A Goal Programming Model for Ranking Product Aspects in Customer Reviews

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Summary

Product aspects are differently handled and not consistent among online reviews. Variable characteristics and importance of each aspect through reviews requires ranking process that enable customers, organizations and marketers to identify and use optimal set of aspects that best support product selection, development, and marketing. Identifying the most representative product aspects, and determine their degree of importance in such a way that best support product selection, development, and marketing has been addressed in this paper. The proposed solution in this paper is to determine the importance degree of each aspect from online reviews to perform aspect ranking. Aspect importance determination is formulated as a multi-criteria decision making (MCDM) problem, several criteria for importance determination have been adopted, and a goal programming (GP) model is constructed to identify and select the best product aspects that can support product purchasing decisions by selecting weight values that best maintain their importance. Several experimental tests are performed and the results showed that using GP can perform aspect ranking and maintain aspect importance at minimum deviation compared to the other related methods.

Keywords:

product aspect, MCDM, GP, aspect ranking, deviation degree

1. Introduction

Vast amount of beneficial information exists through online reviews and can be leveraged for many important purposes, especially for supporting product selection, development and marketing. Despite the subjectivity of consumer evaluations in the reviews, they are often considered more credible and trustworthy than traditional sources of information [5]. Several studies have indicated that online product reviews significantly affect consumer purchase decisions [22,8,43]. Many consumers rely on available Online Consumer Reviews as one of the most trusted sources of information to evaluate their various purchasing alternatives [42]. Compared to information provided by businesses or experts that could be either limited or biased, Online Consumer Reviews provide first-hand usage experience information about products from the perspective of other consumers [4]. Prior research on consumer decision making has established that consumer-generated product information on the Internet attracts more consumers than vendor information [8]. Product users who bought products can provide useful information for potential customers according to their usage experience with these products. Consumers cannot touch or try out products that exhibited on the websites until those products are delivered to them. Thus, information published by consumers who have bought or used the products as product reviews would be helpful for potential consumers to understand the products more clearly [10,32]. Additionally, even when consumers want to buy the products from the physical stores, the consumers can also visit the websites and obtain more product information by reading the related online product reviews. Products are described Through online reviews in terms of usage scenarios and evaluated from the perspectives of their users regarding to certain distinguished features. Online product reviews contain useful information on different aspects of a product for potential buyers to make better comparisons and purchasing decisions [57]. A product user often mentions different product aspects through online review, and different opinions about these aspects expressed using words that indicate positive, negative or neutral evaluation. Each aspect represents a point of interest for users in a product; opinion words are adjectives that represent performance evaluation of that product in satisfying the user with regard to such an aspect. After each purchase, product evaluation is performed with regard to variable aspects according to the consumer experience, preferences, and expectations that the product able to satisfy. Several aspects with various evaluations are exist for the same product.

Manuscript received August 5, 2025
Manuscript revised August 20, 2025
https://doi.org/10.22937/IJCSNS.2025.25.8.17

Efficient exploitation for product aspects can better support product selection, development and marketing. New customers, business firms, product marketers, online aggregators and Online vendors are beneficiaries attracted to revise and investigate product aspects through online reviews to help performing intelligent business processes. However, reading and understanding the huge number of online reviews by large number of buyers is a difficult and time-consuming task. Additionally, products normally have numerous and multiple aspects mentioned and discussed through tremendous number of online reviews. Trade-offs exist among aspects fulfilled by different customer reviews: for certain product, some aspects frequently mentioned and discussed than other aspects, aspects are differently commented and evaluated, some aspects also are more related to their products than others. There is no consensus about certain set of aspects that best represent its correspondent product among product users. Thus, it is not sufficient to just extract and use aspects, but it is essential to determine the most important and suitable aspects that might have greater influence on the interested parties and beneficiaries especially potential consumers.

Being able to identify the most importance product aspects could help Potential customers in making an intelligent purchasing decision [22,8,43].

