THE IMPORTANCE OF AGGREGATION OPERATOR CHARACTERISTICS IN MARKETING RESEARCH

Kris Brijs, Benoît Depaire, Koen Vanhoof, Tom Brijs and Geert Wets
Faculty of Applied Economics, Hasselt University, Campus Diepenbeek, 3590 Diepenbeek, Belgium

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Abstract: Our paper demonstrates that aggregation operator characteristics count as a promising avenue for applied fuzzy set research. It is shown by means of two cases that these characteristics are particularly valuable as proxies for hard to measure domain knowledge within the fields of customer satisfaction and country-of-origin. More in detail, the uninorm's neutral element could be identified as a useful asset for representing customers' expectations while the OWA operator's orness contributes to the quantification of consumers' degree of optimism when evaluating products coming from abroad. Both theoretical and empirical validation is provided to support the basic assumption that aggregation operator characteristics enable us to obtain superior consumer information with substantial managerial relevance.

1 INTRODUCTION

Over the last ten years, a whole range of aggregation operators (AGOPs) have been developed and extensively studied in the lap of fuzzy set and non-classical decision theory (Dubois and Prade, 2004). These mathematically well-founded constructs have found their way into several application domains, such as economics, biology, education, knowledge-based systems and robotics (Torra, 2002).

To which extent an AGOP is useful within a certain domain depends, among others, on how well the AGOP's mathematical properties match the underlying information fusion process. Certain AGOPs possess mathematical characteristics which can be interpreted as behavioral parameters, i.e., their values have an influence on the behavior of the operator (e.g., the orness or maxness determines how strongly the ordered weighted averaging (OWA) operator behaves like the maximum operator).

Past research on AGOP applications has mainly focused on the AGOP's domain representation power or decision-making strength (Torra, 2002). However, as this study shows, certain AGOP's characteristics which play a role in the AGOP's behavior (i.e. behavioral parameters) can be of great importance to practitioners, especially when these behavioral parameters are proxies for domain-specific information which is difficult to measure directly or to derive statistically. In such cases, these AGOP's behavioral parameters become much more than just another mathematical characteristic.

The main objective of this paper is to illustrate that two different AGOPs, i.e., the uninorm and OWA operator, can both be successfully applied within the field of marketing research. More in detail, we will argue that each operator contains a behavioral parameter which can be used as a proxy for marketing-specific knowledge that cannot always be obtained by means of statistical techniques traditionally used by marketing scholars.

As for the outline of this paper, the next two sections present two case studies, one for each AGOP. Section two will discuss the use of uninorms in customer (dis)satisfaction theory. It will be shown that the uninorm's neutral element is a good proxy for customer's expectations. The third section will comment on the estimation of country-of-origin (coo) effects. Here, it will be shown that the use of the OWA operator's orness can be a valuable approach for determining how country-related feelings impact on the formation of consumers' attitude toward foreign sourced

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products. Finally, once the case-study analyses have been completed, a fourth section will be reserved for an overall conclusion.

2 THE UNINORM AGGREGATOR IN CUSTOMER SATISFACTION THEORY

2.1 Marketing Context

Over the last four decades, customer (dis)satisfaction has taken an important role in marketing research, both from an academic as from a managerial point of view. Although this hasn't always been the case, customer (dis)satisfaction is now widely recognized as an important cornerstone for customer-orientated companies, irrespective of the industry they operate in (Vanhoof et al., 2003; Szymanski and Henard, 2001) and has an influence on several important aspects of a competitive business (Szymanski and Henard, 2001; Anderson et al., 1994; Anderson et al., 2004).

The last three decades, the focus of customer satisfaction research has shifted from *what* it was about the product or service that customers found satisfying to *how* and *why* customers became satisfied. Several theoretical models have tried to explain the human behavior in a customer satisfaction context. In this article, we will focus on the expectancy disconfirmation model (Oliver, 1996), which is one of the more dominant models in customer satisfaction research. On the one hand, this model focuses on the discrepancy between perceived performance and customer's expectation and on the other hand on the customer's expectation itself. According to this paradigm, every customer holds pre-purchase product/service expectations, which have a direct influence on the customer's satisfaction. Furthermore, these expectations act as a reference, used by the customer to compare the perceived performance against, which leads to positive or negative disconfirmation. Both expectation and disconfirmation seem to be positively correlated with customer satisfaction (Oliver, 1996), but in most cases one of the two factors will dominate the other.

