Can MCDA Methods Be Useful in E-commerce Systems? Comparative Study Case

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Abstract. Shopping via e-commerce sites is becoming increasingly popular among customers. More and more such sites are being created, and more marketing activities and innovative solutions are needed to attract customers' attention to increase competitiveness and stand out on the market. An effective tactic is to take the consumer's needs into account as much as possible and keep them satisfied to become regular customers and recommend the place to their family and friends. For responding to the customers' needs, it is essential to recognise and understand them. The ever-increasing variety of products on the market and the need to consider an expanding number of technical parameters of equipment and devices make the selection of purchased products and goods by consumers more and more challenging. The problem of selecting purchased products is, therefore, a multi-criteria problem. An intuitive approach and consideration of only the main selection criteria may result in inappropriate choices. Multi-criteria decision-analysis methods (MCDA) are techniques designed to solve this type of problem.

This paper demonstrates an innovative concept based on MCDA methods, including a novel hybrid approach combining COMET with TOPSIS, TOPSIS and VIKOR, used as a tool to support consumer choices in e-commerce systems. The authors performed a comparative analysis of the applied methods using two ranking similarity coefficients: asymmetrical WS and symmetrical r_w. The study was completed with a sensitivity analysis. The results obtained suggest the potentially promising usefulness and suitability of the proposed tool in e-commerce systems.

Keywords: Multi-criteria customer choices · E-commerce · MCDA

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1 Introduction

Nowadays, buying products and equipment requires considering many alternatives available on the market and criteria defining their functionality. It implies that buying decisions for products whose utility is defined by many parameters is a multi-criteria decision problem. Consequently, making an appropriate and satisfactory choice often requires considering opposing criteria and searching for a compromise solution [13]. Compound decision problems are challenging for consumers because an attempt based only on intuition with some criteria is often insufficient. The described situation motivates developing decision support systems based on different methods, both for universal use and specific domains. Multi-criteria decision-making methods (MCDA) are popular and frequently used techniques that allow multiple and conflicting goals to be considered in the decision-making process. The current rapid development of MCDA methods has resulted in the availability of algorithms with different complexity, consideration of criteria and individual preferences of decision-makers, data aggregation, criteria compensation and the possibility of incorporating uncertainty in the data. Thus, while different MCDA methods can improve decision quality, their comparison often yields conflicting results [28]. For this reason, an important stage of research on MCDA methods is a comparative analysis considering several methods [22].

Dynamic digital advancements have now made computers a widely available device and used by most people around the world [10]. Computers simplify people's lives significantly by enabling long-distance communication, storing and providing information, enabling multimedia from anywhere in the world. From a practical point of view, laptops are especially useful devices for work and daily activities because they are mobile, portable and functional [4]. The assortment of laptops available in the market includes many models differing in technical specifications, size, functionality and brand. Objective and complete consideration of all features and parameters that fully satisfy the customer is a complex problem for which an intuitive approach is not enough to solve [1]. Thus, decision support systems seem to be a promising tool to support product purchasing decisions involving electronic devices such as laptops, for example [2].

The aim of this work is to present an innovative approach based on three selected MCDA methods (COMET combined with TOPSIS, TOPSIS and VIKOR), which could be used as a tool to support consumer decisions during multi-criteria problems of purchasing products and devices at e-commerce outlets. In this paper, the authors demonstrate the resolving of a sample multi-criteria problem of choosing the most advantageous laptop model using the concept proposed by the authors. A sensitivity analysis procedure was then performed to determine the robustness of the investigated MCDA models to changes in the criteria weights and to identify the criteria that most strongly affect the final rankings.

The rest of the paper is organised as follows. In Sect. 2 fundamentals and assumptions of the MCDA methods used in the study are provided. Then, in Sect. 3 the problem considered in this article is described. In Sect. 4 final results are presented and discussed. In the last Sect. 5 conclusions and directions for future work are indicated.

2 Preliminaries

2.1 The TOPSIS Method

The algorithm of this method is simple and clear, so this method is popular and widely used in multi-criteria decision-making problems. Furthermore, TOPSIS requires a vector of criteria weights, which can be determined subjectively by the decision-maker or objective techniques. Thus, the TOPSIS algorithm does not require the active involvement of an expert in the computation. A detailed study of the TOPSIS algorithm founded on [3] is given below. This method requires the decision matrix with m alternatives and n criteria represented as $X = (x_{ij})_{m \times n}$.

