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Analysis of Interactions of Key Stakeholders on B2C e-Markets - Agent Based Modelling and Simulation Approach

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Background/purpose: This paper discusses the application of ABMS – agent-based modelling and simulation in the analysis of customer behaviour on B2C e-commerce websites as well as in the analysis of various business decisions upon the effects of on-line sales. The continuous development and dynamics in the field of e-commerce requires application of advanced decision-making tools. These tools must be able to process, in a short time period, a large amount of data generated by the e-commerce systems and enable the use of acquired data for making quality business decisions.
Methodology: The methodology of the agent-based simulation used in this paper may significantly enhance the speed and quality of decision making in electronic trade. The models developed for the needs of this research aim to improve the use of practical tools for the evaluation of the B2C online sales systems in that they allow for an investigation into the outcomes of varied strategies in the e-commerce site management as regards customer behaviour, website visits, scope of sales, income earned, etc.
Results: An agent-based simulation model developed for the needs of this research is able to track the interactions of key subjects in online sales: site visitors – prospective consumers, sellers with different business strategies, and suppliers.
Conclusion: Simulation model presented in this paper can be used as a tool to ensure a better insight into the problem of consumer behavior on the Internet. Companies engaged in the B2C e-commerce can use simulation results to better understand their consumers, improve market segmentation and business profitability and test their business policies.

Keywords: *ABMS, B2C, e-commerce, website, customer behavior*

1. Introduction and literature review

Electronic commerce has been expanding rapidly in the last decade or so and is now present in almost all industry branches and in a majority of developed countries' markets. In order that e-commerce business be successful, it is necessary that quality strategies of entrance on the market should be developed and implemented and that additional services should be offered that grant the customers better purchasing conditions, a possibility of service adapting and additional value for customers (Hyung, 2010).

The development of the electronic commerce model

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has for long been a subject of numerous research attempts. The scientific literature often states the implementation of regression analysis as one of the most common approaches in recognizing the impact of key factors upon the success of a selected model of electronic commerce (Kim et. Al., 2008; Zhu et. Al., 2009; Wang et al., 2010). Besides, neural network based models are increasingly developed (Poh *et al.*, 1994; Russell and Norvig, 2003). To improve the existing solutions and explore new means to support better business decisions, research has in recent years increasingly implemented agent-based models in the analysis of e-commerce business models. Railsback and Grimm (2012) have shown that the agent-based simulation model can successfully add a larger number of characteristics of a realistic system to modelling. They have also shown that agents can adapt their behaviour as regards the current conditions of the environment and of other agents. Grimm et al. (2008) have proven that adaptive behaviour is one of the most vital properties of agents. Hence, complex and dynamic environments such as on-line markets can be successfully modelled and simulated using this methodology. One of the best-known models used in practice was developed by North and Macal (2010) for the needs of the Procter & Gable company. Zhang and Zhang (2007) used the agent-based simulation model to present the effect of introducing a new product on the market to serve as decoy. The authors confined themselves to only explaining the application of the mentioned effect, however, the model itself is far more comprehensive and deals with psychological mechanisms that govern customers in choosing a particular product. Okada and Yamamoto (2009) used the agent-based simulation model to investigate the impact of the eWOM effect upon the habits of customers purchasing on B2C websites. Special attention is paid to the exchange of knowledge (useful information on the product) among customers. Furthermore, literature describes a large number of agent-based simulation models used in customer behaviour studies (Schramm *et.al*, 2010; Roozmand 2011). An interesting example is the CUBES simulator (Customer Behaviour Simulator) (Said *et.al*, 2002), which studies mechanisms of customer interactions and their effect on different economic phenomena. Liu *et al.* (2013) used the agent-based simulation model to investigate into the nowadays common continual price reductions on online markets. In recent years this methodology is successfully used in simulating customer behaviour on social networks and research into the effect of social networks on viral marketing (Hummel *et al.*, 2012; Zutshi *et al.*, 2014).

