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An Agent-Based Behavioral Model of Technology Consumers in a Dynamic Social Network

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Abstract

This article describes the design of a model to identify the relevant factors in the decision-making process of consumers that adopt technology within a dynamic social network. The proposed model includes specific theories and tools from the psychology of consumer behavior, social networks, and complex dynamical systems. The model has been developed to work with the mobile smartphone market and was able to describe trends similar to those described in the real world market.

Keywords: Decision-making process, bounded rationality, agent-based models, social networks, fuzzy logic

1 Introduction

People and social sciences are interested in human behavior analysis to know and understand other people. Observable and measurable actions from individuals are of interest due to these defines their ability to interact with the external environment. The variability of preferences adds complexity to the understanding the behavior of people because of the presence of desire, motivation, affection, thought, and belief. Sometimes, such aspects generate an irrational behavior, raising the inability of human observers to explain their judgments [1]. Otherwise, this behavior can be explained from the concept of Limited Rationality.

Limited Rationality considers that the social actor has rational behavior, but rationality is limited regarding cognitive capacity and the available information [2], and depends on the imperfection of information, the difficulty of anticipation and the limited number of behaviors that are considered [3]. Thus, the behavior of a social actor follows a cycle of three operations: perception, choice, and execution. Perception consists of obtaining information regarding the situation and the context. Choice aims to find the actions that the person can consider, evaluating them, and selecting the one that seems most desirable in the situation in which the person finds themselves, as a function of their objectives. The execution consists of carrying out the previously chosen action, as long as the action is feasible [3]. This concept has been used to study the behavior of consumers.

Consumer behavior analysis includes studying human psychology, group behavior, social aspects, and their relationship with the decision-making process, as emphasized in [4]. Making the correct decision to acquire a product or service it is of common interest for both the selling companies and for the consumer. Consumer behavior is of interest to companies that try to promote and sell their products due to it allows determining: a price scheme that maximizes profits and efficient strategies to provide market access to some new products. The interest for consumers is related to satisfying their needs and expectations avoiding irrational behaviors.

Irrational behavior can be considered as the knowledge that may drive individuals to unexpected behaviors that include actions with high variability. Additionally, personality, mental state and emotions are part of the response, and make behavioral analysis more complex [1]. Furthermore, into a partial information context, people can decide to respect certain rules or not; that is, they can exhibit no normative behavior.

For consumers, a modern way to deal with partial information is to become part of social networks. Customers in a social network share information and opinions from a social system [5]. Social Systems are composed of different entities which have limited rationality, and whose interactions can be direct or indirect [6], making these systems as complex systems [7]. Therefore, to study these systems, it is necessary to have tools and methods that allow the identification of their main properties to understand the underlying relationship which generates the observed behavior.

Agent-based computational simulation paradigm [8], constitute a commonly used tool to study complex systems. It allows the representation of heterogeneous and independent entities, as well as complex interactions and partial connections between objects. Additionally, to represent the diversity of preferences and opinions, as well as the particular knowledge of every single agent into a simulated population, some authors have used fuzzy logic [9]. Table 1 shows works on adopting and decision-making using simulation.

Table 1. Works related to the analysis of adoption and decision-making using simulation.

Author	Domain	SN	H	GB	CP
Schwoon ([10])	Fuel cell vehicles	S	Y	N	Ph
Vag ([11])	Mobile phones	R	Y	N	Ht
Kowalska ([12])	Consumers' decision model	S	N	N	H
Schramm ([13])	Market assessment	S	Y	N	H
Zhang ([14])	Alternative fuel vehicles	R	Y	N	Ph
Chapron ([15])	Analysis of social organizations	D	Y	N	Ph
Kangur ([5])	Adoption of electric vehicles	S	Y	N	Ph
Schoenmacker ([4])	Analysis of lighting market	R	Y	N	H
Serrano ([16])	Social evaluation of decision-making	R	Y	N	Ph
Cho ([17])	Adoption of electric vehicles	S	Y	N	H
Delli Compagni ([7])	Fuel cell vehicles	S	Y	N	H
Rai ([18])	Adoption of energy technologies	S	Y	N	H

SN (Social Network): S-static, D-Dynamic, R-Ramdom; H (Heterogeneity): Y-Yes, N-No; GB (Global Behavior): N-Normative, Nn-No normative; CP (Cognitive processes): Hm-Homogeneous, Ph-Partially heterogeneous, Ht-Heterogeneous.

