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Appliance to Predict the Quality of Hypothetically Modified Products

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Abstract: Customizing the quality of the product to change customer expectations is a necessary action in good, prospering organizations. In enterprises, the most beneficial solutions consider the future satisfaction of customer with the product. This issue is not easy and is not resolved; therefore, integration of different techniques was proposed as part of a single, coherent appliance. Therefore, the aim is to propose the appliance to predict the quality of hypothetically modified products. The appliance was developed by adequately selected and combined techniques, i.e., survey research with the Likert scale, AHP method (Analytic Hierarchy Process), Pareto rule (20/80), WSM method (Weighted Sum Model) and Naive Classifier Bayes. The concept of the proposed appliance concerns the possibility of determining important product attributes and possible combinations of feature states. Based on this, the quality levels were estimated, and then satisfaction with the hypothetical modifications of the product was predicted. The test was carried out on the vacuum cleaner. As a result, four combinations of product modifications were determined, which have been created based on hypothetical and actual attributes. Each modification was satisfying for the customer. Therefore, the proposed apparatus turned out to be effective in predicting customer satisfaction for the modified quality levels. Originality is to propose a new integration of different techniques to predict levels of quality product modification based on current product quality.

Keywords: Analytic Hierarchy Process; decision support; customer requirements; Naive Bayes Classifier; predict; quality level; Weighted Sum Model

1 INTRODUCTION

Customization of products to customer expectations is difficult in view of dynamic market changes [1, 2]. In this area, enterprises are still looking for ways to design new products or make thoughtful improvements to existing products [3]. This issue is not easy because it refers to determining the level of quality of the product before its modification or design. Moreover, this level should be beneficial to the customer, that is, meeting his requirements [4-6].

As part of these actions, it is effective to determine customer satisfaction based on current product quality, i.e., actual existing product. It results from the possibilities to precisely determine customer requirements in relation to what they have (current product) and what they expect (modified product). These actions include predicting product quality, i.e., determining before competition the product quality level that will meet the customer's requirements. These actions allow good economic results or reducing waste [7]. Therefore, enterprises should use appropriate appliances to predict customer expectations of product quality levels.

A literature review on the subject has shown that various techniques were used to predict the expected quality level. For example, customer expectations were obtained, eg as part to use survey research, or interview [8]. Also, analyses were carried out to determine the importance of customer requirements on product attributes. It was realized using, e.g., the Delphi method [9] or the AHP method (Analytic Hierarchy Process) [6, 10]. Furthermore, the customer's requirements were analyzed as part of the QFD method (Quality Function Deployment) [11, 12]. This concerned, for example, assessing the importance of technical requirements, for example, taking into account competition. Furthermore, the quality of the product was verified by using the Kano model [13, 14]. It consisted, for example, of grouping product attributes into categories according to the level of meeting customer requirements. According to the Kano model, attractive or obligatory attributes for the customer were determined. In turn, to predict customer expectations, relatively often the Naive Bayes Classifier [15-18] or Hidden Markov Chain [19] was used. In this case, the prediction was performed according to the actual and past customer requirements. An interesting approach was proposed by the authors of the article [20], in which two business models were compared, that is, business-to-business (B2B) and business-to-customer (B2C). The first model includes the delivery of intermediate goods ordered considering outsourcing. The second model is oriented toward the customer and includes mainly innovative products and finished products. A similar approach was presented in the article [21]. The mentioned B2B has an important impact on business. It was confirmed by the authors of work [22], in which the actions of medium-sized corporations (SMEs) were verified. The analysis was based on, e.g., impact B2B onto actions of these companies. In turn, the authors of the work [23] have focused on the impact of access to credit on process innovation in SMEs. The results have applications to help the managers' policy directions.

Despite that, no single coherent appliance to predict the quality of hypothetical modified products was developed. It applies to the lack of the method to predict customer satisfaction based on actual and future (hypothetical) product attribute values. The lack of this appliance was considered a gap, which is needed to fill.

