A PROPOSAL FOR ESTIMATING CONSUMER BEHAVIOUR MODELS BASED ON FUZZY ASSOCIATION RULES

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Summary

The present paper tries to point out the necessity that firms focused on consumer markets have to understand and predict in a higher efficiently manner the behaviour of their target population. Thus, it is convenient that models of consumer behaviour in which firms are based to take their decisions to be closer to what a real Marketing Management Support System should offer. In this sense, we propose a new application for consumer behaviour modelling, based on fuzzy association rules (FAS) for adjusting the data, as a complementary way to the results obtained by using the classic technique of model estimation based on Structural Equation Modelling (SEM). With this aim, an online behavioural model is proposed being later tested making use of both FAS and SEM. Finally, a comparative analysis of the results is done, focusing specially on our proposal of methodological application.

Keywords: consumer behaviour, marketing modelling, model estimation, structural equation modelling, fuzzy association rules, knowledge discovery

1. INTRODUCTION

It is been deeply highlighted the vital necessity stated by both, marketing academics and practitioners, for knowing and explaining the consumer's behaviour patters in a manner increasingly efficient. Firms focused on final markets are immersed in highly competitive systems in which it is needed that their decision processes to be as correct as possible.

In this sense, models of consumer behaviour, inasmuch as they are marketing models, are considered as a specific case of Marketing Management Support System (MkMSS), and throughout the time have demonstrated to be a source of transcendental relevance for the development of marketing science [see van Bruggen and Wierenga (2000)].

Notwithstanding, actual models of consumer behaviour do not seem to cover all the necessities that it should supposedly satisfy a model which aim to aid on the marketing decision making. With respect to this, based on Gatignon (2000), future models, considering both their theoretical and technical aspects, which try to explain consumers' decision making will have to be clearly focused on users' (demand side) requirements of such models. That is to say, models must be more complete, flexible, and customized to the strategic singularities of the competitive environment which their users operate in. Thus, as the main problem that actually face firms oriented to consumer markets is not the availability of information (data), but the possession of necessary level of knowledge to take the right decisions, the use of avant-garde behavioural models able to exploit it may represent an essential source of competitive advantage.

On the other hand, it is expected that MkMSS will tend to improve their performance taking advantage of synergies caused by the integration of modelling estimation techniques based on classic econometric with expert systems based on artificial intelligence.

In this respect, considering the three pillars in which marketing modelling is based [see Roberts (2000)], and more specifically the consumer behaviour modelling, we focus our work on one of them, i.e.: the modelling estimation techniques and its improvement, presenting theoretically and empirically the potentials that methods of estimation based on *fuzzy association rules* (FAS) present to propose and obtain estimated models of behaviour more exhaustive, complex, flexible, interactive and which offer much more quantity of qualitative information than preceding estimation techniques used in this field [Gatignon (2000); van Bruggen and Wierenga (2000)]. In this sense, FAS can be a plausible alternative to complement, in principle, the results obtained by using Structural Equation Modelling (SEM) techniques which have been the ones usually used in the last decades to estimate complex models of consumer behaviour. Furthermore, even considering the evident utility offered by SEM to test theoretical models proposed, it shows a series of limitations, that could be solved by FAS estimation techniques, inasmuch as: (1) supposes a linear relation among variables of the model, so it does not allow to analyze nor, therefore, interpret relations among several variables when such relations are contemplated with different degrees of intensity; (2) usually works with "simple" or recursive causal models, without considering possible reverse relations among variables, so parameters obtained making use of SEM specific statistical software (e.g.: LISREL, AMOS, etc.) will tend to be biased; and at last but not least (3) estimation techniques based on SEM are useful to test theoretic proposals for a consumer behaviour model, though its utility to support marketing decisions (MkMSS) seems to be restricted by its own results derived from its process of estimation [see Laurent (2000); Steenkamp and Baumgartner (2000)].

Therefore, this paper proposes the use of fuzzy systems as a knowledge discovery tool to allow marketing academics and practitioners to improve the understanding of consumer behaviour. With this aim, the paper is organized as follows. Section 2 highlights the relevance that methods based on FAS can have to help satisfying the previous idea when applied to model consumer behaviour. Thus, a methodological application is proposed based on the Cooperative Rules methodology. Section 3 describes a theoretical model of online consumer behaviour that will be used as a benchmark to show how our methodology works. Section 4 shows the results obtained by making use of both, our application and SEM, and it treats the main implications that results coming from our application have to understand the marketing problem posed. Finally, Section 5 highlights, from a methodological point of view, several interesting findings resulting from our application.

