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The Application of Uninorms in Importance-Performance Analysis

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Abstract: In the field of marketing, Importance-Performance Analysis is a useful technique for evaluating the elements of a marketing program. The importance dimension of this technique is often determined in a regression based approach. However, this approach has certain problems and limitations. A new approach, based on uninorms, is suggested. This article shows that the uninorm approach possesses several strengths for this type of analysis and matches particularly well with the customer satisfaction theory.

Key-Words: Fuzzy Set Operators, Uninorms, Reinforcement Behavior, Compensation Behavior, Importance-Performance Analysis, Expectation-Disconfirmation Paradigm

1 Introduction

In the field of marketing, Importance-Performance Analysis (IPA) is a useful technique for evaluating the elements of a marketing program. Its ease of interpretation makes it an attractive managerial tool for developing marketing strategies [6]. Due to its strength and managerial attractiveness, IPA is also used as part of operations strategy formulation [12], as analysis tool in customer satisfaction management [7, 8] and in service quality improvement programs [11].

The IPA technique calculates the importance and performance of each product/service attribute. Next, these couples of data are plotted on a grid with performance and importance as the two dimensions. The axes divide the grid into four different quadrants, each with their own specific interpretation: concentrate here, keep up the good work, low priority and possible overkill. Each attribute lies in one of these four quadrants, allowing the manager to easily identify the attributes that require the most urgent attention.

Generally, the attribute performance is directly measured, by use of a survey. The calculated mean (or median) of all observed attribute performances are used as the performance dimension coordinate in the IPA grid. This is the standard approach.

With regard to the importance dimension of each attribute, two types of approaches exist, i.e. the directly measured approaches [6, 11, 12] and the indirectly measured approaches [7, 8]. However, recent research results in the field of customer satisfaction question the usability of one of the most common indirectly measurement approaches of attribute importance, i.e. regression coefficients.

In the next section, the problems of the most common regression based approach are empirically demonstrated. Next, a uninorm approach will be suggested. Finally, a case study illustrates the potential of this approach in the field of IPA research.

2 Regression based importance measures

The regression based approach, commonly applied in IPA and customer satisfaction research, regresses the overall satisfaction on the attributes' performances. The impact of these attributes' performances on the overall satisfaction, measured by the regression coefficients, can be used as proxies for the attributes' importance measures [2, 8, 9].

Because this approach tries to fit the data to an a priori defined model, it is important to make the correct assumptions about the data and the regression model. Generally, the following regression model is used, where Y represents the customer satisfaction and X_i represents the performance of attribute i.

$$Y = \alpha_0 + \sum_i \beta_i X_i + u \qquad (1)$$

However, this regression model assumes that the impact of the attribute performance on the overall satisfaction can be represented as a point-estimate, which is in contradiction with results of recent research [8, 9, 11]. Recent research pointed out that the attribute importance is dependent on the attribute performance. According to Sampson et al. [11], this implies that the regression coefficient, which is a point-estimate, only captures a fraction of the true impact. The part that is not captured by the regression coefficient hides inside the error term, making it heteroscedastic and violating one of the assumptions of ordinary least squares (OLS) regression.

Furthermore, Equation 1 also assumes that no interaction effects exist between the attribute performance variables exist. This implies that X_i's impact on overall satisfaction will not alter if attribute X_j's performance drops from e.g. 9 out of 10 to 2 out of 10, given the same performance for X_i and ceteris paribus. However, this seems to be a rather unexpected type of behavior. Therefore, both the (heteroscedastic) nature of the disturbance term and the necessity of interaction terms are empirically tested.

2.1 Data

This research includes data from a customer satisfaction survey within the family entertainment sector. The survey measures 7 attribute performances and 1 overall satisfaction score for each customer. All performance/satisfaction scores were measured on a scale from 1 (extremely low) to 10 (extremely high). In total, this customer satisfaction survey was repeated for 7 companies in the entertainment sector. The number of observations is reasonably high, i.e. minimum 500 cases per company.

2.2 Heteroscedasticity

Heteroscedasticity means that the variance of the disturbance term is related to the values of the independent or dependent variables. To verify the presence of heteroscedasticity in the disturbance term, 7 regressions were performed, one for each company. Each regression follows the model formulated in Equation 1. The regression results show that 77% of all regression coefficients are statistically significant at the level of 1% and 87.5% of all regression coefficients are statistically significant at the level of 5%. The adjusted R^2 lies between 52% and 74%. At first sight, these regression results seem to be reasonably good.

