Combining user preferences and expert opinions: a criteria synergy-based model for decision making on the Web

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Abstract: Customers strongly base their e-commerce decisions on the opinions of others by checking reviews and ratings provided by other users. These assessments are overall opinions about the product or service and it is not possible to establish why they perceive it as good or bad. To understand this "why", it is necessary an expert's analysis concerning the relevant factors of the product or service. Frequently, these two visions are not coincident and the best product for experts may not be the best one for users. For this reason, trustworthy decision making methods that integrate the mentioned views are highly desirable. This article proposes a multi-criteria decision analysis model based on the integration of users' preferences and experts' opinions. It combines the majority's opinion and criteria synergy to provide a unified perspective in order to support consumers' ranking-based decisions in social media environments. At the same time, the model supplies useful information for managers about strengths and weaknesses of their product or service according to users' experience and experts' judgement. The aggregation processes and synergy criteria are modelled in order to obtain an adequate consensus mechanism. Finally, in order to test the proposed model, several simulations using hotel valuations are performed.

Keywords: decision making, multi-criteria decision analysis, criteria coalition synergy, majority aggregation, social media.

1. Introduction

Increasingly it can be seen that consumers base their buying decisions on feedback and opinions from other users. The huge volume of information about positive and negative experiences provides an additional decision tool for buyers. In this context, social media provides Internet-based applications that allow the creation and exchange of user-generated content (Kaplan & Haenlein, 2010) and, also, rating or asking and answering across diverse websites (Hocevar, Flanagin, & Metzger, 2014). Moreover, several works are focused on sentiment analysis in social media (Deng, Sinha, & Zhao, 2017; Ravi & Ravi, 2015; Yu & Cao, 2013) on diverse environments (Ding, Cheng, Duan, & Jin, 2017; Jang, Sim, Lee, & Kwon, 2013; Nguyen, Shirai, & Velcin, 2015). Indeed, social media is very different from traditional media in many areas, such as usability, quality, frequency and immediacy (Agichtein, Castillo, Donato, Gionis, & Mishne, 2008), and these are useful issues for making decision processes.

While this mentioned information is useful for the buyer, it could also be for the seller in order to innovate or improve their products. However, there are two drawbacks to consider: firstly, due to the huge amount of information, it is difficult to keep track and to manage all customers' opinions (Hu & Liu, 2004); secondly, this valuation mechanism is dynamical and it is based on the majority's opinion. To solve the first drawback, several summarising methods can be used. For example, the individual valuations are summarised by using a number of stars, a satisfaction level, etc. I.e. a lot of opinions are represented by a few values. The second drawback is solved by using some aggregation strategy as the arithmetic mean, Ordered Weighted Averaging (OWA) operators (Yager, 1988) for majority's opinion (Karanik, Peláez, & Bernal, 2016; Pasi & Yager, 2003; Peláez, Bernal, & Karanik, 2014; Peláez, Doña, & Gómez Ruiz, 2007; Peláez & Doña, 2003a, 2003b, 2006) or consensus (Dong, Xiao, Zhang, & Wang, 2016; Mata, Pérez, Zhou, & Chiclana, 2014; Wu & Xu, 2012), in order to dynamically summarise all opinions.

In this context, the decision making (DM) process of purchase is only carried out by using preference opinions related to the satisfaction degree, but the influence of a specific criterion over the chosen alternative is not considered (at least not explicitly). That is to say, given the

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majority's opinion about the evaluated alternatives, the question "Which product is the best?" can be answered; however, the question "Why is this product the best?" does not have a clear answer. On other hand, there are tests and benchmarks of specialised publications and websites that use experts' opinion in order to valuate products and services. In general, this kind of valuation is made using Multi Criteria Decision Analysis (MCDA) (Figueira, Greco, & Ehrogott, 2005) and it requires high expertise level in order to evaluate several criteria simultaneously. This evaluation becomes more complex when the criteria quantity grows because it is necessary to evaluate each criterion individually and the interaction between all of them. I.e., modelling MCDA process involves evaluating several alternatives based on multiple criteria and the synergy relations between them (Rubén Bernal, Karanik, & Peláez, 2015). To do this, fuzzy measures and integrals are used in several MCDA (Angilella, Corrente, & Greco, 2015; Branke, Corrente, Greco, Słowiński, & Zielniewicz, 2016; Grabisch & Labreuche, 2016; Joshi & Kumar, 2016; Tan, 2011; Yan & Ma, 2015).

The situation described above implies two different kinds of DM processes: one more informal (majority's opinion) and one more formal (MCDA). In order to use the advantages of both, a hybrid model can be defined as follows. First, in addition to asking about the degree of satisfaction with its purchase, questions could include a few criteria, three or four, of the product or service. Then, all answers, by criteria, can be summarised by using a majority-based operator. Finally, the synergy relationship between criteria can be modelled by using a MCDA technique, taking the experts' opinions into account, in order to obtain the most adequate alternative. Thus, a unified solution for the decision problem can be achieved.

This article proposes and describes a new integrated model that builds the synergy relationship between criteria using the Choquet Integral (Choquet, 1954) with fuzzy measures (Sugeno, 1974) based on (a) the summarised majority's opinion about some products or services criteria and (b) the criteria coalitions which are defined by experts. Both are aggregated by using the SMA-OWA operator (Karanik et al., 2016). In section 3 the basic concepts about majority operators and fuzzy measure model used are described. The proposed model is described in section 4. In section 5 the model is tested and its results are analysed. The impact on the ranking changes is discussed in section **¡Error! No se encuentra el origen de la referencia.**. Finally, in section 7 conclusions and future work are presented.

2. Related Work

Although the decision making process has been extensively studied, the massive use of social media has produced important changes in the way of selecting the best available alternative. In recent years, social commerce characteristics (Huang & Benyoucef, 2013, 2015; Liang & Turban, 2011; Sun, Wei, Fan, Lu, & Gupta, 2016) have gained great importance as element of study about users' relationship that affect the decision making process. In (Baethge, Klier, & Klier, 2016) a deep review of the main aspects covered by the social commerce research as user behavior, website design, enterprise strategies, business models, firm performance and security and privacy policy, among others, can be found. Undoubtedly, social behavior has great influence upon the decision making process, specifically on consumer purchase decision making (Huang & Benyoucef, 2017). Users feel more confident when others' experience is employed as a recommendation mechanism. In this sense, aspects as preference similarity, recommendation trust and social relationship are used in order to define recommendation mechanism (Huang & Benyoucef, 2013; Y.-M. Li, Wu, & Lai, 2013; Sun et al., 2016).

There are two issues related to recommendation process in social environments that are necessary to analyze: the opinions summarization and the criteria interaction. Regarding the first one, it is clear that recommendation in social environments produce massive and heterogeneous opinions and, therefore, a consensus mechanism is necessary in order to resume the importance about analysis criteria. Basically, consensus techniques are based on similarity functions used to establish how close the user's preferences and opinions are (Chiclana, García, del Moral, & Herrera-Viedma, 2015). In this context, several approaches tending to find similarity based on strict or soft coincidence of preferences (Cabrerizo, Moreno, Pérez, & Herrera-Viedma, 2010) are used.

Another way to obtain a representative value from multiple opinions is by using aggregation operators. Specifically, majority's opinion aggregation mechanisms allow estimating a representative value or concept based on different strategies (Karanik et al., 2016; Peláez, Bernal, & Karanik, 2016; Peláez & Doña, 2003a, 2003b). Usually, these kinds of aggregation methods are quicker than consensus methods (Taylor, Hewitt, Reeves, Hobbs, & Lawless, 2013) and this characteristic is very desirable for decision making processes in social media environments.

Regarding criteria interaction, on the one hand, most multi criteria decision models implicitly consider the relation among criteria. Usually, widely used multi criteria decision methods (Figueira et al., 2005) include criteria comparison processes that are generally complex considering pair comparisons. On the other hand, explicit interactions can be defined by using the synergic model proposed by (R. Bernal, Karanik, & Peláez, 2016). In this model, a fuzzy measure is computed in order to set up coalitions among criteria. Positive, negative or no synergy are taken into account. Finally, the Choquet integral (Choquet, 1954) is used to establish the alternatives' ranking in a decision making problem.

3. Preliminaries

3.1. Majority's opinion aggregation

In general, aggregation processes overstate the minority's opinion at expense of the majority obtaining, in this way, an imprecise aggregation. In order to summarise the majority's opinion, some special cases of well-known OWA operators can be used. Given $a=(a_1,...,a_n)\in \mathrm{R}^n$ and S_n be the permutation group of a, an OWA operator (Yager, 1988) is a function $F_w:\mathrm{R}^n \rightarrow \mathrm{R}$, such that:

$$F_w(a)=\sum_{j=1}^{n} w_j a_{\sigma(j)} \tag{1}$$

where $\sigma \in S_n$ is the unique permutation ; and $w=(w_1,...,w_n)\in[0,1]^n$ be such that $w_1+...+w_n=1$.

Notice that the properties and types of OWA operators are out of the scope of this manuscript. They have been extensively studied and a good review of these topics can be consulted in (Fodor, Marichal, & Roubens, 1995; Yager, Kacprzyk, & Beliakov, 2011; Zarghami & Szidarovszky, 2009).