The analysis of processes related to the adoption of recent technology constitutes the primary interest of this study. The specific interest arises because it permits the identification of the factors that influence the decision-making of consumers. Also, we are interested in analyzing how societies adapt to technology, appropriate it, and understand what the specific characteristics that provide benefits according to their needs and expectations are.

This work presents an agent-based model of a social network of consumers, which models the uncertainty on individual preferences by fuzzy-logic reasoning. The relationship between the customers or agents is represented by a means different interaction network model. This model is aimed at recognizing global patterns of consumer behavior in a social network, identifying the relevant factors for decision-making and characterizing emerging effects.

2 Methodology

The proposed method is based on the generic model of human behavior' namely, Cosumat II. It relies on Goal Frame Theory [19], which distinguishes among three behavioral motivations: hedonist, profit and normative. Formally, Consumat declares three motivations concerning needs: existential, social, and personal. Furthermore, it offers a simulation framework that captures important principles discussed in the literature about the behavior of consumers [20]. The components of Consumat are the processes of decision-making, decision strategies and considerations about individual needs, personality, and abilities [20, 5]. Two additional aspects are related with the mental state of agents which determine the decision-making strategy to choose an adequate behavior. These aspects correspond to the satisfaction level and the uncertainness level [5].

2.1 Model of consumer adoption of technology

Heterogeneous preferences are the primary aspect considered in the design of the proposed model, as well as the partial and dynamic characteristics of the relationship between the customer communities. Figure 1 shows the proposed model for consumer decision-making, describing a cyclical process running iteratively. Initially, each of the consumers evaluates a known characteristic of the product according to their needs. Next, a product must be selected which represents the greatest satisfaction. Note that the above steps depend on personal criteria and beliefs so that the model uses fuzzy-logic rules to provide a more realistic simulation. After satisfaction calculation, an uncertainty measure is estimated for both individual and social contexts. Based on individual uncertainty there are two ways to act: adopting the product, and continuing to gather more information about the product. Initially, adopting the product represents irrational behavior. In contrast, consumers may continue to obtain more information, considering satisfaction and uncertainty measures to improve their choice and knowledge: Imitation, inquiry, optimization and repetition; any of these actions generate a change in the knowledge base. For repeated action, the individual consider another product feature to decide whether it should be adopted or not. After any choice, the individuals must update the neighborhood credibility values by appealing to personal preferences and the received information from their neighborhood.

2.2 model assumptions

We add a new state to Consumat scheme called *Adoption*, and a new random variable called *Prudence*. The Prudence variable determines when a consumer moves from the Repeat state to the Adoption state. The *Experience* variable determines the weight of the story. All random variables defining population heterogeneity follow a Normal distribution since it is the most commonly used probability distribution function in works related to modeling and simulation of social systems [21]. The prestabilized link value between the individuals decreases for each iteration. Also, all the individuals in the simulation can acquire any of the evaluated products at any instant of time. The number of individuals that comprise the population is constant, and it is a user-defined parameter.

