Willingness to purchase Genetically Modified food: an analysis applying artificial Neural Networks

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Abstract

Findings about consumer decision-making process regarding GM food purchase remain mixed and are inconclusive. This paper offers a model which classifies willingness to purchase GM food, using data from 399 surveys in Southern Spain. Willingness to purchase has been measured using three dichotomous questions and classification, based on attitudinal, cognitive and socio-demographic factors, has been made by an artificial neural network model. The results show 74% accuracy to forecast the willingness to purchase. The highest relative contributions lie in the variables related to beliefs, especially those link to perceived risks; while the variables with the least relative contribution are age and knowledge on GMO.

Key words: Genetically Modified Food; Willingness to purchase; Artificial Neural Network.
JEL codes: Q13; C45.

1. Introduction

The European Union (EU) has slowed down the adoption process of biotech crops and has only authorized a Genetically Modified (GM) maize and potato event for cultivation, so GM crops have had a marginal adoption rate, except Spain. One of the main reasons is the European consumers' concerns about the potential negative effects of Genetically Modified Organisms (GMO) on both human health and the environment.

A great deal of literature has been assessed consumer decision-making process regarding GM food. Multi-attribute attitude models, e. g. Fishbein and Ajzen (1975), have provided a widely accepted framework for the analysis of consumer behavior towards GM foods. From this framework, variables related to attitudinal (Frewer *et al.*, 1997), cognitive (Hossain and Onyango, 2004) and socio-demographic (Moerbeek and Casimir, 2005) factors have been identified. However, the findings derived from the literature remain inconclusive. This paper offers a model which classifies willingness to purchase GM food, using data from 399 face-to-face surveys in Southern Spain. Willingness to purchase has been measured using three dichotomous questions and classification, based on attitudinal, cognitive and socio-demographic factors, has been made by an artificial neural network model, a standard Multilayer Perceptron (MLP) neural network trained with Extreme Learning Machine (ELM). To our knowledge, this method has not been applied to study consumers' behavior regarding GM food. The paper is structured in the following way. In the next sections, the data collection and the input and output variables are presented. Then the methodology is developed. The results and main conclusions are shown in Section 4 and Section 5.

2. Data collection

Data was compiled using 399 face-to-face surveys taken between January and April 2008. The sampling followed a stratified random methodology with proportional affixation to gender, age and municipality size adapted from the Spanish Statistical Institute (INE, 2008). The validity of the sample was verified by performing a Chi-square test between sample and census variables (Table 1).

Table 1. Sample and population socio-demographic characteristics

Characteristics		Sample (%)	Population (%)	Representativeness[†]
Gender	Female	51.3	50.7	χ^2=0.01; p-value=0.90
Age	≥ 18 years ≤ 34 years	36.0	34.6	χ^2=0.17; p-value=0.98
	>34 years ≤ 49 years	27.9	28.4	
	>49 years ≤ 64 years	19.2	18.8	
	> 64 years	16.9	18.2	

Municipality size(thousand inhabitants)	Rural mun.(< 20) Urban mun. (20 – 100) Metropolitan mun. (> 100)	29.8 33.5 36.7	28.1 34.4 37.5	χ^2=0.14;p-value=0.93
Education level	Primary or no studies Secondary studies University studies	39.0 33.0 28.0		
Household income (€ per month)	≤1400 € >1400 € ≤ 26000 € >2600 €	25.7 46.4 27.9		

[†] The χ^2 values do not exceed the critical values – $\chi^2_{1;0.05} = 3.841$; $\chi^2_{2;0.05} = 5.991$; $\chi^2_{3;0.05} = 7.815$ –, so that we cannot reject the null hypothesis which means non-significant differences between the population and sample.

Source: Elaborated by authors.

