Vol. 34, No. 4 (2024) | DOI: 10.37190/ord240411

OPEN ACCESS

Operations Research and Decisions

www.ord.pwr.edu.pl

OPERATIONS RESEARCH AND DECISIONS QUARTERLY

Triangular fuzzy numbers for satisfactory quality-environmental decisions in product development

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Abstract

The paper presents a novel MCDM model aimed at enhancing satisfactory quality-environmental decisions in product development. The model integrates FAHP, FTOPSIS, Pareto–Lorenz and global sensitivity analyses. It enables to study products with respect to quality level, environmental impact throughout its life cycle and simultaneous consideration on quality level and environmental impact. Results of the research on the example of a smartphone demonstrate that the model successfully identified specific criteria for improvement, offering a valuable tool for enhancing customer satisfaction and promoting environmentally friendly product development. The originality of the research lies in the calculation of the average weights of product criteria with triangular fuzzy numbers, based on the principles of fuzzy logic and FAHP. As a compact, ready-to-use solution, our innovative MCDM model can be employed by organizations to enhance the quality and environmental impact of their products.

Keywords: *FAHP, FTOPSIS, quality, MCDM, production management*

1. Introduction

Management decisions have become increasingly complex, given the growing need to address sustainable development concerns related to product quality and the natural environment [6, 21, 25]. This is a significant issue as sustainable product enhancements account for approximately 80 percent of the overall environmental impact [24]. However, the multifaceted and intricate criteria involved in this process make it challenging to make informed quality-environmental decisions during product development, particularly in the early stages when precise data is often lacking [23, 32]. Therefore, there is an imperative to explore alternative procedures that facilitate the decision-making process in product development,

Received 25 September 2023, accepted 26 September 2024, published online 19 December 2024
ISSN 2391-6060 (Online)/© 2024 Authors

The costs of publishing this issue have been co-financed by the Department of Operations Research and Business Intelligence at the Faculty of Management, Wrocław University of Science and Technology, Wrocław, Poland

considering not only qualitative aspects (product quality) but also environmental impact. Surprisingly, simultaneous analysis of quality and environmental criteria in product improvement is not a commonly practiced approach [27, 35].

In an effort to support the decision-making process in product design, Luna et al. [16] developed a multicriteria decision-making method (MCDM), which involves the analysis of numerous criteria to evaluate alternative products but primarily focuses on quality criteria. Similarly, Ghoushchi et al. [18] adapted the failure modes and effects analysis (FMEA) to make decisions related to product quality. By integrating FMEA with other decision-making techniques such as stepwise weight assessment ratio analysis (SWARA) and grey relational analysis (GRA), Gerus-Gościewska and Gościewski [11] enhanced the process of identifying potential product incompatibilities. Yoshimura [34] presents a methodology for making product decisions, incorporating various criteria and considering the impact of individuals involved in decision-making. Empirical research that takes into account product quality and its impact on the natural environment was described in [12]. The analysis of product alternatives and decision-making possibilities in this research was carried out using the life cycle assessment (LCA), similarly to Macioł and Rębiasz [17]. Additionally, developed a tool using the quality function deployment (QFD) to consider customer and expert requirements as well as environmental aspects in the development of new products [5]. Finally, Yuan et al. [35] mapped research to customer expectations and government regulations to analyse their impact on producers' decisions related to the production of ecological products.

An extensive literature review revealed the existence of numerous methods for supporting the product development process, which primarily focus on analysing quality criteria to meet customer expectations [2, 17]. Moreover, some studies have combined quality and environmental criteria [2]. These methods are primarily designed to make informed decisions during the early stages of product design. Nonetheless, a research gap has been identified where no methods are available to facilitate quality-environmental decision-making as part of the product improvement process. Such an approach would involve assessing the feasibility of product development based on the current level of customer satisfaction with the product quality and its environmental impact. Our proposed model addresses this gap effectively.

Therefore, the aim of this research was to develop an MCDM model to facilitate the anticipation of satisfactory quality-environmental decisions during product development, as in [33]. The secondary goal was to provide a complete application procedure of our solution.

The originality of the model lies in its unique formula, which converts the average weights of the product criteria into weights defined by triangular fuzzy numbers. This procedure is grounded in fuzzy logic and the fuzzy analytical hierarchical process (FAHP). Fuzzy MCDM was discussed by Gawlik [32], Kokoç and Ersöz in [12] proposed its evolution, and Leśniak et al. its application for a complex decision-making problem [15]. Furthermore, model's originality extends to its capacity to analyse product development based on quality levels (customer satisfaction with the product's utility), environmental impact during the product's life cycle, and simultaneous consideration of quality level and environmental impact.

The novelty of the model lies in the integration of different MCDM techniques and quality management tools, including FAHP, Fuzzy Technique for Order Preference by Similarity to an Ideal Solution (FTOPSIS), Pareto–Lorenz rule, and global sensitivity analysis in one compact, ready-to-use solution.

The model was illustrated using a smartphone as a test product, however, it is applicable to any organization or expert seeking to enhance the quality and environmental impact of their products.

2. Model proposal

2.1. Research motivation

Our model involves a comprehensive analysis of various product alternatives to predict satisfactory quality-environmental decisions that would support appropriate product development. The objective of its application is to foresee the trajectory of product evolution, ensuring that it aligns with customer requirements for both quality and environmental sustainability. Our analysis covers several different products of the same range (e.g. several smartphone models), therefore same quality and environmental sustainability criteria apply to each product. Criteria are defined by the catalogue of the SimaPro LCA software. Product development decisions encompass following critical aspects:

- both product quality and its environmental impact are vital, criteria describing both categories above allow us to focus on those improvements, which will assure the highest customer satisfaction,
- product quality is directly linked to customer satisfaction – as it derives from product utility, and will be assessed with quality criteria,
- the environmental impact of a product should be considered for its negative or positive influence on the natural environment.

When making product development decisions, it is essential to determine satisfactory levels of product quality and environmental impact, so that the criteria of all examined product units can be improved accordingly. On basis of this assessment, decisions can be made on how to enhance the product criteria of the whole product range, particularly those with lower quality levels or higher environmental impacts. The importance (weight) of these criteria also plays a crucial role in determining their prioritization and improvement. Most important ones for the customers should be given the highest priority. This can be achieved by developing product rankings that evaluate the current quality and environmental criteria of each product unit, taking into account the significance of these criteria for customers. To achieve this, a three-stage analysis of different product units from the same product range is necessary, considering their quality level, environmental impact, and simultaneously, both quality level and environmental impact.

Product quality is determined by the degree of customer satisfaction, which customers independently define through survey research. Environmental impact is assessed primarily in terms of its negative implications, with use of the LCA. The analysis of products' environmental impacts encompasses considerations at various stages, including raw material acquisition, production, distribution, usage, and disposal. A panel of experts selects specific environmental criteria from a predefined product-specific list. In the survey research phase, customers assess the significance of both quality and environmental criteria using a 1–9 Saaty scale [29]. The collected data is then processed using the developed model. Subsequently, an expert panel takes into account customers' expectations and the products' environmental impact to evaluate overall product quality, employing the FTOPSIS. In result three distinct rankings arise: one for product quality, another for environmental impact, and a third for the simultaneous assessment of quality and environmental impact. The quality and environmental levels are analysed on Kolman's scale of relative states (SRS) [1, 9] to gauge customer satisfaction accurately. Additionally, sensitivity analysis is conducted to ensure precise results and facilitate well-informed decisions regarding product development.

2.2. Model assumptions

The proposed model is grounded in certain assumptions, which derive from a literature review, especially from [5, 20]:

- inclusion of various product ranges,
- analysis of no more than 10 product units (alternatives),
- quality criteria, determined by customers, relating to a product's utility,
- environmental criteria, established by experts, addressing the negative impact of products on the natural environment, based on the LCA,
- evaluation of the importance ratings of quality and environmental criteria using the 1–9 Saaty scale.

The assumptions above serve as the foundational principles for our research design and its methodological framework, which will be elaborated upon in the forthcoming section of the article.

2.3. Model design and application procedure

The proposed nine-stage model integrates such decision-making methods and techniques as fuzzy logic, fuzzy multi-criteria decision making (FMCDM) [8, 31], and quality management tools [10]. The model encompasses the 1–9 Saaty scale [28], triangular fuzzy numbers [34], FAHP [4], and FTOPSIS [33]. The fuzzy Saaty scale [29] was selected to mitigate inconsistencies and imprecision in criteria assessment.

The procedure for processing average criterion weights, based on fuzzy logic, transformed these weights into triangular fuzzy numbers, which were employed in the subsequent stages of the model [16].

FAHP was employed to compare each criterion in pairs, leading to more accurate results and reduced inconsistencies and imprecisions in assessments. This method is suitable for analyzing decision problems characterized by uncertainty, such as the assessment of environmental criteria by customers [20].

FTOPSIS was utilized to compare different product alternatives in terms of measurable and immeasurable criteria, using criteria weights determined as triangular fuzzy numbers. Siwiec et al. [23] mention, that FAHP and FTOPSIS are frequently being used in combination. Therefore both tools were incorporated into our model.