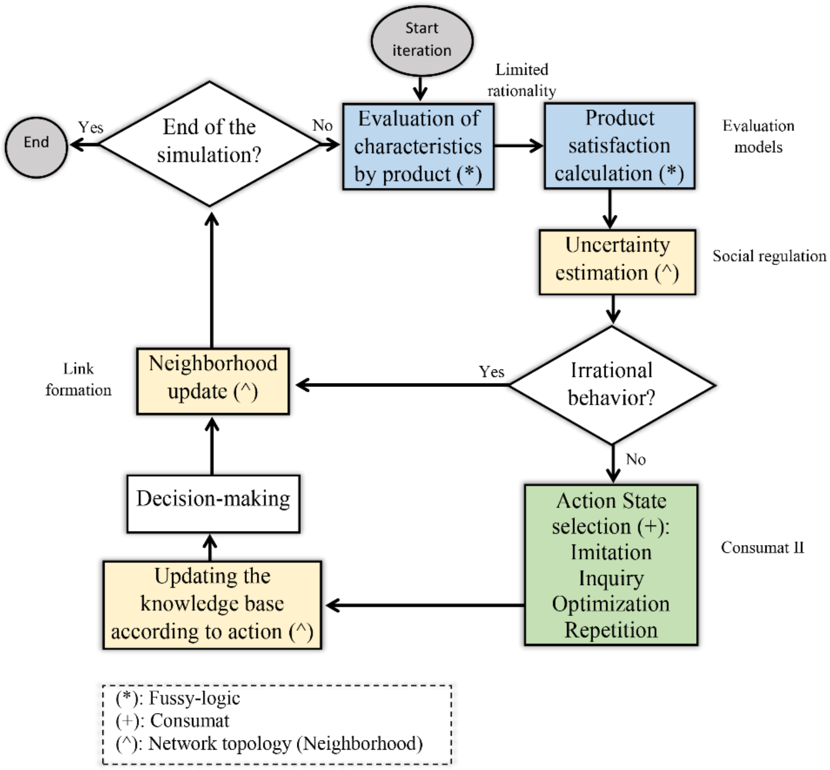


Fig 1. Decision-making simulation process.

2.3 Mathematical modeling

The model is composed of agents and products. An agent I represents consumers having n properties, defined as $I = \{ip_1, ip_2, ip_3, \ldots, ip_n\}$. The product P, has m properties, thus $P = \{p_1, p_2, p_3, \ldots, p_m\}$. The individual properties correspond to: identification, age, gender, satisfaction threshold, uncertainty threshold, knowledge base, and preferences rank. The product properties represent product features such as battery, weight, memory, storage capacity, camera, resolution, size of the screen, and price.

Product evaluation is an example of individual heterogeneity that depends on observable and unobservable factors [22]. To model individual heterogeneity in product evaluation, the consumer uses the constructed a Knowledge Base, which includes the Perceptual Heterogeneity concept [21]. A matrix represents the knowledge base namely B, where rows indicate the relative weight of each individual need, and columns represent the properties which Individual I knows about the products. In order to model the heterogeneity for an individual response, the evaluation process uses fuzzy rules defined in the knowledge base. In this work, two sceneries are considered: the first uses triangular and trapezoidal membership functions; and the second uses Gaussian membership functions [23]. Therefore, each individual estimates the satisfaction value base on their knowledge base, the defined fuzzy sets, the evaluation rules, and the Mamdani inference approach [23].

For satisfaction values estimation, considering i as the i-*th* product and j as the j-*th* characteristic, we build up the qualification matrix C. So, Q_{ij} represents the qualification value of the j-*th* characteristic of the i-*th* product. This qualification is obtained for each individual, based on the diffuse rules over its knowledge base. Therefore, for each individual the normalized evaluation matrix v with n products is defined as:

$$v_{ij} = \frac{1}{n} Q_{ij} \tag{1}$$

The total weighted satisfaction values for each of the evaluated products involving needs are represented by the vs vector, as:

$$vs_i = \frac{1}{ch * nds} \sum_{j=0}^{Ch} \sum_{z=0}^{nds} v_{ij} . mp_{jz} \tag{2}$$

where, i is the index of the product, *nds* is the number of needs, up to 3; based on Consumat II. ch represents the total of characteristics, and mp_{jz} is the weight value of the j-th characteristic for the z-th need. The product selection is made based on maximizing the satisfaction values. Thus, the index of the selected product (*spi*) for individual I is such that:

$$spi = \underset{i}{\operatorname{argmax}}(vs_i) \tag{3}$$

In order to select the action that the individual I will take, it needs the uncertainty value for the selected product. This work considers two types of uncertainty: social and individual. Social uncertainty considers the satisfaction values from the individual neighborhood related to the selected product. The model quantifies the satisfaction values from an individual who has selected and not selected the same product. So, the *same_satisfaction (ss)* and *different_satisfaction* (d*s)* values for I and the selected product p are estimated by:

$$ss_I(p) = \sum_{r=1}^{Nh} vs_p^r \quad | \, spi_r = p \tag{4}$$

$$ds_I(p) = \sum_{r=1}^{Nh} vs_i^r \quad | \, spi_r \neq p \tag{5}$$

where Nh is the size of neighbors of the I, and vs_i^r is the satisfaction value for the product i of the individual r. Finally, the social uncertainty is estimated by:

$$SU_I = \frac{ds_I}{ss_I + ds_I} \tag{6}$$

The personal uncertainty estimation uses: the weight of the experience wex, the ambition amb value represented by the user satisfaction obtained with the previous product selection, and the mark of which the user has had experience $p_{experience}$. Personal uncertainty depends on whether or not the mark of selected product p_i coincides with the marks of products which the user has had any past experience of, thus:

$$SP_I = \begin{cases} wex \cdot (1 - amb) & if \; m(p_i) = m(p_{experience}) \\ wex \cdot amb & if \; m(p_i) \neq m(p_{experience}) \end{cases} \tag{7}$$

where the function $m(p_x)$ obtains the mark of product p_x. p_i is the product selected on i-th iteration.

The total uncertainty TU is the mean value of both uncertainties, social and personal, and is estimated thus:

$$TU_I = \alpha(SU_I) * \beta(SP_I) \tag{8}$$

where α and β are the given weights to social and personal uncertainties.

Using the estimated satisfaction and the total uncertainty each individual can select the next action. Each action selected implies a knowledge-based update, except when Repetition and Adoption are selected. For Action selection, the agents use the next rule:

$$\begin{gathered} irr = rand(0,1) \\ action = \begin{cases} 1 & TU < tol \wedge s < amb \wedge irr > tirr \\ 2 & TU \geqslant tol \wedge s \geqslant amb \wedge irr > tirr \\ 3 & TU \geqslant tol \wedge s < amb \wedge irr > tirr \\ 4 & TU < tol \wedge s \geqslant amb \wedge irr > tirr \\ 5 & irr \leqslant tirr \wedge (accion = 3) = prud \end{cases} \end{gathered} \tag{9}$$

where the numbers represent the action that can be taken by the agent: 1. Inquiry; 2. Optimization; 3. Imitation; 4. Repetition; and 5. Adoption. Irr is a random value determining the probability of irrational behavior. The *amb* value is the threshold value for Ambition. The *tirr* value is the threshold for irrational behavior.

2.3.1 Inquiry action

This action implies that the agent's inquiry to their neighborhood about the product selects the most widely accepted rule, so the selected rule is incorporated or reinforced into the knowledge base. Let $p_{r,j}^{i}$ be the weight of the r-th individual assigned to the i-th product considering the j-th need. Then, $IndexP$ is the index of the product which maximizes the weight among neighborhood, thus:

$$IndexP = ind\left(\max_{i}\left(\sum_{r=0}^{R}\sum_{j=0}^{N} p_{r,j}^{i}\right)\right) \tag{10}$$

where N is the total of needs, and R the neighborhood size.

We defined the needs set $Nset = \{sn, pn, en\}$ including values for social, personal, and existential needs, respectively. Using $Nset$ and $IndexP$ the rule that will be applied is selected. Thus:

$$Kbase_{IndexP,Nset} = \begin{cases} random(R_m, R_v) & siKbase_{IndexP,Fuzzy\_r} < 0 \\ Kbase_{IndexP,Nset} + Reinf & siKbase_{IndexP,Fuzzy\_r} \geqslant 0 \end{cases} \tag{11}$$

where $kbase$ is the rules of knowledge base, and $Reinf$ is the reinforced factor. Thus, if the selected rule does not exist, the rule is incorporated into the knowledge base, or otherwise, it is reinforced.

2.3.2 Optimization, Imitation and Repetition actions

The individual tries to obtain more information about the products. Latest information is reached by:

$$\begin{aligned} ip &= rand(n) \\ B_{ip,tn} &= randn(R_m, R_v) \end{aligned} \tag{12}$$

Imitation action generates that the individual imitates the behavior of a neighbor. The individual partially incorporates the knowledge base of neighbor which has greater credibility. Repetition action implies that the individual does not adjust their knowledge base and continues with the same selection.

