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Application of Preference Selection Index and TOPSIS in Product Aspect Extraction and Ranking

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Abstract: Decision-making methodologies can differentiate between several types of criterion weights. The subjective weights of decision-makers are prone to be influenced by various factors, including their level of knowledge, experience and competency. This may result in the wrong evaluation of the criteria due to the inherent ambiguity of human judgments, leading to unavoidable assessment errors. Beyond that, while assessing the decision alternatives, the majority of Multiple Criteria Decision Making (MCDM) take the evaluation criteria into consideration separately. However, in actual application, most of the criteria are not mutually exclusive. In the context of online customer reviews, it is essential to prioritize product aspects in order to facilitate the purchasing process for potential consumers. Selecting the appropriate product aspects is a difficult task due to the vast quantity of product reviews. This research develops an MCDM solution through the integration of the Preference Selection Index (PSI) with The approach for Order Preference by Similarity to an Ideal Solution (TOPSIS) method for decision-making. The contribution of this study is to enhance the TOPSIS ranking technique by incorporating PSI objective weights as an alternative to subjective weights. PSI offers the benefit of focusing on the convergence of the criteria involved rather than their divergence. This approach will improve the ranking process of TOPSIS by taking into account the interconnectedness of the criteria, hence facilitating the prioritization of significant aspects of a product based on online reviews. A dataset comprising four electronic products was utilized as a reference for conducting a statistical analysis. Through the examination of the outcomes utilizing the discount cumulative gain metric, it becomes apparent that the combination of the TOPSIS approach alongside PSI weights facilitates the identification of the suitable product aspects that effectively differentiate the one that aligns with consumer expectations.

Keywords: PSI, Ranking Criteria, DCG, Aspect Ranking, TOPSIS, Objective Weight, MCDM

Introduction

Social media enables individuals to freely discuss their purchases and usage, regardless of time or location. Online reviews serve as a form of guidance akin to receiving recommendations from a friend prior to making a purchase. They alleviate the apprehension associated with online shopping by providing insights from others who have already acquired the product (Aghakhani *et al*., 2021). Surveys were previously employed by firms to ascertain client satisfaction and gather feedback on their products or services. However, due to the proliferation of online communication and information exchange, firms may find surveys less necessary (Bressmann, 2004; Liu, 2012). Moreover, corporations can readily access online feedback regarding their products at no cost. They no longer need to allocate significant funds for conducting surveys. Alternatively, they can simply peruse the consumer feedback to grasp the merits of their products and areas for improvement. This facilitates firms in making informed decisions. Furthermore, when a company utilizes these reviews, it has the ability to engage in conversations with customers and make informed predictions about their preferences for future interactions. Moreover, the inclusion of user feedback on buying sites enhances the overall sense of integrity and reliability. The website's transparency fosters increased trust among users, as everyone is well-informed about the current situation.

The proliferation of online discourse has significantly increased, posing a significant challenge for conventional firms to manually manage the influx of comments (Aghakhani *et al*., 2021). Consider TripAdvisor as an illustration; it is the platform that individuals utilize to evaluate hotels and vacation services. Their online reviews increased threefold from 200 million in 2014 to nearly 600 million by 2017. There are numerous opinions to analyze and sort through (D'Acunto *et al*., 2020).

Online reviews are valuable sources of information for both consumers and businesses. Therefore, experts have been developing multiple methodologies to automatically analyze these reviews. Their primary methods involve utilizing Natural Language Processing (NLP) and statistical approaches to identify the particular aspects of a product that individuals discuss and to analyze the manner in which they convey their opinions about these aspects. However, a less explored side is the identification of the most crucial aspects that have the potential to significantly influence the decisions made by customers and enterprises (Hu and Liu, 2004; Quan and Ren, 2014). Several studies have conducted a ranking process for candidate product aspects, using statistical information on their occurrences as an additional step to the extraction process. However, the importance of these aspects varies in terms of their impact on customer satisfaction with a product. Specifically, certain aspects of a product may be regarded as more significant than others. In addition, people actively seek high-quality information in online reviews. Directing clients' attention towards crucial product aspects will enable them to make informed purchasing choices.