Additionally, quality management techniques such as brainstorming (BM) [28], Pareto–Lorenz analysis [14], SMART(-ER) method [10], experts selection method [13], research sample selection method [24], Kolman's SRS [1, 9], and global sensitivity analysis [19] were integrated into our solution. Figure 1 represents the application algorithm of the proposed model. Utilised methods and techniques are explained in consecutive stages of model application procedure.

The next part of the paper characterizes consecutive stages of model application.

Stage 1. The selection of products for analysis and its purpose. The entity leading the analysis selects the product units to be examined, all of which belong to the same product range. Mu and Pereyra-Rojas [19] recommend evaluating no more than ten products for their quality (utility satisfaction) and their negative environmental impact.

The analysis's purpose is determined after selecting the products to be assessed. The purpose of applying our model is to forecast satisfactory quality-environmental decisions that can facilitate appropriate product development. This purpose is established by the entity using the SMART(-ER) method, as illustrated in [14].

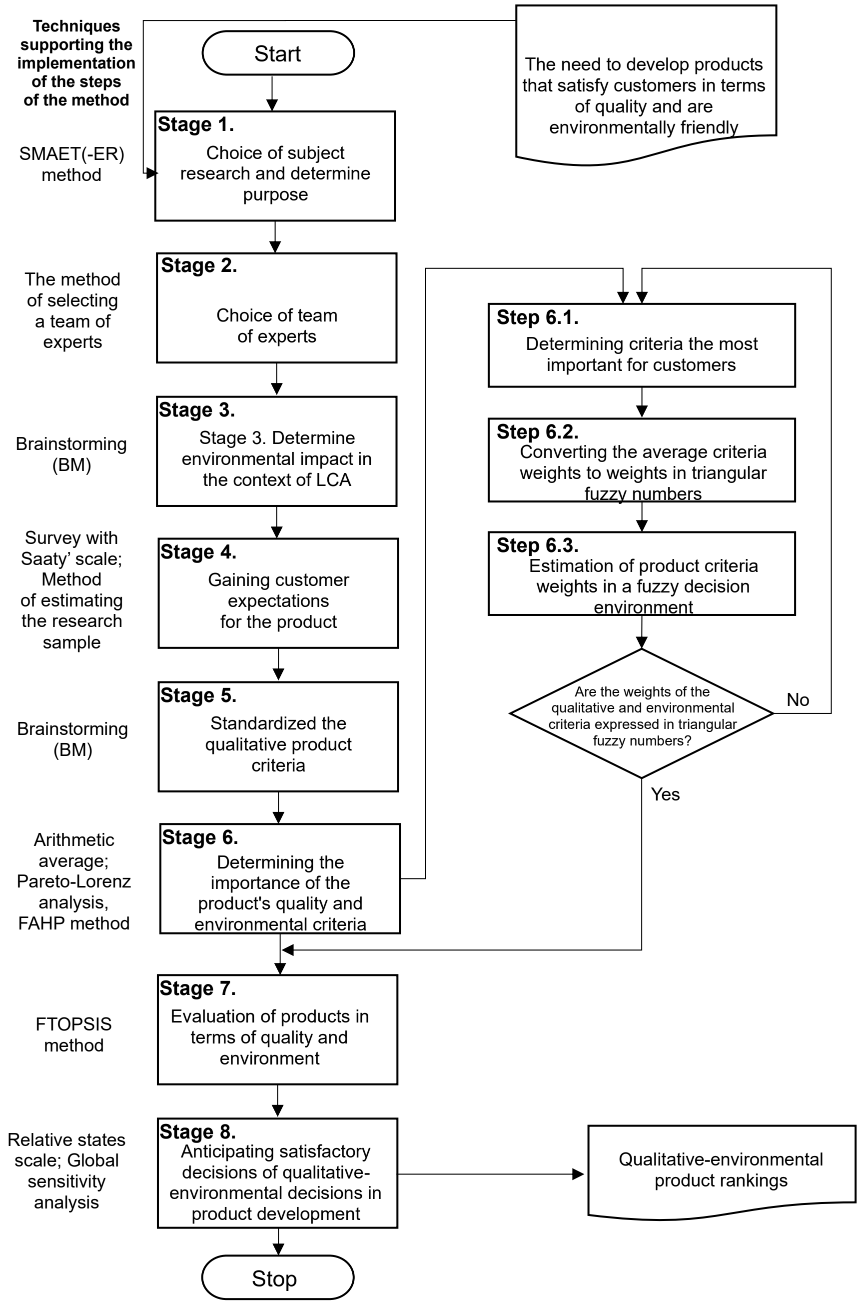

Figure 1. Algorithm of the MCDM model for anticipating satisfactory quality-environmental decisions in product development. Own elaboration based on research design.

Stage 2. Selection of the team of experts. The effective implementation of the proposed model hinges significantly on the collaborative efforts of the team of experts. Consequently, it is paramount to carefully choose individuals possessing extensive knowledge of the product domain, a deep understanding of its environmental implications, and outstanding teamwork capabilities. Notably, our model entails the involvement of an expert team responsible for defining environmental criteria, analysing customer expectations, and evaluating the product. Experts' selection remains a milestone of the model and adheres to the methodology delineated in [13, 26].

Stage 3. Determining environmental impact using LCA. Our model enables the analysis of products with respect to their environmental impact. The environmental criteria gauge the adverse effects that a product may impose on the natural environment throughout its entire life cycle, from the sourcing of raw materials to its disposal [3, 7, 18]. These environmental criteria are established by the team of experts as part of the brainstorming (BM) [27]. We recommend utilizing well-established LCA criteria available in SimaPro, Gabi, or OpenLCA software databases. In our solution, the initially identified 99 environmental criteria from LCA databases were consolidated to 25, as many of them were either identical or of similar significance:

- climate change,
- destruction/depletion of the ozone layer,
- toxicity to humans (including carcinogenic effects or not),
- ecotoxicity of water (fresh/land/sea),
- terrestrial ecotoxicity,
- formation of photo-oxidants,
- acidification (water/soil),
- eutrophication (water/terrestrial),
- global warming,
- depletion of the ozone layer,
- ozone formation (human health/terrestrial ecosystems),
- photochemical oxidant formation potential/photochemical ozone/ photochemical oxidation /photochemical ecotoxicity,
- waste (hazardous/bulky/radioactive/radioactive/deposited),
- abiotic depletion (elements/fossil fuels/other resources),
- particulate matter or inorganic substances in the respiratory system/effects on the respiratory system,
- ionising radiation (human health/ecosystems),
- land development,
- scarcity of resources (mineral/fossil/renewable/aquatic)/mineral extraction,
- water consumption/water track,
- heavy metals in water/soil/air,
- radioactive substances in air/water,
- water pollution,
- noise,
- soil pesticides,
- main air pollutants.

From the list of LCA environmental criteria, the team of experts can choose only those that are pertinent to the products being analysed. These selected criteria will undergo further analysis in the subsequent stages of the model.

Stage 4. Gathering customer expectations regarding the product. To gather information about customer expectations regarding a product, conducting a survey is a recommended approach. The number of customers to be surveyed can be determined using a specific method for estimating the sample size [1]. The survey should aim to collect the following information:

- product quality criteria that are significant to the customers,

- assessments of the validity of the product quality criteria,
- evaluations of the importance of the product's environmental criteria.

Customers commonly identify up to 10 quality criteria related to the product's usability [5, 20, 28]. These criteria can often be vague, inconsistent, and defined in a general manner, similar to the quality function development (QFD) [1]. All criteria mentioned by the customers are assessed for their importance using a 1–9 Saaty scale, where 1 – equally important, 2 – least important, 3 – very little important, 4 – slightly important, 5 – moderately important, 6 – slightly more important than moderately important, 7 – important, 8 – essential, 9 – most important [30].

Following this, customers assess the importance of the product's environmental criteria on the same scale. The criteria have been selected earlier by a team of experts in stage 3 of the model. Additionally, it is advisable to conduct interviews with customers to gather specific requirements regarding the product's parameters. The data collected from customers can be utilized in the subsequent stages of the application of our model.

Stage 5. Standardising the quality product criteria. The findings from the survey can be employed to standardize the quality criteria for the product range. Since customers often provide these criteria in a general format, it is crucial to process them in a standardized manner, a task carried out by a team of experts. Initially, the technical criteria outlined in the product specification sheet must be identified. Subsequently, all criteria mentioned by customers should be consolidated into a single list. Following this, the customer criteria should be aligned with the technical criteria. Any incorrectly entered customer criteria should be disregarded. In cases where customer criteria are named differently but pertain to the same category of customer requirements, standardization should be applied by adopting the criterion name specified in the product specification sheet. This process yields a comprehensive list of standardized product quality criteria that are pertinent to customers when using the product.

Stage 6. Assessing the significance of quality and environmental criteria. The next stage of the process entails a thorough examination of the importance ratings assigned to the product criteria identified by customers through the survey. The objective is to establish weights for each of the product criteria, facilitating further analysis within a fuzzy decision-making framework. This stage comprises three essential steps that must be executed with the utmost precision.