However, these results give no indication about the nature of the disturbance term. To investigate whether heteroscedasticity is in play or not, further tests are necessary. In this research, two heteroscedasticity tests were applied to the data.

The first test is based on the graphical analysis of the disturbance term, which is an informal method. This method plots the squared residuals $\hat{u}_i$, which are a proxy for the variance of the disturbance term [5], against X_i. Any patterns revealed by these plots indicate a relationship between the squared residuals and the independent variables, implying the presence of heteroscedasticity. To measure the strength of the pattern, correlation coefficients were determined between $\hat{u}_i$ and the independent variables X_i. The results are shown in Table 1. Statistically significant correlation coefficients are considered to indicate heteroscedasticity.

First of all, the results of Table 1 show that all seven regressions have a disturbance term which is heteroscedastic, related to at least one independent variable. Secondly, 87.5% of all statistical significant correlation coefficients have a negative sign. These results show that the presence of heteroscedasticity is most likely. However, it is still possible that the magnitude of the problem is underestimated, because the correlation coefficients only test for linear relationships.

Table 1 Correlation coefficients

Attribute	Spearman rank's correlation coefficient						
	Company						
	1	2	3	4	5	6	7
X_1	0.12*	0.07	-0.08‡	-0.09‡	0.01	-0.04	-0.28*
X_2	-0.05	0.00	-0.02	-0.12†	-0.05	-0.13*	-0.23*
X_3	0.05	-0.11†	0.05	-0.05	-0.01	-0.10†	-0.26*
X_4	0.05	0.08	0.10†	0.05	0.07	0.01	-0.12*
X_5	-0.01	-0.09‡	-0.08‡	-0.14*	-0.13*	-0.09‡	-0.26*
X_6	0.12*	-0.11†	0.00	0.00	-0.04	-0.03	-0.31*
X_7	-0.01	-0.08	-0.04	-0.08	0.01	-0.13*	-0.31*

*significant at 1%
†significant at 5%
‡ significant at 10%

Therefore, the more formal Goldfeld-Quandt heteroscedasticity test was applied. "This popular method is applicable if one assumes that the heteroscedastic variance, σ_i^2, is positively related to one of the explanatory variables in the regression model" [5]. However, the correlation coefficients from the previous test indicated a negative relationship in most of the cases. Therefore, we adapted the Goldfeld-Quandt approach to test for both type of relationships.

Traditionally, the G-Q test starts by ranking the observations in increasing order, according to the values of X_i. Secondly, the data is split in two sets, omitting the middle n observations. Next, an OLS regression is fitted to both data set 1 (smallest X_i values) and data set 2 (largest X_i values). If no heteroscedasticity is present, the RSS of both regressions should not differ significantly and Equation 2 should follow the F distribution. To adjust this approach, in order to test for a negative relationship, it suffices to rank the observations in decreasing order or to calculate λ differently, by switching nominator and denominator in the original formula.

$$\lambda = \frac{RSS_1 / df}{RSS_2 / df} \qquad (2)$$

Table 2 shows the heteroscedasticity results for both the correlation coefficients test and the Goldfeld-Quandt test. The G-Q test detects clearly more heteroscedasticity than the correlation coefficients test. However, for all cases except one, when both tests agree on heteroscedasticity, they indicate the same type of relation between the variance of the disturbance term and the independent variable. This validates the fact that both negative and positive relationships exist. Finally, in contrast with the results from the correlation coefficients test, the G-Q test reveals that the variance of u_i is not more likely to be negatively than positively related to X_i. However, we can conclude that heteroscedasticity is present.