Step 1. Normalization of the decision matrix. In this article, the authors applied the Max normalization technique. The normalized values r_{ij} are determined by Eq. (1) for profit and (2) for cost criteria.

$$r_{ij} = \frac{x_{ij}}{\max_j (x_{ij})} \tag{1}$$

$$r_{ij} = 1 - \frac{x_{ij}}{\max_j (x_{ij})} \tag{2}$$

Step 2. Computation of the weighted normalized decision matrix v_{ij} as Eq. (3) shows.

$$v_{ij} = w_i r_{ij} \tag{3}$$

Step 3. Determination of Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) vectors. PIS is represented by maximum values for each criterion (4) and NIS by minimum values (5). There is no necessity to divide criteria into profit and cost because normalization used in step 1 transforms cost criteria into profit criteria.

$$v_j^+ = \{v_1^+, v_2^+, \cdots, v_n^+\} = \{max_j(v_{ij})\} \tag{4}$$

$$v_j^- = \{v_1^-, v_2^-, \cdots, v_n^-\} = \{min_j(v_{ij})\} \tag{5}$$

Step 4. Establishing of distance from PIS and NIS for each alternative as Eqs. (6) and (7) present.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{7}$$

Step 5. Calculation of the score for each alternative as Eq. (8) shows. This value is always in the range from 0 to 1. Better alternatives have scores closer to 1.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{8}$$

2.2 The VIKOR Method

VIKOR is an acronym in Serbian that means VlseKriterijumska Optimizacija I Kompromisno Resenje, and it was introduced by Opricovic [15]. The VIKOR method aims to choose the closest alternative to the ideal solution with all criteria considered. VIKOR, similarly to TOPSIS, takes into account the proximity to ideal objects, so distance measurement is applied in this algorithm [22]. However, the procedures of the two methods differ at particular stages in their operational approach and consideration of closeness to ideal solutions. The subsequent stages of VIKOR are provided below, according to [22]. As showed in [16], the VIKOR method is defined as follows:

Step 1. Calculation of the best f_i^* and the worst f_i^- values for every criteria functions. Equation (9) is applied for profit criteria and (10) is used for cost criteria.

$$f_j^* = \max_i f_{ij}, \quad f_j^- = \min_i f_{ij} \tag{9}$$

$$f_j^* = \min_i f_{ij}, \quad f_j^- = \max_i f_{ij} \tag{10}$$

Step 2. Computation of the S_i and R_i values according to formulas (11) and (12).

$$S_i = \sum_{j=1}^{n} \left[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}) \right] \tag{11}$$

$$R_i = \max_j \ \left[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right] \tag{12}$$

Step 3. Calculation of the Q_i values applying Eq. (13)

$$Q_i = v \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - v) \frac{(R_i - R^*)}{(R^- - R^*)} \tag{13}$$

where
$S^* = \min_i S_i, \quad S^* = \min_i S_i$
$R^* = \min_i R_i, \quad R^* = \max_i R_i$
and v is used as a weight for the strategy named "majority of criteria". Value of $v = 0.5$ was applied in this paper.

Step 4. Ranking alternatives in the procedure of sorting values in S, R, and Q in ascending order. Three ranking lists are provided as a result.

Step 5. S, R and Q ranking lists are considered to suggest the compromise solution or set of compromise solutions, as shown in [15]. In this research, the authors use only Q ranking list.

2.3 The COMET Method

The COMET is an innovative method applied to identify a multi-criteria expert decision-making model for handling decision-making problems [7]. The main advantages of this newly developed method are its complete resistance to the phenomenon known as the rank reversal paradox [12,23,24], accuracy and independence of the complexity of the algorithm from the number of evaluated alternatives. Furthermore, in the innovative hybrid approach used in this work, the time-consuming step of pairwise comparison of a set of characteristic objects by an expert has been replaced by another MCDA method, TOPSIS. This approach was introduced in [12]. This method will be presented in five steps based on [18]:

Step 1. The problem's dimensionality to solve is determined by an expert by choosing number r of criteria, $C_1, C_2, ..., C_r$. Next, the set of fuzzy numbers for every criteria represented by C_i is selected, i.e., $\tilde{C}_{i1}, \tilde{C}_{i2}, ..., \tilde{C}_{ic_i}$. The value of the membership for a given linguistic concept for specific crisp values is determined by each fuzzy number [6,20]. This approach can also be used for non-continuous variables. The result of this step is the result represented by formula (14)

$$\begin{array}{c} C_1 = \left\{\tilde{C}_{11}, \tilde{C}_{12}, ..., \tilde{C}_{1c_1}\right\} \\ C_2 = \left\{\tilde{C}_{21}, \tilde{C}_{22}, ..., \tilde{C}_{2c_2}\right\} \\ ... \\ C_r = \left\{\tilde{C}_{r1}, \tilde{C}_{r2}, ..., \tilde{C}_{rc_r}\right\} \end{array} \tag{14}$$

where $C_1, C_2, ..., C_r$ are the ordinates of the fuzzy numbers for every criterion considered.