Step 6.1. Identifying the criteria of highest importance for customers. As part of the method, a survey will be conducted with customers to determine the weights of both quality and environmental criteria. Quality criteria will encompass factors influencing customer satisfaction with the product's usability, while environmental criteria will capture the product's negative impact on the natural environment throughout its life cycle. Customer weights will be ascertained using a 1–9 Saaty scale and then averaged to calculate the final weights for the quality criteria. For environmental criteria, average weight values will be computed directly from the survey results.

It is worth noting that since customers may hold varying opinions regarding the importance of the criteria, the criteria weight values will be averaged to yield mean values. These mean values will then be used to determine the average weight of the quality criterion. In the case of environmental criteria, average weight values will be calculated directly from the survey results. This approach ensures that the analysis is equitable and impartial, thereby accurately reflecting the preferences of the customer base:

$$w = \left(\frac{w_1 + w_2 + \cdots + w_n}{\sqrt{n}} \right) \tag{1}$$

To determine the most significant quality and environmental criteria, it is crucial to analyse the average weights of each criterion. A Pareto–Lorenz analysis should be conducted twice: to identify the most important quality criteria (i), to pinpoint the critical environmental criteria (ii).

For quality criteria, the analysis involves examining the frequency of each criterion's occurrence, as there may be variations among the criteria provided by customers. This is necessary because customers may submit different criteria, and some of them may overlap. A standardized list of quality criteria is then established based on the average weight ratings of the criteria. Consequently, the most vital quality criteria for customers are those that occur most frequently, aligning with the 20/80 rule [33]. Their importance will be expressed through the estimated average values of their weight ratings.

As for environmental criteria, the analysis focuses on the average values of their weights. This is because each customer in the survey assessed every environmental criterion. Therefore, the weights (average values of the environmental criteria ratings) should be arranged in descending order and analysed by computing the cumulative value and percentage cumulative value for each criterion's occurrences. Based on the Pareto–Lorenz principle, the first 20% of environmental criteria are considered the most important for customers and warrant further analysis [22, 33].

Step 6.2. Transforming the average criteria weights into triangular fuzzy numbers. The weights allocated to the quality and environmental criteria are determined by calculating the mean values of their respective importance ratings. These weights are then converted into triangular fuzzy numbers. In practice, this transformation involves adding up the weight ratings on the 1–9 Saaty scale, which were employed to assess the significance of both the quality and environmental criteria. Following [5, 12, 13], the summation of these values is put into the matrix $M_{ij} = [a_{ij}]_{1x9}$. A visual representation of this process is presented in Table 1.

Table 1. The sum of product criteria importance ratings
(separately for quality criteria and for environmental impacts)

	1	2	3	4	5	6	7	8	9
1	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
2	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00
3	4.00	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00
4	5.00	6.00	7.00	8.00	9.00	10.00	11.00	12.00	13.00
5	6.00	7.00	8.00	9.00	10.00	11.00	12.00	13.00	14.00
6	7.00	8.00	9.00	10.00	11.00	12.00	13.00	14.00	15.00
7	8.00	9.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00
8	9.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00	17.00
9	10.00	11.00	12.00	13.00	14.00	15.00	16.00	17.00	18.00

Subsequently, the quotient of the sum of Saaty's 1–9 ratings from Table 1 are estimated as followsn

$$b_{ij} = \left(\frac{a_{ij}}{2} \right) \tag{2}$$

The b_{ij} values represent the boundary values of the average weights of quality or environmental criteria (Table 2).

Table 2. Boundary values of the average weights of quality or environmental criteria

	1	2	3	4	5	6	7	8	9
1	1.00	1.50	2.00	2.50	3.00	3.50	4.00	4.50	5.00
2	1.50	2.00	2.50	3.00	3.50	4.00	4.50	5.00	5.50
3	2.00	2.50	3.00	3.50	4.00	4.50	5.00	5.50	6.00
4	2.50	3.00	3.50	4.00	4.50	5.00	5.50	6.00	6.50
5	3.00	3.50	4.00	4.50	5.00	5.50	6.00	6.50	7.00
6	3.50	4.00	4.50	5.00	5.50	6.00	6.50	7.00	7.50
7	4.00	4.50	5.00	5.50	6.00	6.50	7.00	7.50	8.00
8	4.50	5.00	5.50	6.00	6.50	7.00	7.50	8.00	8.50
9	5.00	5.50	6.00	6.50	7.00	7.50	8.00	8.50	9.00

The boundary values of the average weights of quality criteria or environmental impact criteria are reduced to triangular fuzzy numbers, which are described by three elements (l_{ij}, m_{ij}, u_{ij}) [3]. Figure 2 shows two fuzzy numbers $\tilde{W}_i = (l_{ij}, m_{ij}, u_{ij})$ and $\tilde{W}_j = (l_{ji}, m_{ji}, u_{ji})$, where $\mu_{\tilde{w}_l}(d)$ is the degree of membership to $\tilde{W}_l$.

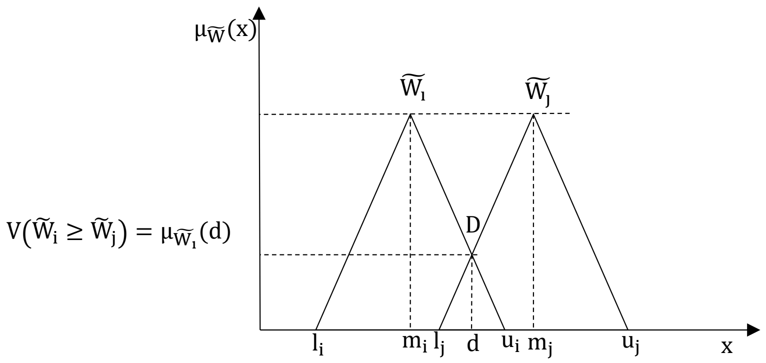

Figure 2. Determination of the coordinates of the point of intersection $\tilde{W}_i$ and $\tilde{W}_j$

Table 3 shows the triangular fuzzy numbers obtained by processing boundary values of the average weights of quality criteria or environmental impact criteria.

Table 3. Triangular fuzzy numbers corresponding to the boundary values of the average weights of quality criteria or environmental impact criteria

	1	2	3	4	5	6	7	8	9
1	1, 1, 1	1, 2, 3	1, 2, 3	2, 3, 4	2, 3, 4	3, 4, 5	3, 4, 5	4, 5, 6	4, 5, 6
2	1, 2, 3	1, 2, 3	2, 3, 4	2, 3, 4	3, 4, 5	3, 4, 5	4, 5, 6	4, 5, 6	5, 6, 7
3	1, 2, 3	2, 3, 4	2, 3, 4	3, 4, 5	3, 4, 5	4, 5, 6	4, 5, 6	5, 6, 7	5, 6, 7
4	2, 3, 4	2, 3, 4	3, 4, 5	3, 4, 5	4, 5, 6	4, 5, 6	5, 6, 7	5, 6, 7	6, 7, 8
5	2, 3, 4	3, 4, 5	3, 4, 5	4, 5, 6	4, 5, 6	5, 6, 7	5, 6, 7	6, 7, 8	7, 8, 9
6	3, 4, 5	3, 4, 5	4, 5, 6	4, 5, 6	5, 6, 7	5, 6, 7	6, 7, 8	6, 7, 8	7, 8, 9
7	3, 4, 5	4, 5, 6	4, 5, 6	5, 6, 7	5, 6, 7	6, 7, 8	6, 7, 8	7, 8, 9	7, 8, 9
8	4, 5, 6	4, 5, 6	5, 6, 7	5, 6, 7	6, 7, 8	6, 7, 8	7, 8, 9	7, 8, 9	8, 9, 10
9	4, 5, 6	5, 6, 7	5, 6, 7	6, 7, 8	6, 7, 8	7, 8, 9	7, 8, 9	8, 9, 10	8, 9, 10

Based on Table 3, the values of quality criteria or environmental impact criteria or combined quality -environmental criteria were compared in pairs. This is a critical step in FAHP application illustrated below.

Step 6.3. Estimating product criteria weights in a fuzzy decision-making environment. The criteria weights for product quality and environmental impact are estimated using the FAHP, which involves separate procedures for each criterion. To accomplish this, a matrix of pairwise comparisons of product criteria is created (equation (3)) [30]:

$$A = a_{ij} = \begin{bmatrix} 1 & \dots & a_{1n} \\ \dots & \dots & \dots \\ \dfrac{1}{a_{1n}} & \dots & 1 \end{bmatrix} \tag{3}$$

The average values of the criteria weights are compared, and the result yields the value of the triangular fuzzy number in Table 3. Subsequently, the fuzzy geometric mean value $\tilde{r_i}$, is computed, as [4]:

$$\tilde{A}_1 \otimes \tilde{A}_2 \ = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \tag{4}$$

where l – first triangular fuzzy number, m – second triangular fuzzy number, u – third triangular fuzzy number, A – compared criterion of the decision matrix.