Therefore, the aim of the article was to propose an appliance to predict the quality of the modification of hypothetical products. An appliance was developed using rightly selected and combined decision support techniques. As part of the analysis, it was accepted that it is possible to predict customer satisfaction based on customer assessment from current and future (hypothetical) product attribute states. In turn, the future state is contractually accepted and achievable. In previous work, product quality was predicted only based on earlier and actual product attribute values, as in works [11, 15, 19]. However, it was not based on future and actual attribute values, as in this approach. Additionally, the future attribute values are hypothetical values, i.e., not existing in a real state, but possible to be achieved while previous works focused on real values, which existed [24, 25]. Moreover, this article is effective for any company in predicting which modification of product will be satisfactory to the customers. It resulted from assumptions based on satisfaction with actual attribute values from which it is possible to precisely determine the expectations of customers in the context of hypothetical (possible) attribute values.

The verification of the proposed appliance was carried out on vacuum cleaner.

2 APPLIANCE OF RESEARCH

The appliance was developed by combined techniques, that is, survey research with the Likert scale [8], the AHP method (analytic hierarchy process) [10], Pareto rule (20/80) [26], the WSM method (Weighted Sum Model) [27-29], and Naïve Classifier Bayes [15-18]. The procedure of predicting product quality includes obtaining customers' expectations by using survey research. This survey allows determining the weights of product attributes and the quality of product attribute states. Using the AHP method, it was assumed to calculate attribute weights, which are grouped into important and not important attributes. Then, for important attributes, the combinations of these states are determined, and the next quality product levels are calculated. For this aim, the WSM method was used. On the basis of the hypothetical quality levels, the expected level according to the naive Bayes Classifier is predicted. An algorithm for the proposed appliance is shown in Fig. 1.

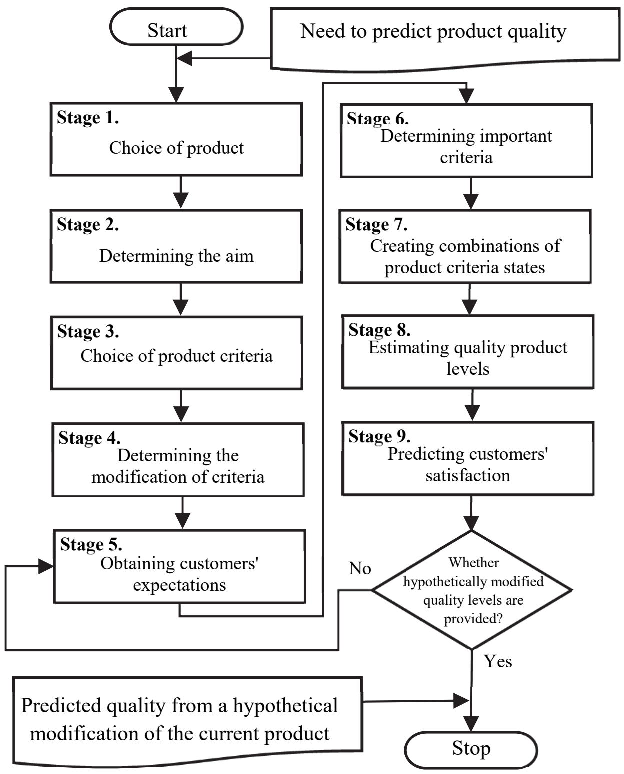

Figure 1 Algorithm for predicting the quality of hypothetically modified products

The choice of survey research with the Likert scale was based on the popularity and efficiency of this technique to obtain customer expectations [5, 8, 26]. Furthermore, the choice of the AHP method was conditioned on the possibility of determining the weights of the attributes of the product by comparison in pairs. Additionally, the AHP method is not complicated and is often used [6, 10]. In turn, the Pareto rule (20/80) was used with the possibility of grouping product attributes into important, or less important where the purpose was to determine important attributes (i.e., 20%) from which it is necessary to start improvement actions [26]. The next method, that is, the WSM method (Weighted Sum Model), was used in turn for its simplicity and the need to estimate the quality level of the product based on customer assessment and weights (importance) of the attributes of the product [27-29]. However, the Naive Bayes Classifier was used because it is not a complicated method, is effective in analyzing qualitative and quantitative data, and also applied to predict [16, 18].