2. CONSUMER BEHAVIOR MODELING BY FUZZY ASSOCIATION RULES

2.1. INTRODUCTION TO KNOWLEDGE DISCOVERY BY FUZZY ASSOCIATION RULES

Fuzzy rule-based systems currently constitute one of the most important areas for the application of fuzzy set theory. These systems are an extension of classical rule-based systems, because they deal with fuzzy rules instead of classical logic rules. They can be considered as a knowledge extraction tool to discover intrinsic relationships contained in a data base [Freitas (2002)]. Thus, by means of association rules (fuzzy rules in our case), we can represent the relation existing among different variables, thus deducing the patterns contained in the examined data. In knowledge discovery, the process to obtain these patterns must be automatic, or semi-automatic, discovered patterns must be comprehensible and they must provide useful information, and data must be invariably presented in substantial quantities [Witten and Frank (2000)].

Useful patterns allow us to do non trivial predictions about new data. There are two extremes to express a pattern: like black boxes, whose internal behaviour is incomprehensible; and like white boxes, whose construction reveals the pattern structure. The difference lies in whether the generated patterns are represented with an easily examined structure, which can be used to reason and to inform of further decisions. In other words, when the patterns are structured in a comprehensible way, they will be able to help in explaining something about the data. This trouble of knowledge discovery, the interpretability-accuracy trade-off, is also being currently faced in fuzzy modelling [Casillas *et al.* (2003a) (2003b)] and will be considered by our proposal.

The use of fuzzy systems when developing the knowledge discovery process has some advantages as follows: they allow us to use uncertainty data; they adequately consider multi-variable relationships; results are easily understandable by a human being; additionally information can be easily added by an expert; the accuracy degrees can be easily adapted to the problem necessity; and the process can be highly automatic with low human intervention.

Therefore, we will use fuzzy logic as a tool to structure the information of a consumer behaviour model in a clear, legible, and close to the human being way. The fuzzy system will allow us to properly represent the interdependence of variables and the non-linear relationships that could exist among them. Finally, optimization algorithms will design the fuzzy system to meet the interpretability and accuracy criteria imposed by the expert.

The following section introduces the methodology followed for applying fuzzy systems to consumer behaviour modelling and a brief description of the specific fuzzy system learning method used in this paper.

2.2. METHODOLOGY FOR CONSUMER BEHAVIOR MODELING WITH FUZZY ASSOCIATION RULES

This section introduces the process we propose to perform the knowledge discovery by fuzzy association rules. Basically, it consists on preparing the data and on fixing the scheme we follow to represent the knowledge existing in the data. Once defined these aspects, a specific learning method is used to automatically design the fuzzy association rule system.

The process is the following:

- **Data collection**: as traditionally done in marketing, it is extracted by means of a questionnaire in a similar way to the models estimated by structural equation modelling.
- **Data processing**: it is necessary to adapt the collected data to a scheme easily tractable by fuzzy system learning methods. Thus, when more than one item is used to asses the same concept, the arithmetic mean value is used.
- **Representation**: fuzzy association rules are used to represent the relationships between the variables. Once fixed by the marketing expert the structural model, a fuzzy rule base is used to relate input with output variables. For example, given the following structural model defined by three latent variables; i.e.: (1) COGAD: cognitive valuations of certain ad, (2) ATTAVSING: overall opinion about advertising, (3) ATTAD: overall opinion about certain ad (see figure 1).

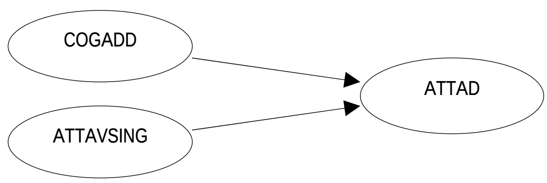

Figure 1: Example of a structural model

We use variables COGADD and ATTAVSING as inputs (antecedent) and ATTAD as output (consequent), arising rules as the following:

IF *COGADD* is high and *ATTAVSING* is low THEN *ATTAD* is medium

Regarding to the membership functions, the numerical scale used in the questionnaire has been translated to a fuzzy semantic as shows the following example (figure 2) for 3 linguistic terms and a 1 to 7 scale:

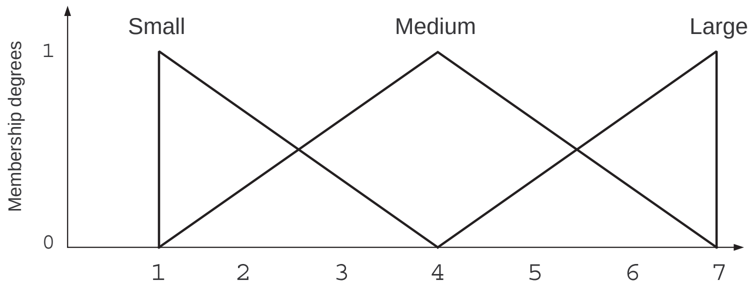

Figure 2: Transformation of a rating scale to linguistic terms

Although some tuning methods have been proposed in the literature to automatically design the membership functions [Karr (1991)], we think that it should be maintained invariable in order to get the maximum interpretability, a very important issue in knowledge discovery.

