

Fuzzy Measurement for Durable Goods Market Segmentation¹

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Abstract: The aim of the research is to apply the results of fuzzy measurement of consumer preferences on the durable goods market for customer segmentation. New phenomena on the durable goods market are manifested in consumer behavior. As a result, the brand acts as the most important feature while purchasing decisions are taken. Brand assessment by the consumer is associated with a complex evaluation process with several criteria, such as reliability, credibility, modernity, and prestige. The important problem here is that assessment criteria for features which by their nature are immeasurable on metric scales are perceived differently by each respondent. Typical quantitative tools used to measure attitudes partly ignore this problem. An alternative approach that attempts to account for differences in the individual assessments by respondents is a measurement technique that relies on the use of fuzzy numbers. Conversion of linguistic expressions to form triangular fuzzy numbers allows for the differences in the assessments of individual respondents, and thus allows for better identification and representation of actual consumer preferences. Classical, multivariate statistical analysis methods modified for fuzzy measurement results may be used for customer segmentation which takes into consideration the nature of the market for high-tech durables. Customer preferences towards the attributes associated with selected brands of durable goods are used for this task. In the study, a market data set on smartphone devices was used.

Keywords: linguistic variable, fuzzy measurement, fuzzy multivariate statistical analysis, preferences study, smartphones brand attractiveness assessment.

I. INTRODUCTION

One of the crucial marketing tasks is market segmentation. The richness of characteristics that may be used for customers' classification results in high complexity of the task. Another issue is the product type market. The topic of analysis here is the durable goods market and its segmentation. Durable goods market (also referred to as durable goods consumption market) deals with material products purchased for consumption, the use of which does not cause immediate destruction so that they can participate in a number of subsequent acts of consumption. For examples of products classification see, among others reference [21]. Other classification systems include: ISIC and NAICS (USA), SIC, FF (France), ICB-ONS and NACE (Euro-Stat). The market for durables has a feature which makes it extremely hard to classify customers into groups (segments). The unique characteristics of consumer durable goods market, require the use of specific methods of consumer preferences analysis, taking into account the nature

of the market and its limitations. On the other hand, the features of consumer durables should be considered and included in the analysis. The specific character and the way in which the consumer durable goods market functions are directly determined by the unique features of these goods. The most important differentiating features of consumer durable goods include their durability, high unit price, and indivisibility. Demand for durable products strongly depends on demographic characteristics, the phase of the household's life cycle, as well as the place of residence and financial situation. This indicates that it is possible to isolate the specific features that distinguish a buyer of durable goods. The purchase of consumer durable goods occurs relatively seldom, and after the purchase the buyers remain outside the market for a relatively long time. The buying acts tend to be thought through and planned. Before the purchase consumers thoroughly examine the market offer.

Demographic factors are considered the most important, as the income of consumers and the prices of goods determine consumer demand. The design of an effective marketing strategy for the company that operates on the durable goods market requires a multifaceted market research, both in terms of existing offers on the competitive market and consumer preferences for these goods. Additionally, this problem becomes more complicated because markets for innovative and traditional consumer durables function by different mechanisms resulting from the specific needs, requirements, expectations and behaviours of buyers. For testing the proposed multivariate statistical techniques with the fuzzy measurement concept, the smartphone market in Poland has been chosen (see for example reference [9]).

Mobile devices play an increasingly important role in our lives. Smartphones, tablets and even smartwatches have become an indispensable part of everyday life for a significant part of the population. Despite the smartphone market development and the growth in the number of new smartphone users, it is a difficult market mainly because of problems of short product lifecycles and rapid technological advancements.

The crucial problem for companies operating on durables market is the existence of imitations and substitutions. Strong brand loyalty and stiff competition, as well as barriers of entry are also typical for this market. Hence, producers should be always aware of consumer preferences and specific needs to be able to stay ahead of competitors. Nowadays, Samsung and Apple occupy the world's top positions. On the Polish smartphone market, Samsung is the un-

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disputed leader. Despite the prestige and recognition of Apple, this brand has a much lower market share in Poland than in the world market.

At the same time, Poland experienced a new trend in which the market share of larger manufacturers is reduced in favour of new brands of smaller producers.

II. MARKED SEGMENTATION ISSUE

Market segmentation is used in order to solve the principal marketing issues. Both the consumer market (products and services), and the industrial market segmentation are focused on identification of relatively homogeneous consumer groups. Here, the terms client, customer, and consumer are used as synonyms. In the marketing management literature they receive a slightly different meaning (see reference [31]). The ultimate goal is to fulfill the specific needs of each identified group. To understand those specific needs one has to thoroughly describe customer characteristics and their behaviour patterns. Customer characteristics are also referred to as variables, descriptive variables, segmentation variables (characteristics), etc. It is crucial in this respect to define the segmentation base, which defines the list of customer characteristics from several possible classes; descriptive – demographic, psychographic, geographic, etc., as well as behavioural – attitudes, tastes, decision style, etc. Segmentation, regardless of the method used, is designed to identify groups of entities (people, markets, organizations) that share certain common features (attitudes, purchase propensities, media habits, etc.).

Market segmentation in the consumer goods market is a typical marketing management task. In contrast, segmentation in the durables market is not as commonly created as in the consumer market, the service market or even the industrial market. There are distinguishable differences in the durable goods market that make it completely unlike other market types. In this respect, it is crucial to recognize these particular issues in which consumers of durables differ from FMCG customers. FMCG (fast moving consumer goods) are goods frequently bought. The main goal of market segmentation is to meet consumer needs, so segmentation process is oriented towards selecting the ideal product that could be fully satisfying for the clients. Segmentation research process is designed to recognize groups of entities that have common characteristics, attitudes, and expectations. There is a variety of segmentation procedures that differ in terms of the goal and the range of marketing research. According to Philip Kotler, there is a three-step procedure for identifying market segments: the first one is called survey stage, the second – the analysis stage and the last one is the profiling stage (see reference [31] p. 181). At each of those three stages, the procedure is divided into separate substeps. W. Muszyńska, by using the example of an existing company which offers household durables, shows that it is crucial for the researcher (or in real life the marketing manager) to define their objectives ahead of the segmentation procedure (see reference [41]). Afterwards, the aggregation of potential customers, understood as the identification of the company's reservoir of potential customers should be described. This description may be based on the variables (customer characteristics) from the list of descriptive and behavioural variables. The definition of the product and the market is done in the second step (of the first part of the research). Hence, the consumer durables market characteristics are as follows:

- This market has typical features like every consumer market, where the main needs of individuals (and their

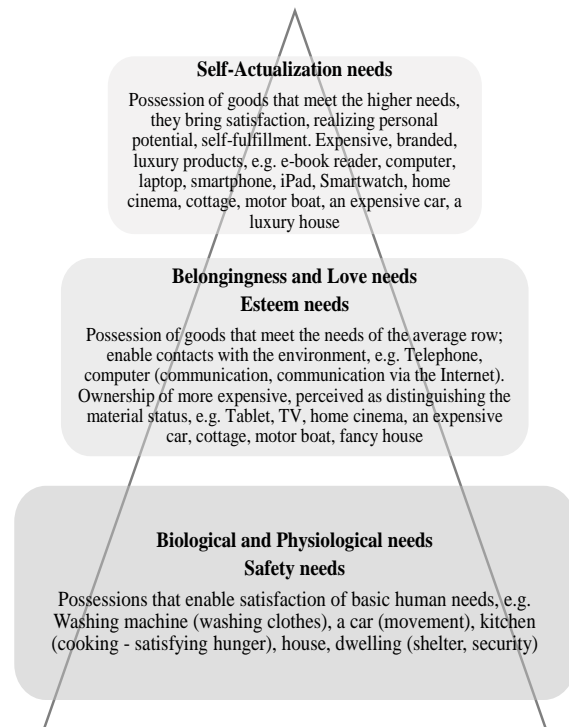


Figure 1. Maslow's hierarchy of needs

Source: Own elaboration based on Maslow [1943].

households) are met.

- An important feature of the durables market is the strong income elasticity of demand.
- Also, the price elasticity of demand is on a high level, therefore, the price is one of the most important marketing instruments.
- Enterprises offering durables operate on large territorial space (usually on international markets), and their number is increasing.
- The number of buyers is unlimited – as a rule, one item is purchased, normally in the retailers' stores.
- The market is complicated by the strong substitution and complementarity. Additionally, the secondhand market attracts numerous purchasers.
- Moreover, seasonality influences the durables market; the level of demand usually being higher in the fourth quarter of the year.

The next step of the segmentation procedure consists in the identification of the potential products purchasers' needs and expectations. Durable goods are involved in the process of satisfying diverse needs of members of the household and the household as a whole. It means that the role of durable goods and their importance in the household is multifaceted and diverse. Some of the durable goods contribute to improving the ease of housework, by reducing the effort and time needed to perform household tasks. Determining the way of spending free time is equally important. In Figure 1, the list of types of needs where durable goods are involved in the process of satisfying diverse needs of members of the household and the household as a whole is

shown. It is important to see that the same product class (e.g. cars) may satisfy needs on different levels. The car may be a status symbol for some households, and in other families it may play the basic role of a transportation tool necessary for the job and everyday family activities. However, in general, consumer durables are relatively high in the needs hierarchy. The surveys in the households finance show that the position of these products in the financing hierarchy is usually located behind food items, clothing, and mandatory payments (see reference [3]). On the other hand, although consumers usually declare their readiness to buy durable products, they actually make those acquisitions after they have met their basic, lower-level needs. In the discussion of characteristics, in respect of which consumer durables differ from most other items of consumer expenditures, a number of distinguishing features are identified and listed. Among the most common of these differences are determinants of demand for consumer durables. Important determinants of demand for consumer durables include the socio-economic status of the household (occupational group, the age of household with the household life cycle stage; existing durable ownership; depreciation level of existing equipment, general economic confidence and availability of bank loans, real estate market prosperity and specific triggers and hindrances to purchases).

Additionally, it has to be stated that consumer durables differ from most other items of consumer expenditure in the characteristics of purchasing process:

- buyer acquires a product and then stays away from the market for a long period, only to return to the market for a short time either to purchase an additional item or to replace an existing durable,
- consumers are in the market for a short period and spend a substantial amount of money in that period,
- the purchase of a durable product, which costs a substantial amount of money, is usually well thought-through, planned long ahead and the market carefully searched for a suitable offer.

The crucial issue of segmentation is to find an appropriate combination of variables that will measure the changes in purchase intentions as an aid for forecasts of demand changes. Segmentation bases which are used to segment the durables market are often similar to those employed on the consumer market.

The difference lies in the way they are adjusted to these market unique characteristics. The segmentation base i.e. the set of segmentation variables (customer characteristics) used to assign potential buyers to homogeneous groups can be classified into main groups of descriptive variables:

- demographics and geographic characteristics: age, gender, marital status, size of household, family life cycle, income, occupation, education, social class, region, density,
- psychographics: lifestyle, personality,
- behavioural: occasions, benefits, user status, and loyalty status.

There are three major approaches to segmentation of consumer durables market. It may be based on:

- socio-economic status of the household,
- general consumer confidence,
- consumer behaviour – perception of product characteristics.

Commonly used measures are easily measurable socio-economic features, such as: age, income, employment status, home ownership, family size and ownership of durables. It does not mean that easily observable variables are of less importance.

For instance, age is an important determinant of behaviour, and therefore age is a critical variable for understanding variations in individual behaviour. In a study by Strober and Weinberg it was proven that younger households purchase earlier than older ones (see reference [54]).

Likewise, Morgan found that income has a significant non-negative effect on the probability of purchase, as it could be intuitively expected (see reference [39]). Empirical evidence indicated that working status is significant in determining family's likelihood of owning major durable goods.

Different segmentation bases are considered, and characteristics to measure the consumers' general economic confidence are often used. As an example, the current state of the economy, as well as personal financial situation contributes to consumer confidence may be indicated. Alternative versions of measures are based on household intentions or expectations to buy a specific durable product within a stated period.

In the W. Muszyńska's example, a specific durable market characteristics (sex, the age of head of household, the size of the family, family status, economic status, occupational group and place of living) were used as segmentation variables. The analysis of a sample consisting of 1200 respondents (company clients) was done in the next stage of segmentation procedure.