Our aim in this paper is to show the manner in which it is possible to model and analyse the Internet consumer decision-making process. The precondition for the development of a quality model is a thorough apprehension of consumers on the Internet. Customer behaviour on the Internet significantly differs from the traditional behaviour since the Internet consumers have different habits and needs. The number of papers and research articles on the subject of customer behaviour in e-commerce today is rather large (Currie and Rowley, 2010; Dyner and Franco, 2004; Furaiji *et al.*, 2012). While a number of papers is devoted to socio-demographic characteristics of e-commerce participants, the other group of articles deal with phenomena affecting the consumer trust, privacy and safety as well as their inclination to buying a particular type of product or brand (Bagozzi *et al.*, 2002).

The approach used in this paper is to consider the possibility of applying agent-based simulation models as basis in B2C business models evaluation for the purpose of improving the existing e-commerce strategies and obtain data that can be used in business decision analysis. Connecting the areas of agent-based modelling and electronic commerce creates opportunities for a better understanding of both the behaviour and the causes of behaviour in *e-commerce* systems. One goal of this research is to investigate into how different consumer habits in purchase decision making affect the complexity of their habits when purchasing on the Internet. The application of the proposed simulation model is meant to enable decision makers to test the consequences of different business policies and track the behaviour of sellers, suppliers and consumers on the B2C electronic sales websites.

2. Simulation model of consumer behaviour

The study of the consumer population, their habits and behaviour serves as basis for the B2C electronic commerce analysis. This analysis is of vital importance for B2C shareholders and managers, marketers, sales people, but also for the consumers themselves. The consumer analysis is to analyse their needs – what, why and how they purchase. Consumer behaviour can be described as a set of activities prospective customers undertake in searching, selecting, valuing, assessing, supplying and using of products and services in order to satisfy their needs and wants. These also include decision-making processes that both precede and follow the above-mentioned activities (Belch 1998; Schiffman *et al.*, 2009; Solomon, *et al.* 2009). In making their decisions to purchase a product, online shopping consumers go through different phases. The phases are similar to those present in traditional shopping, however, the manner in which they are carried out differs. Generally speaking, in their decision-making process, consumers go through the following stages (Engel et al., 1994): problem awareness, information search, evaluation of alternatives, decision on purchase and post-purchase evaluation. The aim of the model is to link consumers, on one side, and the sellers (Internet sales sites) on the other and to determine the manner in which they communicate. Hence, in this model we observe consumers with their social and cultural characteristics, on the one hand, and the market, namely online shops and intermediaries in sales with their e-business and e-marketing strategies, on the other. The model also takes into account the impacts of the on-line community and social networks on forming consumer decisions in online purchase, whose influence increases daily. The model treats the consumer's decision on purchasing as the outcome variable.

The model shown in Figure 1 focuses on three segments: the seller segment, the consumer segment and the communication channel segment. The seller is the Internet site dealing in B2C sales of products and/or services. The most important site characteristics contained in the model are the technical characteristics: infrastructure, software