- **Learning method**: One of the most interesting characteristics of our methodology is that any fuzzy rule learning method for fuzzy rule-based systems can be used as optimization/design process. Anyway, since we force the obtained fuzzy system to be very rigid due to the membership functions are not optimized, a sophisticated fuzzy rule learning method should be used.

  In this paper we propose to use a simple and quick method that has shown to obtain good results in fuzzy modelling keeping a high interpretability of the derived fuzzy models: the method COR (cooperative rules) [Casillas *et al.* (2002)]. It arises as an effort to exploit the accuracy ability of linguistic fuzzy rule based-systems by exclusively focusing on the fuzzy rule base design. In this case, the fuzzy membership functions and the fuzzy model structure keep invariable, thus resulting in the highest interpretability. The method has the final goal of enhancing the *interpolative reasoning* the fuzzy rule-based system develops. This is one of the most interesting features of fuzzy rule-based systems and plays a key role in their high performance, being a consequence of the cooperative action of the linguistic fuzzy rules. To do that, the fuzzy rule base design is made using global criteria that consider the action of the different rules jointly. It is attained by means of a strong, smart reduction of the search space. The main advantages of the COR methodology are its capability to include heuristic information, its flexibility to be used with different optimization or search techniques, and its easy integration within other derivation processes.

  COR consists of two stages:

  1. *Search space construction*, where a set of candidate rules is obtained for each fuzzy input subspace.
  2. *Selection of the most cooperative fuzzy rule set*, where a combinatorial search is performed among these sets looking for the combination of rules with the best global accuracy.

In this paper, we also include an enhance to the original proposal to allow it to eliminate badly defined and conflicting rules with the aim of improving the interpretability (less number of rules) and the accuracy (better cooperation among rules). We use a specific ant colony optimization algorithm as optimization technique. For a deeper description of the COR methodology and the use of this optimization technique, refer to Casillas *et al.* (2003c).

3. AN ONLINE CONSUMER BEHAVIOUR MODEL

First at all, it should be noted that our main aim in this paper will not be focused so much in clarifying problems related with the online consumer behaviour model presented here, as in treating in a deeply manner those questions associated with the results provided by our application in comparison with the other usually used based on SEM.

Specific literature review in this section concludes the need to develop a specific theoretical framework to better understand consumer behaviour in virtual surroundings. Thus, our model hopes to contribute towards the previous literature, by concentrating on the study of certain internal determinants of consumer (real or potential) behaviour on the Internet and on the relationship of consumers with the phenomenon of Internet-based e-shopping.

In this sense, it should be noted, in one hand, that knowledge regarding consumer opinions, beliefs and attitudes with respect to a specific object is essential for understanding consumer behaviour towards said object [see, as e.g., Schiffman and Kanuk (1997)]. On the other hand and with reference to the phenomenon we are dealing with here, users´s attitudes as regard certain aspects of the Internet greatly determine their cyber-behaviour [Hoffman *et al.* (1998)].

Within this context, our model concentrates on the users' general attitude towards Internet and on analysing its influence on the trust consumers have in using it as a way to shop, contributing towards amplifying on the numerous previous studies that look at analysing user attitudes towards a firm's web page and its effects on the trust and purchase intentions consumers might have in said medium [Chen & Wells (1999); Jarvenpaa, S. *et al.* (1999); Cheskin Research and Studio Archetype/Sapient (1999)].

3.1. THEORETICAL SPECIFICATIONS OF THE MODEL AND RESEARCH HYPOTHESES

The model we have put forward for the process of formation of consumer attitudes towards Internet is based on the ABC (Affect, Behaviour and Cognition) attitude model and on the cognitive-affective process of the hierarchy effect model. Thus, we maintain that a user will develop a series of opinions or beliefs (cognition) regarding the various attributes or characteristics of Internet that will determine, at least in part, his overall attitude towards the medium (affect). Furthermore, this general attitude will determine his attitude in terms of certain behavioural aspects related to its object. More specifically, it is to be expected that this general feeling influences consumer trust in Internet as a way to shop. In consequence, our proposal is based on the following constructs:

1. Beliefs regarding certain aspects of Internet: This concept is the cognitive element of the model, and we define it as the cognitive opinions or responses of the user as regards certain attributes pertaining to Internet and the Web. In this sense, the fact that there is very little literature on this topic made the determination of the basic attributes rather difficult, so we decided to use other prior studies on the factors that determine a consumer's evaluation of a web page and on how the image of a virtual establishment is formed [Crawford and Shern (1998); Farquhar *et al.* (1998); Lohse and Spiller (1999); Helander *et al.* (2000)], on the understanding that, in our case, the object of the attitude was not that of a specific web page but, rather, that of Internet in general. Specifically, the model we have put forward includes user beliefs of the following Internet aspects: (1) *Formal aspects* (user conceptions regarding the design and structure of the Internet information and, more precisely, of the Web); (2) *Interaction Speed/Time of Response* (user perceptions on how quickly the interactive process with the medium responds); (3) *Information updates* (user perceptions of content updating of web pages on Internet); and (4) *Privacy* (user perceptions as regards respect for intimacy when surfing),

2. General attitude towards Internet: This concept forms the model's affective element in our study and is defined as the overall evaluation [Schiffman and Kanuk (1997); Solomon (1997)] the user makes of Internet.