2.4 Neighborhood update

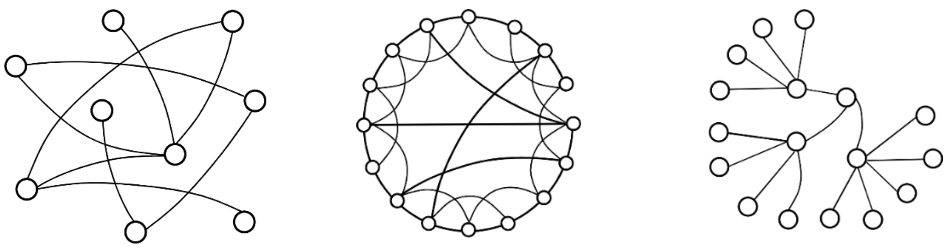
The effects of neighborhood updating depend on the network topology. In this work, we study the following network topologies [24]: random network [25], small-world network [26] and scale-free network [27] (see Fig. 2). An adjacency matrix represents the network topology. The network modification uses the link formation process to build new links or make eliminations, thus:

$$e_{a,b}(t+1) = e_{a,b}(t) + (s_{f,a} - s_{f,b}) - N_f$$
$$e_{a,b}(t+1) = \begin{cases} 1 & if \;\; e_{a,b}(t+1) > 1 \\ 2 & if \;\; e_{a,b}(t+1) < 0 \end{cases} \quad (13)$$

where $e_{a,b}(t)$ is the link value between individual a and b on t-th iteration. $s_{f,a}$ is the satisfaction measure of the individual a related to product f. N_f is the rate of credibility reduction. New links are formed using the defined topology, and the rules are described in [24].

3 Results

We tested the model using data on reported cellphone sales from different providers. The data represents sales for quarters of the year, from the third quarter of the year 2011 to the second quarter of 2012. The dataset used in this section was obtained from Gartner [25, 26, 27, 28]. The results shown were obtained with the model parametrized according to Table 2 y Table 3. Based on Consumat Framework, we considered one week of simulated time equivalent to one interaction of the model in a comparable way as [5]. Due to parameters estimation for social simulation is no a trivial problem, an acceptable alternative is to estimate these from the globally available information. Therefore, the used parameter values for the simulation are shown in Table 2. These have been estimated after to fix the model output to the trends of the used dataset. The selected properties of each one agent or individuals are shown in Table 3.



a) b) c)

Fig 2. Network structures: a) Ramdom, b) Small-World and c) Scale-Free [29].

Figure 3a shows that there is an emergent behavior. This behavior indicates that on average the population improved its satisfaction and uncertainty indicators, which has not been explicitly included in the model. We can use this result to show how a focus group can influence strongly a market, just based in perception of effectiveness in the product. Also, Figure 4a presents the dynamics of preferences for a given product over time through the social network. This figure allows us to see how individuals change products preferences due to some factors included into the model through the cognitive model, specifically, the acquisition of new information from the products and the influence of the environment. This result could be used to adjust the product lifecycle, programmed obsolescence, to improve revenue from cell business. Figure 4b shows the sold units for each evaluated product. It permits to see that, for smart mobile phones scenery, there is a significant proportion of the population that behave as innovators or early adopters. In conjunction with figure 4, it can be inferred that the propagation of preferences and the effective sale of the product are strongly related and are also proportional.

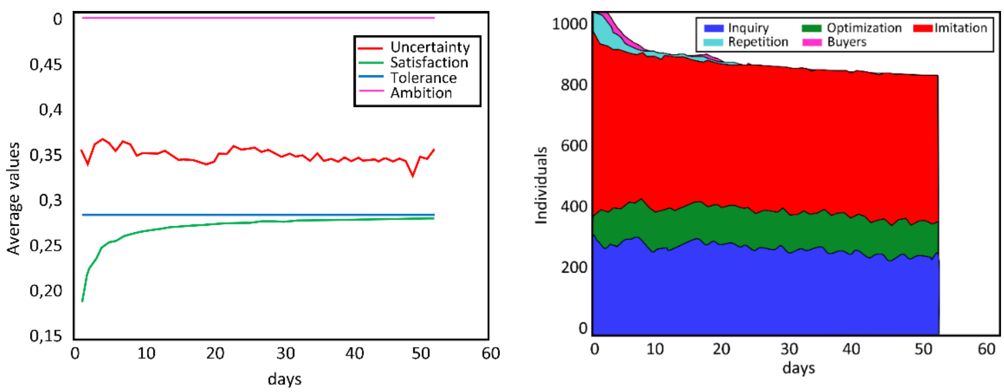
Figure 3b shows the evolution of consumer behavior along the iterations and also sees the process of global state change. The states in which more consumers fall are imitation and inquiry, which are the social states of the consumer's cognitive model. We concluded that the topology of the social network, the structure of the neighborhood and the exchanges of information are essential factors in the decision-making process of consumers.