Step 2. Generation of the characteristic objects (COs), which represent reference points in n-dimensional space. These objects may be real or idealized, which means that they do not exist [17]. (COs)are received using the Cartesian product of fuzzy numbers cores for each criteria [19]. The ordered set of all COs is provided as a result, like formula (15) shows

$$\begin{array}{c} CO_1 = \langle C(\tilde{C}_{11}), C(\tilde{C}_{21}), ..., C(\tilde{C}_{r1})\rangle \\ CO_2 = \langle C(\tilde{C}_{11}), C(\tilde{C}_{21}), ..., C(\tilde{C}_{r2})\rangle \\ ... \\ CO_t = \langle C(\tilde{C}_{1c_1}), C(\tilde{C}_{2c_2}), ..., C(\tilde{C}_{rc_r})\rangle \end{array} \tag{15}$$

where t is a number of CO (16):

$$t = \prod_{i=1}^{r} c_i \tag{16}$$

Step 3. The Matrix of Expert Judgement (MEJ) is determined by an expert in the procedure of pairwise comparison of COs. This step depends entirely on the expert's knowledge and opinion in the classical version of the COMET method [11]. The MEJ structure is as follows (17):

$$MEJ = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1t} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2t} \\ \dots & \dots & \dots & \dots \\ \alpha_{t1} & \alpha_{t2} & \dots & \alpha_{tt} \end{pmatrix} \tag{17}$$

where α_{ij} is a result of comparing CO_i and CO_j by the expert. The object that is preferred more gets 1 point, and the object that is preferred less gets 0 points. When the compared objects are equally preferred, they both get 0.5 points [25]. It depends totally on the expert's knowledge and is represented as (18):

$$\alpha_{ij} = \begin{cases} 0.0, & f_{exp}(CO_i) < f_{exp}(CO_j) \\ 0.5, & f_{exp}(CO_i) = f_{exp}(CO_j) \\ 1.0, & f_{exp}(CO_i) > f_{exp}(CO_j) \end{cases} \tag{18}$$

where f_{exp} is an expert mental judgement function. In this study, however, the TOPSIS method was used as an expert function. This approach is presented in [12].

Then, the vertical vector of the Summed Judgements (SJ) is received as formula (19) presents:

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{19}$$

The number of query is expressed by $p = \frac{t(t-1)}{2}$ because for each element α_{ij} it can be noticed that $\alpha_{ji} = 1 - \alpha_{ij}$. The vector P is provided as an outcome, where i-th row includes the estimated preference value for CO_i.

Step 4. Each characteristic object is transformed into a fuzzy rule, where the grade of membership to particular criteria is a premise for activating inference in the form of P_i as presented in formula (20). Thus the complete fuzzy rule base is received that estimates the expert mental judgement function $f_{exp}(CO_i)$ [29].

$$IF\ C\left(\tilde{C}_{1i}\right)\ AND\ C\left(\tilde{C}_{2i}\right)\ AND\ \dots\ THEN\ P_i \tag{20}$$

Step 5. Every alternative A_i is a set of crisp numbers a_{ri} associated to criteria $C_1, C_2, ..., C_r$. It is expressed by formula (21):

$$A_i = \{a_{1i}, a_{2i}, ..., a_{ri}\} \tag{21}$$

2.4 Rankings Similarity Coefficients

In this study, two similarity coefficients, symmetrical r_w (22) and asymmetrical WS (23), were used to check the convergence of the rankings provided by the three MCDA methods applied [21]:

$$r_w = 1 - \frac{6\sum_{i=1}^{N}(R_i - Q_i)^2\left((N - R_i + 1) + (N - Q_i + 1)\right)}{N^4 + N^3 - N^2 - N}, \tag{22}$$

where R_i represents a position in the compared ranking and Q_i means a position in the reference ranking, and N is a number of evaluated alternatives,

$$WS = 1 - \sum_{i=1}^{N} \left(2^{-R_{xi}} \cdot \frac{|R_{xi} - R_{yi}|}{\max\{|1 - R_{xi}|, |N - R_{xi}|\}} \right), \tag{23}$$

where R_{xi} represents a position in the compared ranking, R_{yi} is a position in the reference ranking, and N is a number of alternatives.