Table 2 Heteroscedasticity results

Attribute	Company 1		2		3		4		5		6		7	
	CC	GQ	CC	GQ	CC	GQ	CC	GQ	CC	GQ	CC	GQ	CC	GQ
X_1	P*	P†		P*	N‡	N*	N‡					N†	N*	N*
X_2		P‡		P*			N†	N*			N*	N*	N*	N*
X_3		P*	N†	P*		P‡		P‡		P*	N†	N*	N*	N*
X_4		P*	N‡	P*	P†	P†		P†				N†	N*	
X_5			N†	N*	N‡	N*	N*	N†	N*	N*	N‡	N*	N*	N*
X_6	P*	P*		N*				P†				N†	N*	N‡
X_7		P*		P‡			N‡			P‡	N*	N†	N*	N†

CC Correlation coefficient test
GQ Goldfeld-Quandt test
P Variance of u_i is positive related to X_i
N Variance of u_i is negative related to X_i
* significant at 1%
† significant at 5%
‡ significant at 10%

"The variance of u_i, homoscedastic or heteroscedastic, plays no part in the determination of the unbiasedness property" [5]. This implies that the OLS estimated regression coefficients are still unbiased and linear. However, they no longer have the minimum variance in the class of linear unbiased estimators. Therefore, the variance of the regression coefficients are overestimated or underestimated on the average, and in general, it is impossible to know if the bias is positive or negative. As a consequence, the conventionally computed confidence intervals and t and F tests are no longer reliable.

2.3 Interaction effects

In Importance-Performance Analysis and other customer satisfaction research, the regression model often implicitly assumes no interaction effects exist among the attributes' performances. The purpose of this study is to test the validity of this 'no interaction' assumption.

This study only considers two-factor interaction effects. The effect of X_i is assumed to increase as the performance of X_j decreases and vice versa. Therefore, interaction effects of the type X_i / X_j are added to the regression model. Equation 3 shows the new regression model, after addition of the interaction effects. Many other and more complex interaction effects can be incorporated into the model. However, it is not our goal to identify all possible interaction effects, but merely to test the 'no interaction' assumption.

$$Y = \alpha_0 + \sum_i \beta_i X_i + \sum_i \sum_j^{j \neq i} \gamma_{ij} \frac{X_i}{X_j} + u \qquad (3)$$

In total 14 regressions were performed, i.e. both the regression with and without the interaction effects for each company. However, because of the high amount of interaction effects, a stepwise variable selection approach was used to add the 42 interaction effects to the model. This approach adds the interaction effect which has the smallest probability of F, if that probability is equal to or less than 0.05. Interaction effects already in the regression equation are removed if their probability of F becomes equal to or larger than 0.10. The method terminates when no more variables are eligible for inclusion or removal.

Table 3 shows the results of the regression for the first company. After completing the stepwise regression, 8 interaction effects were added to the original model, each of them being statistically significant. Furthermore, the adjusted R^2 increases from 51.9% to 58.2%, which indicates that the model with interaction effects is able to explain more variation in the dependent variable.

Furthermore, Table 3 also shows that the regression coefficients differ significantly when interaction effects are added to the regression model. Some of the main effects even get a negative coefficient. However, the interpretation of these negative coefficients has become less trivial with the interaction effects in play.

Table 3 Regression with(out) interaction effects

Independent variables		Model A	Model B
Main effects	Intercept	1.58*	-5.99*
	X_1	0.18*	-0.26
	X_2	0.16*	0.28**
	X_3	0.05**	0.72*
	X_4	0.08**	-0.86*
	X_5	0.01	-0.01
	X_6	0.09*	0.64*
	X_7	0.26*	0.43*
Interaction effects	X_6 / X_3		1.05*
	X_4 / X_7		4.84*
	X_1 / X_2		4.87*
	X_4 / X_2		-4.08*
	X_6 / X_7		-3.52*
	X_4 / X_1		-7.35*
	X_3 / X_1		-5.99*
	X_3 / X_5		1.88**
Adjusted R^2		0.519	0.582

Model A no two-factor interaction effects
Model B with two-factor interaction effects
* significant at 1%
** significant at 5%

Table 4 Regressions with interaction effects - summarized results

Company	Δ Adjusted R^2	# Interaction effects*
1	+ 0.063	7
2	+ 0.032	4
3	+ 0.024	4
4	+ 0.065	8
5	+ 0.038	7
6	+ 0.049	3
7	+ 0.010	1

* significant at 1%

Finally, Table 4 summarizes the results for all seven regressions (with interaction effects). These results strongly indicate that interaction effects are present in the customer satisfaction process. As a consequence, a specification error is made when one leaves the interaction effects out of the regression.

The consequences of omitting a relevant variable depend on the correlation between the omitted variable and the included variables. If they are correlated, the regression coefficients of the included variables are biased. But even in case of no correlation, although the regression coefficients of the included variables are unbiased, their variances are biased, making the t and F tests unreliable.