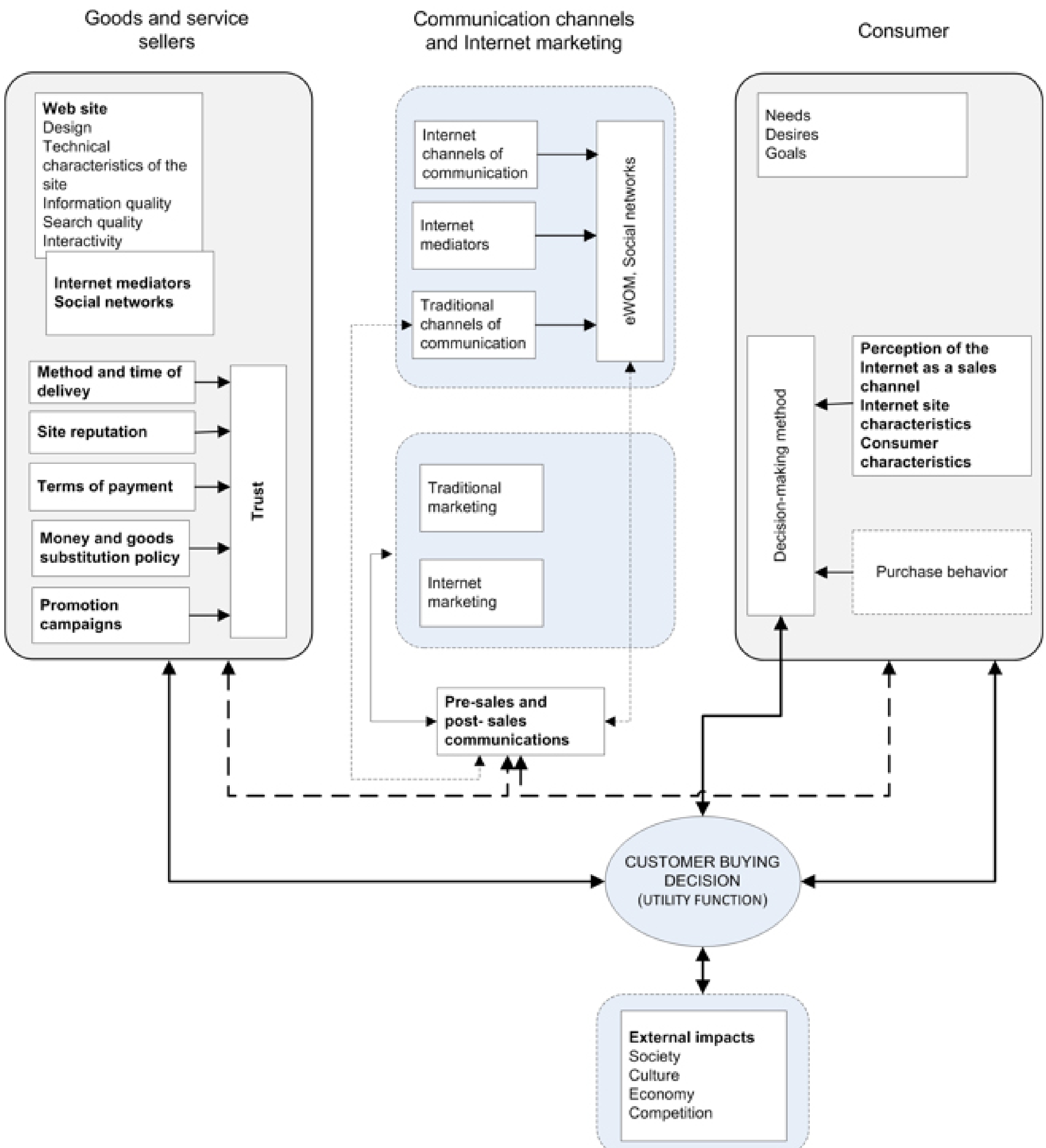

Figure 1: Consumer decision-making model in B2C electronic commerce

support, website design and the quality of information on the products offered via the website. The consumer segment observes online consumers. The model monitors the impact factors concerning their attitudes, goals and beliefs. The communication channels are the online (Internet) and traditional channels of communication. The model under consideration is confined only to the effects of online communication channels application. In addition to the three described segments, the model includes business strategies created by the seller, whose aim is to increase sales and build consumer trust. The model allows for varying the input variables that simulate the effects of implementation of different business strategies, primarily those referring to price changes and product quality attributes. The model also helps track the effects of Internet marketing as a business strategy segment.

In the observed simulation model, the prospective consumers go through all the stages of online purchase. They first find the B2C online shops of interest, then they search for information on the products, form their own opinion of the product and/or service (utility function) and finally make a decision to buy (regardless of whether these are