The short characteristic of the proposed method is shown in nine stages.

2.1 Choice of Product

The first stage is choice of the product to analyse. The choice of product is made by an entity using the proposed appliance. Product selection can be influenced by its popularity, life cycle, or customer feedback.

2.2 Determining the Aim

The second stage is to determine the goal. The SMARTER method (Specific, Measurable, Achievable, Relevant, Time-Based, Exciting, Recorded) [30] can be used to correctly determine the aim. In the proposed method, the objective should be to predict the quality of the modification of product attribute states. Modifications are values determined from the current state, e.g., values above or below the current state.

2.3 Choice of Product Criteria

The third stage is the choice of the product criteria. For this purpose, any criteria that determine the quality of the product should be defined. The choice of criteria is realized on the catalogue (specify) of the product and during brainstorming (BM). According to the literature on the subject [4], the number of criteria should be equal to 14 to 25 criteria.

2.4 Determining the Modification of Criteria

The fourth stage is to determine the modification of the criteria. Modification should be determined based on the product catalogue. It relies on determining for each attribute of the product (from 2.3. stage) the parameter (value) or range values, i.e., current stage. Then, for each attribute, it is necessary to note at least a single modified value (i.e., hypothetical state, which can be used in future). The summary number of states (current and modified) for an attribute is equal to 7 ± 2 [4, 5, 27], where the fewer states of the criteria, the better.

2.5 Obtaining Customer Expectations

The fifth stage is to obtain the expectations of the customers. For this aim, the popular research survey with the Likert scale is used [6]. In these surveys, customers define their expectations regarding product quality by assessing the satisfaction with the status of the criteria and importance (weight) of these criteria. Customers determine the importance of all criteria (from stage 2.3.), where the weight is determined in the context of the use of the product. Additionally, the customer assessed all the criteria states, i.e. the current state and its modification (from Stage 2.4.). Through the comparison of current state with the modification state, it is possible to precisely determine customer expectations. It is recommended to obtain expectations from at least 100 customers [5]. However, to precisely determine the research sample to predict the expected level of product quality considering customer expectations, it is necessary to use the method presented in Reference [5].

2.6 Determining Important Criteria

The sixth stage is to determine important product criteria. It refers to determining which of the criteria should be improved first to achieve an increase in customer satisfaction. In this aim, a combination of methods is used: AHP method [6, 10], and Pareto rule (20/80) [26].

Hence, the analysis was performed based on n customers, and initial estimation results are needed for its future comparison in pairs. According to the authors of the work [5], for a small sample size (n < 100) it is necessary to calculate the median importance of the criteria from all the assessments. Therefore, for a large sample size (n > 100) it is necessary to calculate the average. Therefore, the importance assessments of the criteria were obtained at stage 2.5. in survey research.

Then, it is necessary to create the decision matrix $S = (S_{ij})$, i.e., the square matrix (dominance). In this matrix, the values of median or average are compared. For this purpose, the proportion of the i-th and j-th assessments of the product weights assessments is determined, where $S_{ij} = n \times n$, n - numbers of criteria (Eq. (1) to Eq. (2)) [6]:

$$S_{ij} \approx \frac{w_i}{w_j}, \text{ where } i, j = 1, 2, ..., k \tag{1}$$

$$S_{ij} = \frac{1}{S_{ij}}, \text{ where } i, j = 1, 2, ..., k \tag{2}$$

There are always values equal to 1 on the diagonal, i.e., the compared criteria are equivalent. Above the diagonal, the values from the comparisons of criterium pairs are written, and the reciprocal values under the diagonal.