Potential consumers prefer to have a clear understanding of the details and implications of a purchase prior to making a decision. They search for reliable and reputable web reviews. They desire to prioritize essential aspects and derive happiness from their purchases. Therefore, it is crucial to possess a robust and truthful method for prioritizing the most significant aspects of a product. Providing clients with transparent information regarding the positive and negative aspects of a product or service enables them to make informed choices based on their preferences. Simultaneously, organizations can discern the most crucial aspects to enhance and allocate their financial resources judiciously. By prioritizing the crucial aspects that contribute to customer satisfaction, organizations can enhance their performance and distinguish themselves from competitors.

Many research studies investigated prioritizing the extracted product aspects from Web reviews by employing Multicriteria Decision Making (MCDM) approaches such as TOPSIS and VIKOR (Ahmad Ali Alrababah *et al*., 2016; 2023), The MCDM method serves as an intelligent approach to discerning the crucial aspects of goods that people discuss in online reviews. Its strength lies in its ability to simultaneously analyze multiple factors and discern their relative importance, distinguishing between highly significant factors and those of lesser significance. Typically, in the context of MCDM, a multitude of alternatives are available for selection, accompanied by a set of criteria employed to evaluate each choice. Each alternative is assigned a numerical score (weight) based on its performance in those factors and these scores are used to determine the optimal choice.

The allocation of weights significantly influences the ultimate selection of the preferred option. When making these judgments, there are two methods for determining the importance: One is subjective, based on personal opinion and the other is objective, based on facts or statistics (Terstiege, 2013).

The use of subjective weights is not reliable for evaluating criteria due to the ambiguity inherent in human assessments and it is common for assessment mistakes to occur (Sotoudeh-Anvari, 2022; Wang and Lee, 2009). In addition, contrary to the commonly held view that the decision factors in MCDM issues are independent, this is often not true in several scenarios (Sotoudeh-Anvari, 2022). The importance of objective weighting approaches comes from the ability to determine the weights by employing statistical assessment of the decision matrix or mathematical models without any bias or preference, in which, the fuzziness of the human judgments can be eliminated by using these approaches. Obviously, human evaluations, which are to benefit from subjective approaches, are not considered by objective techniques.

Moreover, the majority of objective weighting techniques generate weights based on the divergence in the performance ratings of each criterion, such as entropy and Standard Deviation (SD) methods, while other techniques support generating criteria weights based on the convergence degree in the criterion performance ratings like Preference Selection Index (PSI) approach (Jahan *et al*., 2012).

The PSI method has demonstrated its efficacy in multiple domains of MCDM (Do *et al*., 2023). It is straightforward and requires minimal calculations. It is particularly useful when there is difficulty in determining the relative importance of the factors under consideration. Furthermore, TOPSIS (Hwang and Yoon, 1981) is a distance-oriented MCDM technique employed to evaluate and rank different alternatives. The TOPSIS method relies on the determination of positive-ideal and negative-ideal solutions, which are determined based on the distance of each alternative from the best and worst-performing alternatives. The TOPSIS notion is logical and comprehensible and the calculation involved is straightforward. Also, it is important to acknowledge the inherent obstacle of accurately determining subjective weights for the criteria (Odu, 2019). Thus, in order to close this disparity and capitalize on the widely employed TOPSIS method and often overlooked PSI method, a proposed methodology combines the TOPSIS-PSI approach to effectively tackle the problem of subjective weight generation in TOPSIS. This approach leverages the PSI technique to assign objective weights to the criteria involved in the decision-making process, thereby enabling the prioritization of the most genuine aspects of a product as highlighted in online reviews. Moreover, the latest trend in MCDM involves integrating multiple methods to create an MCDM approach that overcomes the limitations of individual methods (Velasquez and Hester, 2013). Specifically, this research addresses the problem of the subjective weighting process of assigning weights to criteria in the TOPSIS approach for ranking product aspects, as discussed in a previous study (Alrababah *et al*., 2017a), in order to be improved by generating objective weights using PSI.