To cluster customers into homogeneous groups, six segmentation variables were used. Customers were described according to their occupational group, correlated to their sex, age and economic status. In the described experiment, three customer profiles were identified and characterized: the first one, called young purchasers, second profile, professionally active, and third profile, retired purchasers. In the last stage of the segmentation process, segment profiling was carried out. The *professionally active* segment was considered to be the basic profile that company decided to target on. Its main characteristics were:

- easily identifiable, homogenous, numerous and measurable,
- stable and accessible for marketing efforts.

TABLE I
CLASSIFICATION OF METHODS USED FOR SEGMENTATION

	<i>A priori</i>	<i>Post hoc</i>
Descriptive	Contingency tables Log-linear models	Clustering methods: Non-overlapping Overlapping Fuzzy techniques Mixture models
Predictive	Cross-tabulation Regression Logit analysis Discriminant analysis	Aid, Chaid, Maid CART Conjoint analysis ANN Clusterwise regression Mixture models

Source: Wedel M., Kamakura W. (1998) *Market Segmentation. Conceptual and Methodological Foundations*, Kluwer, p. 18.

III. MULTIVARIATE STATISTICAL METHODS USED FOR MARKET SEGMENTATION

One may indicate two main ways of classifying the segmentation techniques.

Depending on the choice of a statistical method, one can distinguish between *descriptive* and *predictive* approach. *Descriptive methods* analyze the associations across a single set of segmentation bases, with no distinction between dependent and independent variables. *Predictive methods* analyze the association between two sets of variables (one set consists of dependent variables to be predicted by the set of independent variables).

Secondly, segmentation approaches can be classified into *a priori* and *post hoc* approaches.

An application and theoretical discussion of *a priori* descriptive methods such as contingency tables are provided by A. Stanimir (see reference [51] and [52]). Description of *a priori* predictive approaches such as:

- based on discriminant analysis is given in works by Gatnar, Walesiak (see reference [20]), and Lawson (see reference [33]);
- based on regression is given in works by A. Wildt J. McCann (see reference [59]);
- based on cluster analysis application to market segmentation is described, among others in works (see reference [2]; [18]; [46] and [55]).

Post-hoc predictive methods are often employed to segment customers, their description may be found among other in following studies:

- Automatic Interaction Detection (AID), and other AID-like algorithms like Multivariate AID (MAID) (see reference [36]) and Chi-squared AID (CHAID) could be found in references [16]; [48] and [49];
- Classification and Regression Trees (CART) methodology can be found in reference [32];
- Artificial Neural Network (ANN) in reference [4] and [26];
- Conjoint analysis (see reference [17] and [56]) and cluster-wise regression (see reference [58]).

In the literature there is a comprehensive discussion completed on various segmentation methods groups and their applications in each of the four classes

Cluster analysis is a statistical method for classification. Unlike other statistical methods for classification, such as discriminant analysis and automatic interaction detection, it makes no prior assumptions about important differences within a population. Cluster analysis is a purely empirical method of classification and as such is primarily an inductive technique.

The primary use of cluster analysis in marketing has been for market segmentation and it has become a popular tool for the marketing researcher. Hence, illustrative applications of cluster analysis for market segmentation (also to consumer durables market segmentation) have been provided by many authors.

There are interesting studies using agglomerative hierarchical clustering methods. To show some interesting, representative studies, one should mention studies by Claxton, Fry, and Portis. In one of their studies they attempted to classify furniture and appliance buyers in terms of their information search behaviour. Authors employed a complete

linkage cluster analysis. Nature of data used: attribute scores on several pre-purchase activity measures (see reference [11]). An average linkage cluster analysis method described by Kiel and Layton was used to develop consumer taxonomies of search behaviour on the Australian new car buyers' market. The nature of data: factor scores derived from several search variables (see reference [29]).

An interesting example of hierarchical clustering was shown in a study by Furse, Punj and Steward [19]. A cluster analysis of questionnaire data was used to identify six distinctive external information search patterns among purchasers of new automobiles. Researchers employed Ward's and k-means Howard-Harris methods (detailed description in [50]). Data were obtained from over one thousand respondents. They were customers who had purchased a new automobile in 1978. In the next stage, forty-eight sales representatives from various dealers participated in the study.

A common tool for marketing researchers became the k-means Howard-Harris method, one of degglomerative hierarchical clustering methods. P. Green and F. Carmone [22] employed this clustering method to identify similar computers (strata in the computer market) using performance measures for different computer models.

One of the first examples of forming hierarchical clusters by means of the Howard-Harris algorithm is described in a study by Rao and Winter [47]. In their research respondents selected for the study were MBA students who owned cameras. In order to find homogenous groups, the authors used characteristics describing general photography and camera preferences.

Another early illustration of the Howard-Harris algorithm was employed by Green, Tull and Albaum [25]. They used the Howard-Harris techniques to identify similar computers. Forty-seven different computers were characterized by 22 variables describing computer features.

Green, Carmone and Smith [24] also used k-means Howard-Harris method for identifying homogenous groups of cars with similar characteristics. Using ten variables, the authors described 90 types of cars which were on the market in 1987 with prices ranging from 5 to 168 thousand dollars.

An illustrative application of non-hierarchical cluster analysis to market segmentation has been provided by A. Mazur and I. Staniec [38]. They segmented the Polish automobile market with the application of k-means method.

The same, k-means method was applied to PC and cars buyers segment by Morwitz and Schmittlein [40]. The authors investigated the issue whether the use of segmentation could improve the accuracy of sales forecasts based on stated purchase intents. In the study, four different methods for segmenting households were applied. One of them was cluster analysis based on demographic and product usage variables. The three waves of surveys (from 1986 to 1989) were conducted with a consumer panel of as many as one hundred thousand US households. Eventually, they used 24.000 responses for PC and over 28.000 for automobiles users. As a result, consumers were segmented into five homogenous groups.

The same clustering method was applied by S. Lonial, D. Menezes and S. Zaim in their study [35]. The paper focused on the use of cluster analysis for identifying the target segments of the university students as PC buyers. For the study k-means was used to cluster respondents on the basis of

similarity of their utility functions for five PC related attributes and the corresponding attributes levels.