3. Trust in Internet shopping: This concept covers the consumer's general perception regarding the credibility of the messages firms send over the Internet and their will to respect commitments reached with the users. Numerous studies have highlighted the particular influence the trust in virtual establishments has on consumers' purchase decisions [Hoffman *et al.* (1998); Cheskin Research and Studio Archetype/Sapient (1999); Urban *et al.* (2000); Jevons and Gabbott (2000)]. Furthermore, the possibility has been mentioned that consumer confidence in Internet as a way to shop is a direct antecedent of his trust in shopping on a particular website [Urban *et al.* (2000)].

In this way, the existing literature leads us to put forward the following relationships between the aforementioned concepts formulated through the next set of hypotheses:

H1: *There is a positive relationship between user perceptions of the different beliefs of Internet (formal aspects, speed, privacy and information updating) considered here and the user's overall attitude towards Internet.*

> **H1a:** *There is a positive relation between user´s beliefs towards formal aspects of the Internet and websites and user's overall attitude towards Internet.*
>
> **H1b:** *There is a positive relation between user´s beliefs towards interaction speed with the Internet and user's overall attitude towards this medium.*
>
> **H1c:** *There is a positive relation between user´s beliefs towards updating of the contents on the Internet and user's overall attitude towards this medium.*
>
> Lastly, as the concept of privacy has been made operative in our study as user´s opinion regarding invasion of privacy, instead of respect of privacy, its specific relational hypothesis with the consequent is the following:
>
> **H1d:** *There is a negative relation between user´s opinion regarding invasion of his privacy when surfing the Internet and user's overall attitude towards this medium.*

H2: *There is a positive relationship between the consumer's overall attitude towards Internet and consumer trust in this medium as a way to shop.*

Figure 3 demonstrates the structural model proposed.

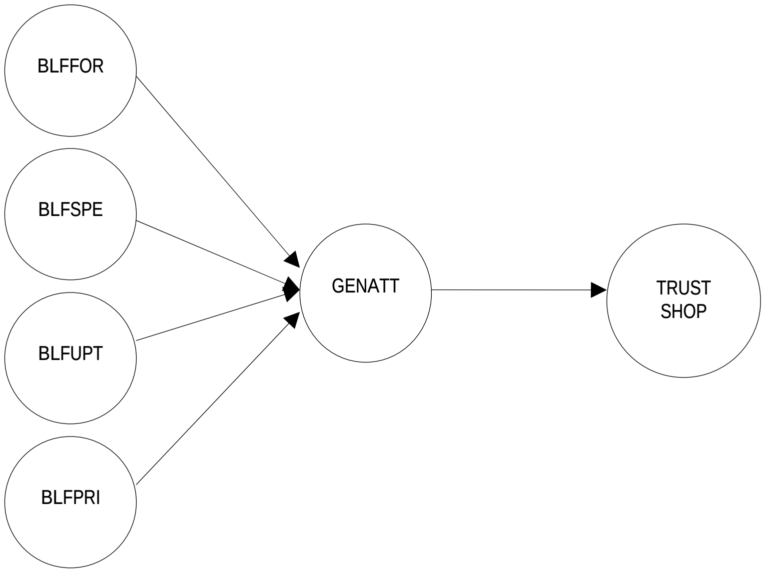

Figure 3: proposal of a structural model of online consumer behaviour

3.2. SURVEY RESEARCH METHODOLOGY

With respect to the methodological aspects related with this study:

- **Sample and sampling procedure:** the population targeted by our study was defined as being made up of university students, habitual Internet users, from Spain. The study sample was obtained using a non-probability sampling procedure (convenience sample).
- After purifying the completed questionnaires, the final sample consisted of 529 individuals.
- **Survey measures:** The measuring instruments used in the questionnaire to asses the study variables on the sample Internet users were consumer rating scales and differential semantic scales with seven points (from 1 to 7).
- **Construct measurements**: Table 1 shows the measurements taken for each of the previously described constructs.