Expectation plays an important role in Oliver's expectation disconfirmation paradigm, both directly and indirectly by acting as a reference point. However, measuring unbiased pre-purchase expectations directly is very difficult. Firstly, post-purchase questionnaires measure post-purchase expectations, which can differ from pre-purchase levels of expectation because expectations and performance are inevitably confounded once performance observations have begun (Oliver, 1996). Second, several levels of expectations exists and it is not always clear which level is used as reference. Oliver summarizes no less than eight types of expectations, ranging from intolerable expectations over needed and deserved expectations to ideal expectations. Also, Cadotte et al. showed that the reference norm does not necessarily have to be the product's or brand's expectation. Other standards, based on experience, are also possible, although expectations cannot be ruled out (Cadotte et al., 1987).

Furthermore, Oliver mentions in a 1980 paper that "disconfirmation takes place at the individual attribute level" (Oliver, 1996). This implies that the consumer has a certain expectation and perceives a specific performance and disconfirmation for each product/service attribute or attribute dimension. Therefore, the consumer must aggregate all these expectations and disconfirmations into an overall satisfaction response. This aggregation is a heuristic based decision-making process. Vanhoof et al. (Vanhoof et al., 2005) identify two main heuristics in the customer's (dis)satisfaction process, i.e., 'anchoring and adjustment' and 'reinforcement'.

The first heuristic, 'anchoring and adjustment' is closely related to the assimilation effect of the expectancy disconfirmation paradigm. If the perceived attributes' performances lie close to the expected performance level, compensation behavior between the perceived disconfirmations will occur, assimilating the overall satisfaction level into the expectation level.

The second heuristic, 'reinforcement', is closely related to the contrast effects in the expectancy disconfirmation paradigm. If attribute performances significantly fall short of or exceed expectations, people tend to increasingly exaggerate evaluations and final (dis)satisfaction. "As a consequence, average attribute-level satisfaction scores that all fall below (exceed) the product-level norm are expected to aggregate to an overall product-level satisfaction score that is lower (higher) than the weighted average of the attribute-level scores" (Vanhoof et al., 2005).

Finally, Oliver also mentions it is unlikely that all customers show the same relationships among performance, expectation, disconfirmation and satisfaction (Oliver, 1996). Therefore, most customers will have a unique expectation level and aggregation process.

2.2 Behavioral Parameter: The Uninorm's Neutral Element

The uninorm aggregation operator is the result of the unification of the t-norm and the t-conorm operator, studied and presented by Yager et al. (Yager and Rybalov, 1996).

Definition 1 *(Yager and Rybalov, 1996) A* uni-norm *U is a mapping $U : [0,1] \times [0,1] \rightarrow [0,1]$ having the following properties:*

i) $U(a,b) = U(b,a)$ *(Commutativity)*

ii) $U(a,b) \geq U(c,d)$ *if $a \geq c$ and $b \geq d$ (Monotonicity)*

iii) $U(a,U(b,c)) = U(U(a,b),c)$ *(Associativity)*

iv) There exists some element $e \in [0,1]$ called the identity *element such that for all $a \in [0,1]$, $U(a,e) = a$*

According to definition 1, a uninorm can be regarded as a function that takes two values (attribute performances) and maps it to the 'aggregated' value (overall satisfaction). The commutativity property implies that the 'aggregated' value is independent of the order of the arguments of the uninorm. The monotonicity is a mathematical property that ensures that the aggregated value cannot decrease as one of the uninorm arguments increases. The associativity allows the extension of the standard uninorm to an n-argument function. These first three properties are also common to the t-norm and the t-conorm operator, but the fourth property is more general in the case of uninorms in that it allows any value for the identity element e. This element acts as the neutral element or null vote, i.e. the argument's impact on the aggregation will be null if its value equals the neutral element.

Furthermore, the neutral element determines whether the aggregation contains reinforcement or compensation behavior. The uninorm shows downward [upward] reinforcement behavior, i.e. $U(a,b) \leq min(a,b)$ [$U(a,b) \geq max(a,b)$], if both the aggregator's arguments belong to the interval $[0,e]$ ($[e,1]$) (cf Table 1 customers 1 and 3). If one argument belongs to the interval $[0,e]$ and the other argument belongs to the interval $]e,1]$, the uninorm shows compensation behavior ($min(a,b) \leq U(a,b) \leq max(a,b)$) (cf Table 1 customer 2).