2.4 Conclusion

The results of our research offer empirical evidence that the simple regression model used in IPA and customer satisfaction research (Equation 1) suffers from both heteroscedasticity and model-specification problems. Both problems have their consequences.

Heteroscedasticity, if not accounted for, leads towards unreliable confidence intervals and unreliable t and F tests. This makes it very dangerous to order the attributes according to their importance (i.e. their regression coefficient). Omitting the interaction effects leads toward unreliable confidence intervals at best and biased regression coefficients at worst. Our empirical results show indeed that the regression coefficients of the simple model differ greatly from the regression coefficients of the model with interaction effects, the latter having more explanatory power.

Based on these findings, we join Sampson et al. in their conclusion that the simple regression model, often used in IPA, is problematic and unreliable. Further research is needed to adjust the regression model in order to avoid both heteroscedasticity and specification errors. However, we believe that a new approach, which will be presented in the next section, based on uninorms, can be an interesting alternative to calculate attribute importance

3 Uninorm based importance measures

3.1 Uninorms in customer satisfaction theory

Importance-Performance Analysis is closely related to customer satisfaction concepts. The importance of an attribute is often interpreted as the impact of the attribute on the customer satisfaction (e.g. [7], [8]).

Furthermore, customer satisfaction theory is an important topic in marketing research and it is widely accepted that customers generate a multi-attribute-based response on their satisfaction with a certain product/service. In a certain way, customer satisfaction can be considered as the aggregation of the customer's attribute-level experiences [15].

This process of information fusion has been thoroughly studied in past research. The last 10 years, an impressive organized collection of aggregative operations has been developed within the field of fuzzy set theory and non-classical decision theory [4]. This collection can be divided into several families of aggregation operators, each of them having specific mathematical and behavioral properties [1]. This research uses the uninorm aggregator family to model the customer satisfaction process.

A uninorm U is a mapping $U: [0,1]x[0,1]\rightarrow[0,1]$ having the following properties [16]:

1. $U(a,b) = U(b,a)$
2. $U(a,b) \geq U(c,d)$ if $a \geq c$ and $b \geq d$
3. $U(a,U(b,c)) = U(U(a,b),c)$
4. There exists some elements $e \in [0,1]$ called the **identity** element such that $\forall\ a \in [0,1]$: $U(a,e) = a$

The above definition shows the mathematical properties of the uninorm operators. We will concentrate on the fourth property, which plays an important role in our research. For a full discussion of the mathematical properties of the uninorms, the reader is referred to [1, 15, 16].

The fourth property defines the neutral element of a uninorm, which plays the role of a null vote in the aggregation process and distinguishes the uninorm from the t-norm and the t-conorm. The neutral element is important because it defines the behavior of the aggregation operator. If the arguments of the aggregation operator are both smaller (larger) than the neutral element, the uninorm will show downward (upward) reinforcement. If one of the arguments is larger than the neutral element while the other argument is smaller (or vice versa), the uninorm will show compensatory behavior.

This behavioral versatility of the uninorm aggregator is one of the main reasons why the uninorm family was selected as the aggregator to model the customer satisfaction process. Furthermore, uninorms are interesting to apply in customer satisfaction theory because they match closely with several customer satisfaction concepts.

"The dominant model in customer satisfaction research is based on the disconfirmation of expectation paradigm (Oliver, 1980 , 1997)"[8]. This model states that customer satisfaction is an additive combination of the expectation level and the resulting attribute-level disconfirmations. This concept differs from the simple regression model, which considers satisfaction as an additive combination of the attribute performances.

In contrast with simple regression models, the uninorm aggregator has a better conceptual fit with Oliver's customer satisfaction model. First of all, research by Vanhoof et al. has shown that the neutral element of the uninorm is a proxy for the expectation level of the customer satisfaction process [14]. Secondly, the uninorm aggregator is mainly determined by the deviation between the argument and the neutral element (disconfirmation), rather than by the absolute value of the argument (attribute performance).

Furthermore, the customer satisfaction aggregation process is also presumed to be a heuristics-based decision-making process [15]. Two heuristics stand out in this process: "anchoring and adjustment" and "reinforcement". Anchoring and adjustment implies that the consumer assesses the attribute-level satisfaction scores against an individual product-level anchor, which is highly complementary to the expectation-disconfirmation concept and which is a behavior that can be modeled well by uninorms. Reinforcement means that customers increasingly exaggerate evaluations when they fall short of or exceed expectations, which is also a behavior that can be modeled by uninorms.