The issue of market segmentation often is related to other methods of data analysis, which are not included in above presented classification. The techniques of this type include multidimensional scaling (MDS) and a group of methods known collectively as the factor analysis, as well as linear ordering techniques. Some of the described methods are applied only in market segmentation, others are suitable both for segmentation and profiling. There are also methods used exclusively either to segments description, or only profiling. Among the most common methods used for profiling of market segments, in addition to simple techniques based on descriptive statistics, one should number, among others, the Multidimensional Scaling and fuzzy linear ordering. Multidimensional Scaling is an important research technique that is normally used in order to solve specific marketing management tasks, e.g. the positioning of products. One has to mention this particular possibility of application of this method for the problem of market segmentation. Multidimensional Scaling is a technique for simplifying the description of multidimensional reality by reducing the dimensions of space. The method can be used to describe the structure of an examined object. It is done by determining the dimensions of the content, based on the similarity and preference of the respondents. The ultimate task is to detect relations between the objects studied using a multidimensional space with radically reduced number of dimensions (see reference [62], p. 101).

The work on the theory of fuzzy sets was initiated by L. Zadeh [63], who negated the unambiguous assignment of objects to individual classes. L. Zadeh suggested that fuzzy measurement and thus fuzzy classification is at least a partial remedy to the disputable assignment of objects to different classes. Based on this idea and its assumptions, the algorithm of fuzzy k-means method and its generalization called FCV (fuzzy c-variety clustering technique) have been developed. The proposed techniques also identify clusters with the chain configuration. H. Hruschka demonstrated the applicability of fuzzy classification techniques for solving some specific marketing management tasks, particularly in segmentation (see reference [28], pp. 117-134). In fuzzy measurement and fuzzy classification, the assumption of a stochastic nature of the phenomena studied is abandoned. The deterministic assumption holds. Espe-

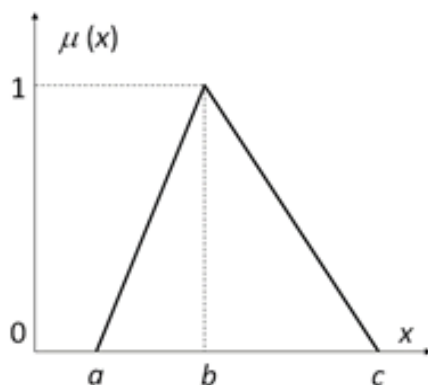


Figure 2. Triangular fuzzy numbers with shape parameters (a,b,c)

Source: Bartkiewicz (2000) p. 83.

cially interesting possibilities are offered by techniques

based on the theory of fuzzy sets, among them earlier mentioned fuzzy linear ordering.

IV. FUZZY NUMBERS AND FUZZY MEASUREMENT

Linguistic variables were used to describe potential users' preference towards analysed products. In this approach, in order to quantify the formulated linguistic statements, the theory of fuzzy measurement and fuzzy numbers were utilized. The fundamental work on sociological and utility measurement is presented in S. Stevens [53]. The specifics of linguistic variables are thoroughly discussed in L. Zadeh [64] and T. Liou M. Wang [34]. A linguistic variable can be defined as a variable where values are determined by verbal categories (see reference [44]). From the point of view of the respondents, the linguistic variable is a convenient and intuitive way to assess their preferences (see reference [6]). However, the choice of parameters of fuzzy numbers which illustrate the perception of linguistic values constituting points of measurement scales is crucial. So, the researcher encounters a difficulty in how to properly code the verbal statements. The use of fuzzy numbers, in which the words of the natural language are identified with specific fuzzy subsets, is one of the possible methods of coding verbal statements (Zadeh [64]). The procedure of coding linguistic statements uses the concept of triangular fuzzy sets defined as a set of three parameters: a, b, c , where $a < b < c$. The values of the membership function of the triangular fuzzy set can be expressed by the appropriate formula (see reference [1]).

In Figure 1, a graphic interpretation of a fuzzy set in triangular form is shown. The use of linguistic variables to study consumers' preferences is based on the respondents' assessment of certain criteria of evaluation by indicating one of the levels of the variable expressed in natural language. In the next step, the levels of the linguistic variable are assigned an equivalent (code) number, which in this case forms the fuzzy number. Variants of the linguistic variable are usually defined and understood by the individual respondents in a non-uniform manner. For this reason, the linguistic expressions in general vary in terms of a numerical interpretation of verbal expressions. The application of triangular fuzzy numbers to quantify the linguistic variable requires a definition of its domain. The examples of the linguistic variable expressed as the triangular fuzzy numbers with their graphic interpretation are presented in Table 1 and Figure 2.

TABLE I.
AN EXAMPLE OF DEFINITION OF THE TRIANGULAR FUZZY NUMBER DOMAIN (SCALE 0–100, IDENTICAL WIDTH INTERVALS, NON-OVERLAPPING INTERVALS)

Equivalent number (a, b, c)		
Linguistic variable	Very low	(0, 0, 20)
	Low	(20, 30, 40)
	Medium	(40, 50, 60)
	High	(60, 70, 80)
	Very high	(80, 100, 100)

Source: Chang, Yeh, (2004).

^a for technical reasons, the first and last fuzzy number has (forced by researcher) shape of rectangular triangle.

In subject literature, numerous proposals for defining numerical equivalents for the linguistic variables are given, including singleton, triangular, trapezoidal, and bell-shaped fuzzy numbers (see, e.g. [8]). The definitions of domains of triangular fuzzy numbers might vary in the width of the individual levels (e.g. identical widths, non-identical widths), their infiltration level (e.g. levels do not overlap, or with overlapping levels) and the scale of fuzzy number, e.g. [0, 1], [0, 10] [0, 100] (see: [34] and [61]).

The figure 2 contains an illustration of possible answers coming from respondents. Some of them will choose non-overlapping fuzzy numbers (a, b, c); some of them will give overlapping statements.

Additionally, for some respondents the definitions of domains of triangular fuzzy numbers might vary in the width of the individual levels (e.g. identical widths, non-identical widths). Also, some respondents will define symmetrical and others nonsymmetrical triangular fuzzy numbers. For the researcher, there is one more difficult decision to make. One has to choose a representation of the fuzzy number for the analysis. The list of possible solutions includes the range, arithmetic mean, median or some other characteristics.