The arithmetic mean can be considered an OWA operator with $w_j=1/n$. The arithmetic mean is a representative value only when the cardinality of all items to aggregate is equal to one. In order to generalise the arithmetic mean when the items to aggregate have cardinalities larger than one, Peláez and Doña (Peláez & Doña, 2003b) have introduced the Majority Additive OWA (MA-OWA) operator. Formally, the MA-OWA operator is defined as follows (Peláez & Doña, 2003b):

Let $a=(a_1,...,a_i,...,a_n)\in \mathrm{R}^n\times \mathrm{N}^n$ with $a_i=(v_i,m_i)$ representing the aggregated value, v_i, and its cardinality, $m_i>0$, and S_n be the aggregate permutation group. Let $\sigma \in S_n$ be any permutation. A MA-OWA operator is a function $F_{\mathrm{MA}}:\mathrm{R}^n\times\mathrm{N}^n \rightarrow \mathrm{R}$ defined as:

$$F_{\mathrm{MA}}(a)=\sum_{i=1}^{n} w_{i,N} v_{\sigma(i)} \tag{2}$$

where $N=\max_{1\le i\le n} m_i$ and the weights are defined by the recurrence relations:

$$w_{i,1}=u_1=1/n \tag{3}$$

$$w_{i,k}=\frac{\gamma_{i,k}+w_{i,k-1}}{u_k} \tag{4}$$

with $2\le k\le N,\ 1\le i\le n$ and,

$$u_k=1+\sum_{j=1}^{n}\gamma_{j,k},\quad 2\le k\le N \tag{5}$$

where:

$$\gamma_{j,k}=\begin{cases}1 & m_{\sigma(j)}\ge k\\ 0 & \text{otherwise}\end{cases} \tag{6}$$

This definition requires that:

$$\sum_{i=1}^{n} w_{i,k}=1 \tag{7}$$

for $k=N$. In fact, Eq. (7) holds for all k. The corresponding proof (and properties and examples of MA-OWA operator) can be found in (Peláez & Doña, 2003b).

Even though MA-OWA operator represents the most typical opinion with larger aggregated cardinality, there are some cases in which it deletes the minority's opinion if the cardinality of the most typical opinion is larger than that of the rest. This situation occurs since cardinalities lower than N generate $\gamma_{i,k}=0$ and $w_{i,N}\rightarrow\infty$ prompt for all weights except for those corresponding to the largest cardinality (which tends to 1) giving the following result:

$$F_{\mathrm{MA}}(a)=1\cdot v_{\sigma(j)} \tag{8}$$

where is the largest cardinality value of a.

In order to deal with this situation, the Selective Majority Additive OWA (SMA-OWA) (Karanik et al., 2016) operator redefines the gamma factor of Eq. (6) as follows:

$$\gamma_{j,k}=\begin{cases}\delta & m_{\sigma(j)}\ge k\\ 1-\delta & \text{otherwise}\end{cases} \tag{9}$$

where δ is the cardinality relevance factor (CRF) with $0\le\delta\le1$.

Clearly, by using the SMA-OWA operator, if $\delta\rightarrow1$ only opinion with the largest cardinality is taken into account and the same behavior of standard MA-OWA operator is obtained. On the contrary, if $\delta\rightarrow0$ the opinion with the largest cardinality is discarded. If the arithmetic mean is obtained. CRF does not change the calculus of MA-OWA operator and, consequently, its mathematical properties remain (Karanik et al., 2016).

SMA-OWA introduces a new issue about majority: the importance assigned to different opinions. For this reason, situations in which all opinions must be considered can be modelled more accurately.

Summarising, SMA-OWA operator is an adequate mechanism to resume the majority's opinion and it returns a value that represents the majority's opinion more accurately as demonstrated in (Karanik et al., 2016).

3.2. Coalitions, fuzzy measures and Choquet integral

In general, the MCDA models do not consider the dependence between criteria. For that, incomplete visions of the decision process are obtained. In order to adequately represent the criteria interaction, an interesting Choquet integral based model is described in (Rubén Bernal et al., 2015). Basically, the criteria synergy is modelled based on the most important criteria relationships and the rest are considered additive. The experts express the interaction characteristics by using different linguistic labels. With these considerations, the coalition model builds a fuzzy measure and the final ranking of alternatives is computed by the Choquet integral calculation. Formally, the model is defined as follows (Rubén Bernal et al., 2015).

Let $\mathbf{A} = \{a_1,...,a_k\}$ a set of alternatives to be assessed respect to a set of n criteria $\mathbf{N} = \{c_1,...,c_n\}$. Each alternative $a_j \in \mathbf{A}$, has a profile:

$$\mathbf{x}^{a_j} = \left(x_1^{a_j},...,x_n^{a_j}\right) \in \mathrm{R}^n \tag{10}$$

where $x_i^{a_j}$ is a partial valuation of a_j w.r.t. the criterion c_i. From $\mathbf{x}^{a_j}$ it is possible to calculate an overall measure $M\left(\mathbf{x}^{a_j}\right)$ for each alternative by an aggregation operator $M : \mathrm{R}^n \to \mathrm{R}$. In addition, $C_1, C_2,...,C_i,...$ are the subsets belonging to $\wp(\mathbf{N})$ and $\mu(C_1), \mu(C_2),...,\mu(C_i)...$ their weights, where $\wp(N)$ is the power set of $\mathbf{N}$.

The criteria coalition model also considers: (a) a set of labels $\mathbf{V} = \{v_1,...,v_i,...,v_j\}$ used to indicate the relative importance of each criteria w.r.t. the objective being evaluated; (b) a set of labels $\mathbf{W} = \{w_1,...,w_i,...,w_j\}$ used to indicate the synergy degree among criteria (even the null label); (c) the set of expertise levels $\mathbf{EL} = \{el_1,...,el_i,...,el_k\}$ where every $el_i \in [1..3]$ characterises each expert and (d) a set $\mathbf{EC}$ of pairs (el_i, lq_i) that provides the number of different linguistic labels of $\mathbf{V}$ for each expert; the values of $lq_i \in [3,5,7]$ on the basis of the expertise level el_i.

The use of linguistic labels and preference relations to establish the importance (weight) of each criterion and groups of criteria are extensively studied and they can be consulted in (Herrera, Herrera-Viedma, & Chiclana, 2001; Herrera, Herrera-Viedma, & Martínez, 2000; Massanet, Vicente Riera, Torrens, & Herrera-Viedma, 2016; Rolland, 2013; Wu & Xu, 2012).

Based on these definitions, the coalition calculation is made as follows: first, the number of linguistic labels (3, 5 or 7) is determined for each expert; second, the expert uses the most adequate linguistic label (from $\mathbf{V}$) to express the importance of each single criterion; third, the criteria coalitions are evaluated, to do this, the expert specifies the sign and degree of the coalition synergy by using linguistic labels of $\mathbf{W}$ and the rest are considered additive; fourth, the fuzzy measure calculation is made for each subset $C_i \in \wp(\mathbf{N}) - \mathbf{N}$, based on the Sugeno definition of fuzzy measure (Sugeno, 1974) and the interaction conditions stated by (Rubén Bernal et al., 2015); fifth, the measures of all coalitions are normalised and the profile of each alternative is determined; sixth the Choquet Integral (CI) (Choquet, 1954) is calculated by using the obtained fuzzy measure by (Rubén Bernal et al., 2015):

$$\mathrm{C}_\mu(\mathbf{x}) = \sum_i^n x_{(i)} \left[\mu\left(A_{(i)}\right) - \mu\left(A_{(i+1)}\right) \right] \tag{11}$$

Where $x_{(\bullet)}$ indicates a permutation such as $x_{(1)} \le x_{(2)} \le ... \le x_{(n)}$; and $A_{(i)} = \{i,...,n\}$; $A_{(n+1)} = \varnothing$; $\mu\left(A_{(n+1)}\right) = 0$.

After CI for every alternative is computed, this obtained value represents the importance of each alternative as a possible solution of the decision problem based on the opinion of the expert e_i. In order to summarise all experts' opinions, some aggregation method is used as proposed in (Rubén Bernal et al., 2015).

4. Proposed Model

As mentioned before, prior to making a decision on purchasing products or contracting services, users usually consider other users' opinions and formal valuations of such products or services. Both provide different views because other users' opinions are global assessments, while formal valuations consider specific aspects (or criteria) of the thing to be evaluated. In order to combine both views, the majority's opinion aggregation and criteria coalition processes are integrated here in a MCDA unified model (**Figure 1**).

The proposed model provides two simultaneous rankings for the product or service to evaluate, one personal (based on the specific user's preferences) and one global (based on all users' preferences). Both rankings have the same calculation process but their data sources are slightly different.

To obtain both rankings, opinions of users and experts are necessary. The users must define: the individual importance of each generic attribute (**Figure 1** flow A) and the assessment over specific alternatives' criteria (**Figure 1** flow B). Having done this, a process of majority's opinion aggregation (in this case, the SMA-OWA operator described in section 3.1) is used in both cases (**Figure 1** Aggregation Process Level 1). Note that the individual importance of generic attributes (**Figure 1** flow A) is made when users define what is being searched and the assessment of specific alternatives' criteria (**Figure 1** flow B) is made after purchasing and using that product. On the other hand, a consensus of the sign and the coalition synergy of each group of criteria are determined by a group of experts (**Figure 1** flow C) and their opinions are also aggregated by using SMA-OWA operator (**Figure 1** Aggregation Process Level 2). In this case, the aggregation process is based on the coalition method explained in Section 3.2.

At this point, two distinct fuzzy measures are necessary in order to calculate the personal and global rankings. For personal ranking, the individual fuzzy measure is constructed based on the individual importance of each generic attribute (**Figure 1** flow A) and the aggregated opinion of experts about coalitions (**Figure 1** flow F). With this individual fuzzy measure (**Figure 1** flow G) and the aggregated valuation about specific products (**Figure 1** flow E), the Choquet integral calculus as aggregation operator is made in order to obtain the final personal ranking of alternatives and their corresponding intensities.