It's obvious that uninorms have several behavioral properties matching closely with aspects of the customer satisfaction process, which provides theoretical validation for our approach. Therefore, we believe that uninorms contain a great potential to model customer satisfaction and to derive attribute importance measures.

3.2 The uninorm aggregator

The uninorm applied in this research is based on the aggregation operators presented by Dombi [3]. He shows that these operators, as long as they follow the axiom system he discusses, can be written by means of a generator function *f(x)*, cf Equation 4.

$$U(x_1, x_2, ..., x_j) = f\left[\sum_j f^{-1}(x_j)\right] \qquad (4)$$

Furthermore, Dombi shows that the generator function *f(x)* displaced by *d*, $f(x+d) = f_d(x)$, generates a new uninorm with a different neutral element. This implies that one generator function can generate several uninorms, each with different neutral elements *e*. This makes it possible to create a unique uninorm, with a specific neutral element for each respondent *y*, based on a single uninorm generator function. The neutral element e_y for each respondent can be calculated by Equation 5.

Once the respondents neutral element e_y, which is a proxy for the respondents expectation level, has been determined, it is possible to calculate A_{jy}^*, which represents the overall satisfaction for respondent *y* if no influence would have been exerted by attribute X_j. The fourth property of the uninorm family allows us to calculate this value by replacing attribute X_j with the neutral value for respondent *y*, as shown in Equation 6.

$$e_y = f\left[\frac{\sum_{j=1}^{n} f^{-1}(x_{jy}) - f^{-1}(A_y)}{n-1}\right] \qquad (5)$$

$$A_{jy}^* = U(X_{1y}, ..., X_{(j-1)y}, e_y, X_{(j+1)y}, ..., X_{ny}) \qquad (6)$$

Finally, the impact I_{jky} can be determined by taking the difference between the reported satisfaction A_y and A_{jy}^*, as shown by Equation 7. This impact I_{jky} can be positive or negative and measures the impact of attribute X_j, which has a performance score of *k*, on the overall satisfaction of respondent *y*.

$$I_{jky} = A_y - A_{jy}^* \quad (7)$$

The impact measures I_{jky} are calculated at the level of a single respondent. However, traditional IPA needs information at the population level, which can be obtained by taking the average of the impact scores. Because recent research shows that the attribute impact is dependent on the attribute performance, conditional averages are taken (cf equation 8).

$$I_{jk} = \frac{\sum\left(I_{jky} \middle| X_{jy} = k\right)}{(number\,of\; X_{jy} \,|\, X_{jy} = k)} \qquad (8)$$

These impact averages represent the average impact of attribute X_j on the overall customer satisfaction, when $X_j = k$. Finally, to derive importance scores, the absolute value of each impact average I_{jk} has to be taken, because a very large negative impact is equally important as a very large positive impact.

The IPA needs two coordinates for each attribute. The first coordinate is the average attribute performance P_j, which is determined by taking the arithmetic mean of all attribute performance scores in the dataset for that specific attribute. The second coordinate is the attribute importance. We could take the arithmetic mean of all importance scores I_{jky} and use its absolute value as the attribute importance coordinate. However, this assumes that the impact of an attribute can be represented by a point-estimate, which is contradicted by previous research [8, 9].

$$I_{jP_j} = I_{jk} + (P_j - k)(I_{j(k+1)} - I_{jk}) \qquad (9)$$

$$where \quad k < P_j < k+1$$

Therefore, Equation 8 is used, which determines the impact of attribute X_j for each possible value *k* of X_j. Next, to determine the impact of attribute X_j, when $X_j = P_j$, the formula in equation 9 is used, which is based on the technique of interpolation. Finally, the absolute value of I_{jPj} is taken as the importance coordinate.

3.3 IPA validation

Past IPA research has mainly been focused on extending the original IPA model [6, 10]. As Oh [10] points out, only few studies have critically considered the conceptual validity of IPA. Recent IPA research [11, 8] and customer satisfaction research [9] have critically questioned the usefulness of a simple linear regression model to model customer satisfaction. Our empirical study showed that a simple regression can indeed deliver biased and unreliable results. But also the use of directly measured attribute importance has been questioned [7, 10]. Firstly, direct measurement of attribute importance brings along methodological discussions, like e.g. the use of univariate versus bivariate measurement scales. Furthermore, Oh points out that direct importance measurement of one attribute at a time is likely to inflate importance ratings, hereby restricting the variation. Finally, Matzler et al. claim that directly measured attribute importance represents the overall attribute importance instead of the attribute importance related to the attribute's current performance level. The performance related attribute importance, which is more useful in IPA analysis, can differ greatly from the overall importance.