Therefore, if the neutral element is different from zero or one, the same uninorm can both model full reinforcement and compensation behavior (Yager and Rybalov, 1998). Because the neutral element plays such a crucial role in the final modeling behavior, we refer to it as a behavioral parameter.

Table 1: Illustration Uninorm and Neutral Element.

Customer	a e.g. Price	b e.g. Taste	$U(a,b)$ Satisfaction	e Expectation
1	3	6	7	2
2	3	6	4	5
3	3	6	1	8

Previous research showed that the neutral element is a proxy for the expectation or reference standard in the customer (dis)satisfaction process (Vanhoof et al., 2003). The expectation or reference standard plays an important role in the customer's (dis)satisfaction response, but is difficult to measure directly. Therefore, this uninorm's behavioral parameter can be of great interest to marketeers.

Of all candidate uninorms, we chose Dombi's aggregation operator (Dombi, 1982), which belongs to the set of generated uninorms. This type of uninorm can be constructed with the help of a generator function $g(x)$ (Fodor et al., 1997), which must be a continuous and strictly increasing generator function, by means of equation 1.

$$U(x_1,x_2) = g\left(g^{-1}(x_1) + g^{-1}(x_2)\right) \qquad (1)$$

Based on the associativity property, this can be generalized into

$$U(X) = g\left(\sum^{X} g^{-1}(x)\right) \qquad (2)$$

Furthermore, Dombi showed that the generator function $g(x)$ displaced by d, $g(x+d) = g_d(x)$, also possesses the properties of a uninorm generator function. The displaced generator function $g_d(x)$ generates a new uninorm with a different neutral element. This implies that several uninorms, each with different neutral elements e, can be generated from one single generator function.

To derive the neutral element, we can use the following property which holds for Dombi's uninorm (Dombi, 1982).

$$U(x,n(x)) = e \qquad (3)$$

The negation function $n(x)$ can be derived mathematically from the generator function by means of equation 4

$$n : [0,1] \rightarrow [0,1] : n(x) = g^{-1}(1 - g(x)) \qquad (4)$$

In sum, first the generator must be learned for each respondent, based on his attribute performance scores, his overall satisfaction score and an 'a priori' specified functional form for the generator. This allows us to construct the corresponding uninorm and the corresponding negation function. By means of the negation function it is possible to calculate the neutral value, which can be interpreted as proxy for the hard-to-measure expectation level in the customer's (dis)satisfaction process.

2.3 Data

This research includes data from a customer satisfaction survey within the financial sector. The survey measures performance on 70 attributes, which can be classified into 8 domains (cf, Table 2). Furthermore, the survey includes an overall satisfaction score and a performance score for all eight plus two additional domains, which are ‘Value for money’ and ‘Quality’. All performance scores were measured on a scale from 1 [extremely low] to 5 [extremely high]. The overall satisfaction score was obtained by means of a scale going from 0 [extremely low] to 10 [extremely high]. The final data set contains 1201 cases.

Table 2: Attribute Dimensions.

Attribute dimension	Number of attributes
Value for money	/
Image	10
Price	6
Quality	/
Products	9
Sales service	10
Maintenance	15
Invoices	6
Administration	6
Communication	8

2.4 Validation

2.4.1 Theoretical Validation

Theoretical validation is provided when the AGOP’s modeling capacities fit the domain’s theoretical framework well. For the domain of customer (dis)satisfaction, an AGOP is needed which is able to model the heuristics present in the (dis)satisfaction formation process. After the previous discussion on the customer (dis)satisfaction process and the uninorm’s properties, it is clear that the uninorm succeeds well in this task.

Firstly, the uninorm’s compensation behavior is capable of modeling the (dis)satisfaction process’ assimilation effect and the ‘anchoring and adjustment’ heuristic. Secondly, the contrast effects and ‘reinforcement’ heuristic can be modeled by the uninorm through its reinforcement behavior. In addition, the uninorm calculates the (dis)satisfaction score based on the attribute’s performance or disconfirmation scores. This reflects the idea that (dis)satisfaction is ultimately formed at the attribute level. Finally, a uninorm can be constructed for each correspondent. This further strengthens the match between the uninorm and the (dis)satisfaction process because it allows us to perform customer (dis)satisfaction analysis at a single-customer level. All these aspects provide substantial theoretical validation, making the uninorm a good candidate to model customer (dis)satisfaction.