3. Modelling willingness to purchase GM food

The output variable, willingness to purchase GM food, has been measured using three dichotomous questions about a concrete GM product which was a ½ kg package of cornflakes with Omega-3 fatty acid. The first question was used in order to learn the consumers' willingness to pay the same price for the GM product and the corresponding non-GM product. With a positive answer, a dichotomous question was made about their willingness to purchase the GM product with a higher price; with a negative answer, we made a question about consumers' willingness to purchase the GM product with a lower price. An ordinal variable was made: 0 when the consumers do not purchase the GM product; 1 when the consumers purchase the GM product both at the same price or with a discount; 2 when the consumers pay a price premium for the GM-product.

Model's input variables were selected from a review of the existing literature. In Table 2, the main statistics describing the input variables are presented, together with those authors who have inspired measures and contained previous results.

Table 2. Statistics descriptive of input variables

Dependent or input variables[a]	Name	Units	Mean	S.D.	Literature
Perceived mean benefits	Bene	Continuous (from 1 to 5)	3.29	0.79	Bredahl (2001); Christoph et al. (2008)
Perceived mean risks	Risk	Continuous (from 1 to 5)	3.21	0.74	
Compare risks for health of eating GM or non GM food	Compa	Likert-scale (from 1 to 5)	3.22	0.88	
Label meat, eggs and milk from animals breeding with GM- feed	Label	Likert-scale (from 1 to 5)	1.97	1.20	
Trust in government and scientists	Trust	Continuous (from 0 to 1)	0.49	0.21	Verdurme and Viaene (2001); Gaskell et al. (2006)
Subjective knowledge	KnowSu	Dichotomous	0.74	0.43	House et al.(2004); Lusk et al. (2004)
Objective knowledge	KnowOb	Dichotomous	0.46	0.49	
Perception of food safety	Concern	Continuous (from 0 to 1)	0.45	0.22	Bredahl (2001); Grunert (2005); Gaskell et al. (2006)
Innovative attitudes toward food	New	Likert-scale (from 1 to 5)	2.89	0.92	

[a] Descriptive analysis of socioeconomic features has been shown in Table 1.

Source: Elaborated by authors.

4. Neural Network Method

A standard MLP neural network with an ELM has been applied. The MLP is the basic structure of neural network. Data is propagated forward and transformed for a classification output, according to the weights affecting the hidden layer. Once the structure is set, a means to quickly obtain the weights is in order. ELM is an efficient way to do this, since it uses a technique that randomly assigns most of the weights of the neural net, adapting the remaining ones to those randomly assigned. The ELM algorithm has a strong generalization capability and considerably reduces the time to train the neural net, presenting the algorithm in Figure 1.

Figure 1. ELM algorithm

Given a training set $D=\{(x_i,t_i): x_i \in \Re^n, t_i \in \Re, i=1,2,...,N\}$, the activation function $g(t)$, and m neurons in the hidden layer:

Step 1: Assign arbitrary input weights for w and bias b.

Step 2: Calculate the hidden layer output matrix H.

Step 3: Calculate the output weights $\hat{\beta} = H^{\dagger}T$.

Source: Elaborated by authors.

Each column in matrix H is made of the values corresponding to each node in the hidden layer evaluated on each x_i pattern of the training set. The ELM algorithm randomly assigns values for all w_i and b_i, and calculates $\beta_M^l \quad l=1,2,...,M$, according to those. This calculation is the least squares solution to the linear system given by the expression in step 3 where $H^{\dagger}=(H^T H)^{-1}H^T$ is the generalized Moore-Penrose inverse matrix. The solution is the lowest Euclidean norm amongst all the solutions of the linear system. Given the whole neural network, the attributes of all observations are averaged into the average pattern. After a neural network has proved to have a good generalization in a test, this average pattern is introduced as if it were an extra test pattern. Attribute by attribute, the average pattern is perturbed to see the effect it has on the output. All patterns are used for perturbation, and sensitivity is measured in terms of how much perturbation it takes for a pattern to change from its actual class to another one. SA returns an ordered ranking of the input variables by relevance. This ranking informs of the factors the method relies upon the most when performing the classification. In the case of ELM for classification, SA uses a large number of neural nets, once it has been verified they have done a good work generalizing. Each one of these neural nets has its own set of random weights. The final list of sensitivities will be averaged from all the classifiers, making the measurement consistent in a statistical sense.