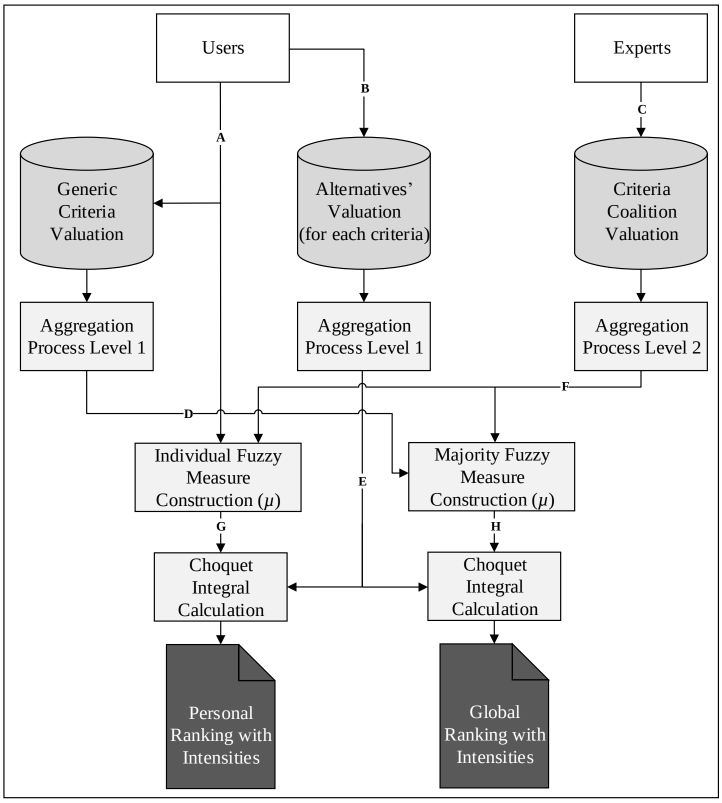

Figure 1. Majority aggregation model with criteria coalition

For global ranking, the same process described above is made. The majority fuzzy measure is constructed based on the aggregated importance of each generic attribute (**Figure 1** flow D) and the same aggregated opinion of experts about coalitions (**Figure 1** flow F) mentioned before. Finally, the global ranking is calculated by using the Choquet integral with this majority fuzzy measure (**Figure 1** flow H) and the aggregated valuation about specific alternatives' criteria (**Figure 1** flow E).

This model has several remarkable points. First, all databases containing individual valuations (generic criteria valuation, specific criteria valuation and coalition criteria valuation) that are updated independently of each other. Thus, no synchronicity between databases is necessary and all opinions from users and experts are stored dynamically. Second, aggregated values are automatically calculated and they are available in order to construct the individual or majority fuzzy measure. The individual fuzzy measure is constructed when a user specifies their general preferences about the product or service he/she is looking for. On the other hand, the majority fuzzy measure is constructed with aggregated values of other users' preferences. Both measure construction processes use the same aggregated values calculated from experts' opinions.

Third, the Choquet integral calculus is the same in order to obtain both rankings. The difference is, while personal ranking is calculated by using the individual fuzzy measure, global ranking is calculated by using the majority fuzzy measure.

Fourth, the global ranking with intensities is always available and reflects the current aggregated values of users' preferences and experts' opinions. Hence, when a user specifies their preferences he/she obtains their personal ranking with intensities and can compare it with what the majority says. Clearly, this characteristic gives the user an important reference point of view.

4.1. Model definition

In this proposed model two levels of aggregation are considered: one for the weight determination of every single criterion, and one for the weight determination of interacting criteria. According with coalition model defined by (Rubén Bernal et al., 2015):

Let $\mathbf{A} = \{a_1,...,a_k\}$ a set of alternatives to be evaluated with respect to a set of n criteria $\mathbf{N} = \{c_1,...,c_n\}$. Every alternative has a profile $\mathbf{x}^{a_j} = \left(x_1^{a_j},\dots,x_n^{a_j}\right) \in \mathrm{R}^n$, where $x_i^{a_j}$ is a partial assessment of w.r.t. the criterion c_i. This profile allows calculating the measure $M\left(\mathbf{x}^{a_j}\right)$ for each alternative as outcome of this coalition model.

Additionally, let's consider the sets defined in section 2.2:

- $C_1, C_2,\dots,C_p,\dots \in \wp(N)$ and their weights $\mu(C_1), \mu(C_2),\dots,\mu(C_p)\dots$.
- $\mathbf{V} = \{v_1,\dots,v_i,\dots,v_j\}$ which indicates the relative importance of each criterion w.r.t. the objective.
- $\mathbf{W} = \{w_1,\dots,w_i,\dots,w_j\}$ which is used to provide the synergy degree between criteria.
- $\mathbf{EL} = \{el_1,\dots,el_i,\dots,el_k\}$ which characterises each expert according to their expertise level.
- **EC** of pairs (el_i, lq_i) which contains the number of linguistic labels of $\mathbf{V}$ that the expert can distinguish according to the expertise level el_i (**Table 1**).

Table 1: Labels for each expertise level

Expertise level el_i	Label quantity lq_i	Labels
1	3	$\mathbf{V} = \{$low, medium, high$\}$ $\mathbf{W} = \{$null, moderate, extreme$\}$
2	5	$\mathbf{V} = \{$very low, low, medium, high, very high$\}$ $\mathbf{W} = \{$null, weak, moderate, strong, extreme$\}$
3	7	$\mathbf{V} = \{$lowest, very low, low, medium, high, very high, highest$\}$ $\mathbf{W} = \{$null, very weak, weak, moderate, strong, very strong, extreme$\}$

In order to calculate the weights the coalition model is divided into two steps: Aggregation Process Level 1 for every criterion and Aggregation Process Level 2 for every criteria coalition. Both processes are described below.

Aggregation Process Level 1: this process is the same for generic criteria valuations as specific criteria valuations. In order to establish the importance, each criterion is evaluated individually to determine its relative importance with respect to the objective.

Due to the fact that this information is supplied by different users on the web, it is necessary to consider the majority's appraisal to determine a consensus value (for each $c_q \in \mathbf{N}$ $(1 \le q \le n)$, $\mu(c_q)$ will be determined). In order to represent the majority's opinion, the proposed model uses the SMA-OWA operator.

The assessments of each criterion will be aggregated in a representative value. For that, it is necessary to determine the cardinality m_i of each assessment v_i from $\mathbf{V}$. To do this, for each criterion $c_q \in \mathbf{N}$ (with $1 \le q \le n$), the set of criteria to aggregate $\mathbf{ca}_{c_q}$ is defined as follows:

$$\mathbf{ca}_{c_q} = \left\langle (v_1, m_1),\dots,(v_i, m_i),\dots,(v_j, m_j) \right\rangle \tag{12}$$

Then, the aggregation process is made using the SMA-OWA operator. The process is shown in **Algorithm 1**.

Algorithm 1: Aggregation Process Level 1

1. **for each** single criterion $c_q \in \mathbf{N}$ with $1 \le q \le n$
2. determine the cardinality m_i for each $v_i \in \mathbf{V}$;
3. obtain $\mathbf{ca}_{c_q} = \left\langle (v_1, m_1),\dots,(v_i, m_i),\dots,(v_j, m_j) \right\rangle$;
4. calculate $\mu(c_q)$ by using SMA-OWA operator;
5. **end for each**
6. **for each** single criterion $c_q \in \mathbf{N}$ with $1 \le q \le n$
7. normalise the values in the interval $[0,1]$
8. **end for each**

Aggregation Process Level 2: the sign and degree of interacting criteria must be defined by the experts in order to determine the weight of each coalition. To do this, linguistic labels to establish the importance (weight) of each group of criteria are used. This information should be aggregated into a single value from the consensus of the majority. I.e., for each $C_p \in \wp(\mathbf{N}) - \mathbf{N}$, $\mu(C_p)$ will be determined.

To define an adequate fuzzy measure, $2^n - 2$ coefficients, as maximum, will be determined (with a set of n criteria and $\mu(\varnothing) = 0$, $\mu(\mathbf{N}) = 1$). Notice that it is not necessary for the experts to provide the synergy degree of all combination of criteria. Only the specific synergy relationships are necessary; the rest is considered additive. In order to represent the majority's opinion, the proposed model also uses the SMA-OWA operator for criteria coalitions. The assessments of each criteria coalition will be aggregated in a representative value. For this, it is necessary to determine the cardinality m_i of each assessment w_i from $\mathbf{W}$. To do this, for each criteria coalition C_p the set of criteria coalition to aggregate $\mathbf{Ca}_{C_p}$ is defined as follows:

$$\mathbf{Ca}_{C_p} = \langle (w_1, m_1), \ldots, (w_i, m_i), \ldots, (w_j, m_j) \rangle \quad (13)$$

The majority aggregation process for level 2 is shown in **Algorithm 2**.

At this point, the individual and the majority fuzzy measures can be constructed by combining the outcomes of **Algorithm 1** and **Algorithm 2**. Note that both processes (**Figure 1** Individual Fuzzy Measure Construction and Majority Fuzzy Construction) are the same, but with different data sources. Finally, to conclude with the aggregation process, it is necessary to supplement the two phases previously analysed using the Choquet integral calculus. The final procedure is shown in **Algorithm 3**.