2.4.2 Empirical Validation

Theoretical validation is a good foundation, but is clearly not enough to prove the useability of a behavioral parameter as proxy for domain-specific knowledge. In addition to the theoretical validation, further empirical validation is required. The latter implies that the results ‘make sense’ in the applied domain.

Previous research has already validated the use of the uninorm’s neutral element as a proxy for the customer’s expected value (Vanhoof et al., 2003; **?**). We will further strengthen this validation by comparing our results with conclusions from Szymanski and Henard’s meta-analysis of 85 existing research studies on customer satisfaction (Szymanski and Henard, 2001). A substantial part of their paper focuses on the relationships between customer satisfaction and several of its antecedents. Table 3 shows the results of Szymanski and Henard, compared with our results.

We limited our study to the correlations between directly measured elements (performance and satisfaction) and uninorm-derived elements (expectations and disconfirmation), with the exception of the ‘performance-satisfaction’ correlate.

According to Szymanski and Henard’s study, performance is predominantly positively correlated with overall satisfaction. In line with these findings, our study establishes that all 10 domain’s performance scores are positively correlated with the overall satisfaction. This indicates a certain level of trustworthiness in the survey’s results.

Table 3 also shows that the uninorm-derived measures, which are expectation and disconfirmation, closely follow the empirically expected patterns. The correlates ‘expectation-satisfaction’ and ‘expectation-performance’ are 100% significantly positively correlated, which is the predominant pattern in other studies. The relation ‘disconfirmation-satisfaction’ shows the weakest similarity with empirical evidence. However, it should be kept in mind that our disconfirmation score represents the objectively calculated disconfirmation, which is not necessarily the same as the subjective disconfirmation. Overall, together with results obtained by Vanhoof et al. (Vanhoof et al., 2003), we can conclude that the uninorm’s neutral element is a valid proxy for customer’s expectation.

2.5 Implications

Figure 1 illustrates the implications of the availability of expectation measures. This figure shows the average performance scores and average expectation measures for each attribute domain. The performance scores for each domain are measured directly by the

Table 3: Validation of the Satisfaction-Related Correlations.

	Szymanski and Henard		Our results	
	Positive Correlations	Negative Correlations	Positive Correlations	Negative Correlations
Expectation† - satisfaction	13	1	1	0
Disconfirmation‡ - satisfaction	121	1	4	1
Performance - satisfaction	136	17	10	0
Expectation† - performance	22	1	10	0

NOTE I Only statistically significant correlations at alpha $\leq$ .05 were considered.
NOTE II Expectation, disconfirmation and performance is measured or derived for the attribute domain level.
† expectation = uninorm's neutral element.
‡ disconfirmation = performance - expectation.

survey. The expectation measures are derived by use of the uninorm approach, with the attribute performances as the uninorm's arguments and the attribute domain performance as the uninorm's aggregated value.

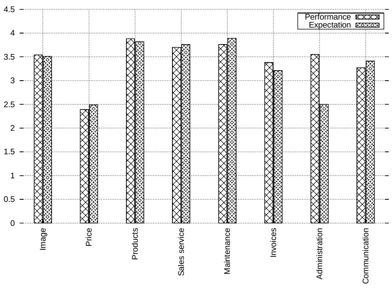

Figure 1: Average domain performance and expectation.

Based solely on the performance scores, a marketeer or manager would conclude that the firm was performing well on all its attribute domains, except 'price'. Furthermore, 'products', 'sales service' and 'maintenance' would be identified as the top three performing domains.

However, the expectation scores create a rather different picture of the company. First of all, it seems that all domain performances lie in the neighborhood of the expected performance, except for 'administration'. Even 'price', the least performing domain, seems to be doing rather well compared to its expected performance. Figure 1 shows that the 'price' domain is not more problematic than the 'sales service' or 'maintenance' domains which are two of the top three domains. On the other hand, it seems that 'administration', which did not belong to the top three domains, is by far the most successful attribute domain.

It is clear that the possibility to derive proxies for expectation scores offers new insights into the company's performance. Also, these expectation scores can offer new possibilities in other contexts. Vanhoof et al. (Vanhoof et al., 2005) for instance use expectation scores to identify an attribute domain as a 'basic', 'performance' or 'excitement'.

In sum, it seems justified to conclude that our AGOP's behavioral parameter approach is valuable in the customer (dis)satisfaction research. Next, we will study a comparable approach in a different marketing domain.