5. Results

A bivariate analysis was performed between each one of the input variables and the output one (Fast Correlation Based Filter). Objective knowledge and socioeconomic variables, except age, were discarded due to the lack of correlation or the presence of another variable which informed in the same way. Related to that, House *et al.* (2004) showed that subjective knowledge had a higher level of influence on the acceptance of GM food than objective knowledge; meanwhile socioeconomic factors have not been produced significant results in studies such as those by Baker and Brunham (2002).

Neural network used 20 nodes in the hidden layer. The dataset was partitioned in a 66.6% sample for training and 33.3% for testing the resulting heuristics, allowing us to forecast consumers' behavior. Both partitions were representative of the complete dataset. 3000 ELM were trained and then tested with these partitions. The best 300 were singled out and used for SA. The following Table presents the averaged sensitivity according to these 300 classifiers:

Table 3. Relative contribution and rank of the attributes from neural network

Input Variable	Average sensitivity (%)	Rank
Bene	55.53	4
Risk	76.48	2
Compared	94.90	1
Label	38.81	6
Trust	26.16	7
KnowSu	1.25	9
Concern	53.98	5
New	56.12	3
Age	16.01	8

Source: Elaborated by authors.

The test sample displays 74% accuracy to forecast the willingness to purchase GM food for Southern Spanish consumers. The highest relative contributions lie in Compared and Risk. The neural network shows that willingness to purchase GM food is very sensitive to people's negative beliefs about it, when GM food is compared to non GM food, as against when GM risks are considered by themselves. Consumers reject GM foods when the perceived risks associated with them are greater than those related to conventional foods or even outweigh GM foods' benefits (Frewer *et al.*, 1997). In fact, perceived benefits present a lower influence on the classification of consumers' choice, although it is the fourth variable in the ranking. Innovative attitude toward food displays a strong link, as does Concern. Hence, to have proactive attitudes to tasting new food and food safety also shape consumers' intentions. Bredahl (2001) found that the reluctance to eat new foods negatively pressured the attitude toward GM food. On the other hand, a subjective perception of modern food safety is a non-studied variable which needs major inclusion in models.

Label is the next ranking variable. Uncertainty surrounded GM food increases the value of information provided under mandatory labeling policies (Hu *et al.*, 2005), even of food produced from animals bred with GM-feed (Roosen *et al.*, 2003). In addition, Trust presents less influence than the variables previously discussed. In models, such as that designed by Sjöberg (1998), trust explanation capacity is limited. Certainly, Frewer *et al.* (2003), instead of stating that trust drives people's attitude to GM food, said that trust influences people's reaction toward the information. The variables with the least relative contribution are Age and KnowSub. Conflicting results can be found in the literature regarding these variables. According to Baker and Burnham (2002) socioeconomic and demographic factors are not important in defining consumers' acceptance of GM food. Regarding knowledge, an increase in knowledge can provoke deep deliberation about risks and benefits, as well as more sceptical attitudes (Frewer *et al.*, 2003). However, the absence of a direct influence of knowledge on purchase intentions is consistent with the results in Bredahl (2001).

6. Conclusions

The model derived from this research supports those general findings from the literature where beliefs play a key role and trust in institutions and scientists can have some influence. General attitudes related to food safety or innovations in food have an influence on our model, but they are not variables widely studied in the literature so they need to be considered in further research into GM food acceptance. Finally, no conclusive factors in the literature such as knowledge and socio-economic features make a very low or none conditional on Southern Spanish consumers' behavior. However, we should not ignore some inherent limitations of the method as it is not to be able to give information about the direction and strength of the relationship between the output and the inputs variables.

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