please rate each of the following pairs of smart phones in terms of how similar they seem to you. Use any criteria you wish as basis for your similarity judgments. If you think the smart phones are very similar, tick the rating of 1; if you think the two smart phones are very different tick a 9. If you are not familiar with one or both smart phones, skip that pair and go on to the next pair.

	1 (2)	2 (3)	3 (4)	4 (5)	5 (6)	6 (7)	7 (8)	8 (9)	9 (10)
Apple iPhone - Nokia Lumia (1)	❍	❍	❍	❍	❍	❍	❍	❍	❍
LG Optimus - Samsung Galaxy (2)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Nokia Lumia - LG Optimus (3)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Apple iPhone - Samsung Galaxy (4)	❍	❍	❍	❍	❍	❍	❍	❍	❍
Samsung Galaxy - Nokia Lumia (5)	❍	❍	❍	❍	❍	❍	❍	❍	❍
LG Optimus - Apple iPhone (6)	❍	❍	❍	❍	❍	❍	❍	❍	❍

Q16 Do you think that smart phones of Apple iPhone

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)
have a beautiful style (1)	❍	❍	❍	❍	❍
are reliable (2)	❍	❍	❍	❍	❍
are durable (3)	❍	❍	❍	❍	❍
do what they are supposed to do (4)	❍	❍	❍	❍	❍
are expensive (5)	❍	❍	❍	❍	❍
are cheap (6)	❍	❍	❍	❍	❍
offer excellent value for money (7)	❍	❍	❍	❍	❍
are widely available (8)	❍	❍	❍	❍	❍
are easy to use (9)	❍	❍	❍	❍	❍
come with a lot of service support (10)	❍	❍	❍	❍	❍
have many uses (11)	❍	❍	❍	❍	❍
can use most applications (12)	❍	❍	❍	❍	❍

Q17 Do you think that smart phones of Samsung Galaxy

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)
have a beautiful style (1)	❍	❍	❍	❍	❍
are reliable (2)	❍	❍	❍	❍	❍
are durable (3)	❍	❍	❍	❍	❍
do what they are supposed to do (4)	❍	❍	❍	❍	❍
are expensive (5)	❍	❍	❍	❍	❍
are cheap (6)	❍	❍	❍	❍	❍
offer excellent value for money (7)	❍	❍	❍	❍	❍
are widely available (8)	❍	❍	❍	❍	❍
are easy to use (9)	❍	❍	❍	❍	❍
come with a lot of service support (10)	❍	❍	❍	❍	❍
have many uses (11)	❍	❍	❍	❍	❍
can use most applications (12)	❍	❍	❍	❍	❍

Q18 Do you think that smart phones of Nokia Lumia

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)
have a beautiful style (1)	❍	❍	❍	❍	❍
are reliable (2)	❍	❍	❍	❍	❍
are durable (3)	❍	❍	❍	❍	❍
do what they are supposed to do (4)	❍	❍	❍	❍	❍
are expensive (5)	❍	❍	❍	❍	❍
are cheap (6)	❍	❍	❍	❍	❍
offer excellent value for money (7)	❍	❍	❍	❍	❍
are widely available (8)	❍	❍	❍	❍	❍
are easy to use (9)	❍	❍	❍	❍	❍
come with a lot of service support (10)	❍	❍	❍	❍	❍
have many uses (11)	❍	❍	❍	❍	❍
can use most applications (12)	❍	❍	❍	❍	❍

Q52 Do you think that smart phones of LG Optimus

	Strongly Disagree (1)	Disagree (2)	Neither Agree nor Disagree (3)	Agree (4)	Strongly Agree (5)
have a beautiful style (1)	❍	❍	❍	❍	❍
are reliable (2)	❍	❍	❍	❍	❍
are durable (3)	❍	❍	❍	❍	❍
do what they are supposed to do (4)	❍	❍	❍	❍	❍
are expensive (5)	❍	❍	❍	❍	❍
are cheap (6)	❍	❍	❍	❍	❍
offer excellent value for money (7)	❍	❍	❍	❍	❍
are widely available (8)	❍	❍	❍	❍	❍
are easy to use (9)	❍	❍	❍	❍	❍
come with a lot of service support (10)	❍	❍	❍	❍	❍
have many uses (11)	❍	❍	❍	❍	❍
can use most applications (12)	❍	❍	❍	❍	❍

Q26 If you buy a smart phone how likely is it that the brand will be:

	Very Unlikely (1)	Unlikely (2)	Somewhat Unlikely (3)	Undecided (4)	Somewhat Likely (5)	Likely (6)	Very Likely (7)
Apple iPhone (1)	❍	❍	❍	❍	❍	❍	❍
Samsung Galaxy (2)	❍	❍	❍	❍	❍	❍	❍
Nokia Lumia (3)	❍	❍	❍	❍	❍	❍	❍
LG Optimus (4)	❍	❍	❍	❍	❍	❍	❍
HTC Desire (5)	❍	❍	❍	❍	❍	❍	❍
Acer (6)	❍	❍	❍	❍	❍	❍	❍
Alcatel (7)	❍	❍	❍	❍	❍	❍	❍
Blackberry (8)	❍	❍	❍	❍	❍	❍	❍
Huawei (9)	❍	❍	❍	❍	❍	❍	❍
Motorola (10)	❍	❍	❍	❍	❍	❍	❍
Sony (11)	❍	❍	❍	❍	❍	❍	❍
Sony Ericsson (12)	❍	❍	❍	❍	❍	❍	❍

Q21 Do you own a smart phone

❍ Yes (1)

❍ No (2)

If No Is Selected, Then Skip To If you had to buy a new smart phone what brand would you buy?

Q22 What brand is the smart phone that you own?

- Apple (1)
- Samsung (2)
- Nokia (3)
- LG (4)
- HTC (5)
- Acer (6)
- Alcatel (7)
- Blackberry (8)
- Huawei (9)
- Motorola (10)
- Sony (11)
- Sony Ericsson (12)
- Other (13)

Q29 If you had to buy a new smart phone what brand would you buy?

- Apple (1)
- Samsung (2)
- Nokia (3)
- LG (4)
- HTC (5)
- Acer (6)
- Alcatel (7)
- Blackberry (8)
- Huawei (9)
- Motorola (10)
- Sony (11)
- Sony Ericsson (12)
- Click to write Choice 13 (13)

Q37 Hereafter you will find descriptions of smart phones that vary in:Brand of the smart phone: Apple iPhone, Nokia Lumia, LG Optimus or Samsung Galaxy. Operating System: Windows Phone 8 by Microsoft, iOS6 by Apple, Android 4.2 Jelly bean by Google Price: 200 Euro, 350 Euro or 500 Euro, and Screen size: 4 inch or 4.8 inch.Please indicate how attractive each phone is to you and how likely it is that you will buy it.

Q7 Brand of the smart phone: Apple iPhone Operating System: Windows Phone 8 by Microsoft Price 200 Euro Screen size 4 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q8 Brand of the smart phone: Nokia Lumia Operating System: iOS6 by ApplePrice 200 EuroScreen size 4 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q9 Brand of the smart phone: LG OptimusOperating System: iOS6 by ApplePrice 350 EuroScreen size 4 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q10 Brand of the smart phone: Samsung GalaxyOperating System: Windows Phone 8 by MicrosoftPrice 500 EuroScreen size 4 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q11 Brand of the smart phone: Nokia Lumia Operating System: Android 4.2 Jelly bean by GooglePrice 200 EuroScreen size 4 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q12 Brand of the smart phone: Samsung GalaxyOperating System: iOS6 by ApplePrice 200 EuroScreen size 4.8 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q13 Brand of the smart phone: Nokia Lumia Operating System: Windows Phone 8 by MicrosoftPrice 350 EuroScreen size 4.8 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q14 Brand of the smart phone: Nokia Lumia Operating System: Android 4.2 Jelly bean by GooglePrice 500 EuroScreen size 4.8 inch

_______ How attractive is this smart phone to you? (1)
_______ How likely is it that you will buy this smart phone? (2)

Q15 Brand of the smart phone: Apple iPhoneOperating System: Android 4.2 Jelly bean by GooglePrice 350 EuroScreen size 4.8 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q34 Brand of the smart phone: Apple iPhoneOperating System: iOS6 by ApplePrice 500 EuroScreen size 4.8 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q36 Brand of the smart phone: LG OptimusOperating System: Android 4.2 Jelly bean by GooglePrice 200 EuroScreen size 4.8 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q38 Brand of the smart phone: Apple iPhoneOperating System: Android 4.2 Jelly bean by GooglePrice 200 EuroScreen size 4 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q40 Brand of the smart phone: Samsung GalaxyOperating System: Android 4.2 Jelly bean by GooglePrice 200 EuroScreen size 4.8 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q42 Brand of the smart phone: Samsung GalaxyOperating System: Android 4.2 Jelly bean by GooglePrice 350 EuroScreen size 4 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q44 Brand of the smart phone: LG OptimusOperating System: Windows Phone 8 by MicrosoftPrice 200 EuroScreen size 4.8 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q46 Brand of the smart phone: LG OptimusOperating System: Android 4.2 Jelly bean by GooglePrice 500 EuroScreen size 4 inch

______ How attractive is this smart phone to you? (1)
______ How likely is it that you will buy this smart phone? (2)

Q20 1. What is your gender?

- Male (1)
- Female (2)

Q22 What year were you born?