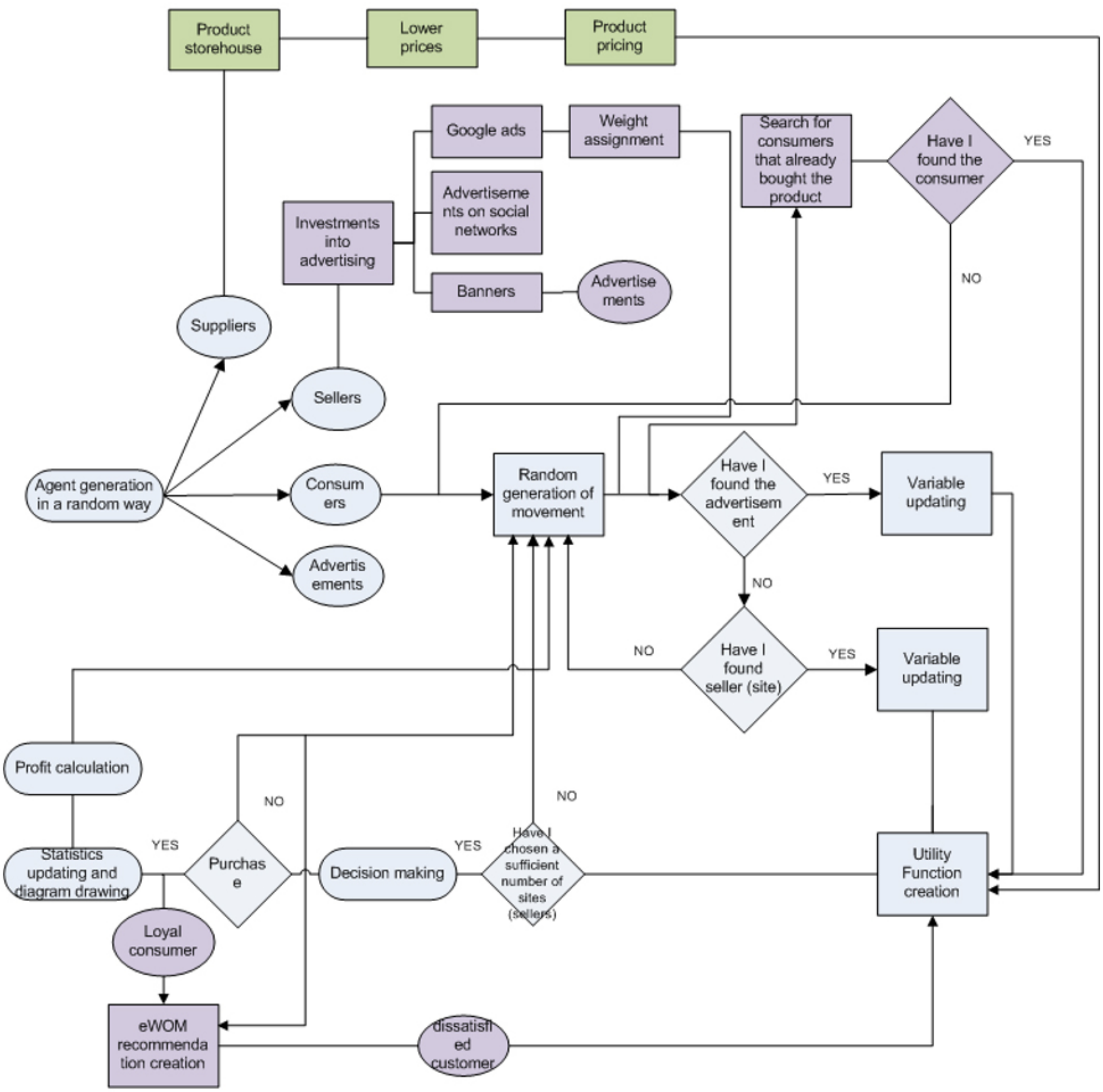

Figure 2: Graph of online purchase flow process in the simulation model (Colours are visible only in the internet version of the paper at http://dx.doi.org/10.1515/orga-2016-0010)

consumers that buy only once or consumers that remain loyal after their first purchase).

Figure 2 shows the basic steps in the simulation model, blue boxes represent the basic simulation flow. In the first step the simulation model forms a virtual market by generating agents: consumers (ConsumerAgents), sellers-Internet sites (SellerAgents), suppliers (SuppliersAgents) and advertisement agents (BannerAgents), on the basis of input variables.

The Consumer Agent models an individual consumer and his/her purchasing habits. The model can observe the behaviour of each individual consumer or a group of consumers. It is of key importance that we identify consumers with similar behaviours and needs and segment them for the purpose of targeted marketing campaigns (Klever, 2009). Agents that represent consumers in the model are generated by categories (on the basis of classification in (Moe 2003; Moe and Fader, 2002), and depending on their intention when visiting an online sales site:

1. **Direct consumers:** they visit the website with the intention to purchase a particular product; they rarely leave the website without having purchased.
2. **Consumers who search/reason:** they generally intend to buy a product from a certain category; it is possible that they make their purchase after several visits and comparisons with other websites and shops.
3. **Hedonic browsers:** initially, they do not intend to purchase a product; if made, a potential purchase is exclusively the result of stimuli from the site.
4. **Information gathering visitors:** visit website to gather information without any intention of buying.