Table 1. Measures used in establishing the structural model

LABEL	CONSTRUCT	MEASURE
BLFFOR	Beliefs (formal aspects)	The information is well structured on the web pages
		Design of the web pages makes it easier to look for information
		Web pages are attractive
BLFSPE	Beliefs (speed)	Interaction with web pages is slow and boring (R)
		The Internet is quick
		Web pages that I usually visit don't download quick enough (R)
BLFPRI	Beliefs (privacy)	When I surf the Internet, I feel my privacy has been invaded
BLFUPT	Beliefs (update)	Information that I find through the different web sites on the Internet is up-dated
GENATT	General Attitude	Negative-Positive
		I don't like it- I like it
		Unfavourable-Favourable
TRUSHOP	Trust in Internet shopping	The Internet is a reliable source of in-home shopping
		On-line companies fulfil their obligations properly to the customer
		Purchase conditions on the Internet are clear

4. APPLICATION OF OUR METHODOLOGICAL APPLICATION TO THE PROPOSED MODEL

As we noted previously, SEM has been the usual statistic method used to estimate complex models of consumer behaviour like ours. Thus, before applying our methodological approach to modelling estimation based of FAS, we consider pretty much convenient to briefly present the main results that would have been obtained in this case making use of SEM. After that, the results obtained by our methodological approach and analysis of them are introduced.

4.1. RESULTS WITH STRUCTURAL EQUATION MODELLING

Estimating the proposed model by SEM was tackled using the Weighted Least Squares (WLS) method, which allows us to obtain asymptotically distribution-free estimates and, therefore, does not demand the fulfilling of the multi-variate normality assumption. The goodness-of-fit indices resulting from the model's estimation suggest that it represents quite well the real relationships existing between its variables. All these indices obtain values that fall within the generally-accepted limits (see Table 2)

Table 2. Goodness of Fit Statistics

INDEX	VALUE
Root Mean Square Error of Approximation (RMSEA)	0.050
90 Percent Confidence Interval for RMSEA	(0.039;0.061)
Normed Fit Index (NFI)	0.95
Non-Normed Fit Index (NNFI)	0.97
Comparative Fit Index (CFI)	0.97
Incremental Fit Index (IFI)	0.97
Relative Fit Index (RFI)	0.94
Critical N (CN)	307.12
Root Mean Square Residual (RMR)	0.077
Standardized RMR	0.077
Goodness of Fit Index (GFI)	0.98
Adjusted Goodness of Fit Index (AGFI)	0.98

On the other hand, results presented in Table 3 allows us to individually test the statistical significance of the different relations set previously on the hypotheses formulation section, as well as the degree of variance of the endogenous latent variables of the model (GENATT and TRUSTSHOP) explained by their antecedents (R^2). Thus, the whole part of the structural parameters in the model is significantly different to zero, so hypotheses have not been rejected, with the exception of the non significant relation BLFUPT – GENATT (H1c). Furthermore, we verified that the exogenous latent variables accounted for 40% of the variance in general attitudes towards Internet (GENATT), which, in turn, were responsible for 20% of the variance referring to trust in Internet as a way to shop (TRUSHOP). We should also note that two reverse items belonging to BLFSPE were transformed for the all three to have the same sense.

Table 3. Structural parameter estimates, (standard error) and *t-value*

DEPENDENT VARIABLE	BLFFOR	BLFSPE	BLFUPT	BLFPRI	GENATT	Error Var.	R^2
GENATT	**0.61**	**0.16**	**-0.0038**	**-0.19**	---	**0.54**	**0.40**
	(0.075)	(0.077)	(0.056)	(0.046)	---	(0.044)	
	8.14	*2.07*	*-0.069*	*-4.13*	---	*12.32*	
TRUSHOP	---	---	---	---	**0.36**	**0.45**	**0.20**
	---	---	---	---	(0.042)	(0.053)	
	---	---	---	---	8.46	8.58	

Therefore, this estimation technique has given to us information about both the significant relations and the degree of intensity and sense of the relation. For example, as we hypothesized, BLFFOR and BLFSPE have a positive linear relation with GENATT, being also BLFFOR the most influential factor in GENATT (parameter estimate of 0.61), while BLFPRI presents a weaker negative relation with such an endogenous variable.

4.2. RESULTS WITH OUR METHODOLOGICAL APPLICATION

However, the application we propose in this paper is able to enrich the previous results obtained by SEM techniques of estimation, allowing us to have a better knowledge about the effects of latent variables jointly considered, as well as a better notion of the behaviour of the relations among latent variables simplifying and considering them in a isolated (bivariable relation) manner.

In this sense, after applying our methodological approach based on FAS to adjust the data, and transforming previously the marketing scales primarily considered to a logic language (linguistic terms), we have obtained the following fuzzy rule set presented in three tables.

Firstly, we focus on GENATT as consequent and on its behaviour in function of its four antecedents. So, in Table 4, where a total of 26 rules is showed (this reduced number of rules was determined by the COR method after applying search space and fuzzy rule reduction processes), it can be seen the together effects caused by the four antecedents (each defined by three linguistic labels, i.e.: small (S), medium (M), large (L)) of GENATT (defined by five linguistic labels, i.e.: very small (VS) , small (S) , medium (M), large (L), and very large (VL)) considered in our model, while in Table 5 we can see the system of rules got for the bivariable relations between GENATT and its four antecedents (linguistic terms used in this case have been defined by five for both, antecedents and consequent). Lastly, in Table 6 , system of rules obtained for the bivariable relation GENATT-TRUSTSHOP is shown (both defined by five linguistic labels).