Next, fuzzy weights $\tilde{w_i}$ of all criteria are computed using equations [34]:

$$\tilde{w_i} = (\tilde{r_i} \otimes (\tilde{r_1} \otimes \tilde{r_2} \otimes \dots \otimes \tilde{r_n})^{-1}, \quad \tilde{A^{-1}} = (l, m, u)^{-1} = \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l}\right) \tag{5}$$

$$(\tilde{r_1} \otimes \tilde{r_2} \otimes \dots \otimes \tilde{r_n})^{-1} = \left((l_1 + \dots + l_n, m_1 + \dots + m_n, u_1 + \dots + u_n)^{-1}\right) \tag{6}$$

where r – fuzzy geometric mean value, i – criterion, $i = 1, 2, \dots, n$.

It is also possible to represent the fuzzy weights as natural numbers using the center of area (COA) defuzzification principle [34]:

$$COA = \left(\frac{l_i + m_i + u_i}{3}\right) \tag{7}$$

where l, m, u – fuzzy values of the weights of a given criterion $i, i = 1, 2, \dots, n$.

Fuzzy values of the weighting of criteria become the inputs into the seventh stage of application of the model.

Stage 7. Assessment of product quality and environmental impact. In the process of anticipating satisfactory quality and environmental decisions to support product development, an evaluation of existing products, often referred to as alternatives, is employed. Experts conduct product assessments based on their expertise and the customer expectations gathered during initial interviews. The team of experts conducting the evaluation relies on parameters provided for these products, as well as Saaty's 1–9 fuzzy scale (Table 3) and other pertinent literature, including [31]. To assess the products, the team utilizes the following equation to express the evaluation of products in accordance with the criteria represented by triangular fuzzy numbers:

$$\tilde{x_{ij}} = (l_{ij}, m_{ij}, u_{ij}) \tag{8}$$

where l – first triangular fuzzy number (leftmost), m – second triangular fuzzy number (middle), u - third triangular fuzzy number (rightmost).

FTOPSIS is a widely utilized evaluation technique for appraising various product alternatives based on specific criteria. Product evaluation can be executed through three distinct approaches: considering quality criteria, environmental criteria, or both, contingent upon the entity's needs.

To initiate the evaluation process, a consolidated decision matrix must be constructed, drawing from expert assessments. This involves amalgamating all evaluation matrices provided by T experts and representing them using equations (9) and (10) [29]:

$$\tilde{A_{ij}} = (l_{ij} + m_{ij} + u_{ij}) \tag{9}$$

$$\begin{cases} l_{ij} = \min(l_{ij}^T) \quad \forall T \\ m_{ij} = m_{ij}^{T\,1/n} \quad \forall T \\ u_{ij} = \max(u_{ij}^T) \quad \forall T \end{cases} \tag{10}$$

where $\tilde{A_{ij}}$ – values obtained after multiple comparisons of wrong opinions in relation to the ith item assessed against the jth item, T – expert, l_{ij} is the minimum value on the left end, m_{ij} – the geometric mean of the middle values, u_{ij} – the maximum value on the right.

A normalized fuzzy decision matrix is established based on the combined decision matrix. Normalization requires to define benefit criteria and cost criteria. Benefit criteria are those for which higher values are preferable, while cost criteria are those for which lower values are preferable. The responsibility of designating whether the criteria are favourable or unfavourable lies with the team of experts, taking into consideration the criterion's values or value range.

For environmental criteria, cost criteria are applied, signifying that a more negative environmental impact is less favourable. In contrast, quality criteria may encompass various categories. Depending on the nature of the criterion, the values that delineate the criteria for benefit and cost criteria must be determined [34]:

$$\begin{cases} \tilde{r_{ij}} = \left(\dfrac{l_{ij}}{{u_i}^*}, \dfrac{m_{ij}}{{u_i}^*}, \dfrac{u_{ij}}{{u_i}^*}\right) {u_j}^* = \max u_{ij} \\ \tilde{r_{ij}} = \left(\dfrac{{l_j}^-}{u_{ij}}, \dfrac{{l_j}^-}{m_{ij}}, \dfrac{{l_j}^-}{l_{ij}}\right) {l_j}^- = \min l_{ij} \end{cases} \tag{11}$$

where l, m, u – triangular fuzzy numbers, i – criteria, j – products (alternatives), $i, j, 1, 2, \ldots, n$, $\max u_{ij}$ – for benefit criteria, $\min l_{ij}$ – for cost criteria.

A crucial step in the decision-making process is the development of a weighted normalized decision matrix. This involves merging the values from the normalized fuzzy decision matrix with the criteria weights [5]:

$$\begin{cases} \tilde{v_{ij}} = \tilde{r_{ij}} \otimes w_{ij} \\ (l_{ij}^r, m_{ij}^r, u_{ij}^r) \otimes (l_{ij}^w, m_{ij}^w, u_{ij}^w) = (l_{ij}^r \times l_{ij}^w, m_{ij}^r \times m_{ij}^w, u_{ij}^r \times u_{ij}^w) \end{cases} \tag{12}$$

where r – values from the normalized decision matrix, w – criterion weight, l, m, u – values in terms of fuzzy triangular numbers, $i, j = 1, 2, \ldots, n$.

Subsequently, the next part of the solution is calculated [25], which involves determining the fuzzy positive ideal solution (FPIs for A^*) and fuzzy negative ideal solution (FNIs for A):

$$\begin{cases} A^* = (\tilde{v_1}^*, \tilde{v_2}^*, \dots, \tilde{v_n}^*, \quad \tilde{v_j}^* = \max v_{ij3} \\ A^- = (\tilde{v_1}^-, \tilde{v_2}^-, \dots, \tilde{v_n}^-, \quad \tilde{v_j}^- = \min v_{ij1} \end{cases} \tag{13}$$

where v – values from the weighted normalized decision matrix, i, j – $1, 2, \dots, n$.

The following equations are utilized to calculate the distance between each alternative and both the positive and negative ideal solutions [5]:

$$\begin{cases} d(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{3}\left((l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right)} \\ d_i{}^* = \sum d(\tilde{v}_{ij}, \tilde{v}_j^*) \\ d_i{}^- = \sum d(\tilde{v}_{ij}, \tilde{v}_j^-) \\ CC_i = \dfrac{d_i{}^-}{d_i{}^- + d_i{}^*} \end{cases} \tag{14}$$

where l, m, u – triangular fuzzy numbers corresponding to a weighted normalized decision matrix and a fuzzy positive ideal solution or a fuzzy negative ideal solution, $i, j - 1, 2, \dots, n$.

Products are sorted based on the values of CC_i. The highest value secures the top position in the ranking, signifying the most advantageous product. Depending on the chosen approach to product analysis, a product ranking is established based on: product quality $(Q - CC_i)$, environmental impact $(E - CC_i)$ or combined quality-environmental perspective $(QE - CC_i)$. Additionally, it is feasible to conduct three separate analyses where the ultimate quality and environmental decisions concerning product development are determined by examining individual product rankings, possibly considering factors such as the company's production capacity.

Stage 8. Anticipating satisfactory decisions for quality-environmental product development. Within the framework of the developed method, it is feasible to ascertain the degree of customer satisfaction, considering both quality and environmental criteria. This is accomplished by employing the CC_i (derived from step 7 of our model). The satisfaction level is determined using Kolman's SRS [1, 9], as illustrated in Figure 3.

The utilization of Kolman's SRS allows for a descriptive definition of the expected satisfaction level regarding a specific product range. This entails assigning values to individual CC_i values to determine the corresponding level of satisfaction. Such an approach facilitates informed decisions regarding the development of other products that can be adjusted to meet customer needs.

As our analysis encompasses both quality and environmental criteria, a sensitivity analysis can be conducted to assess the impact of these criteria on the final product ranking. This analysis provides insight into more appropriate development decisions by determining the extent to which each criterion affects the final decision-making process. Statistical software such as STATISTICA can be employed to perform sensitivity analysis.

Sensitivity analysis implies the development of a neural network model. The input (explanatory) variables are the indicator values (CC_i) for the analysis data, both for the quality criteria $(QE - CC_i)$ and for the environmental criteria $(E - CC_i)$. The output (dependent) variable under consideration is a result derived from a quality-environmental indicator referred to as $(QE - CC_i)$. Since the analysed variables are non-linear, the analysis is performed with use of a regression model. To enhance the neural network's ability to generalize data, it is recommended to use three distinct sets of data: a training sample (70%), a test sample (15%), and a validation sample (15%). The generator value is set at 1000. The optimal neural network is selected after testing multiple models with varying numbers of neural networks in the hidden layer or activation function.