V. THE SURVEY RESEARCH

The survey research was conducted in the first quarter of the year 2015. It included 451 full-time and part-time students of the University of Economics in Wroclaw (the set of respondents was selected using the convenience approach (see reference [10], pp. 497–500.) Therefore, the described study should be considered a pilot study and was conducted in order to test the possibility of an application of the proposed approach. The questionnaire covered the issues regarding the ownership of smartphones, as well as

the preferences of the respondents for the selected smartphone brands.

Additionally, the possible smartphones' applications and the most important characteristics of the devices were of interest. The respondents were young people, 68% were not yet 21 years old, and only 7% were older than 24 years. The majority in the analysed student group were women (63.2%). About 40% of the respondents at the time of the study were employed (full-time or part-time). A similar group (45%) stated that they did not work, and 15% indicated casual employment. The respondents evaluated their financial situation relatively well: over 70% considered their situation as good or very good. Only about 5% of the respondents rated their living conditions as unsatisfactory (poor and very poor financial situation). In the selected group of students over 89% owned at least one smartphone, 6% intend to purchase the device in the near future, while another 2% admitted to the lack of possibility of purchasing the smartphone due to financial constraints. Barely about 3% of the respondents declared a total lack of interest in this device. In the analysed group of respondents, the ownership of the durable product in question was similar to that in the analogical age group (20–29 years) for the entire Polish population, where 88% declared to be users of smartphones (see reference [45]). Students are not only frequent owners of smartphones, but they can also be regarded as the current and future consumers. For this reason, their preferences for brands of smartphones are very interesting research issue from a practical point of view.

The presented research attempted to investigate consumers' preferences for smartphones, in particular in regard to various technical characteristics, such as screen size and resolution, internal memory and operating system. Among the surveyed students small devices were the least popular,

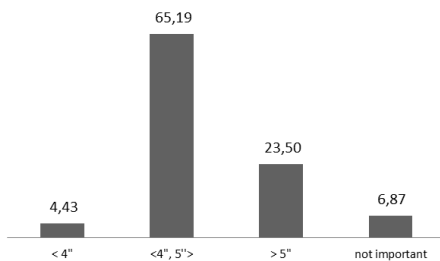


Figure 3. Preferences for screen size (in %)

Source: own elaboration.

Figure 1.

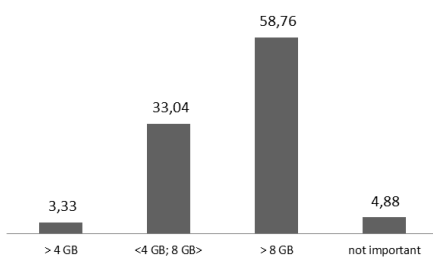


Figure 5. Preference for internal memory (in %)

Source: own elaboration.

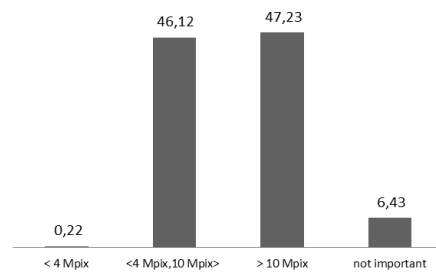


Figure 4. Preference for screen resolution (in %)

Source: own elaboration.

Figure 2.

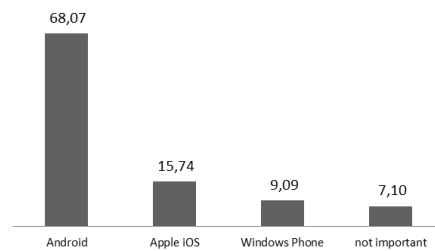


Figure 6. Preference for operating system (in %)

Source: own elaboration.

smartphones with screen size smaller than 4" would be the

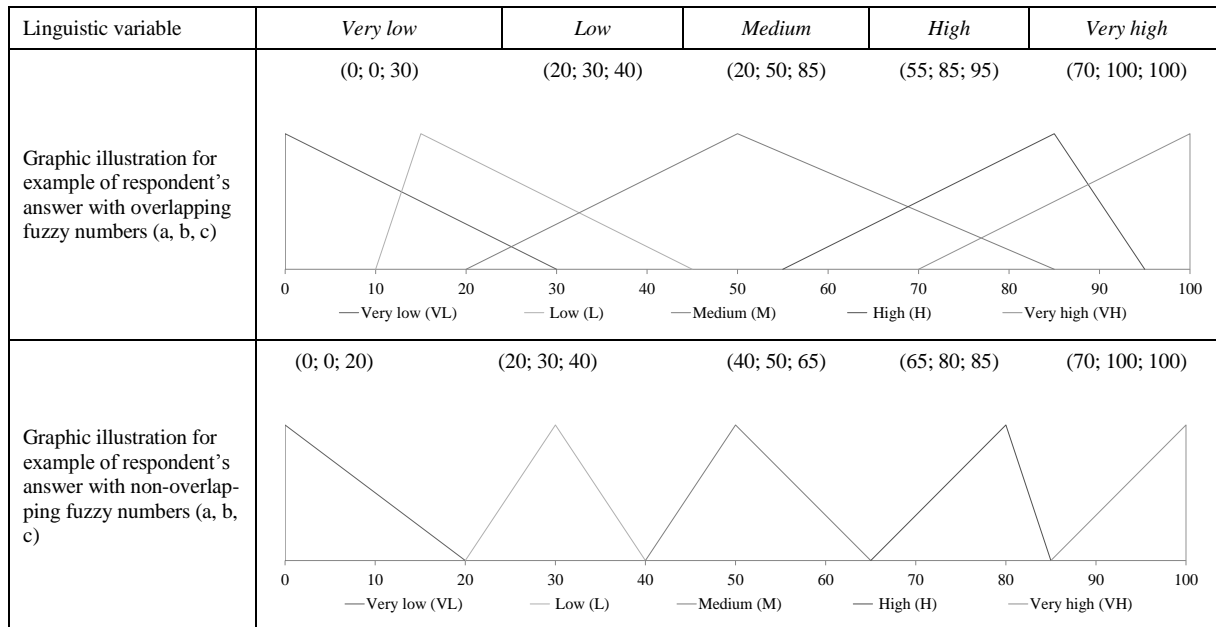


Figure 7. Examples of respondents' subjective definitions of the triangular fuzzy number domain for linguistic variable: non-overlapping intervals and strongly overlapping middle intervals Triangular fuzzy numbers with shape parameters (a,b,c)