3 THE OWA OPERATOR IN COUNTRY-OF-ORIGIN THEORY

3.1 Marketing Context

Research on country-of-origin (coo) effects is concerned with the influence this marketing stimulus exerts on the formation of consumers' attitude toward foreign sourced products (Bilkey and Nes, 1982). The basic premise is that coo can be a valuable asset for the positioning of products on the international market.

Most studies approach the coo-phenomenon from an information theoretic perspective. It is assumed that the processing of coo-cues is mainly cognitively driven. In other words, people's attitudinal disposition toward a product is believed to be the outcome of logical reasoning with rational use being made of country-related information offered. For instance, German made cars are positively evaluated based on the idea that Germany is a well known car producing country.

Recently however, several scholars have questioned the overwhelming predominance of this cognitively oriented stream (Verlegh and Steenkamp, 1999). As they argue, classic studies neglect the coo-cue's capacity to arouse all kinds of symbolic and emotional connotations that might interfere in the process of forming an attitude toward internationally marketed products. The boycott of Danish products in the Middle East, due to the publication of a series of controversial Muslim cartoons, indeed supports the idea that country-specific feelings can be of capital importance for the positioning of products in other countries.

The lack of knowledge on how these country-related feelings precisely operate, explains the urgent need for more insight into this particular topic.

The concept of 'attitude' can be defined as an overall evaluative judgement toward a person, object or event (Eagly and Chaiken, 1993). One of the most popular models on product attitude formation is the Expectancy Value Model (Fishbein and Ajzen, 1975). It is based on the key proposition that overall product evaluation is mediated by the evaluation of salient attribute beliefs. Thus, people integrate knowledge about the product's attributes in order to arrive at a final evaluation.

Interestingly, the literature on advertising and emotions has put some of the basic principles behind this theory into a broader perspective. More specifically, it was posited by Peterson et al. (Peterson et al., 1986) that advertising cues (like coo) elicit various affective reactions which can influence product attitude formation.

According to the Encoding Specificity Theory developed by Tulving and Thomson (Tulving and Thomson, 1973), such ad-related affects experienced by the individual can activate internally stored thoughts that are relevant and related to those affects. Or, as put by Cacioppo and Petty (Cacioppo and Petty, 1989), such affects can "bias issue-relevant thinking by making affectively consonant thoughts and ideas more accessible in memory." This way for instance, happy people have been found to show better recall of positive material offered to them (Isen, 1989). Thus apparently, ad-affects regulate an individual's processing of information about a product's attributes in such a manner that greater (lesser) receptiveness goes out toward the attribute-related information which corresponds most (least) intimately to the individual's actual emotional state. This brings us to the following hypothesis:

> "Consumers expressing more positive feelings toward the product's coo will process the favorable (i.e., the stronger valued) attribute beliefs while consumers expressing less positive feelings toward the product's coo will process the unfavorable (i.e., the weaker valued) attribute beliefs."

Paraphrased somewhat differently, we might say that the emotional state into which consumers have been brought by advertisement stimuli will determine consumers' degree of optimism (or pessimism) during their evaluation of the product being confronted with.

Unfortunately, the marketing literature has no scales at its disposition that might help us in assessing the evaluator's level of optimism. In addition, conventional statistical techniques used to study coo-effects are not capable of distracting this kind of information from the data. As will become clear throughout the following sections, it is here more precisely that the application of aggregation operators can become particularly useful. More in detail, we will demonstrate that the orness can provide us with the desired quantification of the evaluator's degree of optimism. Also, the interpretation of the orness is much more straightforward than the rather complex LISREL-models as they have been traditionally used within the literature.

3.2 Behavioral Parameter: The Owa Operator's Orness

The ordered averaging operator (OWA) was selected as evaluation function, which allows for aggregation of product attribute satisfaction scores, unifying conjunctive and disjunctive behavior (Yager and Rybalov, 1998).