After calculation, the personal and global rankings (with their intensities) are available to the user. Besides these outcomes that are important for the user, there are other intermediate results such as the aggregated generic criteria valuation, the aggregated specific criteria valuation and the aggregated criteria coalition valuation (**Figure 1** flows D, E and F) that are important to traders, manufacturers and service providers.

This information allows knowing what product (or service) aspects are considered relevant by users and experts. Clearly, this is useful feedback information in order to improve different product (or service) features.

4.2. Model functionality

The proposed model explained in previous section combines the majority's opinion of the users with experts' knowledge in order to create a DM method based on criteria coalition. In this way the best characteristics of these two views are summarised and they are used to choose the more adequate alternative for a DM problem. In order to resume the overall process, the steps to obtain personal and global rankings are explained in detail.

Criteria definition phase. First of all, it is necessary to define what is important in a product (or service) evaluation. Consequently, most relevant criteria about the product (or service) must be established. There are many ways to do that, for example, a manufacturer can define which aspects he/she considers the most important to evaluate, an expert can describe the relevant product characteristics or, even, the criteria can be gathered from users' opinions on the web. It is important to keep in mind that this criteria definition is a key factor and the success of evaluation depends on it.

Algorithm 2: Majority aggregation process of the second level

1. determine the number of labels lq that the experts can distinguish;
2. establish a mapping between each linguistic label of $\mathbf{W}$ on N_0;
3. **for each** subset $C_p \in \wp(\mathbf{N}) - \mathbf{N}$ with cardinality $1 < p \leq n$
4. $\mu(X) = \max(\mu(X_j))$; $X_j \subseteq C_p$; // with $|X_j| = p - 1$
5. $\mu(Y) = \mu(C_p - X_j)$;
6. $\lambda_{\min} = \dfrac{\max(\mu(X), \mu(Y)) - (\mu(X) + \mu(Y))}{\mu(X)\mu(Y)}$;
7. $\lambda_{\max} = \mathrm{abs}(\lambda_{\min})$;
8. **for each** expert (if coalition exists) **do**:
9. determine the sign of synergy (positive or negative);
10. **if** synergy is positive **then** register the synergy degree in $\mathbf{Ca}_{C_p} = \langle (w_j, m_j) \rangle$ **end if**
11. **if** synergy is negative **then** register the synergy degree in $\mathbf{Ca}_{C_p} = \langle (-w_j, m_j) \rangle$ **end if**
12. **end for each**
13. Aggregate SMA-OWA operator to obtain $M(\mathbf{Ca}_{C_p})$;
14. $\Delta_\lambda = \lambda_{\max} / (lq - 1)$;

$\lambda = M\left(\mathbf{Ca}_{C_p}\right)\Delta_\lambda$;

$\mu\left(C_p\right) = \mu(X) + \mu(Y) + \lambda\mu(X)\mu(Y)$;

end for each

for each subset $C_p \in \wp(\mathbf{N})$

$\mu\left(C_p\right) = \mu\left(C_p\right) / \mu(\mathbf{N})$; // normalise the values in the interval $[0,1]$

end for each

Algorithm 3: Final aggregation using the Choquet integral

for each alternative $a_j \in \mathbf{A}$

$\mathbf{x}^{a_j} = \left(x_1^{a_j}, x_2^{a_j}, \ldots, x_n^{a_j}\right) \in \mathrm{R}^n$; // compute the profile

end for each

for each alternative $a_j \in \mathbf{A}$

compute the discrete Choquet Integral $\mathrm{C}_\mu\left(a_j\right)$; // w.r.t. fuzzy measure μ

end for each

Data compilation phase. This stage implies to obtain three kinds of information: (a) users' valuations about how important each criterion is for a product or service that he/she is looking for (in a generic way), (b) users' valuations about how good the specific alternatives' criteria (product or service) that he/she purchased or used are (for each criterion), and (c) experts' valuations about criteria coalitions (sign and level of synergy between criteria). The valuations about generic criteria (a) are generally made when user is searching for some product (or service), and valuations about aspects of specific product (b) are made before using it. Concerning experts' opinions about coalitions there is a key factor to consider: the expertise. In this sense, reliable mechanisms are needed to determine the evaluator's expertise. One interesting characteristic of these types of information can be gathered using different methods such as numeric scales, stars, satisfaction degree with slide bars, etc. Notice that (a), (b) and (c) correspond with individual opinions and they are stored in a cumulative way.

Data aggregation phase. In this stage, the two aggregation methods described in the previous section are made. For generic criteria valuation and specific criteria valuation, the aggregation process is the same. I.e. by using SMA-OWA, under conditions described in (Karanik et al., 2016), the aggregation process is performed. An aspect worth mentioning is that the Cardinality Relevance Factor δ used for SMA-OWA operator, is calculated using the dispersion of cardinalities. Regarding criteria coalition valuation, as described before, a combination of coalition model with SMA-OWA operator is employed. The individual fuzzy measure combines the weights obtained from the user valuation about generic criteria and the aggregated criteria coalition valuation. In the same way the majority fuzzy measure combines the weights obtained from aggregated majority process about generic criteria and the aggregated criteria coalition valuation. In this sense, the proposed model gives two different points of view about the same decision problem.

Ranking determination phase. The last stage is the application of Choquet integral over both fuzzy measures. This process is made as indicated in (Rubén Bernal et al., 2015). The calculus is simple and the final rankings (and the intensity for each alternative ranked) are obtained.

The entire process is depicted in **Figure 2**. Notice that, except for criteria definition phase, no sequence is defined by the rest. I.e. the number of user valuations can change dynamically and the rankings are constantly updated. This feature provides a great flexibility to the model.

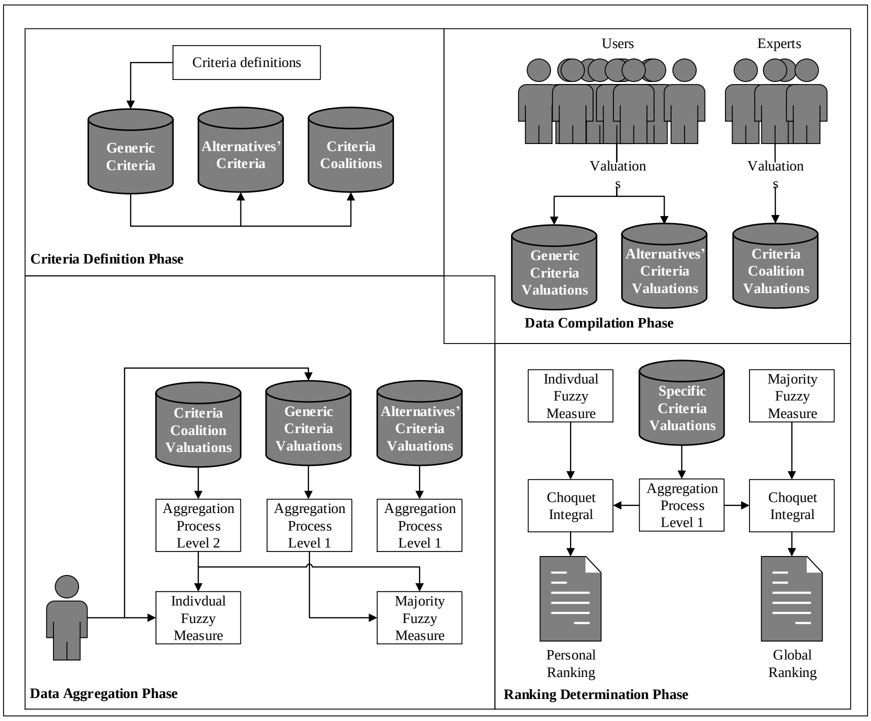

Figure 2. Model scheme

5. Simulation and Results

In this section, in order to show the specifications and benefits of the proposed model, users' opinions about three hotels are analysed:

$$\mathbf{A} = \{\text{Hotel1, Hotel2, Hotel3}\}$$

In this context, the multi-criteria decision process is modelled, where the importance of criteria and criteria coalition information is calculated by using a majority aggregation process for both cases. In addition, individual ranking with the same criteria coalitions is calculated with the aim of comparing it with the majority's point of view.

For practical reasons, opinions about hotel criteria preferences were collected from forty users in an academic environment, also they were consulted about their experience in three popular hotels (if they had stayed in any of them) and ten expert users were asked for their opinions about criteria coalitions. This information can be showed in Appendixes A, B and C.

The experiments are organized into three subsections; the first one involves the global ranking calculation based on aggregated generic criteria valuations (made by users), aggregated alternatives' criteria valuations (made by users) and aggregated coalition criteria valuations (made by experts); the second one contains the individual ranking calculation based on the same data used for global ranking calculation except for individual generic valuation (made by a specific user) instead of aggregated generic criteria valuations; and the third one encloses the analysis of the special cases about ranking calculation with this model. Previously, the data description is made.

5.1. Data Description

For all tests, the importance of five criteria is analysed considering the users' opinion. This information is collected by using different linguistics labels. In addition, four different criteria coalitions are considered (two criteria in each one). Notice that the interpretation of interaction for more than two criteria is much more difficult (Grabisch, 1997); thus it is sufficient to consider a semantic analysis with two criteria.