Source: own elaboration.

best choice for only 4.4% of the respondents. Smartphones screen sizes from 4" to 5" were the most popular (65.2% preferred this size). Smartphones with the largest screens (above 5") proved to be highly desirable as well (23.5%). Less than 7% of the respondents declared that the screen size is not a significant criterion in the purchase decision process (Figure 3). Similar results were observed in the case of screen resolution; more than 6% of the group believes that this feature is not an essential criterion for the selection of smartphone. The least popular proved to be the smartphones with the lowest resolution (less than 4 megapixels). More than 46% would choose a smartphone with a resolution of 4–10 megapixels, while about 47% stated the preference for a screen resolution higher than 10 megapixels (Figure 4). In the case of internal memory, devices with

storage over 8 GB proved to be the most popular (about 60% of the respondents).

Almost no one would buy a smartphone with the lowest internal memory (up to 4GB). About one third preferred the memory storage from 4 to 8 GB. Again, less than 5% of the group declared that the internal memory is not an essential criterion for the selection of the device (Figure 5). By far the most popular operating system was Android (68.1%). Almost 16% of the students in the group would choose a device running on Apple's iOS. Windows Phone was the desired operating system for just over 9% of users. More than 7% of the group declared that the operating system is not an essential criterion for the selection of the device (Figure 6).

TABLE II
THE FREQUENCY (IN %) OF ANSWERS DEFINING BEGIN, MIDDLE AND TOP VALUE OF FUZZY DESCRIPTION OF THE FEATURE ASSESSMENT VARIANT

Frequency	Very low		Low			Medium			High			Very high	
	a, b	c	a	b	c	a	b	c	a	b	c	a	b, c
0	100	2	0	0	0	0	0	0	0	0	0	0	0
10	0	13	22	0	0	0	0	0	0	0	0	0	0
20	0	54	57	16	2	6	0	0	1	0	0	0	0
30	0	20	16	56	17	18	1	0	3	0	0	0	0
40	0	7	4	21	46	47	12	2	2	1	0	0	0
50	0	3	1	5	25	24	55	9	9	3	0	1	0
60	0	1	0	0	2	3	11	6	5	1	0	1	0
70	0	0	0	1	4	2	18	48	47	13	2	2	0
80	0	0	0	0	2	0	3	26	28	49	9	8	0
90	0	0	0	0	2	0	0	5	5	25	50	49	0
100	0	0	0	0	1	0	0	3	0	8	39	39	100

Source: own calculation on collected data.

Note: the first and last fuzzy number has (forced by researcher) shape of rectangular triangle.

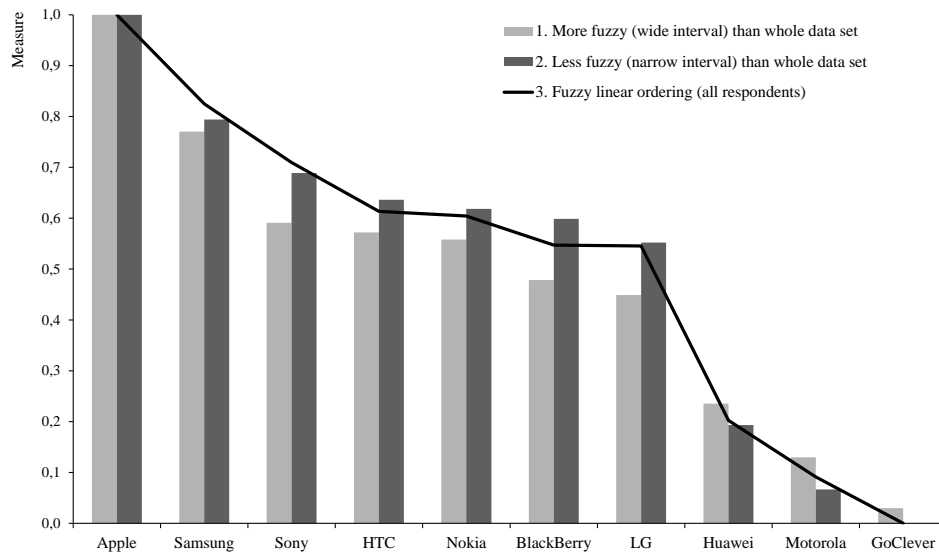


Figure 8. Fuzzy linear ordering of respondents' statements on analysed smartphone brands
 Source: own calculation on collected data.

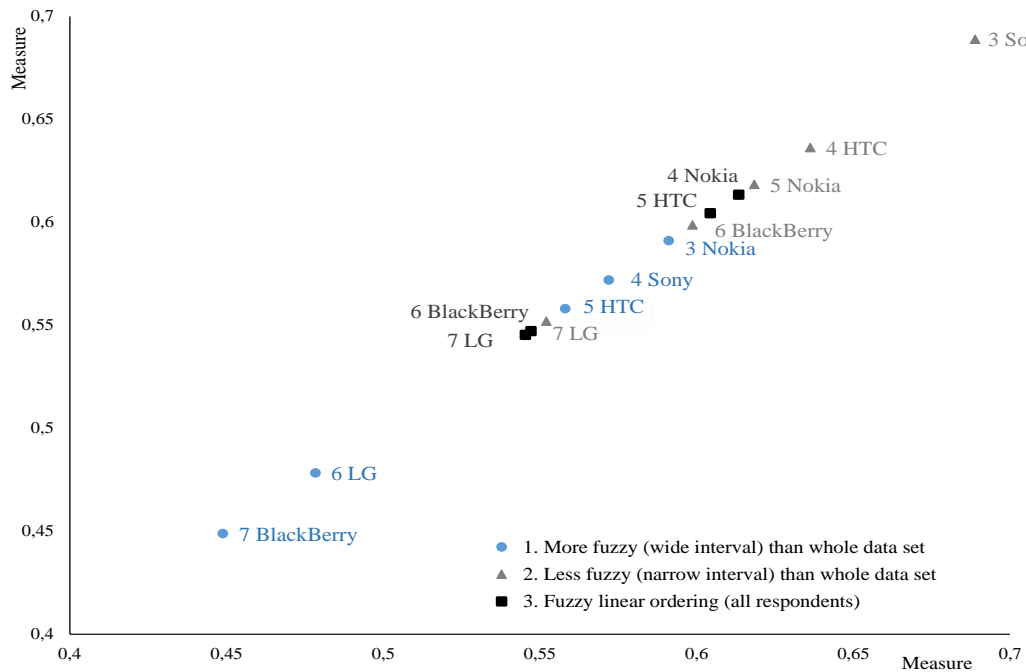


Figure 9. Fuzzy linear ordering of respondents' statements (middle part of smartphone brands hierarchy)
 Source: own calculation on collected data.