Each table also shows the mean square error (MSE) obtained by each fuzzy association rule set over the tackled data. MSE is defined as:

$$MSE = \frac{1}{2N}\sum_{i=1}^{N}(F(x_1^i,\ldots,x_n^i) - y^i)^2 \ ,$$

with $F(x_1^i,\ldots,x_n^i)$ being the output obtained form the fuzzy system when the example data $e^i = (x_1^i,\ldots,x_n^i,y^i)$ is used, and y^i being the known desired output. The closer to zero the measure is, the higher the global performance and, thus, the better the rule cooperation.

Table 4: System of rules for GENATT considering together the four antecedents

MSE = 0.416517					
Rule	BLFFOR	BLFSPE	BLFUPD	BLFPRI	GENATT
1	L	L	L	S	VL
2	L	M	L	L	VL
3	L	M	L	M	VL
4	L	M	L	S	VL
5	L	M	M	M	VL
6	L	S	L	S	VL
7	L	S	M	L	VL
8	L	S	M	M	L
9	L	S	M	S	VL
10	L	S	S	S	VL
11	M	M	L	L	L
12	M	M	L	M	L
13	M	M	L	S	VL
14	M	M	M	M	L
15	M	M	M	S	L
16	M	M	S	S	VL
17	M	S	L	S	M
18	M	S	M	L	M
19	M	S	M	M	L
20	M	S	M	S	VL
21	M	S	S	M	L
22	M	S	S	S	M
23	S	M	L	L	L
24	S	S	L	M	L
25	S	S	M	M	L
26	S	S	S	L	S

Table 5: System of rules for GENATT considering separately the four antecedents

MSE	0.556464	0.597823	0.588862	0.560186
Antecedent label	BLFFOR-GENATT	BLFSPE-GENATT	BLFUPT-GENATT	BLFPRI-GENATT
VL	L	L	VL	L
L	VL	VL	L	—
M	L	L	L	L
S	L	L	L	L
VS	VS	L	L	VL

Table 6: System of rules for TRUTSHOP

MSE = 0.498801		
Rule	GENATT	TRUSTSHOP
1	VL	M
2	L	M
3	M	M
4	S	S
5	VS	VS

4.3. ANALYSIS OF THE RESULTS OBTAINED WITH OUR METHODOLOGICAL PROPOSAL

With the aim of analyzing and interpreting these results, if we follow usual practise in marketing modelling testing, we should take a look to the bivariable relations integrating the model (see table 5). Thus, even when we are conscious of both, on one hand, this approach underuses the potentials of our application and, on the other, it is not certainly correct due to in a isolated relation variations of the consequent are not only explained by alterations in certain antecedent since there are another influencing factors, we consider this can be useful to get a first idea about variable relationships which can aid to clarify the overall results obtained for variables (antecedents and consequent) altogether.

Thus, BLFFOR presents the higher variety of results for the consequent since GENATT takes really low values when beliefs towards formal aspects of the Internet are the lowest, and improves amazingly inasmuch as BLFFOR takes values of small or higher. In this sense, it is interesting to note that, as this does not occur with the rest of antecedents, the consequent GENATT takes the lowest value only when BLFFOR is very small. Furthermore, it should be noted that, as it can be seen observing the graphical representation obtained by combining the system of rules for both variables, does not look as if a linear relation between such variables fits with real data distribution.

The rest of antecedents do not seem to be so influencing as the previous mentioned, as GENATT keeps the same good valuation (large) regardless their values modification. Furthermore, their influence in the overall opinion about Internet is almost non significant since variations on them do not cause modifications on the consequent. However, we have perceived that is exists a reaction of GENATT when these three factors take certain punctual values. In this sense, GENATT takes the highest value (very large) when BLFUPT is on its highest or when BLFPRI is on its lowest. Furthermore, BLFUPT and BLFPRI has a really similar influence in GENATT if we realize that the former is formulated positively and the latter negatively (invasion of privacy), with the exception, and this is interesting to note, that our application has not considered that there are a label of L (large) for BLFPRI (when considering five linguistic label). Finally, considering the antecedent BLFSPE, GENATT only changes its constant acceptable position of good value L (large) to the excellent value of VL (very large) when BLFSPE takes the value of L (large).

On the other hand, taking into account the partial model of GENATT and their antecedents as a whole (Table 4), together with the previous results arisen from Table 5, the next main findings should be highlighted:

- Factors BLFFOR and BLFPRI, specially the former, are the two that really present the potential to discriminate or influence in a considerable manner over consequent GENATT. In this sense, it can be observed how high beliefs (label Large) regarding formal aspects are determinant for overall opinion towards the Internet takes the highest value (label Very Large) regardless values showed by the rest of factors. Thus, taking a look to the system of rules got when BLFOR is the highest, it can be seen that, from a total of ten, nine confirm this idea. However, the influence of BLFOR is not so clear when taking intermediate (label Medium) or low (label Small) values. In these cases, the other factors play a more important role as moderators of GENATT.