However, despite the questionable validity of the existing IPA techniques, IPA has become an important and widely accepted managerial tool and should not be discarded as a whole. Yet, this leaves us in a nearly impossible position to validate our results directly because no 100% valid technique exists to measure or derive the true attribute importance. Therefore, we are limited to validating the underlying customer satisfaction modeling approach which is the foundation of our importance measures.

Section 3.1 already addressed the theoretical validation of uninorms to model customer satisfaction. It was shown that a theoretical match exists between the uninorm's properties and customer satisfaction behavior. In addition to the theoretical validation, further empirical validation is required, which can be provided by comparing our results with the conclusions from Szymanski and Henard's meta-analysis of 85 existing customer satisfaction studies [13]. A substantial part of their paper focuses on the relationships between customer satisfaction and several of its antecedents.

Table 5 shows the results of Szymanski and Henard, compared with our results. Our results closely follow the empirical results from other customer satisfaction research, indicating an empirical match between the uninorms behavior and the customer satisfaction behavior. All these results, both theoretical and empirical, provide evidence that uninorms are able to model customer satisfaction, which indirectly supports our uninorm IPA approach.

Table 5 Empirical validation

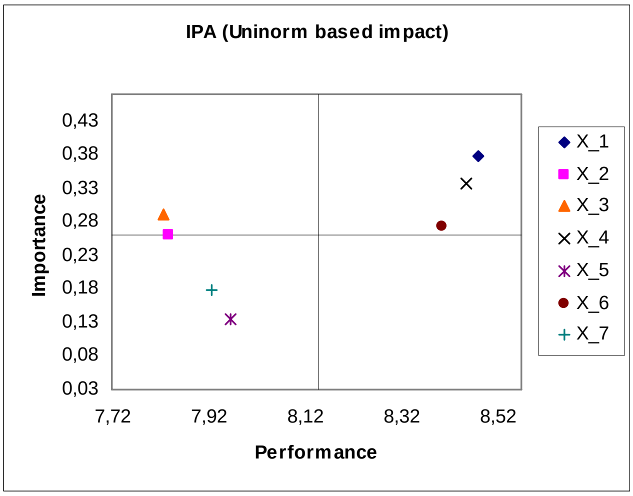
	Szymanski and Henard		Our results	
	Positive Correlations	Negative Correlations	Positive Correlations	Negative Correlations
Expectation* – Satisfaction	13	1	7	0
Disconfirmation** – Satisfaction	121	1	49	0
Expectation* – Performance	22	1	16	0

NOTE I Only statistically significant correlations at alpha ≤ .05 were considered.
NOTE II Expectation, disconfirmation and performance are measured or derived for each company at attribute level.
* expectation = uninorm's neutral element.
** disconfirmation = performance – expectation.

3.4 Case study

The purpose of this case study is to illustrate the application of the uninorm-based IPA approach. Figure 1 shows the IPA for the first company in our dataset. The positioning of the X-axis (Y-axis) is based on the center of the highest and the lowest x (y) coordinates. Other ways of positioning the axes exist, e.g. taking the average of the x (y) coordinates of all attributes as cut-point for the Y-axis (X-axis). However, the main point of an IPA analysis is the relative positioning of the attributes, rather than the absolute positioning [6].

Fig. 1 Uninorm based IPA



Analysis of this grid shows that attributes X_1, X_4 and X_6 fall in the upper right quadrant, where both performance and importance are high. This is the "Keep up the good work" zone. Attributes X_5 and X_7 are located in the lower left quadrant. These attributes have a low performance, but are also low in importance. This area is called the "Low priority" zone. Attributes X_2 and X_3 lie in the upper left quadrant or the “Concentrate here” zone, where the importance is high but the performance is low. Finally, the lower right quadrant, which is the “Possible overkill” zone, is empty.

This type of analysis allows the manager to formulate a strategy to enhance customer satisfaction. Based on the IPA of Figure 1, the company should concentrate on attributes X_2 and X_3, while maintaining efforts on X_1, X_4 and X_6.