2.5 Sensitivity Analysis

A sensitivity analysis procedure is used to identify the most susceptible criteria to weight changes and most significantly affect the final rankings. This technique also allows the identification of tolerable changes in criteria weights to which the rankings are robust. The authors of this paper performed a sensitivity analysis using the two approaches presented in paper [14].

The first stage's goal was an analysis to determine the number of changes in ranking after increasing or decreasing the weights of each criterion. The described procedure allows independent determination of the effect of each criterion under consideration on the rankings provided by MCDA. The technique involves increasing or decreasing the weight of each criterion individually by 5% and by 50%. The results of this procedure are relative sensitivity coefficients that determine the number of changes in rankings caused by a change in criterion weight.

The second step of the sensitivity analysis involves determining the percentage of tolerable weight change for each criterion that does not result in a change in ranking. The sensitivity coefficient of a given criterion C_j is defined as SC_j and is a measure of the sensitivity to changes in the criterion weight. The sensitivity coefficient is given by Eq. (24).

$$SC_j = \frac{1}{D_j},\ j = 1, 2, \ldots, n \tag{24}$$

where D_j represents the smallest relative change in criterion weight in percentage that causes changes in the ranking.

3 Study Case

This study aimed to answer the multi-criteria problem of choosing the most advantageous laptop model among fifteen available alternatives. Three different MCDA approaches were used to evaluate the alternatives: a novel hybrid approach combining COMET with TOPSIS, TOPSIS and VIKOR. Nine sample criteria were considered in the evaluation procedure: the laptop parameters given in Table 1.

Table 1. Criteria C_1–C_9 with their names, types and units for assessment of alternatives A_1–A_{15}.

C_i	Name	Type	Unit
C_1	Price	Cost	Polish złoty [PLN]
C_2	Hard disk capacity	Profit	Megabyte [MB]
C_3	Random-access memory (RAM)	Profit	Gigabyte [GB]
C_4	Screen size	Profit	Inch [in]
C_5	Battery capacity	Profit	Ampere hour [mAh]
C_6	Refresh rate	Profit	Hertz [Hz]
C_7	Weight	Cost	Kilogram [kg]
C_8	Graphics card memory	Profit	Megabyte [MB]
C_9	Processor cache memory	Profit	Megabyte [MB]

Table 2. Decision matrix containing criteria values for alternatives.

A_i	Alternative name	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	HP Pavilion Gaming	4549	1512	32	16.1	4323	144	2.35	4096	8
A_2	Dell Inspiron 3793	3599	256	16	17.3	3500	60	2.79	2048	6
A_3	Lenovo Legion 5-15	4049	512	16	15.6	5350	120	2.46	6144	11
A_4	ASUS TUF Dash F15	4999	512	16	15.6	4940	144	2.06	6144	12
A_5	Lenovo IdeaPad L340-17	3449	512	16	17.3	4000	60	2.78	3072	8
A_6	HP Pavilion 15	3949	512	16	15.6	3440	60	1.73	2048	8
A_7	Dell Inspiron G3	4799	1512	8	15.6	4255	120	2.34	4096	8
A_8	ASUS TUF Dash F15	5199	512	24	15.6	4940	144	2.06	6144	12
A_9	ASUS TUF Gaming FX506IH	3599	512	8	15.6	4240	144	2.04	4096	11
A_{10}	Lenovo Legion Y540-15	3999	512	8	15.6	4670	60	2.30	6144	12
A_{11}	MSI GL65	2999	256	8	15.6	3834	60	2.30	4096	8
A_{12}	MSI GL65	3599	1256	32	15.6	3834	60	2.30	4096	8
A_{13}	Dell Vostro 5301	5299	512	8	13.3	3500	60	1.25	2048	12
A_{14}	MSI GL75	4649	512	16	17.3	3834	144	2.50	4096	8
A_{15}	MSI GL75	5099	1512	32	17.3	3834	144	2.50	4096	8

The advantages of MCDA methods are the individual approach to the solved problem and the possibility of interaction with the user, so there is also the opportunity to choose other criteria expressed in numbers relevant to the customer. Seven of mentioned criteria are of the profit type, and two are of the cost type. The decision matrix that includes the values of each criterion for all alternatives considered is presented in Table 2.