Definition 2 *(Yager and Kacprzyck, 1997)* *An OWA operator is a mapping* $f : \mathbb{R}^n \rightarrow \mathbb{R}$ *having an associated weighting vector* $\mathbf{W} = [W_1 \quad W_2 \quad \dots \quad W_n]^T$ *such that* $\sum_i W_i = 1$, $W_i \in [0,1]$ *and* $f(a_1, \dots, a_n) = \sum_{i=1}^{n} W_i b_i$, *with* $(b_{k1}, \dots, b_{kn})$ *being the value-ordered (in decreasing order) set of attributes* $(a_1, \dots, a_n)$ *of a specific instance k.*

A fundamental aspect of the OWA operator is the re-ordering step. This way, a weight W_i is associated with a particular ordered position i of the arguments, instead of a specific argument a_i. The 'orness' quantifies the structure of the weight vector and can be used to express the nature of the behavior of the evaluator like pessimistic or optimistic. This characteristic is defined as:

$$orness(W) = \frac{1}{n-1} \sum_{i=1}^{n} (n-i) W_i \qquad (5)$$

If the orness of a weight factor equals 1, the OWA operator degenerates to the maximum operator, aggregating the set of attributes into the value of the largest attribute. In contrast, an orness value of zero indicates that the OWA operator behaves as the minimum operator, aggregating the set of attributes into the value of the smallest attribute. Consequently, a large orness value indicates more emphasis on the highly valued attributes during the aggregation process, thereby modeling optimistic behavior. A small orness value implies low-valued attributes dominate the aggregation process, thereby modeling pessimistic behavior (Salido and Murakami, 2003) (cf Table 4).

Table 4: Illustration OWA and Orness.

a_1	a_2	a_3	W_1	W_2	W_3	$f(a_1,a_2,a_3)$	Orness
4	7	3	1	0	0	7	1.00
$(=b_2)$	$(=b_1)$	$(=b_3)$	0.7	0.2	0.1	6	0.80
			0.1	0.1	0.8	3.5	0.15
			0	0	1	3	0.00

As will be indicated next under the data section, our specific case-study corresponds to a situation where a collection of k respondents (observations) are given, each comprised of an n-tuple of product belief values $(a_{k1}, a_{k2}, \ldots, a_{kn})$ called the arguments and an associated single value d_k, referred to as the aggregated value (i.e., the quality of the product).

Our goal will be to obtain a single OWA operator for a given group of respondents $K = 1, \ldots, k$, hereby learning the weighting vector $\mathbf{W}$ and its associated orness. This results in the following constrained minimization problem, with e_k being the error made for each customer k:

$$Min. \quad e_k = \tfrac{1}{2}(b_{k1}W_1 + b_{k2}W_2 + \ldots + b_{kn}W_n - d_k)^2$$
$$s.t. \begin{cases} \sum_{i=1}^{n} W_i = 1 \\ W_i \in [0,1], \quad i = (1, \ldots, n) \end{cases} \tag{6}$$

Introducing the following transformation

$$W_i = \frac{e^{\lambda_i}}{\sum_{j=1}^{n} e^{\lambda_j}} \tag{7}$$

the weights W_i will be positive and will sum to 1 for any value of the parameters λ_i, resulting in the following unconstrained nonlinear programming problem:

$$\begin{aligned} &Minimize && \text{the instantaneous errors } e_k \\ &where && e_k = \tfrac{1}{2}\Bigg(b_{k1}\frac{e^{\lambda_1}}{\sum_{j=1}^{n} e^{\lambda_j}} + \\ &&& \qquad b_{k2}\frac{e^{\lambda_2}}{\sum_{j=1}^{n} e^{\lambda_j}} + \ldots + b_{kn}\frac{e^{\lambda_n}}{\sum_{j=1}^{n} e^{\lambda_j}}\Bigg)^2 \\ &\text{with respect to the parameters } \lambda_j \end{aligned} \tag{8}$$

The gradient descent method was used to learn the weights (Filev and Yager, 1998).

It should be noticed that the methodology described above measures the orness from a sample rather than a population, making it susceptible to random error. Yet, it would be interesting to infer statistically about the results based on a sample. Such inference could answer questions whether the orness (or any other similar characteristic) differs between different groups, to construct confidence intervals for the quantities under investigation and to test hypotheses for the population values. To our knowledge, however, there is no such technique for statistical inference available. We base our statistical inference on resampling methods, namely non-parametric bootstrap (Efron and Tibshirani, 1993). For details about implementation of this technique, we refer to (Brijs et al., 2006).

3.3 Data

In order to test our basic theoretical assumption, a large-scale field survey was designed. Two products and two countries-of-origin were chosen in order to determine how coo-related feelings affect consumers' cognitive processing of attribute beliefs. Products selected were beer and DVD-players. The decision to work with two different product categories (the former being utilitarian in nature while the latter is rather hedonic-oriented) was taken so that the external validity of our study could be incremented. Spain and Denmark were selected as countries-of-origin for two particular reasons. First of all, respondents were sufficiently familiar with both countries. Secondly, two samples could be obtained of which the overall level of intensity of country-specific feelings aroused substantially varied.