4 Conclusions

Importance-Performance Analysis is an important managerial marketing tool. However, as shown in our empirical study, the simple regression model, often used to determine the attributes’ importance scores, has its problems. Further research on the nature of and solutions to these problems are necessary. In this work, we presented an alternative approach, based on uninorm aggregators, to determine attribute importance measures.

Firstly, the uninorm based approach calculates impact measures at the level of a single respondent. Even when averaging these impact measures, to obtain population level figures, we preserve the benefit of population level impact scores which are conditional to the performance score.

Secondly, the uninorm approach implicitly takes interaction effects into account and focuses on disconfirmation instead of attribute performance, allowing a close match with existing customer satisfaction models.

Furthermore, because of its properties like compensatory behavior, reinforcement behavior and the neutral element as anchor, the uninorm approach matches considerably well with the theoretical fundamentals of customer satisfaction theory. Besides the theoretical validation, we also provided empirical validation for the use of uninorms in a customer satisfaction context.

In short, the use of aggregation operators, such as the uninorm, possesses a great deal of potential as a novel technique in the field of customer satisfaction research and Importance-Performance Analysis. The integration of uninorms in IPA, as performed in this article, should be considered as a preliminary study of the uninorm’s applicability in this specific marketing field.

References:

[1] Detyniecki, M, Fundamentals on aggregation operators. *This manuscript is based on Detyniecki’s doctoral thesis and can be downloaded from* http://www.cs.berkeley.edu/~marcin/agop.pdf.

[2] Dolinsky, A.L., Caputo, R.K., Adding a competitive dimension to importance-performance analysis: An application to traditional health care systems, *Health Marketing Quarterly*, Vol. 8, No. 3/4, 1991, pp. 61-79.

[3] Dombi, J., Basic concepts for the theory of evaluation: The aggregative operator, *European Journal of Operational Research*, Vol. 10, 1982, pp. 282-293.

[4] Dubois, D. Prade., H., On the use of aggregation operations in information fusion processes, *Fuzzy Sets and Systems*, Vol. 142, 2004, pp. 143-161.

[5] Gujarati, D.N., *Basic Econometrics*, McGraw-Hill, Inc., 1995.

[6] Martilla, J.A., James, J.C., Importance-performance analysis, *Journal of Marketing*, Vol. 41, No. 1, 1977, pp. 77-79.

[7] Matzler, K., et al., Importance-performance analysis revisited: The role of the factor structure of customer satisfaction, *The Service Industries Journal*, Vol. 23, No. 2, 2003, pp. 112-129.

[8] Matzler, K., et al., The asymmetric relationship between attribute-level performance and overall customer satisfaction: a reconsideration of the importance-performance analysis, *Industrial Marketing Management*, Vol. 33, No. 4, 2004, pp. 271-277.

[9] Mittal, V., et al., The asymmetric impact of negative and positive attribute-level performance on overall satisfaction and repurchase intentions, *Journal of Marketing*, Vol. 62, No. 1, 1998, pp 33-47.

[10] Oh, H., Revisiting importance-performance analysis, *Tourism Management*, Vol. 22, 2001, pp. 617-627.

[11] Sampson, S.E., Showalter, M.J., The performance-importance response function: Observations and implications, *The Service Industries Journal*, Vol. 19, No. 3, 1999, pp. 1-25.

[12] Slack, N., The importance-performance matrix as a determinant of improvement priority, *International Journal of Operations & Production Management*, Vol. 14, No. 5, 1994, pp. 59-75.

[13] Szymanski, D.M., Henard D.H., Customer satisfaction: A meta-analysis of the empirical evidence, *Journal of the Academy of Marketing Science*, Vol. 29, No. 1, 2001, pp. 16-35.

[14] Vanhoof, K., et al., An indirect measurement for customer expectation, *Principles of Fuzzy Preference Modelling and Decision Making*, Academia Press, 2003, pp.109-122.

[15] Vanhoof K., et al., Penalty-Reward Analysis with Uninorms: A Study of Customer (Dis)Satisfaction, *INTELLIGENT DATA MINING. Techniques and Applications,* Springer, 2005, pp.237-252.

[16] Yager, R.R., Rybalov, A., Uninorm aggregation operators, *Fuzzy Sets and Systems*, Vol. 80, 1996, pp. 109-122.