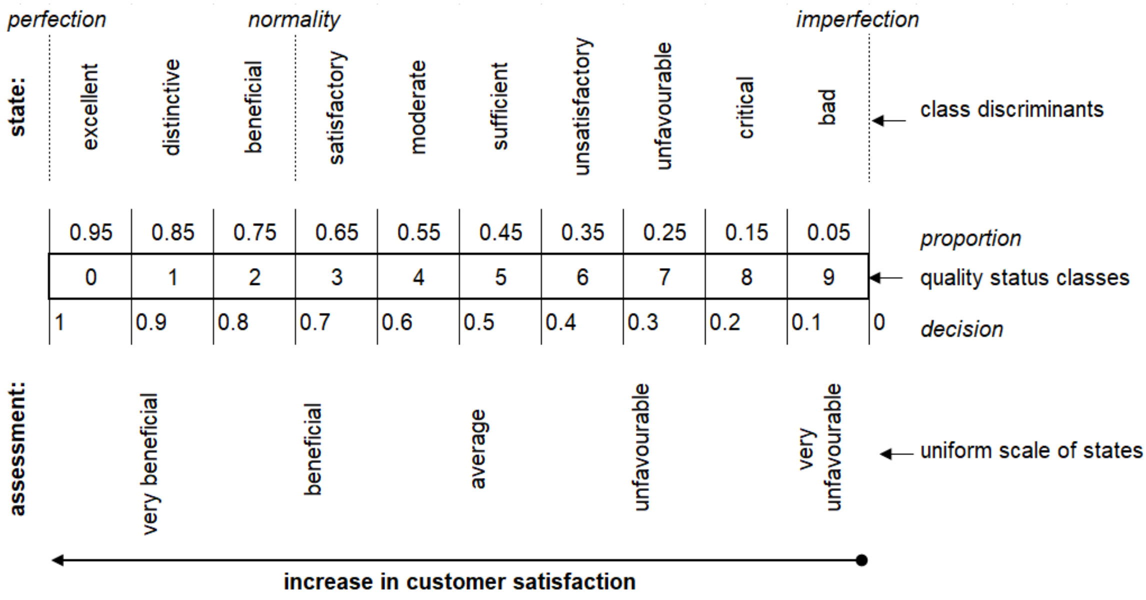

Figure 3. Kolman's scale of relative states

After the neural network is chosen, a global sensitivity analysis is performed. If a given type of criteria yields a global sensitivity analysis value exceeding 1, it is considered significant and has a substantial impact on the product classification. The sensitivity analysis values for the quality criteria and the environmental criteria should be compared. If the values are relatively similar, they may have a comparable effect on the final product ranking. If they are not, emphasis should be placed on the criteria with the predominant value of the sensitivity analysis. Based on the findings of the analysis, decision-makers can anticipate satisfactory quality and environmental decisions in product development, culminating in the final phase of our model.

3. Results

The illustration of the developed method was conducted on a range of smartphones. The illustration procedure was carried out meticulously, following an eight-step method in a comprehensive manner.

Stage 1. The selection of products for analysis and its purpose. Our study focused on smartphones, chosen due to their widespread customer usage and the rapidly changing market dynamics. However, the proliferation of newer smartphone models has raised environmental concerns and promoted consumerism, which necessitates addressing these issues. The analysis included ten different smartphones from various manufacturers, all belonging to the new-generation category, and they were conventionally labelled as P1 to P10. In line with the research topic, the analysis purpose was established using SMART(ER). In this method, the goal was to anticipate satisfactory quality and environmental decisions in the development of smartphones.

Stage 2. Selection of the team of experts. The application of our model requires a precise selection of a team of experts responsible for overseeing the chosen stages of model application. The team was carefully chosen following [13]. The selected individuals possessed extensive knowledge about the products under analysis, including their environmental impact. In the model illustration phase, the team of experts included the authors of the article and a production worker.

Stage 3. Determining environmental impact using LCA. The criteria for assessing the environmental impact of smartphones throughout their life cycle were carefully selected. These criteria were chosen during a BM session conducted by the team of experts. They were selected from the LCA software databases, as mentioned above. The team reached a unanimous consensus that all the proposed criteria were pertinent to the analysis of the selected research subject. Consequently, all the criteria were included in the survey, which was the subsequent step of this method.

Stage 4. Gathering customer expectations regarding the product. Subsequently, customer expectations regarding smartphones were gathered through surveys, which were conducted in June 2023 and involved 83 randomly selected customers. Each survey consisted of three stages. Initially, customers were asked to identify up to ten quality criteria that they considered important for smartphones. Following this, customers rated the importance of all the criteria they had identified using a 1–9 Saaty scale. In the final stage, customers assessed the importance of environmental criteria using the same scale. Additionally, customer interviews were conducted to gain insight into their initial expectations regarding the product parameters. The data collected from these surveys provided valuable insights for the subsequent stages of model application.

Stage 5. Standardising the quality product criteria. A standardized list of criteria was developed based on the quality criteria obtained from the customer surveys. This list was based on the technical specifications found in the smartphone product sheets. The technical criteria were then aligned with the corresponding customer criteria. Any customer criteria that were incorrectly provided, such as opinions, material, ease of use, replaceable parts, components, brand, prestige, or those that were ambiguous, were excluded. The remaining criteria were categorized as shown in Table 4.

The outcome was a standardized list of 29 criteria for smartphones that were considered relevant to customers. These criteria were subjected to further analysis in the subsequent steps of model application.

Stage 6. Assessing the significance of quality and environmental criteria. The evaluation of smartphone criteria, as indicated and assessed by customers in the survey, aimed to determine their relative importance. This stage's objective was to establish criteria weights for further analysis within a fuzzy decision-making environment.

Customers assigned weights to quality criteria influencing their satisfaction with the smartphone's usability and environmental criteria related to the smartphone's entire life cycle. Weights were assigned on a 1–9 Saaty scale.

For quality criteria, customer-assigned weights were matched to the corresponding 29 criteria from a predetermined list (as outlined above, in Step 5 of model application). From these weight assessments, the average weight for each quality criterion was calculated. For environmental criteria, the average weight values were directly computed from the survey results using equation (1).

Table 4. Smartphone criteria defined by customers

Criteria for analysis	Exemplary customers' criteria
Camera	camera, good camera, quality of camera
Stylus	stylus
Payment	payment
Face ID	face ID
Multiple wallpapers possible	multiple wallpapers possible
Frequent updates	frequent updates, updates
Security	privacy protection
Functionality	functionality
Availability of programs/accessories	access to programs, availability of accessories, availability
Fingerprint reader	fingerprint reader, fingerprint, fingerprints
Communication	communication, microphone, call quality, infrared
Multimedia	speaker, speakers, sound quality, speaker quality
Software	built-in memory, RAM, number of processor cores, amount of memory, memory, software memory, etc.
Guarantee	long system support, long life, many years, year of production, durability
Housing colour	design, aesthetics, colour, housing colour, appearance
Waterproof	resistance, waterproof
Dual SIM	dual SIM
Processor model	processor type
NFC	NFC
USB	type of USB input
Touchscreen	touch screen, screen, type of screen, touch
Screen diagonal	size (inches), screen size, screen diagonal, screen width
Screen resolution	screen resolution
Battery capacity	battery life, battery capacity, battery endurance, battery consumption
Battery type	good battery, battery, charging power
Wireless charging	charger, fast charging, charging speed
Dimensions	large, compact, size, dimensions, size, handiness, compatibility
Weight	weight, size of the smartphone
Case	housing, metal housing, softness, shape, build quality

The most important criteria for customers were subsequently identified from both the quality and environmental criteria using Pareto–Lorenz analysis. In our model, the analysis of quality criteria involved assessing the frequency of their appearances in the specified list of criteria. This entailed determining how many times a particular quality criterion appeared in the list, sorting them in descending order, and calculating the cumulative value and percentage cumulative value of the frequency of these criteria. The Pareto–Lorenz principle was then applied to identify the top 20% of criteria that were the most significant to customers in terms of quality. The results of this analysis are illustrated in Figure 4.

Based on the Pareto–Lorenz analysis, following the 20/80 rule, it was determined that the most crucial criteria for customers were: software, camera, housing colour, battery type, warranty, battery capacity, dimensions, and screen diagonal. The number of 8 criteria modifies the Pareto rule to a 25–75 ratio, which is the result of our arbitrary decision to include additional two close criteria, for their relatively high importance for the research subject (smartphone). These criteria have been duly accounted for in the subsequent stages of model application.