Data collection was done by means of two surveys (one for Spain/Spanish products and one for Denmark/Danish products). The sample consisted of respectively 616 and 609 Belgian graduate students. More details about the data collection procedure can be found in (Brijs et al., 2006).

3.4 Validation

3.4.1 Theoretical Validation

Marketing theory expects certain attributes to be more influential than others during the evaluation process in function of coo-related feelings. The basic principle is that optimistic (pessimistic) customers will assign higher (lower) weights to the better (worse) performing attributes. Of particular interest for theoretical validation is that the attributes' weights depend on their relative performance and that the OWA operator is able to model this heuristic.

Firstly, the OWA operator uses weights to aggregate the arguments (attribute scores) which allows certain attributes to be more influential in the aggregation process. Secondly, OWA's re-ordering step allows us to give the better performing attributes higher or lower weights, rather than assigning weights to specific attributes.

3.4.2 Empirical Validation

Tables 5(a), 5(b), 5(c) and 5(d) present the results of the orness and the OWA weights (with standard errors between brackets) for Spanish/Danish DVD players and beer based on the outcome of the questionnaire. Standard errors are based on B=1000 bootstrap replications using the procedure described above.

Table 5: OWA and Country-Of-Origin Effects.

(a) Results for Spanish DVD players.

Data set	*Orness*	W_1	W_2	W_3	W_4
All cases (616)	0.4742	0.1338	0.2758	0.4695	0.1207
	(0.0259)	(0.0326)	(0.0858)	(0.0870)	(0.0382)
Group A: (137)	0.5499	0.1931	0.3866	0.2971	0.1230
	(0.0619)	(0.0682)	(0.2188)	(0.2191)	(0.0734)
Group B: (134)	0.4061	0.1495	0.2065	0.3567	0.2871
	(0.0556)	(0.0560)	(0.1350)	(0.1734)	(0.1124)
Significance	*S*	*NS*	*NS*	*NS*	*NS*

(b) Results for Spanish beer

Data set	*Orness*	W_1	W_2	W_3	W_4
All cases (616)	0.4290	0.1554	0.3171	0.1866	0.3407
	(0.0220)	(0.0299)	(0.0706)	(0.0798)	(0.0471)
Group A: (137)	0.4489	0.2015	0.1483	0.4452	0.2047
	(0.0521)	(0.0620)	(0.1568)	(0.1983)	(0.1038)
Group B: (134)	0.3438	0.1824	0.1907	0.1023	0.5243
	(0.0443)	(0.0666)	(0.1070)	(0.1217)	(0.0938)
Significance	*NS*	*NS*	*NS*	*S*	*S*

(c) Results for Danish DVD players

Data set	*Orness*	W_1	W_2	W_3	W_4
All cases (609)	0.5265	0.1901	0.3774	0.2544	0.1780
	(0.0215)	(0.0473)	(0.07370)	(0.0651)	(0.0310)
Group A: (194)	0.5336	0.2491	0.2712	0.3107	0.1688
	(0.0504)	(0.0919)	(0.1652)	(0.1670)	(0.0595)
Group B: (74)	0.5133	0.1727	0.3005	0.4207	0.1060
	(0.0582)	(0.1030)	(0.1934)	(0.1867)	(0.0902)
Significance	*NS*	*NS*	*NS*	*NS*	*NS*

(d) Results for Danish beer

Data set	*Orness*	W_1	W_2	W_3	W_4
All cases (609)	0.4216	0.2099	0.1683	0.2983	0.3233
	(0.0204)	(0.0372)	(0.0732)	(0.0759)	(0.0399)
Group A: (194)	0.4166	0.2399	0.1223	0.2855	0.3522
	(0.0357)	(0.0699)	(0.1116)	(0.1205)	(0.0780)
Group B: (74)	0.3733	0.2266	0.0775	0.2849	0.4109
	(0.0548)	(0.07800)	(0.1238)	(0.1406)	(0.0867)
Significance	*NS*	*NS*	*NS*	*NS*	*NS*

If we compare the group of respondents with high positive feelings toward coo (group A) versus those expressing less positive feelings toward coo (group B), Table 5(a) shows that the orness for group A is higher than for group B. When constructing 95% confidence intervals we found that for group A the interval is [0.439, 0.672], while for group B [0.347, 0.521], which implies a certain overlap. Statistically speaking, the differences between group A and B are not significant on a 5% level. According to our bootstrap results, it is however significant on the 10% level although this decision depends on the bootstrap experiment used. Qualitatively also, it is clear that group A has a larger orness, which somehow confirms our hypothesis that people expressing high positive feelings toward coo tend to use a more optimistic evaluation function toward evaluating the quality of Spanish DVD-players. They tend to base their quality evaluation more on the more positively evaluated attributes.