Several potential customers, especially when first time purchase, are unaware of many hidden product features or aspects that represent interesting points of each available product. Indeed, product aspects present important guidelines and robust evaluation references that can inspire the others and valuable real-time information about products and more convincing compared to the product information provided by merchants [25]. Google My Business, Facebook, and Amazon are common consumer and business review websites aimed to guide first time consumers engage with customers before making any decision [23]. Firms also interested to know the most important product aspects mentioned by product users to help enhance their product development strategies [20]. marketers can depend on the most common product aspects to guide their marketing strategies. online aggregators also can serve their customers better by listing aspects of a product according to their importance. Online vendors could also benefit from identifying the most helpful aspects to ensure they provide an associated response for each especially in the case of critical aspects. Therefore, a main objective in this study is to identify and present the most useful aspects for a product from reviews [57].

Finding the most suitable key aspects for a certain product that best support the interested parties and beneficiaries is a concern in this paper. aspect importance in this study is adopted to indicate the degree to which an aspect is considered as valuable by potential beneficiaries, especially consumers who are contemplating to purchase same product. The value of an aspects can be judged according to the collective judgment of all product users who already use such product and provide online review. collective judgment represents an agreement among all product users that not directly mentioned and need to be inferred and extracted based on several influencer factors. Predicting aspect importance, and perform aspect ranking based on their importance can enable customers, organizations and marketers to identify and use optimal set of aspects that best support product selection (purchasing decisions), development, and marketing in such multi-dimensional environment.

In fact, identifying the most important aspects and predict a weight that represent a degree of importance is considered a challenging multi-dimensional decision making problem. The challenge relays in the availability multiple aspects for the same product with contradicting evaluation and rating through online reviews; multiple product users with their different contradicting subjective opinions about the same aspect.

The viewpoints and opinions of product users presented through online reviews are variable and most probably conflicting; there is no agreement about unified set of product aspects among customers. Each aspect mentioned and concerned by variable number of product users: some aspects that attain high interest among set of users, attain less interest among others, and might not mentioned by the rest. Consequently, some aspects attain high interest among set of users from one perspective, and attain less interest from another perspective among them. Some users might provide a positive opinion regarding a product but might not be satisfied with all the ‘aspects of that product. Indeed, aspects have variable characteristics and importance within intended online reviews and not consistent across all reviews.

The problem to be addressed in this paper can be encapsulated in the following question:

- How to prioritize the most representative product aspects and predict a degree of importance that best represent the collective opinions from online reviews?

To adequately handle such complexity, aspect ranking and predicting their importance with respect to multiple and possibly conflicting criteria is formulated as a multi-criteria decision making (MCDM) problem. A set of key factors that can influence aspect importance are investigated from the literature and adopted as evaluation criteria. The ability of aspects in satisfying such criteria are measured through customer reviews and quantified as weights to represent their importance. A Goal Programming (GP) model is constructed to find a degree of importance weight for each aspect that best represent the collective opinions in the reviews. The degree of importance is an aspect weight that represent its ability to help and benefit potential customers according the collective opinions of all customers. The remainder of this paper is organized as follows: the related works are reviewed in section 2. Section 3 presents the requirements and a detailed design of the proposed solution. Evaluation result and discussion is introduced in section 4. Finally, some conclusions are given in section 5.

2. Related Works

In many cases, product user might provide a positive opinion regarding a product but might not be satisfied with all the ‘‘aspects” of that product. Aspect-based analysis is than required to mine and analyze such information by decomposing the entity into aspects, then classify each aspect sentiment.

More precisely, extracting product aspects mentioned in the reviews, inferring the user’s rating for each identified aspect, and estimating the weight posed on each aspect by the product users are main important opinion mining tasks that can support product selection, development, and marketing strategies [35].

Much work has been introduced including summarizing users’ opinions [2.21], extracting information from reviews [31,33,48,55], analyzing user sentiments [16,36,46,47], and so on. Several researchers proposed methods for dealing with product aspect extraction, inferring the user’s aspect rating, and estimating aspect weight. In this paper, the focus is mainly on estimating aspect weights by measuring their importance degree observed from online reviews. Specifically, aspect weight is a collective parameter from different extraction criteria, which is mainly used in a ranking approach to prioritize the most important aspects in online reviews.