VI. THE ANALYSIS

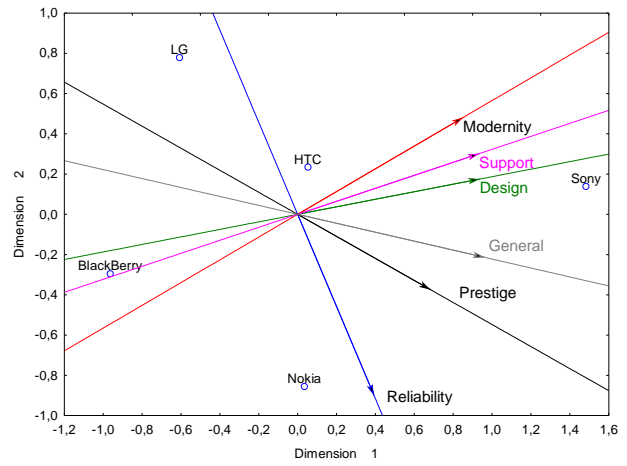


Figure 10. PROFIT for all respondents (without Apple, Samsung, Motorola, Huawei and GoClever)
 Source: own elaboration (SPSS).

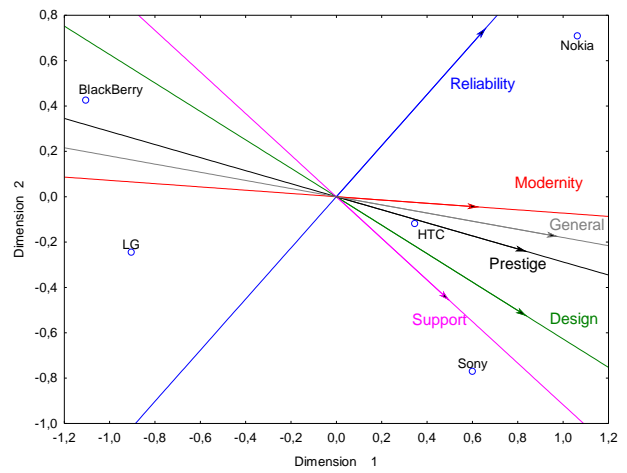


Figure 11. PROFIT; respondents whose declarations were more fuzzy (wide interval), without Apple, Samsung, Motorola, Huawei and GoClever
 Source: own elaboration (SPSS).

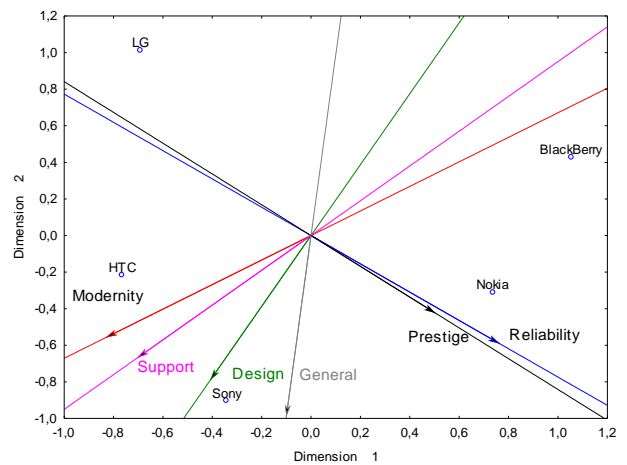


Figure 12. PROFIT; respondents for those whose declarations were less fuzzy (narrow interval), without Apple, Samsung, Motorola, Huawei and GoClever
 Source: own elaboration (SPSS).

In the course of the study, the respondents were asked to evaluate ten chosen brands of smartphones in terms of reliability, modernity, design, technical support, prestige and overall evaluation of the brand. Each brand of smartphones was evaluated by selecting one of the proposed verbal terms: very low, low, medium, high, very high assessment of the brand. In addition, respondents were asked to indicate their subjective numerical equivalent for these variants of answers. So each respondent independently, defined their numerical equivalent for linguistic assessment. In accordance with the suggestion of Chang and Yeh [7], for technical reasons, the first and the last fuzzy number have the shape of a rectangular triangle (enforced by the researcher). It means that each category was quantified by defining the beginning, the middle and the end of the interval (on the scale from 0 to 100). The analysis of respondents' subjective definitions of the triangular fuzzy number domain for linguistic variables confirmed the earlier assumptions about the non-uniform understanding and interpretation of the verbal terms. One may see that in most cases, the differentiation of the beginning, middle and top value of fuzzy description of the feature assessment lays inside the interval of some thirty points.

Only the mid variants manifest wider interval, up to fifty points. Yet, another group of respondents was the students who were not able to properly transform the linguistic expressions into the triangular numbers.

About 25% of the answers were incorrect and thus were removed from the data set. For an insight into the structure of brand recognition, a linear ordering with the so-called development measure technique has been made. Originally, the method was proposed by Z. Hellwig [27]. The technicalities may be found in [14]. The Figure contains results of linear ordering of respondent's statements on analysed smartphone brands.

Three variants have been prepared. The solid line shows ordering results for all respondents, pale grey histogram corresponds with statements of these respondents who gave most fuzzy answers (wide fuzzy numbers intervals). Dark grey histograms correspond with statements of respondents, who gave the least fuzzy answers (narrow fuzzy numbers intervals). One may see that the diagram for all (solid line) and the dark grey histograms do not substantially differ. It means that a majority of respondents have strong opinions (narrow intervals).