  On the other hand, factor BLFPRI seems to be more decisive to determinate a higher range of values of the consequent GENATT to the extent that when it is in the lowest (label Small) GENATT usually shows the highest (label Very Large), and when in an intermediate position GENATT is good (label Large) for the most of rules obtained (seven of nine). In turn, when user´s perception about privacy invasion is the highest (label Large), deterministic power of BLFPRI over GENATT is not so strong, being mainly moderated the consequent by values taken by other three factors.
- Unlike two previous factors, BLFSPE and BLFUPT have not seemed to be so influencing in determining GENATT by themselves. In this respect, their influence is weaker than the others and differs when considering their range of values, being their role limited to moderate GENATT in certain combination of values of BLFFOR and BLFPRI (e.g.: rule 17 and 26).

- The whole majority of rules seem to confirm the relations hypothesised between antecedents and consequent GENATT. In this sense, as an example, if we take rule 1 and 26 which coincide with the two possible extreme cases for determining GENATT, being the former defined by the best beliefs that can present the four factors considered and vice versa for the latter, such an endogenous dependent variable takes the best and the worst value. Notwithstanding, we have found certain rules where the effects produced by combinations of values of the four factors do not seem to have a correspondence with the value that in theory should have taken GENATT considering the significant sense of relationships tested firstly statistically by means of LISREL and by our application later. In this way, should it be thought that results of our application based of FAS are inconsistent? Certainly, relations showed by several rules seem to be apparently contradictory, so deeper analysis of the same is necessary in order to clarify this.

In Table 7 several pairs of contradictory rules extracted from table 4 are showed. Furthermore, we reflect on both, expected value that should have taken the consequent GENATT according to previous results, and consistency of rules system obtained by our application analysing the behaviour of MSE associated with the model when modifying the consequent label in function of such an expectation.

Table 7: Contradictory rules found

SETTING	RULE	BLFFOR	BLFSPE	BLFUPD	BLFPRI	GENATT	Model MSE	MSE Variation
Observed	7	L	S	M	L	VL	0.416517	
	8	L	S	M	M	L		
Expected	8	L	S	M	M	***VL***	0.422708	+0.006191
Observed	15	M	M	M	S	L	0.416517	
	16	M	M	S	S	VL		
Expected	15	M	M	M	S	***VL***	0.453628	+0.037111
	16	M	M	S	S	***L***	0.422980	+0.006463
Observed	21	M	S	S	M	L	0.416517	
	22	M	S	S	S	M		
Expected	22	M	S	S	S	***L***	0.419026	+0.002509
	22	M	S	S	S	***VL***	0.427267	+0.010750

The first contradiction comes from matching rule 7 and 8. At the extent that a negative relation has been detected between BLFPRI and GENATT, it is expected that, *ceteris paribus*, a reduction in BLFPRI will cause an improvement in GENATT or, as minimum, invariability in such a consequent if the degree of variation of BLFPRI is not enough to cause changes. However, our application has observed such a paradoxical situation by rule 8. Under these circumstances, we consider that if a modification in the consequent (expected rule), adjusting it to its expected value, is able to reduce the MSE of the model, then it would be a sign of that modification of rules system done according to what it was expected fits in better with observed patterns of data, otherwise initial solution would be more appropriate. In this sense, it can be seen that RMS of the partial model increases with this modification. The same occurs for the other contradictory pairs of rules found, where the MSE variation has depended on the degree of modification considered for the consequent.

Furthermore, it can be conclude at this respect that those contradictory effects shown by those pairs of rules in GENATT were just apparent, and that results are not due to a local optimum fall of the search algorithm, since better accuracy degrees are obtained with the apparent contradictions. So, a plausible argument to explain this is that of free this application presented here from responsibilities and make responsible for this to a deficient specification of the theoretical marketing model. Due to that fact, other relevant factors not considered explicitly in our conceptual model, which can also influence in GENATT, would be the answer to contradictions found in our system of rules.
Finally, with respect to TRUSTSHOP, the other endogenous latent variable of the proposed behavioural model, table 6 shows the results after applying our algorithm of approximation (Five linguistic terms have been used for both variables). In this sense, initially considering that users of our sample do not really show a considerable trust in Internet shopping, pattern of relation between both variables does not present a linear behaviour. Thus, GENATT seems to be an influential factor in TRUSTSHOP as the former causes a gradually improvement over its consequent when overall opinion towards Internet increases from low to intermediate positions. However, GENATT is not influential when taking intermediate or higher values at the extent that TRUSTSHOP keeps a moderate place.