Plenty of research has been conducted to study the selected criteria that affect customers' choices when booking a hotel. Normally, these decisions are affected by the traveler's origin, marital status, sex, education level, annual income, age, occupation, social status, etc. (Sohrabi, Vanani, Tahmasebipur, & Fazli, 2012). In (Lockyer, 2005) it can be found a list of factors that have a strong influence on travelers' hotel selections. Keeping these issues in mind, a set of five criteria used in (G. Li, Law, Vu, & Rong, 2013) come to consideration. These include value for money (Money Value or MV), hotel location (Hotel Location or HL), quality of room (Room Quality or RQ), room cleanliness (Room Cleanliness or RC), and additional service (Additional Services or AS). I.e.:

$$\mathbf{N} = \{\text{MV, HL, RQ, RC, AS}\}$$

In order to determine a consensus value of the importance of each generic criterion, the information provided by 40 users is analysed. The users can distinguish five different labels in order to provide their assessment related to importance of criteria, i.e.:

$$\mathbf{V}=\left\{\begin{array}{l}\text{Very Low}(\text{VL}),\ \text{Low}(\text{L}),\ \text{Medium}(\text{Me}),\\ \text{High}(\text{H}),\ \text{Very High}(\text{VH})\end{array}\right\}$$

The cardinality of each one for each criterion is shown in **Table 2**. All individual valuations can be seen in Appendix A.

Table 2: Cardinality values of each label for each criterion

Criteria	VL	L	Me	H	VH
MV	5	8	11	11	5
HL	4	5	3	21	7
RQ	2	7	16	9	6
RC	5	4	9	12	10
AS	9	15	4	5	7

Using WAM and SMA-OWA aggregation operators, the values of **Table 3** are obtained. In each case, the mapping $\langle \text{VL}\to 1, \text{L}\to 2, \text{Me}\to 3, \text{H}\to 4, \text{VH}\to 5\rangle$ is used to compute the importance of all criteria. The Cardinality Relevance Factor δ used for each criterion (for SMA-OWA operator), is calculated using the dispersion of cardinalities as suggested in (Karanik et al., 2016).

Table 3: Importance of each criterion using majority aggregation and WAM operator

Criteria	Importance (SMA-OWA)	δ	Importance (WAM)
MV	0.206	0.800	0.192
HL	0.227	0.894	0.222
RQ	0.189	0.860	0.203
RC	0.218	0.815	0.216
AS	0.160	0.843	0.166

In the same way, criteria of three specific hotels are evaluated by users after staying there. Notice that the number of valuations is distinct for each hotel because not all users have stayed in the three hotels. Here the individual valuations are made in the $[1..10]$ scale. The aggregated value of criteria by using SMA-OWA operator for each hotel is shown in **Table** 4. Additionally, all users valuations about hotels can be observed in Appendix B.

Table 4: Cardinality values of criteria for each hotel

Candidate	MV	HL	RQ	RC	AS
Hotel1	5.589	5.736	5.485	5.605	4.735
Hotel2	5.849	6.332	5.945	6.081	4.318
Hotel3	6.119	5.767	5.382	5.849	5.374

This is the second useful outcome, in **Table** 4 it can be observed what users think about every characteristic of each hotel. Clearly, these values can be used for managers to improve the service weaknesses (notice that, in this case, the values are in the $[1..10]$ range).

Regarding coalitions, a consensus value related to the interaction degree of criteria is obtained by majority aggregation process. This aggregation is performed again using SMA-OWA operator. In this case, the assessments of several experts are used and the Cardinality Relevance Factor δ is also calculated using the dispersion of cardinalities. The number of labels lq that the experts can distinguish is 7, thus:

$$\mathbf{W}=\left\{\begin{array}{l}\text{Null}(\text{N}),\ \text{Very Weak}(\text{VW}),\ \text{weak}(\text{W}),\\ \text{Moderate}(\text{Mo}),\ \text{Strong}(\text{S}),\\ \text{Very Strong}(\text{VS}),\ \text{Extreme}(\text{E})\end{array}\right\}$$

The mapping used for positive synergy is:

$$\left\langle\begin{array}{l}\text{N}\to 0,\ \text{VW}\to 1,\ \text{W}\to 2,\ \text{Mo}\to 3,\\ \text{S}\to 4,\ \text{VS}\to 5,\ \text{E}\to 6\end{array}\right\rangle$$

and for negative synergy is:

$$\left\langle\begin{array}{l}\text{N}\to 0,\ \text{VW}\to -1,\ \text{W}\to -2,\ \text{Mo}\to -3,\\ \text{S}\to -4,\ \text{VS}\to -5,\ \text{E}\to -6\end{array}\right\rangle$$

As a comment, experts agree that such criteria as location, room quality and service appear to be correlated with the value for money. In case of location, it may be that a better location could minimise the cost of transportation. Room quality and service improve with the increase of the price of booking. On the contrary, the service criterion has a positive interaction with room quality. This suggests that hotels must improve both of these criteria at the same time in order to satisfy travelers' expectations. Taking account of these issues, the cardinalities of pair-wise interaction opinions of 10 experts are analysed. **Table 5** shows only coalitions with non-additive synergy (determined a priori). The other coalitions are considered additive. For positive or negative synergy, the cardinalities were distributed for each label in *W*. Additionally, individual experts' opinions about coalitions are shown in Appendix C.

Note that, when an expert considers that interaction degree between criteria is insignificant or null; its assessment is counted in the Null column (as in the {MV, HL} coalition case). This value does not affect the aggregation process to compute the interaction degree.

Table 5: Experts' opinions related to criteria coalition

Coalitions	Negative Synergy							Positive Synergy						Interaction Degree (SMA-OWA)
	E	VS	S	Mo	W	VW	Null	VW	W	Mo	S	VS	E	
{MV, HL}	**1**	**1**	**2**	**4**	0	0	**2**	0	0	0	0	0	0	-2.535
{MV, RQ}	**4**	**3**	**1**	**1**	**1**	0	0	0	0	0	0	0	0	-3.610
{MV, AS}	0	**2**	**5**	**3**	0	0	0	0	0	0	0	0	0	-3.214

{RQ, AS}	0	0	0	0	0	0	0	0	0	0	**2**	**4**	**4**	+4.570

The information contained in **Table 5** is the third useful outcome for managers. It can be used to know what the experts consider important by analysing the sign and value of the synergies for every coalition. In this way, strategic decisions can be adopted to improve those characteristics that, joined, enhance the service quality. In this case, the values can be converted to their respective linguistic labels in order to aid managers to understand them.

5.2. Global Ranking Calculation

With data described previously and by using **Algorithms 1** and **2**, a fuzzy measure is automatically constructed (**Table 6**). Using the Choquet Integral as aggregation operator (**Algorithm 3**) with respect to μ, global scores are obtained. The analysis is performed by comparing the results obtained by using the WAM and Choquet Integral operators. **Table 7** summarises the obtained results (notice that the symbols "=", "∧" and "∨" mean "maintaining the same position in the ranking", "ascending in the ranking" and "descending in the ranking", respectively).

At this point, the proposed model returns the first useful outcome for users: "what the majority says about" (in this case about hotel1, hotel2 and hotel3).

Table 6: Fuzzy measure μ

Coalition	Weight	**Coalition**	Weight	**Coalition**	Weight
{MV}	0.181	{HL, AS}	0.340	{HL, RQ, AS}	0.627
{HL}	0.199	{RQ, RC}	0.358	{HL, RC, AS}	0.532
{RQ}	0.166	{RQ, AS}	0.428	{RQ, RC, AS}	0.620
{RC}	0.192	{RC, AS}	0.332	{MV, HL, RQ, RC}	0.819
{AS}	0.140	{MV, HL, RQ}	0.546	{MV, HL, RQ, AS}	0.801
{MV, HL}	0.276	{MV, HL, RC}	0.572	{MV, HL, RC, AS}	0.713
{MV, RQ}	0.224	{MV, HL, AS}	0.521	{MV, RQ, RC, AS}	0.808
{MV, RC}	0.373	{MV, RQ, RC}	0.539	{HL, RQ, RC, AS}	0.738
{MV, AS}	0.228	{MV, RQ, AS}	0.609	{MV, HL, RQ, RC, AS}	1.000
{HL, RQ}	0.366	{MV, RC, AS}	0.513		
{HL, RC}	0.391	{HL, RQ, RC}	0.558		

Table 7: Ranking of alternatives obtained with WAM and Choquet Integral

Candidate	MV	HL	RQ	RC	AS	**Global Ranking**		
						WAM	**CI**	**Variation**
Hotel1	5.589	5.736	5.485	5.605	4.735	5.430	5.381	=
Hotel2	5.849	6.332	5.945	6.081	4.318	5.705	5.605	∨
Hotel3	6.119	5.767	5.382	5.849	5.374	5.698	5.679	∧

In **Table 7** can be observed that using the Weight Arithmetic Mean operator, the best candidate is Hotel2, because, on average, it has the best partial values. However, results are not adequate because this operator does not take into consideration the interacting criteria ({MV, HL}, {MV, RQ}, {MV, AS} and {RQ, AS}). On the contrary, by using the CI, Hotel2 loses its position because it is unbalanced for the Room and Service criteria (which are positively correlated). Hotel3 goes up one position (comparing with WAM), appearing to be the best ranked when correlated criteria were considered (due to balanced scoring in all criteria). In addition, there was a decrease in the global score of all alternatives due to the negative synergy between "Value and Location", "Value and Room" and "Value and Service". This avoids overestimates in high scores.

5.3. Individual Ranking Calculation

In this section, in order to obtain personalised ranking, rather than the criteria importance assessments given by the 40 users (**Table** 2), the users' preferences are considered. Notice the users' valuation about Hotel1, Hotel2 and Hotel3 (**Table** 4) and the experts' valuations about coalitions (**Table 5**) remain in order to construct the individual fuzzy measure.