The data was collected from various websites through which laptops can be purchased. These websites provide the technical specifications of the laptops from which the parameters were selected as evaluation criteria. Criteria weights for methods requiring weights such as TOPSIS and VIKOR were determined by the objective equal weights method [26]. The decision matrix was normalized using the Maximum normalization method. The result of the normalization of the matrix conducted for the TOPSIS and VIKOR methods requiring it is displayed in Table 3.

Table 3. Normalized decision matrix.

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.1415	1.0000	1.00	0.9306	0.8080	1.0000	0.1577	0.6666	0.6666
A_2	0.3208	0.1693	0.50	1.0000	0.6542	0.4166	0.0000	0.3333	0.5000
A_3	0.2358	0.3386	0.50	0.9017	1.0000	0.8333	0.1182	1.0000	0.9166
A_4	0.0566	0.3386	0.50	0.9017	0.9233	1.0000	0.2616	1.0000	1.0000
A_5	0.3491	0.3386	0.50	1.0000	0.7476	0.4166	0.0035	0.5000	0.6666
A_6	0.2547	0.3386	0.50	0.9017	0.6429	0.4166	0.3799	0.3333	0.6666
A_7	0.0943	1.0000	0.25	0.9017	0.7953	0.8333	0.1612	0.6666	0.6666
A_8	0.0188	0.3386	0.75	0.9017	0.9233	1.0000	0.2616	1.0000	1.0000
A_9	0.3208	0.3386	0.25	0.9017	0.7925	1.0000	0.2688	0.6666	0.9166
A_{10}	0.2453	0.3386	0.25	0.9017	0.8729	0.4166	0.1756	1.0000	1.0000
A_{11}	0.4340	0.1693	0.25	0.9017	0.7166	0.4166	0.1756	0.6666	0.6666
A_{12}	0.3208	0.8306	1.00	0.9017	0.7166	0.4166	0.1756	0.6666	0.6666
A_{13}	0.0000	0.3386	0.25	0.7687	0.6542	0.4166	0.5519	0.3333	1.0000
A_{14}	0.1226	0.3386	0.50	1.0000	0.7166	1.0000	0.1039	0.6666	0.6666
A_{15}	0.0377	1.0000	1.00	1.0000	0.7166	1.0000	0.1039	0.6666	0.6666

For the COMET method, characteristic objects were determined using three characteristic values: the minimum, mean, and maximum values for the criteria of the alternatives studied. In this procedure, the TOPSIS method was used to evaluate a set of characteristic objects. The result of the TOPSIS method, in this case, is the vector SJ, which is used in the next COMET step to construct the vector P. By using the TOPSIS method to evaluate the characteristic objects instead of performing a time-consuming and subjective pairwise comparison by an expert, the procedure is faster, easier and objective. In addition, COMET combined with TOPSIS retains all the advantages of the classical version of the COMET method, such as rank reversal free, accuracy and independence of the algorithm complexity from the number of evaluated alternatives. Furthermore, it is possible because TOPSIS works here on a set of characteristic objects instead of evaluating alternatives directly.

There is no need for labour-intensive filling of the MEJ matrix for this approach because TOPSIS provides the SJ. Nevertheless, it is possible to reconstruct the MEJ matrix for a visualisation based on the P vector. The MEJ matrix is visualised in Fig. 1. Green fields in the MEJ matrix indicate the advantage of the compared object over the other object and have a value of 1. Red fields represent comparisons with a value of 0 in which the compared object is worse than the other object, and blue fields with a value of 0.5 indicate a tie between the compared objects.

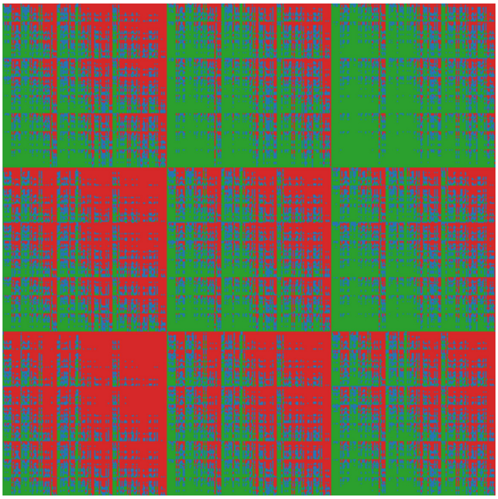

Fig. 1. The MEJ matrix as the stage of the COMET method. (Color figure online)