It can be seen that there are brands with strong, unequivocal assessment. Those are at the beginning, and at the end of the hierarchy. To get a better insight into the problem part of the analysed set, a separate hierarchy was constructed (Figure 8).

The analysis of the statements in data sets consists of an attempt to identify groups of brands, where an in-depth analysis should be performed. Different, alternative analyses are described in the Author's publications [12]; [13] and [15]. As stated earlier, the whole group of respondents consisted of 451 people. For the analysis, they were divided into those whose declarations were fuzzier (wide interval of fuzzy numbers) and those whose declarations were less fuzzy (narrow interval of fuzzy numbers). Respondents were divided according to the way they coded linguistic variables with a numeric equivalent. As a result, three groups arose labelled 1, 2, and 3. The group was tested for a specific tendency, whether those who choose a more radical way of transferring the linguistic assessments into

equivalent numeric values, also differ in assessing the brands of smartphones. An analogous check has been performed for those with more fuzzy answers. Of interest was the attitude towards particular criteria and their impact on brand assessment. The criteria list may be seen in the presentation of the PROFIT analysis (Figure 11 and 12. For crosscheck, a hierarchical classification has been made. Three variants of classification were performed. Figure 9 presents results of classification for all respondents; Figure 10 represent those whose declarations were more fuzzy (wide interval) than the whole data set (left part).

It can be seen that although the obtained groups in their variants are similar, the relatively smaller differences in Figure 9 were observed for those on the right part, whose declarations were less fuzzy (narrow interval). It indicates an asymmetric density of answers. The observed skewness is toward positive assessment. The extensive description of the dataset can be found in [12]. Regardless of which classification technique has been used, the next step is to describe preferences inside groups. In the described analysis, the division of the hierarchy obtained in the linear ordering into groups may be done with the Hotteling test. An alternative approach is to apply the hierarchical classification (see [14]). Another useful tool for this task is offered by the PROFIT (PROpertyFITting) technique (See reference [5] and [43]). The variant using fuzzy numbers was applied.

Since the brands situated on extreme (top and bottom) positions are distinct and do not need additional description, a PROFIT analysis has been made for those occupying middle positions, i.e. without Apple, Samsung, Motorola, Huawei and GoClever. This way it is possible to see from Figures 11 and 12 (left) that high-level of *modernity*, *support*, *design*, and *prestige* are attributed to Sony, with BlackBerry on the opposite position. An analogous pair is made up of Nokia and LG. Figure 12 shows that those respondents (buyers) with a wide interval of fuzzy numbers need additional care. Their preferences differ from the majority, and from those with narrow intervals.

VII. CONCLUDING REMARK

To conclude, it may be stated that the statistical analysis of survey data proved that the results may be a good base for decision recommendations. Respondents consider the fuzzy measurement easier to implement in the quantification of linguistic statements. Groups of respondents may be identified by the way they define the intervals for fuzzy numbers.

The merit analysis of the collected data shows that there are respondents with strict opinions, manifested with narrow, non-overlapping fuzzy answers. This group is probably not ready to accept marketing communication signals which are not in line with their assertive judgments.

A more interesting group for marketing communication signals are customers with uncertain, insecure opinions, which are manifested with broad, often overlapping, fuzzy judgments.

Profiling groups of respondents may be a good base for marketing policy design, especially pricing decisions. As an example, one may show that although the values of development measures of Apple and Samsung brands differ only slightly, the price of Apple is substantially higher. One may suggest there is some room for price corrections (increase) by Samsung.

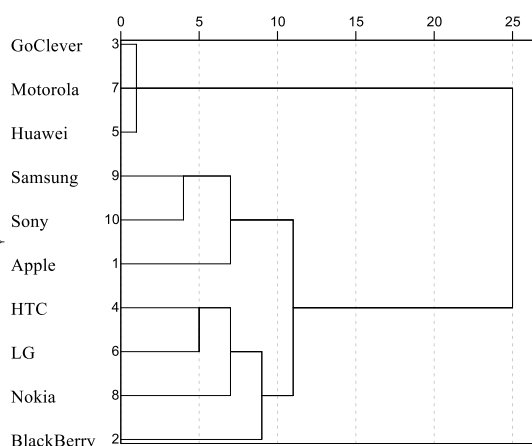


Figure 13. Dendrogram for all respondents

Source: own elaboration (SPSS).

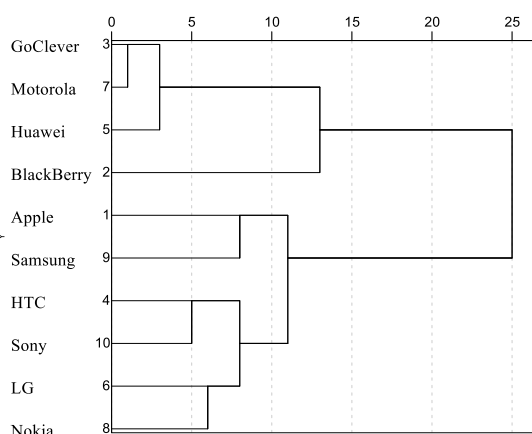


Figure 14. Dendrogram for those whose declarations were fuzzier (wide interval)

Source: own elaboration (SPSS).

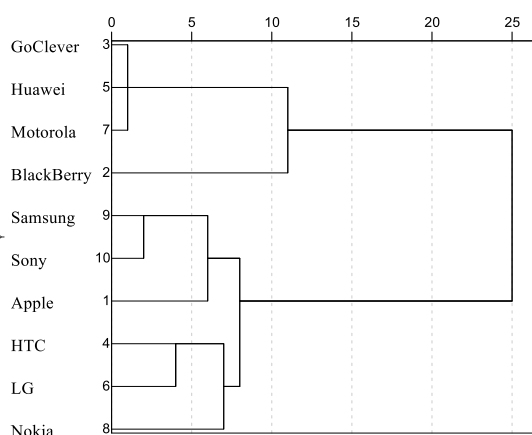


Figure 15. Dendrogram for those whose declarations were less fuzzy (narrow interval)

Source: own elaboration (SPSS).

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