For illustrative purposes user #2 and user #7 (from the list showed in Appendix A) are selected to obtain the individual fuzzy measures and individual rankings. The personal preferences are:

user #2: {MV = 4; HL = 3; RQ = 5; RC = 5; AS = 5} user #7: {MV = 4; HL = 5; RQ = 5; RC = 5; AS = 1}

Again, with data described previously and by using **Algorithms 1** and **2**, a fuzzy measure is automatically constructed and by using the Choquet integral the individual rankings for users #2 and #7 are calculated. The analysis is performed by comparing the results obtained in the previous global ranking. **Table 8** summarises the results achieved. User #2 has similar preferences to the majority and their personal ranking is close to the global one. On the other hand, user #7 has an insignificant valuation for Additional Services (AS) and, in this way, all coalitions containing AS affect the final ranking and Hotel2 obtains better aptitude. Clearly, individual rankings reflect more accurately the user's preferences but he/she can compare them with the majority's opinion (i.e. the global ranking).

Table 8: Ranking of alternatives comparison (global and individuals users #2 and #7)

Candidate	MV	HL	RQ	RC	AS	Rankings				
						Global	**User #2**	**Variation**	**User #7**	**Variation**
Hotel1	5.589	5.736	5.485	5.605	4.735	5.381	5.287	=	5.527	=
Hotel2	5.849	6.332	5.945	6.081	4.318	5.605	5.424	=	5.907	∧
Hotel3	6.119	5.767	5.382	5.849	5.374	5.679	5.624	=	5.727	∨

This is the second useful outcome for the users. The proposed model returns personalised rankings that can be compared to "what the majority says about". This is very important because it gives the user a reference point in the decision making process.

5.4. Special Cases of Ranking Calculation

Model features allow handling the importance of criteria and interaction degree by majority aggregation in two levels set apart. In order to show the model versatility, a number of interesting examples are proposed. In all of them the criteria, alternatives and criteria coalition are taken as fixed parameters. Furthermore, the importance of criteria and interaction degree are the model parameters that take different values.

Case 1: The importance of criteria is variable and there are no coalitions (all experts consider that the interaction degree is null for all coalitions).

In this case, the importance of criteria is calculated using SMA-OWA operator. It can be appreciated that the values obtained with SMA-OWA operator represent the majority's opinion of all experts, which causes a different final ranking as shown in **Table 9**. In this case Hotel2 has better score in more important criteria (according to the majority).

Table 9: Global ranking obtained with and without coalitions for Case 1

Candidate	MV	HL	RQ	RC	AS	Global Ranking		
						With Coalitions	**Without Coalitions**	**Variation**
Hotel1	5.589	5.736	5.485	5.605	4.735	5.381	5.470	=
Hotel2	5.849	6.332	5.945	6.081	4.318	5.605	5.783	∧
Hotel3	6.119	5.767	5.382	5.849	5.374	5.679	5.722	∨

Case 2: Suppose that importance of criteria computed with SMA-OWA operator matches the arithmetic mean and there are no coalitions (experts' opinions are uniform and they consider that the interaction degree is null for all coalitions). The importance values are shown in **Table 10**. In these circumstances and due to the properties of the SMA-OWA operator the computed aggregated values (**Table 11**) are coincident (with WAM and SMA-OWA). In this case SMA-OWA operator works as arithmetic mean of cardinalities as was stated in operator description (Karanik et al., 2016).

Case 3: Again, suppose the importance of criteria computed with SMA-OWA operator matches the arithmetic mean whichever coalitions between criteria are considered. Consider the importance values of **Table 12** and aggregated values for hotels' valuations and criteria coalitions of Appendixes B and C.

Values in **Table** 12 the ranking calculated but using WAM operator shows Hotel2 as the best candidate because on average it has the best partial values. However, given the fact that the interacting criteria are not taken into account, the results contain partial information about criteria importance. On the other hand, by using the CI (even without differences in the importance of the criteria in level 1 of aggregation) Hotel2 loses the first position because it is the most unbalanced for the Room Quality and Additional Services criteria (that are positively correlated).

These examples show the versatility of the proposed model. In certain conditions it may simulate the weighted arithmetic mean and also behaves properly at both levels of majority aggregation.

Table 10: Cardinality values of each label for each criterion and its importance for Case 2

Criteria	VL	L	Mo	H	VH	Importance (WAM)	Importance (SMA-OWA)
Value	4	9	14	9	4	3.000	3.000
Location	9	6	10	6	9	3.000	3.000
Room	6	9	10	9	6	3.000	3.000
Cleanliness	10	7	6	7	10	3.000	3.000
Service	5	8	14	8	5	3.000	3.000

Table 11: Ranking of alternatives obtained with WAM and Choquet Integral without coalitions for Case 2

Candidate	MV	HL	RQ	RC	AS	Global Ranking		
						WAM	CI	Variation
Hotel1	5.589	5.736	5.485	5.605	4.735	5.430	5.430	=
Hotel2	5.849	6.332	5.945	6.081	4.318	5.705	5.705	=
Hotel3	6.119	5.767	5.382	5.849	5.374	5.698	5.698	=

Table 12: Ranking of alternatives obtained with WAM and Choquet Integral with coalitions for Case 3

Candidate	MV	HL	RQ	RC	AS	Global Ranking		
						WAM	CI	Variation
Hotel1	5.589	5.736	5.485	5.605	4.735	5.430	5.328	=
Hotel2	5.849	6.332	5.945	6.081	4.318	5.705	5.501	$\vee$
Hotel3	6.119	5.767	5.382	5.849	5.374	5.698	5.650	$\wedge$

6. Concluding Remarks

The proposed model shows the dynamical variation of the rankings obtained according to the users' preferences. These modifications are associated to the operation of the model and they are adapted to the variation of these valuations. This same event is faced by other models, for example, in (De Maio, Fenza, Loia, Orciuoli, & Herrera-Viedma, 2016) a framework that supports group decision making during the execution of the business process is described. They use an updating mechanism based on past experiences and reinforcement learning techniques in order to establish the relative importance of decision makers. Also, in (Muzychuk, 2011) the weight update is made based on additional information obtained from the problem environment as feedback mechanism. In general, this kind of updating process is useful to make reliable decisions. This is the reason why the integrated model proposed in this article, has an updated mechanism that uses the SMA-OWA operator. Additionally, the updating process is fast and it does not require excessive computational resources.

Another important aspect is related to the way of obtaining users' preferences. In (Bernroider & Schmöllerl, 2013; Cabrerizo, López-Gijón, Martínez, Morente-Molinera, & Herrera-Viedma, 2017; Huang & Benyoucef, 2017) several systems of user's satisfaction surveys are proposed. Information gathering is made by using web forms that provide a friendly mechanism and it allows the user to evaluate the service features. This is a good way of interaction and, combined with an adequate information updating process, it provides the useful technique used in this proposed model in order to establish the criteria importance.

These two mentioned characteristics implemented in the model proposed in this article are highly desirable in order to keep the data updated, especially in dynamic and heterogeneous environments such as social media.

7. Conclusions

In this article a MCDA model based on majority's opinion and criteria coalition was described. This proposed model combines the users' preferences and the experts' opinions in order to obtain an integrated response for a DM problem.

The proposed model is able to dynamically compute the global ranking for products or services with low computational cost. The individual and majority's valuations are updated and the majority-based ranking is automatically calculated. In addition, with the same computational effort, taking account of the particular user's preferences, the individual ranking is computed at the same time. This is a useful tool for users to compare their opinions with the majority ones.

The proposed model allows not only to know what product or service is the best but also to explain the reasons. This is possible because aggregated valuations about every criterion and the criteria synergy are computed. This information is valuable for managers, traders and manufacturers in order to know how to improve the product or service.

An important issue is that the criteria synergy is modelled based on the majority's opinion of experts. The aggregation process uses linguistic labels that provide an adequate abstraction level according to the granularity associated to every expert.

The proposed method is mathematically robust because it is based on reliable operators, fuzzy measures and fuzzy integrals. It reduces the effort to determine the importance of each criteria combination by focusing only on relevant interactions.

Finally, the proposed model was developed and implemented taking account of the immediacy and dynamism of social media environments.

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Additional Resources

In order to check the proposed method the examples used in Section 4 can be found in the next URL. The package is distributed containing source code files, data samples and examples used in this manuscript.

https://github.com/IntangiblesChair/majorityandcoalitions

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

Agichtein, E., Castillo, C., Donato, D., Gionis, A., & Mishne, G. (2008). Finding high-quality content in social media. In *Proceedings of the international conference on Web search and web data mining - WSDM '08* (pp. 183–194). New York, New York, USA: ACM Press. https://doi.org/10.1145/1341531.1341557

Angilella, S., Corrente, S., & Greco, S. (2015). Stochastic multiobjective acceptability analysis for the Choquet integral preference model and the scale construction problem. *European Journal of Operational Research*, *240*(1), 172–182. https://doi.org/10.1016/j.ejor.2014.06.031

Baethge, C., Klier, J., & Klier, M. (2016). Social commerce—state-of-the-art and future research directions. *Electronic Markets*, *26*(3), 269–290. https://doi.org/10.1007/s12525-016-0225-2

Bernal, R., Karanik, M., & Peláez, J. I. (2015). Fuzzy measure identification for criteria coalitions using linguistic information. *Soft Computing*, 1315–1327.