Types of Criteria Weighting Elicitation in MCDM

The criteria' weights demonstrate how significant they are. Assigning equal weights to the criteria is the easiest option and has been used in numerous research (Wang *et al*., 2009). Nevertheless, the final assessment outcomes are inappropriately reliant on criterion weights (Magableh, 2023). To get criteria weights, several approaches have been proposed. There are a total of three types of weighting algorithms: Subjective, objective and hybrid. In subjective techniques, decision-maker preferences determine the weights of the criteria. A few examples of subjective approaches are the Simple Multi Attribute Ranking Technique (SMART), AHP, direct ranking and point allocation (Jahan *et al*., 2012). When the number of criteria rises, these systems become inefficient, which is their biggest drawback. To rephrase, decision-makers engage in mental effort while expressing preferences and the more criteria there are, the less accurate those choices will be (Odu, 2019). Different subjective and objective weighing methods are combined in hybrid methods. These approaches mimic the attributes of others without introducing any new ones. Hybrid approaches have the potential to provide more accurate weights since they can incorporate both the preferences of decision-makers and decision-matrix data (Chen, 2020). Establishing the significance of criteria can be accomplished in a more solid and trustworthy manner through the use of objective methodologies. In this investigation, the PSI method was applied in conjunction with the TOPSIS methodology in order to determine objective weights for the criteria that were included in the ranking process of the product aspects that were retrieved from online reviews. The purpose of this research is to provide a ranking of product aspects that is more accurate and objective for probable customers by applying objective methodologies. This research aims to overcome the limits of subjective weighting. The ability of the PSI approach to take into account the convergence among all of the involved criteria rather than the divergence is the significant factor that contributes to its significance in this research by taking into account the interrelationships that exist between the criteria. Consequently, this will result in an improvement in the ranking process of the product aspects.

Preference Selection Index

The Preference Selection Index (PSI) was proposed by Maniya and Bhatt (2010) as an aggregation function to solve the material selection decision-making problem. Unlike other MCDM approaches, PSI does not require the assignment of weights to criteria before starting the ranking process for alternatives. Instead, it calculates the overall preference value of the criteria using statistical concepts (Arifin and Saputro, 2022). Hence, when there is a conflict in determining the relative significance of the criteria, it becomes beneficial for the decision-maker (Jahan *et al*., 2012). PSI as an analytical tool has many applications, from product development to the social sciences, economics and psychology. This approach enables us to enhance our comprehension of individual or collective preferences and priorities in complex decision-making scenarios. By utilizing PSI, we can ascertain the significance of each option, quantify the extent to which preferences are fulfilled and make more intelligent decisions based on this data (Yudistira and Science, 2022). Through the utilization of PSI, companies can discern the characteristics that are highly sought after by consumers and allocate resources in a more effective manner to cater to market preferences. This aids companies in enhancing their competitiveness in the fiercely competitive market. In addition, PSI can make decision-making more transparent by assigning clear weights to each factor or indicator and basing the final ranking on quantifiable factors (Rahma and Maryana, 2023).

The PSI methodology comprises seven steps, as outlined by Maniya and Bhatt (2010). The process involves the following steps: (1) Creating a decision matrix; (2) Creating a normalized decision matrix; (3) Calculating the average value of the normalized decision matrix; (4) Calculating the preference variation value; (5) Calculating the deviation in the preference variation value; (6) Calculating the overall preference value; and (7) Calculating the preference selection index.

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In the literature, a number of research studies investigated the PSI method in many MCDM problems It has been used to assess machine performance (Bilgin Sarı, 2019), propose a waste recovery method for electrical/electronic products (Sari, 2020), select an automated system development method for scholarship recipients (Arifin and Saputro, 2022), make decisions regarding tooth restoration/beautification materials (Yadav, 2022), determine life cycle design solutions for product systems (Attri and Grover, 2015), choose technological parameters for turning (Vara Prasad *et al*., 2018), select parameters for electrical discharge machining (Phan *et al*., 2022), determine technological parameters for the grinding process (Hoang Tien *et al*., 2021) and rank types of materials for engineering (Maniya and Bhatt, 2010). Thus, The PSI method has been used well for making complex choices in a lot of different areas. The obtained outcome enhances the applicability of the PSI approach in a new domain of product aspect ranking.

The PSI approach has the advantage of directly evaluating the performance of alternatives and calculating the rating score. However, a drawback of this strategy is that it does not allow the user to take into account qualitative elements (Noryani *et al*., 2018). This pertains to a methodology that relies on computations to ascertain the significance of criteria within its own system.