4 Results and Discussion

Table 4 displays the outcome values of the preference function and the rankings for the evaluated alternatives obtained by the three MCDA methods used in this study. The outcome rankings are visualised in Fig. 2. It can be observed that A_1 (HP Pavilion Gaming) was identified as the leader of all the rankings received. This laptop has a very high value of the profit criteria C_2 (Hard disk capacity), C_3 (Random-access memory (RAM)) and C_6 (Refresh rate). Second place was taken in all rankings by different alternatives. In the COMET ranking, the A_8 (ASUS TUF Dash F15) was ranked second. A_8 has a high value for profit criteria C_3 (Random-access memory (RAM)), C_5 (Battery capacity), C_6 (Refresh rate), C_8 (Graphics card memory) and C_9 (Processor cache memory). In the TOPSIS ranking, A_8 was ranked third, and in the VIKOR ranking, it was ranked sixth. In the TOPSIS ranking, second place was taken by A_{15} (MSI GL75). This model has a very beneficial value of profit criteria C_2 (Hard disk capacity), C_3 (Random-access memory (RAM)), C_4 (Screen size), C_6 (Refresh rate), but cost criteria C_1 (Price) and C_7 (Weight) are quite high, that is, not preferred. In the VIKOR ranking, second place belongs to A_3 (Lenovo Legion 5–15). This laptop has very high values of profit criteria C_5 (Battery capacity), C_8 (Graphics card memory) and C_9 (Processor cache memory). Third place in the COMET and VIKOR rankings was occupied by A_4 (ASUS TUF Dash F15). Third place in the COMET and VIKOR rankings was taken by the A_4 (ASUS TUF Dash F15). This model has a very favourable criterion value of C_6 (Refresh rate), C_8 (Graphics card memory) and C_9 (Processor cache memory).

Table 4. Results including preference values and ranks for alternatives A_1–A_{15} for TOPSIS, VIKOR and COMET method.

A_i	Preference			Rank		
	COMET	TOPSIS	VIKOR	COMET	TOPSIS	VIKOR
A_1	0.7517	0.6556	0.0193	1	1	1
A_2	0.1627	0.2316	1.0000	15	15	15
A_3	0.7122	0.5168	0.1887	4	6	2
A_4	0.7145	0.5412	0.3055	3	5	3
A_5	0.3095	0.3031	0.8463	11	13	11
A_6	0.2096	0.3058	0.9154	13	12	13
A_7	0.4533	0.4939	0.7318	10	7	10
A_8	0.7462	0.5805	0.4239	2	3	6
A_9	0.5865	0.4533	0.6360	6	8	7
A_{10}	0.5037	0.4309	0.6979	8	9	9
A_{11}	0.2537	0.3015	0.8863	12	14	12
A_{12}	0.5344	0.5546	0.6756	7	4	8
A_{13}	0.1982	0.3427	0.9820	14	11	14
A_{14}	0.4579	0.4163	0.4038	9	10	4
A_{15}	0.6812	0.6230	0.4073	5	2	5

The results obtained show that profit criteria and parameters that enhance the usability and capabilities of the laptop have a strong influence on which alternative is selected as a ranking leader. In the case of this study, the alternative that was identified as rankings leader was not cheap compared to the other alternatives. The results demonstrate that a very favourable value for one criterion is not sufficient for an alternative to getting the first ranking. Furthermore, it can be observed that the rankings of the various methods are different. This observation confirms the fact that various MCDA methods can give different results for the same problem.

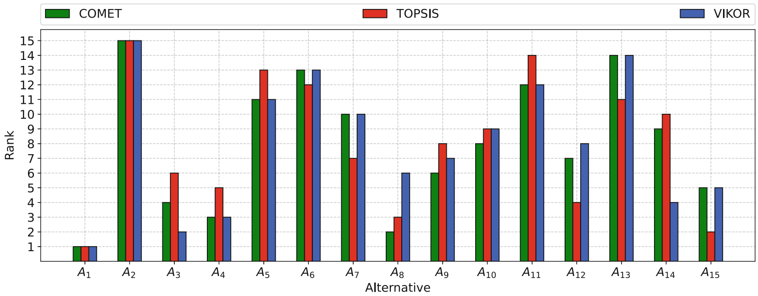

Fig. 2. Column charts illustrating the rankings of alternatives A_1–A_{15} for TOPSIS, VIKOR and COMET methods.

The next stage of the comparative analysis in this work was to compare the convergence of the obtained rankings using two ranking similarity coefficients: asymmetrical WS and symmetrical r_w. The results of this examination are displayed in Fig. 3. It can be observed that the highest convergence occurs for the rankings provided by COMET and TOPSIS, and COMET and VIKOR, and the lowest for VIKOR and TOPSIS.