Bernal, R., Karanik, M., & Peláez, J. I. (2016). Fuzzy measure identification for criteria coalitions using linguistic information. *Soft Computing*, *20*(4). https://doi.org/10.1007/s00500-015-1589-5

Bernroider, E. W. N., & Schmöllerl, P. (2013). A technological, organisational, and environmental analysis of decision making methodologies and satisfaction in the context of IT induced business transformations. *European Journal of Operational Research*, *224*(1), 141–153. https://doi.org/10.1016/j.ejor.2012.07.025

Branke, J., Corrente, S., Greco, S., Słowiński, R., & Zielniewicz, P. (2016). Using Choquet integral as preference model in interactive evolutionary multiobjective optimization. *European Journal of Operational Research*, *250*(3), 884–901. https://doi.org/10.1016/j.ejor.2015.10.027

Cabrerizo, F. J., López-Gijón, J., Martínez, M. A., Morente-Molinera, J. A., & Herrera-Viedma, E. (2017). A Fuzzy Linguistic Extended LibQUAL+ Model to Assess Service Quality in Academic Libraries. *International Journal of Information Technology & Decision Making*, *16*(1), 225–244. https://doi.org/10.1142/S0219622015500406

Cabrerizo, F. J., Moreno, J. M., Pérez, I. J., & Herrera-Viedma, E. (2010). Analyzing consensus approaches in fuzzy group decision making: advantages and drawbacks. *Soft Computing*, *14*(5), 451–463. https://doi.org/10.1007/s00500-009-0453-x

Chiclana, F., García, J. M. T., del Moral, M. J., & Herrera-Viedma, E. (2015). Analyzing Consensus Measures in Group Decision Making. *Procedia Computer Science*, *55*, 1000–1008. https://doi.org/10.1016/j.procs.2015.07.103

Choquet, G. (1954). Theory of capacities. *Annales de L'institut Fourier*, *5*, 131–295.

De Maio, C., Fenza, G., Loia, V., Orciuoli, F., & Herrera-Viedma, E. (2016). A framework for context-aware heterogeneous group decision making in business processes. *Knowledge-Based Systems*, *102*, 39–50. https://doi.org/10.1016/j.knosys.2016.03.019

Deng, S., Sinha, A. P., & Zhao, H. (2017). Adapting sentiment lexicons to domain-specific social media texts. *Decision Support Systems*, *94*, 65–76. https://doi.org/10.1016/j.dss.2016.11.001

Ding, C., Cheng, H. K., Duan, Y., & Jin, Y. (2017). The power of the "like" button: The impact of social media on box office. *Decision Support Systems*, *94*, 77–84. https://doi.org/10.1016/j.dss.2016.11.002

Dong, Y., Xiao, J., Zhang, H., & Wang, T. (2016). Managing consensus and weights in iterative multiple-attribute group decision making. *Applied Soft Computing*, *48*, 80–90. https://doi.org/10.1016/j.asoc.2016.06.029

Figueira, J., Greco, S., & Ehrogott, M. (2005). *Multiple Criteria Decision Analysis: State of the Art Surveys*. *Methods* (Vol. 78). New York, NY: Springer New York. https://doi.org/10.1007/b100605

Fodor, J., Marichal, J.-L., & Roubens, M. (1995). Characterization of the ordered weighted averaging operators. *Fuzzy Systems, IEEE Transactions on*, *3*(2), 236–240. https://doi.org/10.1109/91.388176

Grabisch, M. (1997). k-order additive discrete fuzzy measures and their representation. *Fuzzy Sets and Systems*, *92*(2), 167–189. https://doi.org/http://dx.doi.org/10.1016/S0165-0114(97)00168-1

Grabisch, M., & Labreuche, C. (2016). Fuzzy measures and integrals in MCDA. *International Series in Operations Research and Management Science*, *233*, 553–603. https://doi.org/10.1007/978-1-4939-3094-4_14

Herrera, F., Herrera-Viedma, E., & Chiclana, F. (2001). Multiperson decision-making based on multiplicative preference relations. *European Journal of Operational Research*, *129*(2), 372–385. https://doi.org/10.1016/S0377-2217(99)00197-6

Herrera, F., Herrera-Viedma, E., & Martínez, L. (2000). A fusion approach for managing multi-granularity linguistic term sets in decision making. *Fuzzy Sets and Systems*, *114*(1), 43–58. https://doi.org/10.1016/S0165-0114(98)00093-1

Hocevar, K. P., Flanagin, A. J., & Metzger, M. J. (2014). Social media self-efficacy and information evaluation online. *Computers in Human Behavior*, *39*(0), 254–262. https://doi.org/http://dx.doi.org/10.1016/j.chb.2014.07.020

Hu, M., & Liu, B. (2004). Mining and Summarizing Customer Reviews. In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 168–177). New York, NY, USA: ACM. https://doi.org/10.1145/1014052.1014073

Huang, Z., & Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications*, *12*(4), 246–259. https://doi.org/10.1016/j.elerap.2012.12.003

Huang, Z., & Benyoucef, M. (2015). User preferences of social features on social commerce websites: An empirical study. *Technological Forecasting and Social Change*, *95*, 57–72. https://doi.org/10.1016/j.techfore.2014.03.005

Huang, Z., & Benyoucef, M. (2017). The effects of social commerce design on consumer purchase decision-making: An empirical study. *Electronic Commerce Research and Applications*, *25*, 40–58. https://doi.org/10.1016/j.elerap.2017.08.003

Jang, H.-J., Sim, J., Lee, Y., & Kwon, O. (2013). Deep sentiment analysis: Mining the causality between personality-value-attitude for analyzing business ads in social media. *Expert Systems with Applications*, *40*(18), 7492–7503. https://doi.org/10.1016/j.eswa.2013.06.069

Joshi, D., & Kumar, S. (2016). Interval-valued intuitionistic hesitant fuzzy Choquet integral based TOPSIS method for multi-criteria group decision making. *European Journal of Operational Research*, *248*(1), 183–191. https://doi.org/10.1016/j.ejor.2015.06.047

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68. https://doi.org/10.1016/j.bushor.2009.09.003

Karanik, M., Peláez, J. I., & Bernal, R. (2016). Selective majority additive ordered weighting averaging operator. *European Journal of Operational Research*, *250*(3), 816–826. https://doi.org/10.1016/j.ejor.2015.10.011

Li, G., Law, R., Vu, H. Q., & Rong, J. (2013). Discovering the hotel selection preferences of Hong Kong inbound travelers using the Choquet Integral. *Tourism Management*, *36*(0), 321 – 330. https://doi.org/10.1016/j.tourman.2012.10.017

Li, Y.-M., Wu, C.-T., & Lai, C.-Y. (2013). A social recommender mechanism for e-commerce: Combining similarity, trust, and relationship. *Decision Support Systems*, *55*(3), 740–752. https://doi.org/10.1016/j.dss.2013.02.009

Liang, T.-P., & Turban, E. (2011). Introduction to the Special Issue Social Commerce: A Research Framework for Social Commerce. *International Journal of Electronic Commerce*, *16*(2), 5–14. https://doi.org/10.2753/JEC1086-4415160201

Lockyer, T. (2005). The perceived importance of price as one hotel selection dimension. *Tourism Management*. https://doi.org/10.1016/j.tourman.2004.03.009

Massanet, S., Vicente Riera, J., Torrens, J., & Herrera-Viedma, E. (2016). A model based on subjective linguistic preference relations for group decision making problems. *Information Sciences*, *355–356*, 249–264. https://doi.org/10.1016/j.ins.2016.03.040

Mata, F., Pérez, L. G., Zhou, S.-M., & Chiclana, F. (2014). Type-1 OWA methodology to consensus reaching processes in multi-granular linguistic contexts. *Knowledge-Based Systems*, *58*, 11–22. https://doi.org/10.1016/j.knosys.2013.09.017

Muzychuk, A. (2011). OWA weight updating in repeated decision making under the influence of additional information. *International Journal of Intelligent Systems*, *26*(7), 591–602. https://doi.org/10.1002/int.20472

Nguyen, T. H., Shirai, K., & Velcin, J. (2015). Sentiment analysis on social media for stock movement prediction. *Expert Systems with Applications*, *42*(24), 9603–9611. https://doi.org/10.1016/j.eswa.2015.07.052

Pasi, G., & Yager, R. R. (2003). Modeling the Concept of Fuzzy Majority Opinion. In T. Bilgiç, B. De Baets, & O. Kaynak (Eds.), *Fuzzy Sets and Systems --- IFSA 2003: 10th International Fuzzy Systems Association World Congress Istanbul, Turkey, June 30 -- July 2, 2003 Proceedings* (pp. 143–150).

Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-44967-1_16

Peláez, J. I., Bernal, R., & Karanik, M. (2014). Majority OWA operator for opinion rating in social media. *Soft Computing*, 1047–1055.

Peláez, J. I., Bernal, R., & Karanik, M. (2016). Majority OWA operator for opinion rating in social media. *Soft Computing*, *20*(3). https://doi.org/10.1007/s00500-014-1564-6

Peláez, J. I., & Doña, J. M. (2003a). LAMA: A linguistic aggregation of majority additive operator. *International Journal of Intelligent Systems*, *18*(7), 809–820. https://doi.org/10.1002/int.10117

Peláez, J. I., & Doña, J. M. (2003b). Majority additive–ordered weighting averaging: A new neat ordered weighting averaging operator based on the majority process. *International Journal of Intelligent Systems*, *18*((4)), 469–481.