Then the criteria weights are estimated. The values of the domination matrix are used for that. The normalized geometrics of the S_{ij} matrix is used to estimate the weights of the Eq. (3) [10]:

$$w_i^w = \frac{\left[\prod_{j=1}^{k} S_{ij}\right]^{\frac{1}{k}}}{\sum_{i=1}^{k}\left[\prod_{j=1}^{k} S_{ij}\right]^{\frac{1}{k}}}, \text{ for } i, ..., 1, ..., k \tag{3}$$

The sum of the values obtained should be equal to 1. Then, we conclude about correctness of calculations, where values w_i^w are product criteria weights. In turn, to verify persistence of preferences, the following coefficients are calculated: nonconformity coefficient (λ_{max}), concordance ratio of the pairwise comparison matrix (***CI***), and concordance ratio (***CR***). Eq. (4) to Eq. (6) are used for [6, 10]:

$$\lambda_{max} = \frac{1}{w_i}\sum_{j=1}^{k} w_{ij} w_j \tag{4}$$

$$\boldsymbol{CI} = \frac{\lambda_{max} - n}{r(n-1)} \tag{5}$$

$$\boldsymbol{CR} = \frac{\boldsymbol{CI}}{r} \tag{6}$$

where: w - the value of the normalized geometric average, n - the the number of criteria, r - mean value of a random index according to Saaty, i, j = 1, 2, …, k.

If $\lambda_{max} = 0$, $\boldsymbol{CI} = 0$, and $\boldsymbol{CR} = 0$ complete consistency of preferences is achieved. Acceptable consistency is achieved if $\lambda_{max} \approx$ n, and for $\boldsymbol{CI} < 0{,}1$ and for $\boldsymbol{CR} < 0{,}1$ [6]. Complete or acceptable consistency of preferences should be achieved. This means repeating the calculations until the correct result is obtained.

The Pareto rule (20/80) is used to choose important criteria. The choice is made based on estimated weights of criteria (w_i^w).The Pareto-Lorenz method is shown, e.g., in [26]. According to the 20/80 rule, 20% are important criteria, but 80% are less important criteria. According to the continuous development [26, 27, 29], the important criteria should be first refined.

2.7 Creating Combinations of Product-Criterion States

The seventh stage is to create combinations of product-criterion states. The combinations are determined for important product criteria (from stage 2.6.). To determine all possible combinations, Eq. (7) is used:

$$C_n^k = \frac{n!}{k!(n-k)!} \tag{7}$$

where: n - the number of all important criteria, k - the number of states for important criteria.

Combinations are determined for all possible states for important criteria. The combination includes a single state for the criterion. If the current state and future state (modified) are determined for each category, the combinations are created by Eq. (8):

$$C_{ij} = \left[s_1^1, s_2^1, s_3^1, ..., s_i^j\right] \tag{8}$$

where: s - state for important category, i - category; j - state, i, j = 1, 2, 3, …, n.

To determine a small number of combinations, it is helpful to create a relation tree between category states.

After determining all combinations (equal C_n^k) it is necessary to realize the next stage.

2.8 Estimation of Quality Product Levels

The eighth stage is to estimate the levels of quality products. In this aim, the WSM method (Weighted Sum Model) is used. The customers' assessments for criteria states (from stage 2.5.) have to be included. When the number of customers is above 100, it is necessary to estimate an arithmetic average as the satisfaction for attribute state. Therefore, for fewer customers, it is necessary to estimate a median [5]. Furthermore, attribute weights (from stage 2.6.) must be included. The quality levels are determined according to combinations of attribute states (from Stage 2.7.). Therefore, the number of quality levels is equal to the number of combinations of attributes. The quality level in the WSM method is estimated according to Eq. (9) [27-29]:

$$A_i^{WSM-score} = \sum_{j=1}^{n} w_j a_{ij} \tag{9}$$

where: w - weight of the i_{th} attribute, a - median or average of assessments for the j_{th} attribute state, $i, j = 1,2, \dots, n$.

As a result, quality level values are obtained for all combinations of attribute states. On the basis of that, it is possible to initially estimate customer satisfaction from product quality. The higher the value, the higher customer satisfaction with the level of quality of the product. For example, the maximum value of the product quality level is the most satisfying for the customer, and the minimum value is the least satisfying for the customer.