Several approaches are proposed to handle such task; the approach in [35] The aspect weights have been calculated by leveraging the aspect words frequency within the review and the aspect consistency across all reviews. It takes into account the occurrences of words discussing the aspect within a review and the frequency of text sentences discussing the same aspect across all reviews. Li et al. [31] proposed page ranking algorithm based feature opinion to rank the product aspects based on the number of opinion words utilized along with a feature. Hai et al. [21] considered domain relevance of an opinion feature to identify features. Liu Lizhen et al. [34] proposed a weighting algorithm for sentiment analysis of Chinese product reviews based on rich sentiment strength related information. [18] identifies the more representative features of products and assigns overall weights to each one based on the opinion words expressed in the title of the review. Zhang [56] investigated the importance of various aspects for the same product and ranked the aspects with the help of aspect relevance and aspect frequency.

The works of Yu[53] and Wu [50] proposed a probabilistic regression algorithm to rank different aspects by taking in account the aspect frequency and user’s opinions on that particular aspect (sum of weights of opinion word). Choi and Cardie[13] approach ranked the aspects based on the polarity of their opinion words. The authors in [1] perform the aspect rating based only on the number of users who have rated the aspects.

Zheng-Jun Zha [54] designed a probabilistic aspect ranking approach to extract the importance of aspects by considering aspect frequency and the influence of consumer opinions given to each aspect over their overall opinions. Some other methods [49, 53] estimate both aspect’s rating and weight at the same time. The key point of these methods is to use the polarity of opinion words, to calculate weights. Even though sentiment words can usually correctly reflect the user’s rating for each aspect, but other factors should be considered to identify the importance of the aspect for the probable customers.

However, several factors identified as impacting aspect importance and need to be considered simultaneously when predicting aspect weights. Previous researches adopted various factors but not all together to rank aspects which is not enough to reflect a collective opinion of all product users about importance of an aspect. Additional factors that might influence aspect importance and reflect an interest for product users through their reviews are also required. Finding and considering all key factors would greatly enhance the aspect ranking and result in best repetitive aspect set. Thus, predicting aspect weight with regard to all key influencer factors using MCDM is proposed.

Few studies have addressed the problem of aspect ranking using MCDM approaches with regards to various multiple criteria. TOPSIS is an MCDM method that has been adopted in [2] to find the weight for aspects based on several criteria jointly. (TOPSIS and VIKOR) approaches have been re-contextualized in [3] to address the aspect ranking problem. Another related research focus on measuring the performance of various normalization techniques in addressing the product aspect ranking problem in [17]. It concludes that using an MCDM approach achieved efficient results in prioritizing product aspects. In fact, several existing functions have been proposed to handle similar tasks and can be used to aggregate aspect performance values into an aspect weight. Coulouris recommends using the MAJORITY function for a group of processes in order to select one value [15]. The MAJORITY function returns the value that occurs most often among its arguments. Simple Additive Weighting (SAW) is a simple and widely used Multiple Attribute Decision Making method [9] that can aggregate several values into one value. A final selected value using SAW can be determined by multiplying participating values by their relative weights.

However, aggregating extracted information from reviews about aspects with regards to different perspectives without guidance or measure (e.g. considering the deviation or distance principle), may lead to lose part of aspect significance [41,45]. Distance is the gap or deviation degree of the selected weight value for an aspect among a set of correspondent candidate values that obtained from reviews. The distance can achieve more representative aspect importance which is the ranking measure adopted in this paper. The closer aspect weights to their related information are, the more significance and representative are the aspects. Minimizing deviation help to find an optimal solution for each aspect that best represent their importance among all correspondent product users. Thus, minimize the distance when calculating aspect weights is an objective when predicting importance weights. There is no previous work focus on achieving minimum deviation for aspect importance evaluation and ranking.