Table 2. Cellphones adoption base scenario parameterization

Variable	Value	Variable	Value
Population size	1000	Threshold prudence	2,0
Network type	3	Irrational behavior probability	1,0
Average tolerance	0,1	Credibility reduction factor	0,07
Average ambition	0,5	Average weight experience	0,5
Membership function	Gaussian	Variability of fuzzy sets	0,8

Table 3. Included features of individuals

Properties	
Mark	Store Memory (Mbyte)
Battery	Camera (Mega-pixel)
Weight	Resolution(ppi)
RAM Memory (Mbyte)	Screen (mm)
Price (USD)	



a) b)

Fig 3. a) Evolution of average values for individuals uncertain and global satisfaction, b) Evolution of average values of uncertain and global satisfaction.

3 Conclusions

In this work, an agent-based model has been described for the problem of technology adoption using a mobile cellphone scenario. The proposed model uses a network topology to represent individual and social interactions which are generated by a typically human decision-making process. These interactions are governed by psychological and social theories modeled by a set of fuzzy rules and computational tools. The model takes into account several aspects of human behavior such as heterogeneous individual preferences, fuzzy evaluation, individual knowledge-base, nonprescriptive behavior, and information exchange between neighbor on a dynamical and partially connected network. Collectively, these aspects permit the recognition and characterization of the main factors in a human decision-making process, as well as in individual connections and the flow of information in a context in which the market offers similar technological products to satisfy a particular need.

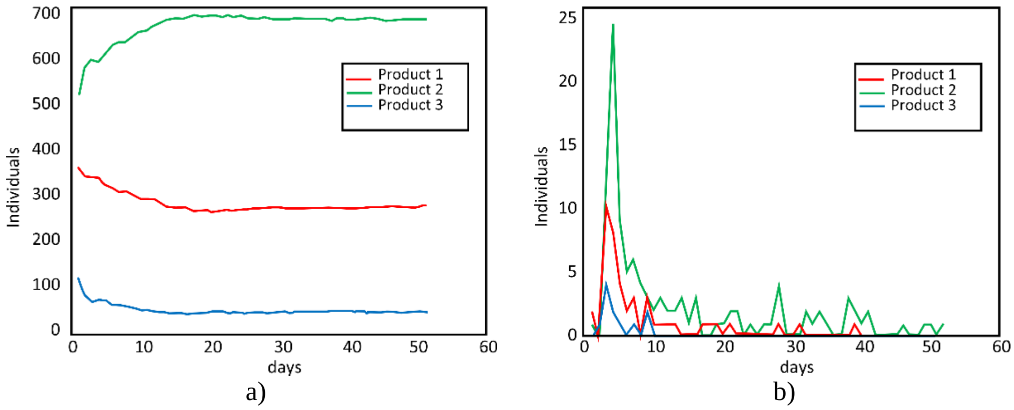


Fig 4. a) Evolution of average values of uncertain and global satisfaction, b) Evolution of average values of uncertain and global satisfaction.

The computational implementation allowed to obtain the initial values of the model parameters. These were adjusted using an empirical approach to avoid biases due to the partial data obtained from the real world or rules derived from general theories. Multiple executions let to reproduce the behavior of the propagation/adoption dynamics described in [8]. The obtained product sales curves describe trends similar to those described in the real-world market. It evidences the importance of considering limited rationality, irrational behavior and the social network in the individual decision-making simulation. The proposed model allows to use it in other consumer contexts since the parameter lists, and the defined thresholds are all configurable.

As a future work, we propose the inclusion of dynamic thresholding of satisfaction and uncertainty for each of the agents. Additionally, it is interesting to analyze the effect of others types of topologies and dynamics in social links.

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