Peláez, J. I., & Doña, J. M. (2006). A majority model in group decision making using QMA-OWA operators. *International Journal of Intelligent Systems*, *21*(2), 193–208. https://doi.org/10.1002/int.20127

Peláez, J. I., Doña, J. M., & Gómez Ruiz, J. A. (2007). Analysis of OWA operators in decision making for modelling the majority concept. *Applied Mathematics and Computation*, *186*(2), 1263–1275. https://doi.org/10.1016/j.amc.2006.07.161

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems*, *89*, 14–46. https://doi.org/10.1016/j.knosys.2015.06.015

Rolland, A. (2013). Reference-based preferences aggregation procedures in multi-criteria decision making. *European Journal of Operational Research*, *225*(3), 479–486. https://doi.org/10.1016/j.ejor.2012.10.013

Sohrabi, B., Vanani, I. R., Tahmasebipur, K., & Fazli, S. (2012). An exploratory analysis of hotel selection factors: A comprehensive survey of Tehran hotels. *International Journal of Hospitality Management*, *31*(1), 96–106. https://doi.org/10.1016/j.ijhm.2011.06.002

Sugeno, M. (1974). *Theory of fuzzy integrals and its applications*. Tokyo Institute of Technology.

Sun, Y., Wei, K. K., Fan, C., Lu, Y., & Gupta, S. (2016). Does social climate matter? On friendship groups in social commerce. *Electronic Commerce Research and Applications*, *18*, 37–47. https://doi.org/10.1016/j.elerap.2016.06.002

Tan, C. (2011). A multi-criteria interval-valued intuitionistic fuzzy group decision making with Choquet integral-based TOPSIS. *Expert Systems with Applications*, *38*(4), 3023–3033. https://doi.org/10.1016/j.eswa.2010.08.092

Taylor, E., Hewitt, K., Reeves, R. A., Hobbs, S. H., & Lawless, W. F. (2013). Group Decision-making: Consensus Rule Versus Majority Rule. *Procedia Technology*, *9*, 498–504. https://doi.org/10.1016/j.protcy.2013.12.055

Wu, Z., & Xu, J. (2012). A consistency and consensus based decision support model for group decision making with multiplicative preference relations. *Decision Support Systems*, *52*(3), 757–767. https://doi.org/10.1016/j.dss.2011.11.022

Yager, R. R. (1988). On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decisionmaking. *IEEE Transactions on Systems, Man and Cybernetics*, *18*(1), 183–190. https://doi.org/10.1109/21.87068

Yager, R. R., Kacprzyk, J., & Beliakov, G. (2011). *Recent Developments in the Ordered Weighted Averaging Operators: Theory and Practice* (1st ed.). Springer Publishing Company, Incorporated.

Yan, H.-B., & Ma, T. (2015). A group decision-making approach to uncertain quality function deployment based on fuzzy preference relation and fuzzy majority. *European Journal of Operational Research*, *241*(3), 815–829. https://doi.org/10.1016/j.ejor.2014.09.017

Yu, Y., & Cao, Q. (2013). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems*, *55*(4), 919–926. https://doi.org/10.1016/j.dss.2012.12.028

Zarghami, M., & Szidarovszky, F. (2009). Revising the OWA operator for multi criteria decision making problems under uncertainty. *European Journal of Operational Research*, *198*(1), 259–265. https://doi.org/10.1016/j.ejor.2008.09.014

Appendix A. Individual valuations for criteria

User	MV	HL	RQ	RC	AS
#1	4	4	3	4	5
#2	4	3	5	5	5
#3	1	4	2	1	2
#4	3	1	4	4	1
#5	4	2	3	1	1
#6	4	4	5	4	3
#7	4	5	5	5	1
#8	3	4	3	3	2
#9	4	4	2	5	1
#10	2	1	4	3	1
#11	4	4	2	4	3
#12	4	4	3	4	5
#13	5	2	4	2	2
#14	3	4	3	2	1
#15	3	4	1	5	4
#16	3	4	4	3	4
#17	5	4	4	4	2
#18	2	4	3	5	1
#19	4	4	2	4	1
#20	5	2	3	5	4
#21	5	2	3	3	2
#22	2	5	4	5	5
#23	3	5	3	3	2
#24	3	1	1	5	2
#25	3	4	3	2	3
#26	1	5	3	4	2
#27	2	1	2	3	5
#28	2	5	2	1	5
#29	4	4	3	3	3
#30	1	3	3	1	2
#31	3	3	3	4	4
#32	1	4	5	1	2
#33	2	5	4	2	2
#34	5	4	3	4	2
#35	4	4	4	3	4
#36	3	4	3	5	2
#37	1	2	4	4	2
#38	2	4	5	5	5
#39	3	5	5	3	1
#40	2	4	2	4	2

Appendix B. – Users' valuations about Hotel1. Hotel2 and Hotel3

User	Hotel	MV	HL	RQ	RC	AS
#1	1	6	7	8	3	2
	3	8	2	6	2	4
#2	2	3	7	5	10	3
#3	1	7	7	5	5	6
	2	10	8	8	7	3
	3	7	5	5	8	2
#4	1	7	9	5	9	2
	3	8	5	2	7	5
#5	2	4	8	9	5	2
	3	8	7	5	7	5
#6	1	5	6	6	8	1
#7	1	3	7	6	3	2
	2	3	9	8	10	4
	3	8	7	4	7	5
#8	1	9	5	4	5	2
	3	8	7	4	9	5
#9	1	6	6	3	9	3
	2	9	6	9	8	7
	3	8	7	5	5	4
#10	1	7	7	3	6	6
	3	8	7	5	7	5
#11	1	6	10	6	5	1
	2	8	9	8	4	8
	3	8	7	2	9	2
#12	2	7	5	10	9	9
	3	8	5	5	7	4
#13	1	6	8	7	4	2
	3	8	7	6	2	8
#14	1	3	6	6	6	1
	2	7	6	9	8	2
	3	8	6	8	6	2
#15	1	7	7	5	6	9
	2	9	9	8	8	1
	3	7	2	2	4	1
#16	3	8	8	4	9	5
#17	1	4	8	3	4	3
	2	9	2	8	3	5
	3	8	7	5	7	9
#18	1	5	10	6	2	8
	3	7	7	4	7	5
#19	1	4	8	9	5	1
	2	9	9	9	8	4
	3	10	7	2	6	5
#20	1	5	5	6	6	9
	3	8	4	5	1	5
#21	1	6	5	5	6	5
	2	7	4	7	8	1
	3	8	8	5	6	5
#22	1	9	7	4	6	8
	2	7	7	8	5	7
	3	5	7	5	7	4
#23	2	8	6	9	7	3
	3	8	7	1	7	5
#24	1	4	7	8	9	2
	2	7	10	7	2	4
	3	8	7	5	8	5
#25	1	3	7	5	6	5
	2	6	9	8	8	3
#26	2	7	8	8	8	2
	3	9	7	5	7	1
#27	1	6	7	10	7	2
	3	8	4	8	9	4
#28	1	6	7	5	4	6
	2	7	7	6	4	1
	3	8	3	9	7	2
#29	1	5	6	6	1	1
	3	3	4	7	7	5
#30	1	6	7	4	5	5
	2	6	5	8	4	1
	3	8	7	6	3	10
#31	1	6	7	4	6	2
	3	8	8	4	6	4
#32	1	3	7	4	6	4
	2	9	6	8	8	2
#33	1	6	10	2	7	5
	2	7	9	10	6	5
	3	1	7	5	7	3
#34	1	8	6	3	7	4
	2	2	7	10	8	1
	3	8	7	10	7	5
#35	1	8	6	5	5	7
	2	9	6	10	9	2
#36	1	8	6	7	8	3
	3	8	4	5	7	1
#37	2	3	8	5	1	3
#38	2	7	8	6	7	3
	3	8	6	4	10	5
#39	2	4	3	4	6	6
#40	2	6	7	10	5	2

Appendix C. Experts' valuations about criteria coalitions

Expert	Coalition	Synergy	Degree	Value
#1	MV. HL	Negative	Extreme	-6
	MV. RQ	Negative	Very Strong	-5
	MV. AS	Negative	Very Strong	-5
	RQ. AS	Positive	Extreme	6
#2	MV. HL	Negative	Moderate	-3
	MV. RQ	Negative	Extreme	-6
	MV. AS	Negative	Strong	-4
	RQ. AS	Positive	Extreme	6
#3	MV. HL	Negative	Strong	-4
	MV. RQ	Negative	Weak	-2
	MV. AS	Negative	Moderate	-3
	RQ. AS	Positive	Strong	4
#4	MV. HL	Negative	Very Strong	-5
	MV. RQ	Negative	Very Strong	-5
	MV. AS	Negative	Strong	-4
	RQ. AS	Positive	Very Strong	5
#5	MV. HL	Negative	Moderate	-3
	MV. RQ	Negative	Extreme	-6
	MV. AS	Negative	Moderate	-3
	RQ. AS	Positive	Extreme	6
#6	MV. HL	Negative	Strong	-4
	MV. RQ	Negative	Moderate	-3
	MV. AS	Negative	Strong	-4
	RQ. AS	Positive	Very Strong	5
#7	MV. HL	Null	Null	0
	MV. RQ	Negative	Extreme	-6
	MV. AS	Negative	Very Strong	-5
	RQ. AS	Positive	Strong	4
#8	MV. HL	Negative	Moderate	-3
	MV. RQ	Negative	Strong	-4
	MV. AS	Negative	Strong	-4
	RQ. AS	Positive	Extreme	6
#9	MV. HL	Negative	Moderate	-3
	MV. RQ	Negative	Extreme	-6
	MV. AS	Negative	Strong	-4
	RQ. AS	Positive	Very Strong	5
#10	MV. HL	Null	Null	0
	MV. RQ	Negative	Very Strong	-5
	MV. AS	Negative	Moderate	-3
	RQ. AS	Positive	Very Strong	5