Accordingly, GP approach that finds numerical weights according to their characteristics mentioned in customer reviews is introduced. In order to maintain the significance of aspects according to their providers, the GP function is constructed to seek for weight value for each aspect with minimum distance to its related evaluation information about criteria. Hence, it achieves better agreement among product users up on set of product aspects to be reference for ranking. GP is a MCDM approach characterized and distinguished by minimizing deviations from an anticipated set of goals [14].

GP is adopted to accommodate problem requirements in this paper where there is an immense need to maintain the aspect importance when calculating their weights from reviews. GP can analyze the aspect information at multiple aspiration levels, relax some of the model constraints, and incorporate the opinions of product users for multiple conflicting perspectives [30]. Although GP and its variants have been used under similar situations in various fields such as group consensus [28], scheduling [29], Big Data [6],data mining [27], group decision support [26], to the best of our knowledge this is the first GP approach applied to aggregate product aspect information from customer reviews and predict their weights.

3. The Evaluation of Aspect Importance

The proposed solution for identifying the most representative product aspects is to quantify their importance based on predetermined criteria evaluated from the existing reviews. The resulted weights will be used to rank the aspects to support product selection, development, and marketing. The aspects are selected from online reviews and their key attributes are investigated with respects to predetermined criteria adopted for such purpose. A MCDM solution is proposed to handle such multi-dimensional environment due to the existence of several and possibly conflicting opinions about aspects. Fig. 1

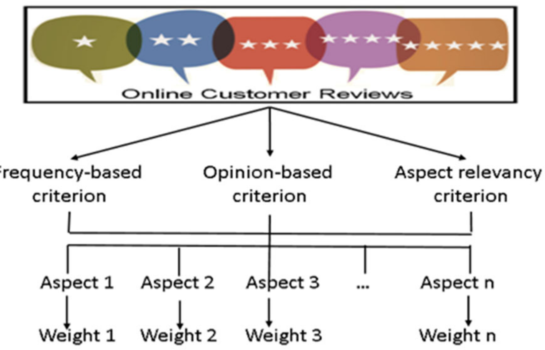

Fig. 1: The structure of MCDM aspect ranking

illustrate the structure of MCDM aspect ranking.

1. Aspect Importance

Aspects of a product are handled differently among its users and it is essential to determine the worth or significance of each aspect according to their potential impact from viewpoints of all product users. some aspects that attain high interest among set of product users, attain less interest among others, and might not mentioned by any users at all. Consequently, some aspects attain high interest among set of product users from one perspective, and attain less interest from another perspective among them. Some consumers might provide a positive opinion regarding a product but might not be satisfied with all the ‘aspects of that product. Therefore, aspect importance is used as a measure for aspect ranking that indicate the degree to which an aspect is considered as valuable by potential consumers. More precisely, aspect importance is the quantifying its ability to achieve the pre-defined set of key influencer criteria that can be measured or evaluated from customer online reviews.

2. Evaluation Criteria

Aspect ranking mainly depends on the Importance degree for each one. Measuring such degree cannot by directly performed because there are no standard measures. several factors might contribute and significantly impact aspect importance are required as criteria to evaluate the Importance of each aspect. Hence, Frequent aspect (Fr), opinionated aspect (Op), and domain-specific (Dc) factors identified as impacting the importance degree of aspect and formulated as evaluation criteria for predicting aspect weights. such criteria present a benchmark, against which performance, and suitability of an aspect is measured, and can be seen as a proxy to determine the available information about a product aspect in customer reviews. The adopted criteria for aspect importance evaluation are summarized in table 1 and described as follows:

Frequency-based criterion: The general belief is that the more aspect of a product is mentioned in online reviews, the more important they are to both consumers and products/services providers. The frequency of referring to a particular product aspect could influence consumers’ choice of the most suitable product or service among several others. For several kinds of research, the most recurrent aspect in Web reviews shows the domain of human supervision for a product-based aspect [24,25,39,44].