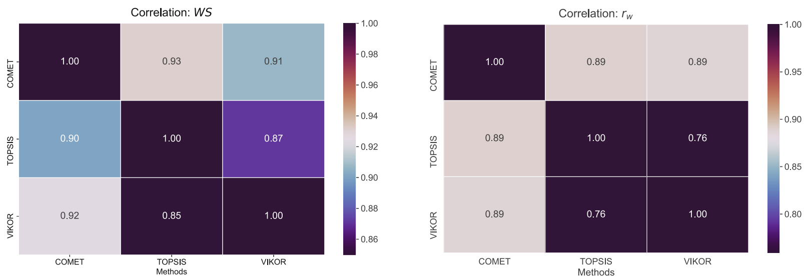

Fig. 3. Visualisation of values of rankings similarity WS and r_w.

4.1 Sensitivity Analysis

Table 5 provides the results of the first stage of sensitivity analysis, which are relative sensitivity coefficients. This step aimed to investigate the effect of individual weights changes for each evaluation criteria on the number of changes in the rankings. The values of individual weights were increased and decreased by a small value (5%) and a large value (50%). As a result, it can be observed that the TOPSIS model has the lowest relative coefficients indicating the fewest changes in ranking and the highest robustness to small (by 5%) and significant changes (by 50%) in weight values in comparison to the other two MCDA models. The VIKOR model showed to be the least resistant to changes in the criteria weights. It is evidenced by the highest values of relative sensitivity coefficients.

For COMET and VIKOR, the results were most strongly affected by changes in the weights of criterion C_3 (Random-access memory (RAM)), while for TOPSIS, the criterion with the most significant effect was C_2 (Hard disk capacity). Both of the criteria mentioned are of the profit type. No criterion was identified for which changes in weight values would leave the rankings unchanged. It means that all nine evaluation criteria used in this study significantly impact the results, so actions such as eliminating any of them or replacing them with another are not recommended.

Table 5. Values of relative sensitivity coefficients in the number of changes in the ranking for modification of criteria weights by 5% and 50%.

Method	COMET				TOPSIS				VIKOR			
Weight modification	Increase		Decrease		Increase		Decrease		Increase		Decrease	
	5%	50%	5%	50%	5%	50%	5%	50%	5%	50%	5%	50%
C_1	2	22	0	10	0	12	0	2	2	44	4	10
C_2	2	16	2	12	0	8	2	20	6	34	0	4
C_3	0	16	4	18	0	10	2	12	10	38	4	18
C_4	0	16	2	10	0	2	0	2	6	6	0	2
C_5	4	12	0	8	0	6	0	2	4	24	0	2
C_6	0	10	4	12	0	12	0	6	8	8	2	12
C_7	0	14	2	10	2	6	4	8	8	44	0	2
C_8	2	10	0	10	4	16	0	6	4	10	0	6
C_9	2	16	0	14	0	8	0	12	4	24	0	4

The second stage of the sensitivity analysis was to investigate the robustness of the rankings provided by the MCDA models applied in this research, measured as the percentage of tolerable change in the weights of each criterion. The results of this study are included in Table 6. The highest percentages of tolerable changes in criteria weights were noticed for the TOPSIS model. It shows the highest robustness of this model to changes in criteria weights. On the other hand, the VIKOR model appeared to be the least resistant to modifications of the criteria weights. Even small changes in the values of the weights caused changes in the ranking.

Table 6. Values of tolerable weights change in % for modification of criteria weights.

Method	COMET		TOPSIS		VIKOR	
Tolerable weights change	Increase [%]	Decrease [%]	Increase [%]	Decrease [%]	Increase [%]	Decrease [%]
C_1	1	5	5	26	0.8	0.1
C_2	1	2	8	4	0.4	13.2
C_3	11	3	19	2	0.4	1.7
C_4	9	1	9	6	0.4	31
C_5	2	11	15	42	0.5	8.6
C_6	10	2	7	14	0.5	1.8
C_7	7	2	4	2	0.1	11.8
C_8	3	18	2	13	0.5	6.4
C_9	2	5	15	18	0.5	6.4

Figure 4 displays, in the form of a column chart, the values of the sensitivity coefficients SC_j for each criterion C_j for the MCDA models studied, when criteria weights are increased. High values of this coefficient mean that even small changes in the weights of these criteria cause changes in the rankings. Rankings provided by the COMET model are most sensitive to changes in C_1 and C_2, TOPSIS in C_8 and C_7, and VIKOR in C_7, C_2, C_3, and C_4.