4.4. IMPLICATIONS OF THE PREVIOUS RESULTS BASED ON THE PROPOSED APPLICATION FOR EXPLAINING THE ONLINE CONSUMER BEHAVIOR MODEL

Results from using our application allows to confirm that, in one hand, the different beliefs towards the Internet contemplated here have a significant influence over user´s general opinion towards the Internet, though their influential power and intensity differ depending on both the factor and the value taken by each of them. On the other hand, attitude towards the Internet has also been a significant factor to determinate users´s trust in Internet shopping, though a similar reflection could be made on its degree of influence according to its value taken.
Thus, opinion about formal aspects of the Internet and web sites is been the most relevant belief to discriminate values taken by the overall attitude towards the Internet. In this respect, that can be seen more clearly when considering their relation in an isolated way. Furthermore, high opinions about formal aspects usually assure really good attitudes towards the Internet. That is to say, when users present the highest opinion about this factor, the rest of beliefs do not seem to be really influential. So, online business should take care of this aspect at the extent that, making use of a parallel though, it will have a considerable effect on the users´s affective response toward their website. Notwithstanding, the degree of influence of this factor is not so clear when it has an intermediate or low presence.
With respect to the belief invasion of privacy when surfing the web, it neither shows a constant degree of influence over general opinion towards the Internet. In this sense, it seems to be more influential when takes low or intermediate values. So, a creation on an online environment able to highly respect the users´s privacy will also generate good affective responses to certain website, at the extent that this issue has demonstrated to be more influential when being good valuated.

Beliefs towards interaction speed, considering previously that our sample of users have not really showed good perceptions about this due to that the whole part of individuals present an intermediate or bad valuation of this, have a residual influence over the attitude towards the Internet. This fact is contradictory with ideas defended by Lin and Lu (2000) when highlighting that this factor is the most for the development of the user´s beliefs toward certain a web site. On the other hand, a similar influence has been found for the case of beliefs towards content updating of websites. Thus, even when both previous factors do not determine in a transcendental manner formation of the overall opinion towards the Internet, we have found certain cases, those when influence of factors formal aspects and invasion of privacy do not have a influence so clear, where the one or the other can moderate the value of the dependent variable.
Finally, primarily considering that users´ population show certain reserves to get involved in Internet shopping yet, as it can be deduced from observing the overall level of trust, overall attitude towards the Internet seems to be an important variable to generate trust till certain point, and beyond there this variable does not discriminate such a trust. In this respect, attitude toward the Internet does not improve trust in Internet shopping when taking the former values from the intermediate to the highest level. So, the main problem should be focused on thinking about why the current situation occurs and how to generate higher levels of consumer trust.

5. CONCLUDING REMARKS

As it was pointed out in the initial section related with the motivation of this work, a tool for estimating a proposed consumer behaviour model should not be only useful to test a set of theoretical relationships which form such a model, but it must be also able to be helpful for the marketing management function to have a good perspective of certain marketing problem and to take the right decisions.
With that aim, we have empirically tested the theoretical relations of our model by making use of both SEM and FAS, so several conclusions could be drawn when comparing them.
In one hand, when using SEM we obtain results that allow us to know how well the model fits to the data as well as which are the significant relations. Furthermore, we get different coefficients (parameters) that give us information about the sense and intensity of the relation.
However, after applying our methodological proposal we have confirmed some previous ideas. In this sense, when real relations between variables are not linear, parameters resulted from SEM are deficient to really explain and give information about how certain variable (antecedent) influences another (consequent), so it is not correct to consider that a lineal coefficient of relation with the dependent variable keeps the same for all the values that the antecedent can take.
Therefore, our application allows the user's model (e.g.: a marketing manager) to know which is the exact behaviour of the relations among variables for certain market situation. In this sense, results from this application are pretty much useful that SEM results for helping MkMSS, at the extent that it does not only allow to test the model proposed, but it is also able to give deep qualitative information about the relations according to the degree of intensity of the antecedents.

On the other hand, SEM results can show, as it is the case for BLFUPT-GENATT in our example model, that a relation is not statistically significant, while results from our application indicate that such a factor can be decisive in moderating the consequent in certain cases. Thus, a lineal approximation to estimate a complex model of consumer behaviour, though it is helpful, could be too much simplistic to get a true perspective of the relations.

Furthermore, a case for future treatment is that of why some factors are antecedents statistically significant and not others by basing on SEM results, if when we take a look to the results from our application it can be seen that they present a similar relational patter with the consequent. That could be due to the inherent philosophy of adjusting to the data in which it is based SEM.

In conclusion, though a deeper work is necessary to purify the potentials of our application to the consumer marketing modelling issue, basing on the previous results, it can be said that our application is able to give higher qualitative information about how the relations among variables behave. Thus, in principle, it is pretty convenient to make use of this kind of approximation to explain relations in a complex model of consumer behaviour as a complement to the classic techniques based on SEM used till now.

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