Opinion-based criterion: In extracting the opinions of product consumers online, the subjective nature of the discussions become valuable as it provides a reasonably accurate picture of consumer’s feelings about a particular product. It is therefore unusual to find sentiment, emotions, viewpoints e.t.c. in reliable product aspects which will go a long way in affecting the choices of potential consumers. For the fact that this criterion encourages several expressions of opinions, several research methods employ it to study potential product aspects [18,38,51,52].

Aspect relevancy criterion: This criterion simply expresses the need for selected aspects to be related to and vital to the threshold of consumer reviews (for instance, hotels, camera, cars, and so on). In other words, it is important that every domain product should have specific aspects representing it. This is due to the fact that the selection of aspects is also dependent on the threshold of the particular product [40,7,11,12]

Table1: Description of the evaluation criteria

Evaluation criteria	**Description**
Frequent aspect (Fr)	indicates to the raw frequency of each extracted candidate aspect
Opinionated aspect (Op)	numerical score of each candidate aspect which indicates to the number of times an aspect is opinionated in the reviews,
Domain-specific (Dc)	the correlation score of aspect A to a specific domain product, which is indicated by the number of synsets that shared between the domain product name (like ‘camera’) and the aspect (like ‘battery’) using the lexicographer files in WordNet

3. Importance Evaluation

Aspect importance is the subject of the evaluation. Aspect evaluation is the process of measuring the ability of each aspect in satisfying importance factors according to the customer reviews. This enable determination of the worth or significance of each aspect from viewpoints of product users. To better handle the complexity and multidimensional nature of predicting aspect importance and ranking, the problem is formulated as MCDM and a GP model is constructed. The proposed solution is to investigate aspect attributes from online reviews and measure their ability in achieving the adopted criteria. Consequently, the GP model is constructed to aggregate aspect evaluations and predict a weight that best represent such evaluations at minimum deviation. The predicted aspect weights represent a collective opinion or agreement of all product users about the (usefulness or helpfulness of aspects) ability of aspects to help and benefit potential customers. The details of the proposed solution presented in table 2.

Table 2: Predicting aspect importance from online reviews

step	Description /Actions
1	Define importance factors / evaluation criteria $(\boldsymbol{C_j}, \boldsymbol{j} = \mathbf{1}, \dots \boldsymbol{m})$
2	Select the product (P)/ select all potential

	aspects for a product ($\boldsymbol{S_i}$, $\boldsymbol{i = 1, \dots n}$)
3	Determine the importance of aspects $\boldsymbol{w_i}$
4	Evaluate the ability each aspect in satisfying each criterion from each review
	Evaluate the ability each aspect in satisfying each criterion through all reviews
	Evaluate the ability each aspect in satisfying all criteria from all reviews (weight determination)
5	Use the weights $\boldsymbol{w_i}$ for ranking the aspects

The evaluation of product aspects performed initially by determine the performance score ($\boldsymbol{w_{ij}^k}$) of each aspect (i) with respect to each evaluation criterion (j) from each customer review (k). Secondly, performance scores need to be aggregated into a collective scores ($\boldsymbol{w_{ij}}$) that represents performance of each aspect with respect to each evaluation criterion from all reviews. Lastly, aggregate collective scores into a final score ($\boldsymbol{w_i}$) which represents overall performance of each aspect with respect to all evaluation criteria from all reviews together. Different evaluation levels and scores of the problem is expressed in table 3:

Table 3: Evaluation levels and scores of the problem

Performance score (w_{ij}^k)	Ability of the aspect i to satisfy the criterion j obtained from customer review k
	$w_{i\square j}^1 = \begin{bmatrix} w_{1\square 1}^1 & w_{1\square 2}^1 & \cdots & w_{1\square m}^1 \\ w_{2\square 1}^1 & w_{2\square 2}^1 & \cdots & w_{2\square m}^1 \\ \cdots & \cdots & \cdots & \cdots \\ w_{n\square 1}^1 & w_{n\square 1}^1 & \cdots & w_{n\square m}^1 \end{bmatrix} \dots w_{i\square j}^k = \begin{bmatrix} w_{1\square 1}^k & w_{1\square 2}^k & \cdots & w_{1\square m}^k \\ w_{2\square 1}^k & w_{2\square 2}^k & \cdots & w_{2\square m}^k \\ \cdots & \cdots & \cdots & \cdots \\ w_{n\square 1}^k & w_{n\square 1}^k & \cdots & w_{n\square m}^k \end{bmatrix}$
collective scores (w_{ij})	Ability of the aspect i to satisfy the criterion j according to all customer reviews.
	$w_{i\square j}^{\square} = \begin{bmatrix} w_{1\square 1}^{\square} & w_{1\square 2}^{\square} & \cdots & w_{1\square m}^{\square} \\ w_{2\square 1}^{\square} & w_{2\square 2}^{\square} & \cdots & w_{2\square m}^{\square} \\ \cdots & \cdots & \cdots & \cdots \\ w_{n\square 1}^{\square} & w_{n\square 1}^{\square} & \cdots & w_{n\square m}^{\square} \end{bmatrix}$
Final score (w_i)	Ability of the aspect i to satisfy all criteria according to all customer reviews.
	w_i

However, finding a solution that best achieve all criteria across all reviews concurrently is a challenging part; There are multiple aspects for each product with contradicting characteristics; multiple and conflicting evaluation criteria with incomplete or unknown weightings; multiple product users with their different opinions. The degree that an aspect can satisfy one criterion might not be the same degree that an aspect can satisfy the others. Furthermore, the importance degree according to some opinions of product users might not be the same degree from the viewpoints of other product users. Indeed, aspect importance is not consistent across online reviews and cannot be directly obtained. Hence, the solution requires a compromise that takes into account all criteria and all reviews concurrently.

Consequently, the GP model is constructed and formulated to find optimal importance value that best satisfies corresponding multiple criteria through online reviews. Performance scores with respect to Fr, Op, and Dc factors for each aspect are calculated based on available information obtained dynamically from the underlying online reviews and used as input variables for the GP model. The GP model then aggregate such variables to find their corresponding collective and final scores. Indeed, the GP aggregate performance scores into a collective scores represents all customer reviews, and then aggregate collective scores into a final score represents all criteria. The main objective function formulated in the GP model is to find for each aspect the best value at minimum deviation /distance to its correspondent performance score values. Distance is a measurement of how far new values is from the original performance score values, minimum distance represent higher importance of each aspects. Thus, finding final scores that best satisfy corresponding performance scores at minim deviation offers better results. Set of related constraints developed and used in the proposed GP model. The proposed GP model is presented in Fig.2:

$$\begin{aligned} &\boldsymbol{Minimize} \sum\nolimits_{i=1}^{n} F_i^+ + F_i^- + O_i^+ + O_i^- + D_i^+ + D_i^-; \\ &where \\ &for\ i = 1 \dots n \\ &\quad w_i - Fr - F_i^+ + F_i^- = 0; \\ &\quad w_i - Op - O_i^+ + +O_i^- = 0; \\ &\quad w_i - Dc - D_i^+ + D_i^- = 0; \\ &for\ i = 1 \dots n \\ &\quad F_i^+, F_i^-, O_i^+, O_i^-, D_i^+, D_i^-, w_i >= 0; \end{aligned}$$

Fig. 2: The proposed GP model

Where n are the numbers of aspects, F, Op, and Dc are evaluation criteria, $F_i^+, F_i^-, O_i^+, O_i^-, D_i^+, D_i^-$ are over and under deviational variables and w_i are decision variables which are the intended output for the model that represent weights for aspects that used for ranking. Higher weight value w_i represents higher importance for an aspect.