According to the study of Maniya and Bhatt (2010), The PSI method's computing technique begins with a process of normalizing the performance of alternatives by applying the linear scale transformation-Max approach, which serves as the Eq. 1 for benefit criteria:

$$r_{ij} = \frac{x_{ij}}{x^+} \quad (1)$$

The term x^+ denotes the highest level of performance among the alternatives in the decision matrix. The subsequent procedure involves calculating the sample variance for each criterion j by utilizing Eq. 2 to get the preference variation value PV_j:

$$PV_j = \sum_{i=1}^{m}(r_{ij} - \overline{r}_j)^2 \quad (2)$$

The above relation sets the PSI method apart from other weighting approaches such as entropy and SD. If there is a significant conflict and divergence among the performance ratings of the alternatives, then the criterion is considered to be of great importance in these approaches. On the other hand, PSI examines the level of convergence in the performance assessments of the criterion. The greater the agreement in the ratings, the more significant that criterion becomes. The value of PV_j represents the level of variability in the ratings of the alternatives. A greater PV_j indicates a lower level of significance for the criterion. The degree of deviation is calculated to determine the quantity of information emitted by the j^{th} criterion. The magnitude of variation in the preference value for each criterion is calculated using Eq. 3:

$$\Phi_j = 1 - PV_j \quad (3)$$

According to the preceding analysis, a criterion with a higher value of Φ_j emits a larger amount of information and is considered more important. The criteria weight, which indicates the overall preference of the criterion, is normalized using the Eq. 4:

$$w_j = \frac{\Phi_j}{\sum_{j=1}^{n}\Phi_j} \quad (4)$$

Materials and Methods

The product aspect ranking is formulated as an MCDM problem, where several factors are taken into account to determine the most appropriate aspect ranking. As illustrated in Fig. 1, the sequential procedure for implementing the hybrid TOPSIS-PSI approach is outlined.

Step 1: The initial phase of the suggested approach involves discerning the pertinent assessment criteria. To determine what aspects of a product are most crucial, the suggested method relies on three primary evaluation criteria; First, there are aspects of products that are based on frequency; these refer to the occurrence of every potential aspect that has been extracted and is referred to as freq (A). The second criterion is The Opinionated Score for an Aspect OS (A) which is a numerical value that is assigned to each potential candidate aspect. This score conveys the number of times that an aspect is mentioned with opinions in the reviews (like "good battery life", or "bad zoom"). The last factor is Aspect relevance, which refers to the ratio of the number of synsets shared between the name of the domain product (such as "camera") and the aspect (such as "battery") using Wordnet (Alrababah *et al*., 2017b), which indicates the correlation score of aspect A to a given domain product.

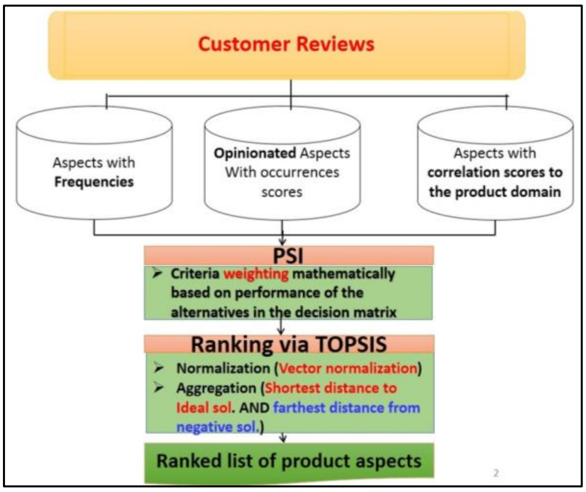

Fig. 1: Aspect ranking framework using TOPSIS-PSI

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Step 2: This step involves using all of the available criteria data that have been mentioned in step 1 to create a decision matrix. The performance values of different alternatives according to different criteria have been used to generate the decision matrix. Figure 2 shows the layout of our matrix, where X_{i1}, X_{i2} and X_{i3} represent the aspect performance score in relation to the extraction criteria freq (A), OS (A) and Aspect relevance (A, P) correspondingly.

Step 3: During this stage, the decision matrix that was created earlier has been normalized, which means that it has been made dimensionless within the range of 0-1. In order to make the comparison between the numerous criteria easier to understand, this was done in order to transform the performance rating using different data that was measured according to the decision matrix. Equation 5 has been utilized in order to create a normalized decision matrix that is based on the features of the individuals involved (beneficiary or non-beneficiary):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{5}$$

Step 4: Determining the relative significance of each criterion. The PSI approach has been employed in this stage to allocate weights to the evaluation criteria, following the procedure described in the previous section. Where $W_j \geq 0$ and $\sum_{j=1}^{n} W_j = 1$.