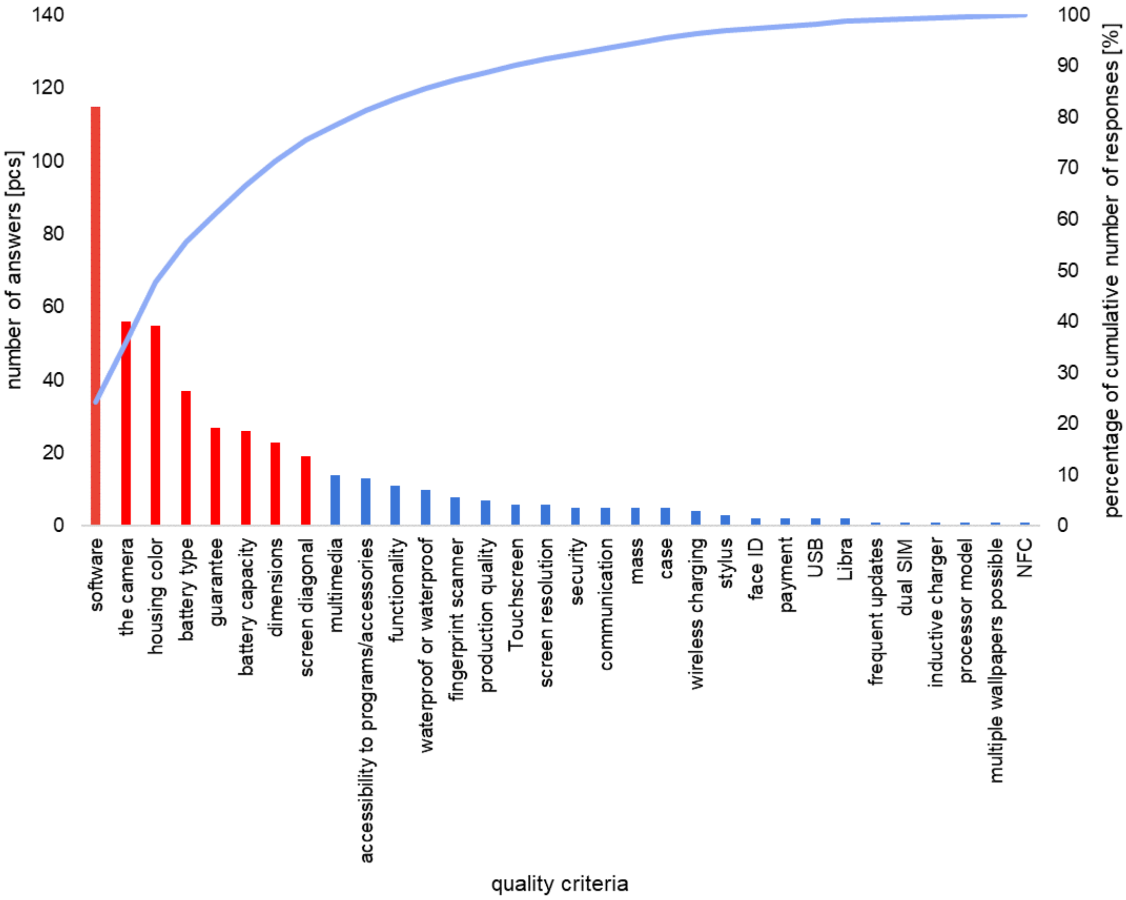

Figure 4. Pareto–Lorenz analysis for quality criteria. Own elaboration based on research results.

Furthermore, the environmental criteria underwent a Pareto–Lorenz analysis, employing the average values of their weights. The criteria were arranged in descending order of their average values. Subsequently, the cumulative value and cumulative percentage of the occurrence frequency of the criteria were calculated. In line with the Pareto–Lorenz principle, the top 20% of criteria were regarded as the most significant for customers. These criteria include:

- main air pollutants,
- radioactive substances into air/water,
- water pollution,
- waste,
- heavy metals,
- human toxicity,
- global warming,
- water consumption/water footprint.

Table 5 displays the average values of the importance ratings assigned by customers to various criteria for smartphones.

Table 5. Average values of the weights of quality criteria and environmental impact

No.	Quality criterion	Average weight value	Environmental criterion	Average weight value
1	Software	7.50 ≅ 8.00	major air pollutants	6.47≅ 6.00
2	Camera	7.52 ≅ 8.00	radioactive substances	6.31 ≅ 6.00
3	Housing colour	6.05 ≅ 6.00	water pollution	6.16 ≅ 6.00
4	Battery type	7.86≅ 8.00	waste	6.12 ≅ 6.00
5	Guarantee	7.56 ≅ 8.00	heavy metals	6.08 ≅ 6.00
6	Battery capacity	8.15 ≅ 8.00	toxicity to humans	6.07 ≅ 6.00
7	Dimensions	6.39 ≅ 6.00	global warming	5.96 ≅ 6.00
8	Screen diagonal	6.79 ≅ 7.00	water consumption/water footprint	5.73 ≅ 6.00

Average weights have been rounded to whole numbers.

Following the design of our decision-making model, triangular fuzzy numbers were employed to process the average weights of the quality criteria and their impact on the natural environment, following the approach outlined in Step 6.2. The FAHP method was used to determine the final values of the weights for the smartphone criteria. It's important to note that this method was exclusively applied to quality criteria, as the average weights for environmental criteria were uniform. Therefore, it was assumed that all environmental criteria had weights in triangular fuzzy numbers equal to (5, 6, 7).

Regarding quality criteria, a pairwise comparison matrix was developed using equation (3). This matrix was constructed based on the average weights of these criteria and Table 3, which provided the corresponding triangular fuzzy numbers. The results are presented in Table 6.

Table 6. Matrix of pairwise comparisons of quality criteria in the FAHP method

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Q1	1, 1, 1	1, 1, 1	6, 7, 8	1, 1, 1	1, 1, 1	1, 1, 1	6, 7, 8	7, 8, 9
Q2	1, 1, 1	1, 1, 1	6, 7, 8	1, 1, 1	1, 1, 1	1, 1, 1	6, 7, 8	7, 8, 9
Q3	6, 7, 8	6, 7, 8	1, 1, 1	6, 7, 8	6, 7, 8	6, 7, 8	6, 7, 8	7, 8, 9
Q4	1, 1, 1	1, 1, 1	6, 7, 8	1, 1, 1	1, 1, 1	1, 1, 1	6, 7, 8	7, 8, 9
Q5	1, 1, 1	1, 1, 1	6, 7, 8	1, 1, 1	1, 1, 1	1, 1, 1	6, 7, 8	7, 8, 9
Q6	1, 1, 1	1, 1, 1	6, 7, 8	1, 1, 1	1, 1, 1	1, 1, 1	6, 7, 8	7, 8, 9
Q7	6, 7, 8	6, 7, 8	1, 1, 1	6, 7, 8	6, 7, 8	6, 7, 8	1, 1, 1	6, 7, 8
Q8	7, 8, 9	7, 8, 9	6, 7, 8	7, 8, 9	7, 8, 9	7, 8, 9	6, 7, 8	1, 1, 1

Q1 – software, Q2 – camera, Q3 – housing colour, Q4 – battery type, Q5 – warranty, Q6 – battery capacity, Q7 – dimensions, Q8 – screen diagonal.

Subsequently, equation (4) was applied to compute the fuzzy geometric mean value of these criteria $\tilde{r}_i$. Following this, equations (5) and (6) were utilized to calculate the fuzzy weights $\tilde{w}_i$. The results are presented in Table 7.

Fuzzy weights of quality criteria $\tilde{w}_i$ have been incorporated into the FTOPSIS method. However, the process for estimating the fuzzy weights for the environmental criteria was omitted due to the identical average values of these criteria. Therefore, it was assumed that the weights of all environmental criteria are represented by triangular fuzzy numbers with values of (5, 6, 7).

Table 7. Fuzzy weights of quality criteria in the FAHP method

	Fuzzy geometric mean value $\tilde{r}_i$			Fuzzy weights $\tilde{w}_i$		
Q1	2.00	2.11	2.21	0.07	0.08	0.09
Q2	2.00	2.11	2.21	0.07	0.08	0.09
Q3	4.89	5.58	6.26	0.17	0.21	0.26
Q4	2.00	2.11	2.21	0.07	0.08	0.09
Q5	2.00	2.11	2.21	0.07	0.08	0.09
Q6	2.00	2.11	2.21	0.07	0.08	0.09
Q7	3.83	4.30	4.76	0.13	0.16	0.20
Q8	5.28	5.97	6.64	0.18	0.23	0.28

Q1 – software, Q2 – camera, Q3 – housing colour, Q4 – battery type, Q5 – warranty, Q6 – battery capacity, Q7 – dimensions, Q8 – screen diagonal.

Stage 7. Assessment of product quality and environmental impact. To anticipate satisfactory quality and environmental decisions in the development of smartphones, a comprehensive assessment was conducted to determine their current quality and environmental impact. This assessment involved evaluating smartphones using three approaches: considering only quality criteria, only environmental criteria, or both quality and environmental criteria. The FTOPSIS method was employed to evaluate alternative products based on these criteria, with a team of experts tasked with conducting the evaluations using Saaty's 1–9 fuzzy scale.

Initially, the quality criteria were analysed. A combined decision matrix for these criteria was developed based on expert assessments using equations (9 and (10). The resulting matrix is presented in Table 8.