2.9 Predicting Customer Satisfaction

The ninth stage is to predict customer satisfaction. It is realized based on quality levels and initially estimated satisfaction from these levels. To predict, the Naive Bayes Classifier is used, which is a machine learning method. This classifier supports determining in which of the satisfaction groups is the quality level [15-18]. The Naive Bayes Classifier is operated on the program computer, e.g., STATISTICA 13.3. as a tool for mechanic learning. That is, the analysis of large data is more effective.

Customers' assessments about satisfaction from the criteria states are so-called vectors $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_r]$, whose components are so-called attributes ($\boldsymbol{x}_r$), where r - number of attributes. This set is divided into classes that are separable and its sum is equal to the whole space. Therefore, each point belongs to a single class, where C - set of all classes, c - a single class, and cC. The Bayes formula determines a probability condition, where A and B - observation of random events, $P(A)$ - probability of event A, but $P(A|B)$ - probability of A occurrence provided that B has occurred Eq. (10) [15, 16]:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{10}$$

where: $A \cap B$ - simultaneous occurrence of A and B, therefore the probability is determined also as Eq. (11) [17]:

$$P(A|B) = \frac{P(B|A)P(B)}{P(A)} \tag{11}$$

Additionally, the expression analyzed can be presented as the most probable class (np) (Eq. (12) to Eq. (13)) [18]:

$$c_{np} = arg \max_{c \in C} P(c|x_1, x_2, \dots, x_r) \tag{12}$$

$$c_{np} = arg \max_{c \in C} \frac{P(x_1, x_2, \dots, x_r|c)P(c)}{P(x_1, x_2, \dots, x_r)} \tag{13}$$

The elements included in the denominator are independent of class, therefore the result of classification. Hence, it is obtained Eq. (14) [15]:

$$c_{np} = arg \max_{c \in C} P(x_1, x_2, \dots, x_r|c)P(c) \tag{14}$$

If the probability obtained by Eq. (14) is known or it is possible to estimate it, it should be applied directly to the classification. The model created on the basis of this formula is the so-called optimal Bayesian classifier [15, 17].

In the proposed method, the number of the applications of Naive Bayes Classifier is equal to the number of combinations of criteria states. On the basis of obtained results, it is predicted which modification of the product states is the most favourable. This means anticipating what changes to the current product should be made to meet customer expectations at a satisfactory level of quality.

3 RESULTS

As part of verifying the proposed appliance, test research was carried out.

Following the first stage, the product to be analyzed, i.e., a vacuum cleaner for household use, was selected. It is commonly used, therefore it is considered that customers will easily determine their satisfaction and expectations.

As in the second stage, the objective was determined, i.e., predicting the quality of the hypothetically modified vacuum cleaner where modifications are values determined from the current state, e.g., values above or below the current state.

In the third stage, the criteria were selected. For this purpose, brainstorming (BM) was used. There were 10 basic attributes from the catalogue (specification) of the vacuum cleaner, i.e.: engine power, suction power, power cord length, operating range, power cord winding system dimensions, weight, noise level, cord width, on/off type. According to the order, these criteria were marked from C1 to C10. The characteristics of attributes are generally available, e.g. in vacuum cleaner catalogues.

According to the fourth stage, the attribute states were determined. For each attribute, a single current and modified state was noted. The modified (future) state was assumed to be a value above the current state. It resulted from the concept of an approach, i.e. determining the satisfaction of possible changes in the current state.

Then, in the fifth stage, customer expectations were obtained. In this aim, pilot research was carried out in 2020 in 24 customers. The Likert scale was used, i.e., 1 - the least satisfying criteria state or the least important criterion, 5 - the most satisfying criteria state or the most important criterion. The first part of the survey included the importance of the attributes of the vacuum cleaner in the context of its use. The second part of the survey included satisfaction from current and modified (future) states of the attributes of the vacuum cleaner. As part of the sixth stage, the important attributes were determined. Based on survey research, the median of 24 customers' assesses was calculated. Based on the median values, the analysis of the AHP method was carried out. According to Eq. (1) to Eq. (3), the decision matrix was created and the criteria weights were estimated (Tab. 1).