4. Evaluation and Results

The function of the proposed GP model is to find an importance value that best represents or is closest to the values of candidate importance criteria. The closer is the selected importance value to the candidate values; the more significance aspects that might have greater impact and benefit to the potential new customers according to the collective viewpoints of users. Therefore, minimizing the distance between the selected value and each candidate value obtained from online reviews is an objective which represent a precise measure of an aspect importance. Distance is the gap or deviation degree of the selected weight value among a set of related candidate values. The less the distance achieved is, the more important and representative the aspects are. The selected weight value and the candidate criteria values are used to calculate the total distance for all aspects through the following equation:

$$\mathrm{Deviation} = \sum_{i=1}^{n} (w_i - Fr_i) + (w_i - Op_i) + (w_i - Dc_i)$$

Where (n) is number of aspects and FR,Op,Dc are the candidate criteria values obtained from the reviews about aspect i. We evaluate the performance of the GP model in predicting aspect importance based on the collective opinions in reviews and compare the result with the SAW function using the benchmark dataset of customer reviews of electronic products that have been introduced by Bing Liu [25].

The results showed that the GP outperforms SAW function in minimizing the deviation and achieves a lower distance or deviation degree. Our findings reveal that the GP model can identify the most important aspects according the collective opinions in the reviews. The significance of the identified aspects would be higher and their predicted weights better reflect collective opinions in the reviews. Fig. 3 shows the performance comparison between SAW and GP methods in prioritizing the most important product aspects according to collective opinions

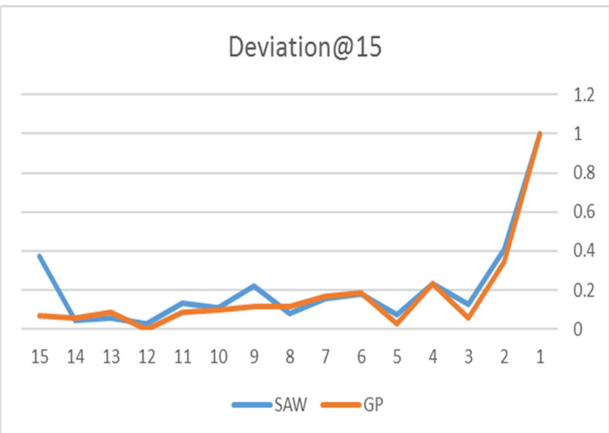

Fig.3: Performance of aspect ranking in terms of Deviation@15

by considering the deviation in terms of top ranked 15 aspects. Furthermore, Table 4. Shows the aspect ranking outputs of a product "Digital camera1: Nikon" using SAW and GP.

Table 4: Top 15 aspects ranked by two methods for Nikon

#	SAW	GP
1	camera	camera
2	picture	picture
3	photo	feature
4	lense	battery
5	autofocus	shot
6	auto	setting
7	closeup	nikon
8	pixel	photo
9	telephoto	scene
10	feature	image
11	setting	access
12	cable	manual
13	battery	lense
14	array	quality
15	camper	size

Table 4 presents the results of product aspect ranking using the 3 ranking criteria based on SAW and GP. The top 15 aspects are shown for the product "Digital camera1: Nikon". From this table, we can discuss the following investigations:

- GP outperformed SAW in identifying and prioritizing important aspects like "battery", "setting" and "image", which are considered a real and more important aspects of a product and can support the customer decision in comparing the products.

- GP and SAW methods considered the name of the product "camera" as an important aspect, as many customers may publish general opinion about the product without any specification of an aspect. So, it is important to consider the name of the product as a real aspect.

- Aspect such as "lense" is identified by GP as less priority aspect (rank 13) compared to higher priority (rank 4) due to the collective opinions extracted from the reviews. Indeed, the GP raking reflect the actual importance posed by all product users.

5. Conclusions

The current paper presents the significance of using Goal Programming method in a new domain of product aspect ranking. We show that GP approved its ability to prioritize important product aspects in online reviews to better support the customer's decision in choosing the appropriate product. Precisely, three extraction criteria have been employed together to prioritize the product aspects that have been extracted from consumer reviews; frequent-based, opinion-based, and aspect relevancy. SAW has been used to compare its performance against GP in aspect ranking. Even though GP and SAW used different aggregation functions, but both methods are more suitable to identify important product aspects. However, more comparative research studies using other MCDM methods with larger datasets should be conducted to show the significance of MCDM approach to address the product aspect ranking problem.

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