Table 8. Fragment of the combined decision matrix for quality criteria in the FTOPSIS method

	Q1	Q2	Q3	Q4	...	Q8
P1	3.00, 4.33, 6.00	3.00, 4.67, 6.00	3.00, 5.33, 7.00	4.00, 6.00, 8.00		4.00, 5.67, 7.00
P2	3.00, 4.33, 6.00	5.00, 7.33, 9.00	1.00, 2.33, 4.00	4.00, 6.00, 8.00		4.00, 5.67, 7.00
P3	3.00, 4.33, 6.00	7.00, 8.67, 10.00	5.00, 6.67, 8.00	4.00, 6.00, 8.00		5.00, 7.00, 9.00
P4	5.00, 6.67, 8.00	6.00, 8.00, 10.00	4.00, 5.00, 6.00	4.00, 6.00, 8.00		7.00, 8.00, 9.00
P5	5.00, 6.67, 8.00	7.00, 8.67, 10.00	1.00, 2.33, 4.00	4.00, 6.00, 8.00		3.00, 4.67, 6.00
P6	5.00, 6.67, 8.00	6.00, 8.00, 10.00	3.00, 4.00, 5.00	4.00, 6.00, 8.00		3.00, 4.67, 6.00
P7	1.00, 2.33, 4.00	7.00, 8.67, 10.00	1.00, 2.33, 4.00	3.00, 4.67, 6.00		6.00, 7.00, 8.00
P8	3.00, 4.67, 6.00	4.00, 5.67, 7.00	1.00, 2.33, 4.00	3.00, 4.67, 6.00		6.00, 7.67, 9.00
P9	1.00, 2.33, 4.00	4.00, 5.67, 7.00	6.00, 8.00, 10.0	3.00, 4.67, 6.00		3.00, 4.00, 5.00
P10	3.00, 4.33, 6.00	6.00, 7.67, 9.00	6.00, 8.00, 10.0	5.00, 6.33, 8.00		6.00, 7.67, 9.00

Q1 – software, Q2 – camera, Q3 – housing colour, Q4 – battery type, Q5 – warranty, Q6 – battery capacity, Q7 – dimensions, Q8 – screen diagonal, P1–P10 – smartphone models.

From the combined decision matrix, a normalized fuzzy decision matrix was created. Quality criteria were divided into benefit and cost categories. The benefit criteria group included software, camera, battery type, warranty, battery capacity, and screen diagonal, while the cost criteria group included housing colour and dimensions. The weighted normalized decision matrix, positive and negative ideal solutions were calculated using equations (11)–(13). The fuzzy values of the quality criteria weights that were previously defined were incorporated into the matrix. Tables 9 and 10 present a portion of these matrices.

Table 9. Fragment of the weighted normalized decision matrix in the FTOPSIS method

	Q1	Q2	Q3	Q4	...	Q8
$\tilde{w}_i$	0.07,0.08,0.09	0.07,0.08,0.09	0.17,0.21,0.26	0.07,0.09,0.08		0.18,0.23,0.28
BC	benefit	benefit	cost	benefit		benefit
P1	3.00, 4.33, 6.00	3.00, 4.67, 6.00	3.00, 5.33, 7.00	4.00, 6.00, 8.00		4.00, 5.67, 7.00
P2	3.00, 4.33, 6.00	5.00, 7.33, 9.00	1.00, 2.33, 4.00	4.00, 6.00, 8.00		4.00, 5.67, 7.00
P3	3.00, 4.33, 6.00	7.00, 8.67, 10.00	5.00, 6.67, 8.00	4.00, 6.00, 8.00		5.00, 7.00, 9.00
P4	5.00, 6.67, 8.00	6.00, 8.00, 10.00	4.00, 5.00, 6.00	4.00, 6.00, 8.00		7.00, 8.00, 9.00
P5	5.00, 6.67, 8.00	7.00, 8.67, 10.00	1.00, 2.33, 4.00	4.00, 6.00, 8.00		3.00, 4.67, 6.00
P6	5.00, 6.67, 8.00	6.00, 8.00, 10.00	3.00, 4.00, 5.00	4.00, 6.00, 8.00		3.00, 4.67, 6.00
P7	1.00, 2.33, 4.00	7.00, 8.67, 10.00	1.00, 2.33, 4.00	3.00, 4.67, 6.00		6.00, 7.00, 8.00
P8	3.00, 4.67, 6.00	4.00, 5.67, 7.00	1.00, 2.33, 4.00	3.00, 4.67, 6.00		6.00, 7.67, 9.00
P9	1.00, 2.33, 4.00	4.00, 5.67, 7.00	6.00, 8.00, 10.0	3.00, 4.67, 6.00		3.00, 4.00, 5.00
P10	3.00, 4.33, 6.00	6.00, 7.67, 9.00	6.00, 8.00, 10.0	5.00, 6.33, 8.00		6.00, 7.67, 9.00
A^*	0.04, 0.07, 0.09	0.05, 0.07, 0.09	0.09, 0.04, 0.26	0.04, 0.06, 0.09		0.14, 0.20, 0.28
A^-	0.01, .002, 0.05	0.02, 0.04, 0.06	0.02, 0.03, 0.04	0.03, 0.05, 0.07		0.06, 0.10, 0.15

Q1 – software, Q2 – camera, Q3 – housing colour, Q4 – battery type, Q5 – warranty, Q6 – battery capacity, Q7 – dimensions, Q8 – screen diagonal, P1–P10 – smartphone models.

Table 10. Ideal positive and negative solution for quality criteria in the FTOPSIS method

A^*	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
P1	0.02	0.03	0.11	0.01	0.00	0.04	0.03	0.06
P2	0.02	0.01	0.00	0.01	0.03	0.04	0.03	0.06
P3	0.02	0.00	0.13	0.01	0.03	0.00	0.01	0.03
P4	0.00	0.01	0.12	0.01	0.00	0.02	0.01	0.00
P5	0.00	0.00	0.00	0.01	0.00	0.02	0.05	0.09
P6	0.00	0.01	0.10	0.01	0.00	0.01	0.05	0.09
P7	0.04	0.00	0.00	0.02	0.00	0.00	0.03	0.03
P8	0.02	0.02	0.00	0.02	0.03	0.00	0.03	0.01
P9	0.04	0.02	0.13	0.02	0.00	0.04	0.00	0.10
P10	0.02	0.01	0.13	0.00	0.00	0.04	0.01	0.01
A^-	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
P1	0.02	0.00	0.03	0.02	0.03	0.01	0.02	0.04
P2	0.02	0.02	0.13	0.02	0.00	0.00	0.02	0.04
P3	0.02	0.03	0.01	0.02	0.00	0.04	0.04	0.09
P4	0.04	0.03	0.02	0.02	0.03	0.03	0.04	0.10
P5	0.04	0.03	0.13	0.02	0.03	0.03	0.00	0.02
P6	0.04	0.03	0.03	0.02	0.03	0.03	0.00	0.02
P7	0.00	0.03	0.13	0.00	0.03	0.04	0.02	0.08
P8	0.02	0.01	0.13	0.00	0.00	0.04	0.02	0.10
P9	0.00	0.01	0.00	0.00	0.03	0.00	0.05	0.00
P10	0.02	0.02	0.00	0.02	0.03	0.01	0.04	0.10

Q1 – software, Q2 – camera, Q3 – housing colour, Q4 – battery type, Q5 – warranty, Q6 – battery capacity, Q7 – dimensions, Q8 – screen diagonal, P1–P10 – smartphone models.

Next, the distance between each alternative smartphone and the positive and negative ideal solutions was calculated using equation (??). A product ranking was established based on the CC_i values. The results of the analysis using the FTOPSIS method are presented in Table 11.

Table 11. Ranking of products
according to quality criteria in the FTOPSIS method

	d_i^*	d_i^-	$Q - CC_i$	Ranking
P1	0.29	0.1	6 0.36	7
P2	0.20	0.25	0.55	4
P3	0.23	0.24	0.52	5
P4	0.16	0.30	0.66	3
P5	0.16	0.30	0.66	3
P6	0.26	0.20	0.43	6
P7	0.11	0.33	0.75	1
P8	0.13	0.32	0.71	2
P9	0.36	0.08	0.18	8
P10	0.22	0.24	0.52	5

P1–P10 – products.

During the evaluation of products based on quality criteria, it was determined that the smartphone labeled as P7 is the most advantageous option with a $Q - CC_i$ value of 0.75. Product P8 achieved a slightly lower value of this indicator (0.71) compared to P7. This analysis allows for satisfactory decisions regarding product quality. However, we still need and want to consider environmental impacts in this decision-making process. Therefore, the FTOPSIS method was employed to reassess environmental criteria. The same procedure was followed as for the analysis of quality criteria. Initially, a combined decision matrix was developed for environmental criteria based on expert evaluations, using equations (9) and (10). Table 12 presents this matrix.

Table 12. Fragment of the combined decision matrix for the environmental criteria in the FTOPSIS method

	E1	E2	E3	E4	...	E8
P1	2.00,4.00,7.00	2.00,3.67,5.00	2.00,3.67,5.00	3.00,4.67,6.00		3.00,4.33,6.00
P2	2.00,4.00,6.00	2.00,3.67,6.00	4.00,5.00,6.00	3.00,4.67,6.00		5.00,6.00,7.00
P3	2.00,3.67,5.00	2.00,3.67,5.00	3.00,4.67,7.00	2.00,3.67,5.00		3.00,4.67,6.00
P4	3.00,4.67,7.00	3.00,4.00,5.00	3.00,4.67,6.00	3.00,4.33,6.00		2.00,3.67,5.00
P5	2.00,4.00,6.00	2.00,3.67,6.00	4.00,5.00,6.00	4.00,5.00,6.00		5.00,6.00,7.00
P6	3.00,4.33,6.00	2.00,.3.67,5.00	2.00,3.67,5.00	2.00,3.33,5.00		4.00,5.67,7.00
P7	2.00,3.33,5.00	2.00,3.67,5.00	3.00,4.33,6.00	2.00,3.67,5.00		3.00,4.00,5.00
P8	2.00,3.67,6.00	2.00,3.33,5.00	3.00,4.00,5.00	4.00,5.00,6.00		3.00,5.33,7.00
P9	2.00,3.33,5.00	2.00,3.67,5.00	2.00,4.00,6.00	2.00,3.67,6.00		3.00,5.00,7.00
P10	2.00,4.00,6.00	3.00,4.00,5.00	3.00,4.67,6.00	2.00,4.00,6.00		3.00,4.67,6.00

E1 – main air pollutants, E2 – radioactive substances, E3 – water pollution, E4 – waste, E5 – heavy metals, E6 – human toxicity, E7 – global warming, E8 – water consumption/water footprint.