Table 1 Fragment of decision matrix for criteria weights

S_{ij}	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Weight
C1	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12
C2	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15
C3	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12
…											
C9	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06
C10	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06
where: C1 - engine power, C2- suction power, C3 - power cord length, C4 - operating range, C5 - power cord winding system, C6 - dimensions, C7 - weight, C8 - noise level, C9 - cord width, C20 - on/off type.											

The sum of the weight values was equal to 1. It was shown that the calculations were carried out correctly. The persistence of preferences was then checked. For this aim, the calculations from Eq. (4) to Eq. (6) were done. The results are shown in Tab. 2.

Table 2 Results of persistence of preferences for attribute weights

Attribute	Marked	Sum of weights	Weight	Indicator	Result
engine power	C1	1,21	0,12	λ_{max} = 10,00 ***CI*** = 0,00 ***CR*** = 0,00	complete consistency of preferences
suction power	C2	1,52	0,15		
length of the power cord	C3	1,21	0,12		
work range	C4	1,21	0,12		
power cord winding system	C5	0,91	0,09		
dimensions	C6	0,91	0,09		
scales	C7	0,91	0,09		
noise level	C8	0,91	0,09		
wire width	C9	0,61	0,06		
on / off type	C10	0,61	0,06		

Complete consistency of preferences, where λ_{max} = 10, ***CI*** = 0, ***CR*** = 0. Therefore, the attribute weights were correctly calculated. On the basis of this, the important attributes were selected. For this purpose, the Pareto-Lorenz analysis was realized. The results are shown in Tab. 3.

Table 3 Pareto-Lorenz analysis for attribute weights of vacuum cleaner

No.	Attribute	Weight	Cumulative value	Cumulative value / %
1	suction power	0,15	0,15	15,15
2	engine power	0,12	0,27	27,27
3	length of the power cord	0,12	0,39	39,39
4	work range	0,12	0,52	51,52
5	power cord winding system	0,09	0,61	60,61
6	dimensions	0,09	0,70	69,70
7	scales	0,09	0,79	78,79
8	noise level	0,09	0,88	87,88
9	wire width	0,06	0,94	93,94
10	on / off type	0,06	1,00	100,00

According to the 20/80 rule, the important attributes were selected, that is, suction power and engine power.

In the seventh stage, combinations of states of important attributes were determined. According to Eq. (8), $C_n^k = 4$ combinations for important attributes were determined. Based on these combinations, the product quality levels were estimated.

In the eighth stage, quality product levels were estimated by using the WSM (Weighted Sum Model) method. For this purpose, it was based on customer satisfaction with the attributes states and attribute weights. Due to the pilot studies (n = 24 customers), the median customer satisfaction rating was determined for attribute states. Then, based on the median from the assessments and attribute weights, the quality levels were estimated Eq. (15) to Eq. (18):

$$A_1^{WSM-score} = 3,12 \tag{15}$$

$$A_2^{WSM-score} = 3,18 \tag{16}$$

$$A_3^{WSM-score} = 3,18 \tag{17}$$

$$A_4^{WSM-score} = 3,12 \tag{18}$$

As a result, the 4 quality levels were estimated, which was the result of a combination of important attribute states. The quality level equal to 3,18 $\left(A_2^{WSM-score} \text{ and } A_3^{WSM-score}\right)$ was considered as satisfactory, e.i. maximum value. Therefore, the quality level equal to 3,12 was considered as less satisfactory, that is, the minimum value. On their basis, the quality level of the product was predicted, i.e., the ninth stage.

Based on the ninth stage, the expected quality level was predicted. It was realized based on initial customers' satisfaction for combinations of important attribute states.The Naive Bayes Classifier in STATISTICA 1.3. The program was used for that (Tab. 4).

Table 4 Predicting customer satisfaction

Quality level	*A priori value*	*Average value*	*Standard deviation*
satisfying	0,500	0,312	0,015
less satisfying	0,500	0,318	0,016

It has been shown that, with the assumptions adopted, the proposed modifications of the states of important product attributes will not affect the quality level of the vacuum cleaner. It is preferable to identify other possible modifications to these characteristics and reverify customer satisfaction.