Step 5: During this stage, the TOPSIS approach will be utilized in identifying the product aspects that exhibit superior performance across all criteria. The approach initiated by Identifying the positive ideal solution as $A+$ and the negative solution as $A-$ as seen in Eqs. 6-7:

$$A_i^+ = \{r_1^+, r_2^+, \dots, r_n^+\} = (\max r_{ij}^+ \mid j \in J) \tag{6}$$

$$A_i^- = \{r_1^-, r_2^-, \dots, r_n^-\} = (\min r_{ij}^- \mid j \in J) \tag{7}$$

Step 6: Calculate the separation metrics for each alternative from $A+$ and $A-$ separately. Initially, the Euclidean distance metric has been employed in TOPSIS, as demonstrated in Eqs. 8-9:

$$S_i^- = \sqrt{\sum_{j=1}^{n} \omega_j \left(r_i^- - r_{ij}\right)^2} \tag{8}$$

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \omega_j \left(r_i^+ - r_{ij}\right)^2} \tag{9}$$

Step 7: Arrange all of the alternatives provided in descending order based on their performance index value (*CI*), which represents the best desirable viable solution based on Eq. 10:

$$C_i^* = S_i^- / \left(S_i^+ + S_i^-\right) \tag{10}$$

Discussion

In this section, we will compare the outcomes of product aspect ranking using classical TOPSIS with the suggested approach that uses hybrid TOPSIS-PSI. We conducted this experiment utilizing the widely-used datasets of four electronic devices introduced by Bing Liu, based on user reviews (Hu and Liu, 2004). A cell phone, an MP3 player, two digital cameras. Using association mining, Bing Liu's dataset primarily aims to extract all nouns and noun phrases that exist in customer evaluations. Our research, on the other hand, focuses on the aspects that have been explicitly characterized by multiple consumers as having strong opinions, whether good or unfavorable. As a result, this study's evaluation process solely takes into account review sentences that contain opinions regarding the proposed product aspects. Table 1 displays the details of all product datasets utilized in our investigations.

One of the most important metrics for ranking quality compared to many ranking measures (Tikait *et al*., 2015) is Discounted Cumulative Gain at top k (DCG@k), which has been used to demonstrate the efficacy of the proposed hybrid TOPSIS-PSI and the classical TOPSIS product aspect ranking. DCG@k is defined as seen in formula Eq. 11:

$$DCG@k = \sum_{i=1}^{k} \frac{2^{t(i)} - 1}{\log(1+i)} \tag{11}$$

In this case, $t(i)$ denotes the weight that each candidate aspect of the product at index i deserves. We have largely imitated the assessment strategy proposed in the study of Zha *et al*. (2014) to ascertain the aspect's significance. Human judgments form the basis of the aspect importance evaluation approach. Three annotators are asked to rate the aspect's importance using three levels: "Unimportant," "ordinary," and "important." The numbers "1, 2" and 3" represent these levels of importance, respectively. In detail, to determine what aspects are most important, the annotators ought to examine each customer review in the dataset. However, the annotators will find this process to be both challenging and time-consuming. To tackle this issue, we compiled the top-k aspects derived from all ranking criteria and will use DCG@k to determine their importance. Afterward, the annotators were given a random sample of 100 review statements from the dataset that mentioned the collected aspects. Their job is to rank the relevance of each aspect.

Using DCG@5, 10 and 15 as metrics, Figs. 2-4 compare the effectiveness of the TOPSIS-PSI and classical TOPSIS techniques in determining which product aspects are most crucial.

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Table 1: Descriptions of the review dataset

Product description opinionated	Total review sentences	Total aspects
Digital camera 1: Nikon coolpix 4300	148	59
Digital camera 2: Canon G3	172	69
Cell phone: Nokia 6610	261	76
Mp3 player: Creative labs nomad jukebox Zen xtra 40 GB	721	117