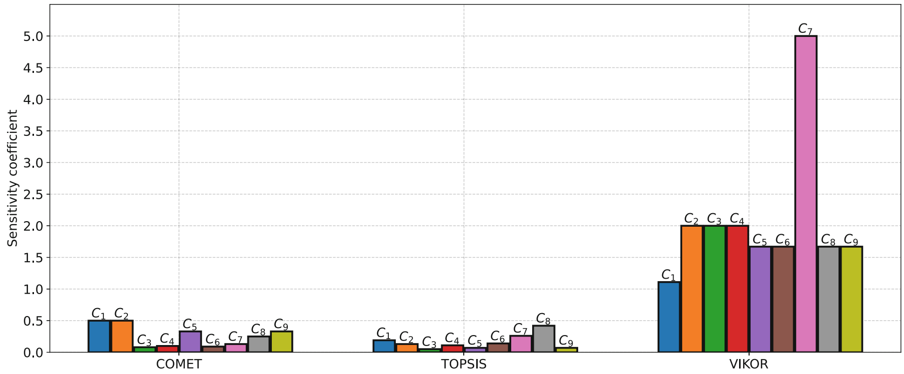

Fig. 4. Values of criteria sensitivity coefficients SCj for increasing of criteria weights.

The values of the similarity coefficients for decreasing the values of the criteria weights are visualised in Fig. 5. The most significant impact on the changes in the COMET rankings is the modification of the weights C_4, C_2, C_6, and C_7. For TOPSIS, these are C_7 and C_3, and for VIKOR, they are C_1, C_3, and C_6.

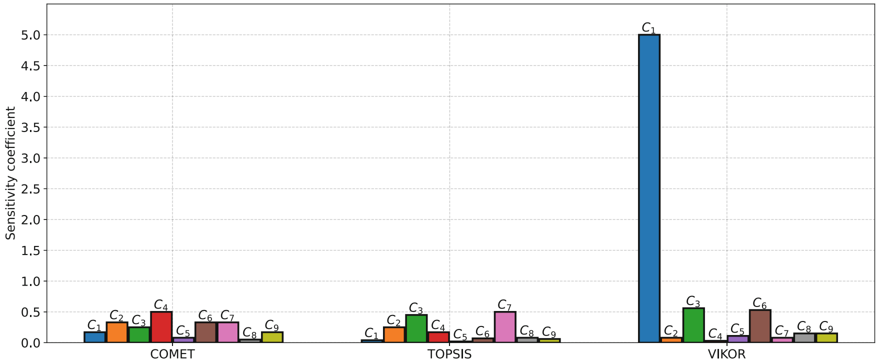

Fig. 5. Values of criteria sensitivity coefficients SCj for decreasing of criteria weights.

5 Conclusions

In this work, the authors present an innovative approach based on MCDA methods as a tool to support consumer decision-making in e-commerce on the illustrative example of the multi-criteria problem of choosing the most advantageous laptop model. The MCDA methods used in the study successfully identified the most favourable alternatives and enabled the identification of the criteria that had the most significant impact on alternatives reaching high ranks. The most important criteria proved to be C_2 (Hard disk capacity), C_3 (Random-access memory (RAM)), C_5 (Battery capacity), C_6 (Refresh rate), C_8 (Graphics card memory) and C_9 (Processor cache memory). These criteria are the parameters that determine the functionality of laptops and the quality of work on them. Thus, it turned out that it is not the low price but the technical parameters that play the most significant role in the rankings in the study performed by the authors.

The observed differences in the rankings obtained by the three MCDA methods used in this study are due to differences in the algorithms of each method and are natural [27]. Because of this, a comparative analysis of the rankings provided by the different MCDA models is helpful in an insightful and critical evaluation of the final results of the decision procedure. The sensitivity analysis performed proved that the sensitivity of the rankings to changes in the criteria weights is dependent on both the MCDA methods used and the criteria.

The study results prove that a tool based on MCDA methods could successfully support consumers in making multi-criteria decisions regarding the purchase of various products and devices at e-commerce sites. In contrast to decisions based on intuition and considering only the main selection criteria, MCDA methods enable objective, quick and fully automated evaluation regardless of the number of alternatives and criteria.

The obtained outcomes encourage further research, including MCDA methods as a basis for tools supporting multi-criteria consumer decisions. Furthermore, due to the notable differences in the rankings provided by the investigated methods, another appropriate direction of research seems to be the comparison of the obtained results with other MCDA methods such as SPOTIS [5,24], COPRAS [8], PROMETHEE II [9].

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