4 DISCUSSION

Improvement of product quality is realized on customers' expectations. However, changes in customer satisfaction require their prediction [4, 5, 22, 25]. Therefore, the device was proposed to predict product quality levels. This prediction includes determining the combinations for different product states. A vacuum cleaner appliance test was carried out. As a result, small differences between customer satisfactions from different product modifications were observed. It was concluded that it is possible to predict product quality based on the actual and hypothetical attribute value. Therefore, previous works have concerned actual and/or earlier attribute values [11, 15, 19].

The results resulted from, e.g.:

- small sample size,
- possible from a small number of product states,
- small difference in customers' satisfaction for attribute states.
- generalization results in view of the calculation of a median of assessment of weights and satisfaction of attribute states, hence, future analysis will be concerned with the following:
- obtain a larger sample size (n > 100),
- determine more than two attribute states,
- analyze according to the arithmetic average from customers' assessments about attribute weights and satisfaction from attribute states.

Selected benefits from the proposed appliance are, e.g.:

- predicting product quality for different modifications of attribute states,
- predicting customer satisfaction from possible modification of the current product,
- develop a competitive product ahead of the competition,
- prevention of actions which will not beneficially impact product quality level.

In turn, a disadvantage of the proposed appliance is the tendency to generalize the data when the sample size is small. Therefore, future analysis will be about a larger sample size and use the arithmetic average in the main part of calculations.

5 CONCLUSION

The need to improve products caused by dynamic customer expectations generated a need to use different solutions in products. It covers the need to predict expected product modifications to develop a competitive product. Therefore, the objective was to propose an appliance to predict the quality of the hypothetical modification of products. This modification affected different combinations of product attribute states. The appliance was developed by combined techniques, that is, survey research with the Likert scale, the AHP method (Analytic Hierarchy Process), the Pareto rule (20/80), the WSM method (Weighted Sum Model) and Naïve Classifier Bayes. A vacuum cleaner appliance test was carried out. The modification of the product was determined as current and future states, i.e., value above current state. These states were determined for ten attributes, which were chosen during brainstorming (BM). As part of the test, expectations were obtained from 24 customers. These expectations were obtained by survey research with the Likert scale. In the survey, it was possible to determine the weights of vacuum cleaner attributes (i.e. importance) and satisfaction with the state of these attributes. The weightings of the attributes were transformed using the AHP method. As a result, the importance of these attributes was estimated according to the Pareto rule (20/80). Then combinations of important attributes were determined. According to the proposed appliance, four possible combinations of attribute states were determined. Next, for these combinations, the product quality levels were determined by using the WSM method (Weighted Sum Model). Initially, the quality levels for the second and third combinations were determined as satisfying quality levels, i.e. a maximum value equal to 3,18. Other quality levels were less satisfactory. Then, using the Naive Bayes Classifier, the product quality level was predicted. It has been shown that, with the adopted assumptions, the proposed modifications of the states of important product attributes determine a lack of change in the quality of vacuum cleaner.Therefore, it was necessary, for example, to identify other possible modifications of these attributes and to verify customer satisfaction.

The proposed apparatus turned out to be effective in predicting customer satisfaction for modified quality levels. Therefore, it can be used to predict the satisfaction of various products as part of product design or improvement activities.

6 A LIST OF ABBREVIATIONS AND SYMBOLS

λ_{max} - nonconformity coefficient [10],

- AHP – Analytic Hierarchy Process [6, 10],

- B2B - business-to-business [21],
- B2C - business to customer [22],
- Brainstorming (BM) [5],
- **CI** - comparison matrix (CI) [10],
- **CR** - concordance ratio [6],
- medium-sized companies (SMEs) [23],
- QFD - Quality Function Deployment [11, 12],
- $S = (S_{ij})$ - square matrix (dominance) [6],
- SMARTER (Specific, Measurable, Achievable, Relevant, Time-Based, Exciting, Recorded) [30],
- w_i^W - weights of criteria [10, 6],
- WSM - Weighted Sum Model [27, 28].

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