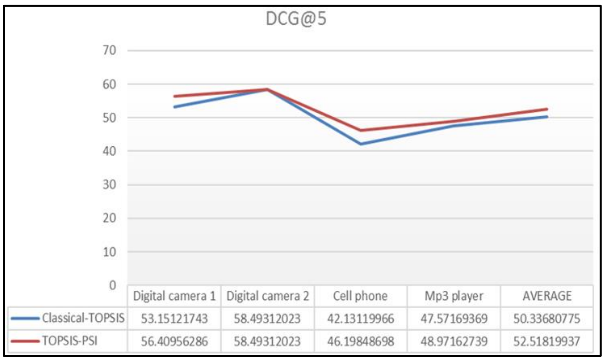

Fig. 2: Performance of TOPSIS-PSI and classical TOPSIS in terms of DCG@5

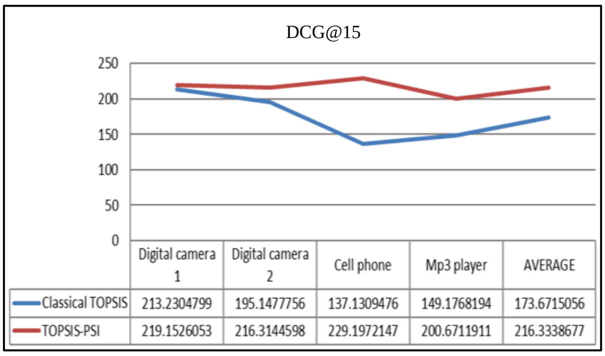

Fig. 3: Performance of TOPSIS-PSI and classical TOPSIS in terms of DCG at 10

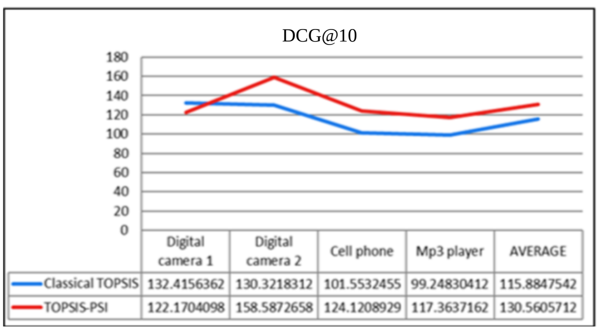

Fig. 4: Performance of TOPSIS-PSI and classical TOPSIS in terms of DCG @ 15

Table 2: Top 15 aspects of the "Mp3 player" product as determined by classical TOPSIS and TOPSIS-PSI

#	Classical TOPSIS	TOPSIS-PSI
1	Player	Player
2	Software	Software
3	iPod	Battery
4	Battery	Ipod
5	Music	Sound
6	Sound	Music
7	Price	Price
8	Quality	Quality
9	File	Screen
10	Nomad	Headphone
11	Scroll	Playlist
12	Button	File
13	Xtra	Nomad
14	Screen	Storage
15	Headphone	size

The proposed approach, which objectively weights the criteria, demonstrates superior performance compared to the subjective weighting in subjective TOPSIS. Specifically, in terms of DCG@5, the PSI approach outperforms the subjective approach by more than 2.18%. Similarly, in terms of DCG@10, the proposed approach outperforms the subjective approach by more than 14.67%. Furthermore, in terms of DCG@15, TOPSIS-PSI outperforms the other approach by more than 42.66%. Hence, the integration of PSI and TOPSIS surpasses the conventional TOPSIS method in effectively ranking product aspects. based on user feedback. In addition, the results of the hybrid TOPSIS-PSI and classical TOPSIS aspect rankings for the product "Mp3 player " are displayed in Table 2.

Conclusion

An essential part of making decisions based on multiple criteria is figuring out how much weight to give each. In most cases, researchers will classify weighting techniques as either subjective or objective. The subjective weights of criteria are determined by the direct judgments and views of the decision-makers. Alternatively, objective weighting systems rely less on subjective decision-making and more on mathematical models that automatically compute the criterion weights based on the known facts in the decision matrix. In addition, where trustworthy subjective weights are unavailable, objective methods are more suited for use. By implementing these strategies, the subjective nature of human judgments can be eradicated. The objective weights for the criteria used to score the product aspects gathered from online reviews were determined in this research by combining the PSI approach with the TOPSIS methodology. Using objective approaches, this study aims to rank product aspects in a more accurate and objective way for potential customers. Subjective weighting has its limitations and this study intends to find a solution. The PSI technique is significant in this research because it considers the interrelationships between the criteria and unlike other approaches, it focuses on the convergence rather than the divergence among all of the included criteria. To put the methodology to the test, we used a benchmark dataset of electronic equipment to compare the findings achieved by classical TOPSIS and the hybrid TOPSIS-PSI method. According to DCG@5, 10 and 15, the proposed TOPSIS-PSI approach produces the best outcomes. In order to overcome the limitations of particular methodologies, this research may inspire other scholars to investigate and include various MCDM approaches.

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Author's Contributions

Both the authors have equally contributed to this manuscript.

Ethics

This article is unique and its contents have not been published before. The corresponding author verifies that the other author has reviewed and endorsed the work and there are no ethical concerns present.

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