Confirmation of the encoding-specificity principle should, however, also be reflected by the individual OWA weights (W_1 to W_4) such that for group A versus group B, the ordered weights W_1 and W_2 should show higher values and the ordered weights W_3 and W_4 should show lower values. Based on results depicted in Table 5(a) we can conclude that indeed W_1 and W_2 are higher in group A compared to group B. However, their individual differences are not statistically significant. Similarly, it can be seen from the values for W_3 and W_4 that they are higher in group B compared to group A, although their individual differences are again not statistically significant.

Table 5(b) presents the results obtained for Spanish beer. Here also, the orness for group A is surpassing that for group B, although in this case the difference is not statistically significant. The 95% confidence interval for group A is [0.351, 0.555] while for group B [0.262, 0.435]. Yet, there is a clear indication that group A has a larger orness. This can again be seen as supportive evidence for our hypothesis. However, in this case the results for the weight values are less convincing since the value of W_2 is larger in group B than in group A, and the value of W_3 is larger in group A than in group B.

Table 5(c) and 5(d) show the results for Danish DVD-players and beer. Even though there is a tendency that the orness is again slightly higher for group A than for group B, the differences are much smaller compared to the results for Spain and not statistically significant. For example, for Danish DVD-players, the 95% confidence interval for group A is [0.435, 0.626] and for group B [0.402, 0.641], showing a large overlap. With respect to the values of W_1 to W_4 the results are not consistent.

3.5 Implications

From a practical point of view, our second case-study shows how milder coo-specific feelings serve as a useful device for advertisers to direct consumers' processing of attribute beliefs. More in detail, their functioning can be understood as some kind of encoding-specificity mechanism. That is, consumers during their product evaluation ascribe most importance to those attribute beliefs which are closer in line with their internal affective state.

From a technical point of view, we opted for an alternative methodology in using the OWA-operator. In our opinion, this is a useful approach while the interpretation of the OWA-weights is more straightforward compared to the more complex LISREL-models as they have been traditionally used for instance by Han (1988). An additional advantage lies in the fact that the 'orness' gives us the needed quantification of the optimistic degree of an evaluation. This aspect is already a huge advantage of the fuzzy set approach compared to the more traditional LISREL approaches where this degree of optimism cannot be extracted from the data. Finally, we introduced a bootstrap procedure to estimate the orness and the level of uncertainty around it. This enables us to construct confidence intervals and conduct hypothesis tests. As far as we know, estimating this degree of uncertainty of the orness has never been introduced in the literature before.

4 CONCLUSION

Within the fuzzy set field, past application-oriented research has mainly been focused on AGOP's domain representation power or decision-making strength. As far as we know, the AGOP's characteristics themselves have not been of any significant importance in this particular type of research.

However, this paper has demonstrated that the value of certain characteristics for applied research should not be disregarded. It is illustrated that aggregation operator characteristics carry the potential of functioning as valid proxies for domain specific knowledge, which is hard to measure directly or to derive statistically from the data.

The presence of such potential has been proven to exist by means of two marketing case-studies. The first case-study examined the use of the uninorm in customer satisfaction theory. It could be established that the uninorm's neutral value is a proxy for customers' expectations. This approach in turn provides the manager with new and important information about the company's performance. The second case-study has explored the value of the OWA operator for country-of-origin research. The orness was found to be suitable for the quantification of the customers' degree of optimism (pessimism) during the process of product evaluation. Such method for quantification in itself already counts as a technical contribution toward the coo-field. In addition, managers have gained more insight into the precise role of coo-related feelings. As such, they are capable now of dealing more effectively with this particular marketing phenomenon.

The validity of both operator characteristics as domain specific proxies has been verified theoretically as well as empirically, which adds indirectly to the value of our findings.

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