Based on the combined decision matrix, the FTOPSIS method followed the same procedure as with the quality criteria for the environmental criteria. This resulted in a normalized fuzzy decision matrix, with all environmental criteria categorized as cost criteria. Equations (11)–(13) were used to compute a weighted normalized decision matrix, which included both the positive and negative ideal solutions. The previously defined fuzzy values of the environmental criteria weights were then applied to the matrix. Subsequently, the distance between each smartphone alternative and the positive and negative ideal solutions was calculated using equation (14). Finally, a product ranking for environmental criteria was established based on CC_i. The results are presented in Table 13.

Table 13. Classification of products according to environmental criteria in the FTOPSIS method

	d_i^*	d_i^-	$E - CC_i$	Ranking
P1	8.53	5.11	0.37	5
P2	10.40	4.42	0.30	6
P3	9.70	4.73	0.33	7
P4	8.84	10.92	0.55	2
P5	13.59	2.01	0.13	9
P6	9.43	6.60	0.41	4
P7	6.14	7.92	0.56	1
P8	11.39	3.10	0.21	8
P9	6.74	7.39	0.52	3
P10	7.32	9.20	0.56	1

P1–P10 – products.

The FTOPSIS analysis was conducted on various smartphones to assess their environmental criteria. The analysis determined that the smartphones marked as P7 and P10 were the most beneficial, with an $E - CC_i$ value of 0.56. While in terms of quality criteria, the P10 product ranked fifth. It is possible to prioritize either quality or environmental criteria based on the entity's needs when making development decisions. To make development decisions that consider both quality and environmental criteria, a re-analysis of these products was necessary. Therefore, the FTOPSIS method was repeated, taking into account the combined decision matrix results for both quality and environmental criteria. The remaining steps were the same as for the separate FTOPSIS analysis of these criteria.

Using equations (11–(13), a weighted normalized decision matrix, a positive and negative ideal solution were calculated. Then, according to equation (14), the distance between each of the smartphone alternatives to the positive and negative ideal solution was calculated. Based on resulting CC_i values, a product ranking was created for both quality criteria and environmental criteria. The final results are presented in Table 14.

Table 14. FTOPSIS product classification for both quality criteria and environmental criteria

	${d_i}^*$	${d_i}^-$	$QE - CC_i$	Ranking
P1	8.83	8.50	0.49	4
P2	10.60	10.18	0.49	4
P3	9.92	10.25	0.51	3
P4	9.00	9.32	0.51	3
P5	13.75	13.20	0.49	4
P6	9.69	10.34	0.52	2
P7	6.25	7.05	0.53	1
P8	11.52	11.77	0.51	3
P9	7.10	6.85	0.49	4
P10	7.54	7.07	0.48	5

P1–P10 – products.

According to the analysis, the P7 smartphone has been identified as the most favourable product in terms of both quality and environmental impact. However, the products P6, P3, P4, and P8 have only slightly lower $QE - CC_i$ values. Therefore, when making decisions regarding smartphone development, it is crucial to consider the quality criteria and environmental impact of all products, including those that have lower indices. This evaluation process is conducted in Step 8 of our model application.

Stage 8. Anticipating satisfactory decisions for quality-environmental product development. Finally, the levels of customer satisfaction regarding the quality and environmental levels were determined based on the value CC_i and Kolman's SRS. The results are presented in Table 15.

Table 15. Satisfaction with the combined quality-environmental levels of products

	$Q - CC_i$	Level	$E - CC_i$	Level	$QE - CC_i$	Level
P1	0.36	unsatisfactory	0.37	unsatisfactory	0.49	sufficient
P2	0.55	moderate	0.30	unsatisfactory	0.49	sufficient
P3	0.52	moderate	0.33	unsatisfactory	0.51	moderate
P4	0.66	satisfactory	0.55	moderate	0.51	moderate
P5	0.66	satisfactory	0.13	critical	0.49	sufficient
P6	0.43	sufficient	0.41	sufficient	0.52	moderate
P7	0.75	beneficial	0.56	moderate	0.53	moderate
P8	0.71	beneficial	0.21	unfavourable	0.51	moderate
P9	0.18	critical	0.52	moderate	0.49	sufficient
P10	0.52	moderate	0.56	moderate	0.48	sufficient

P1–P10 – products.

Kolman's SRS can be utilized to determine the expected level of satisfaction with a given product. To assess the retrospective impact of quality and environmental criteria on the final product rankings, a sensitivity analysis was conducted following the proposed model design. The analysis was performed using the STATISTICA software (ver. 13.3).

After testing various models, the MLP 2-9-1 type neural network was selected due to its high network learning rate (99%). This network consists of two input neurons, nine neurons in the hidden layer, and one output neuron. Subsequently, a global sensitivity analysis was carried out using this network, resulting in quality criteria scoring 414.49 and environmental criteria scoring 233.60. This analysis demonstrated that quality criteria had a greater influence (56%) on determining the final quality and environmental product rankings than environmental criteria.

Therefore, it is recommended that in the development of a final product, primary attention should be directed towards adapting it to customer requirements based on its quality criteria. It is backed by study results, which prove, that product quality had a more significant impact on overall customer satisfaction than the environmental impact of the product. Products labelled as P7 and P8 ranked highest in both the combined quality-environmental and quality rankings, and thus, they should be given priority in development. However, the final decision rests with the entity utilizing the proposed method (e.g., an entrepreneur).

Consequently, development decisions should specify which criteria need improvement to maximize customer satisfaction in terms of both quality and environmental aspects. This can be achieved by determining the most favourable level of quality, coupled with the highest level of environmental friendliness.

Additionally, the importance of each criterion can guide the order in which they should be improved, with the most critical criteria for customers taking precedence.

4. Dissussion

The research aimed to develop an MCDM model supporting the anticipation of satisfactory quality and environmental decisions during product development, with a smartphone used as a case study. The results demonstrated that by assessing the current quality and environmental impact, it is possible to anticipate improvements in product satisfaction. The proposed model offers several significant advantages, including:

- The ability to determine the importance of quality criteria related to customer satisfaction with product usability, as well as the significance of environmental criteria concerning a product's negative impact on the environment throughout its lifecycle.
- An effective way of ranking products of the same type based on customer satisfaction and environmental impact, facilitating decision-making for criterion improvement.
- Providing decision-makers with a valuable tool to align product criteria with customer expectations and reduce environmental harm.
- Its simplicity allows any entity to conduct market analyses while minimizing inconsistencies and uncertainties through the use of the Saaty fuzzy scale.

The limitations of the model are the following: it is applicable at once only to one product range, and its application requires the availability of a team of experts with product-specific knowledge.

Therefore, future research shall focus on adapting the model for the analysis of various product ranges simultaneously and test its efficiency on different types of products.

5. Conclusions

Tailoring products to meet customer needs can be complex and challenging endeavor due to shifting customer expectations, increased competition, and the increasing demand for production. This process often leads to resource wastage and adverse environmental effects. Hence, our research aimed to develop a method supporting the anticipation of satisfactory quality and environmental decisions during product development. The method was illustrated on ten distinct smartphone models, following eight key stages outlined in the developed framework.

Initially, the investigation established its objectives and assembled a team of experts to facilitate model implementation. Subsequently, environmental criteria were delineated within the smartphone life cycle context and evaluated with customer participation. In successive stages, the significance of customer criteria was determined and translated into the Saaty fuzzy scale using the FAHP method. The study then evaluated smartphone quality levels, their environmental impact, and their quality-environmental performance using the FTOPSIS method, yielding three separate product rankings. These rankings were subsequently validated using Kolman's SRS and sensitivity analysis.

Based on this investigation, it was concluded that the final decision regarding product development is contingent upon the entity employing the proposed method. This method's applicability extends to enhancing various product types and forecasting product improvement decisions predicated on prevailing quality levels and their impact on the natural environment.

In summary, this study has yielded an MCDM model capable of addressing the challenges associated with customizing products to meet customer requirements, concurrently mitigating environmental repercussions and optimizing product quality. Our model can prove invaluable to professionals seeking to refine their product development processes, aiding them in making well-informed decisions grounded in reliable, data-driven insights.

Funding

The publication presents the result of the project No. 037/GAZ/2023/POT co-financed from the subsidy granted to the Krakow University of Economics and the Visegrád Fund, project ID: 22230264, *Qualitative-environmental aspects of products improvement*, carried out from February 1, 2023 to March 31, 2024. Applicant: Rzeszow University of Technology.

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