The ConsumerAgents are assigned colours so that their behaviour in the model should be tracked separately. In generating ConsumerAgents, each agent is assigned characteristics shown in Table 1.

The Internet sellers (B2C e-commerce websites) are modelled as SellerAgents. The model presumes that each sales website sells one brand, and the seller is assigned a particular colour for the purpose of identification and visual tracking in the model during the experiment. When generating at the beginning of the simulation, agents are randomly assigned attributes shown in Table 2.

In addition to consumers and sellers, the model includes SupplierAgents, which are also generated at the beginning of the simulation, under the assumption that they have an unlimited storage of products. One supplier is generated for every brand and is assigned the same colour as the respective SellerAgent.

The fourth type of agents are BannerAgents. They

Table 1: ConsumerAgents input parameters

Label	Definition	Value	Distribution
G_i	i-th ConsumerAgent gender	input variable	Random 50%
A_i	i-th ConsumerAgent age	input variable	(18 + random 60)
I_i	i-th ConsumerAgent income	input variable	(5 + random 10)
RS_i	i-th ConsumerAgent sensitivity to website rating	input variable	Random (0-1)
K_i	i-th ConsumerAgent sensitivity to product price	input variable	Depends on I_i – wealthier consumers are less sensitive to price
W_{ij}	i-th ConsumerAgent sensitivity to a particular product attribute	input variable	Random (0-1)
ADS_i	i-th ConsumerAgent sensitivity to advertisements	input variable	Random (0-1)
Ft_i	i-th ConsumerAgent sensitivity to other agents – consumers' decisions	input variable	Random (0-1)

Table 2: SellerAgents input parameters

Label	Definition	Value	Distribution
brand_seller	type of brand sold by SellerAgent		Random
cbrand-price	initial product price	input variable	Random(0-100)
sales-volume	number of sales	output variable	
R_i	site rating	site rating by consumers +1 = positive, -1 = negative	
Find me	initial search weight	input variable	Random(0-100)

serve to model the effect of Internet advertisements (banners) on purchase decision-making. When they are generated, they are assigned the colour on the basis of which they are tracked in the simulation experiment.

Upon generating agents and forming a virtual market, ConsumerAgents start searching for and evaluating products. The search is carried out via agents' random surfing through virtual market where they interact with other ConsumerAgents, SellerAgents and BannerAgents. With the proposed model it is possible to observe the effects of different strategies of SellerAgents on the effects of Internet sales.

Purple boxes on Figure 2 together with the basic model (blue boxes on Figure 2) show the model that takes into consideration different business strategies of Internet advertising. The development of social networks and Google services resulted in B2C e-commerce companies predominantly using these channels to market their products today. Customers with previous experience with online purchases display a tendency to share both positive and negative experiences about the purchase they made (eWOM effect) (Godes and Mayzlin, 2004; Said and Drogoul 2002). When making a decision on purchasing a certain product, a negative comment is 7.5 times more important in comparison with a positive comment (Dellarocas, 2003; Harrison-Walker, 2001). The model employs the following marketing tools:

- eWOM (interaction with other agents).
- Search weight (weights on the basis of which agents search the websites);
- Advertisements with banners (BannerAgents);

While surfing, the ConsumerAgent randomly finds Internet websites (SellerAgents). Finding different sellers may be entirely random or affected by search weight attributed to certain SellerAgents (input parameter of the model) to which the ConsumerAgent react. The model also allows for simulating a better "visibility" of the website on the Internet by generating the larger number of ConsumerAgents of a particular colour. Apart from finding SellerAgents, ConsumerAgents can conduct interactions among themselves in a given radius (input parameter of the model) while surfing through a virtual market and sharing positive and negative comments about products (eWom effect).

The basic model presented in Figure 2 (blue boxes) can be expanded for the purpose of observing a business strategy related to promotional price reduction (green boxes on Figure 2). Promotional prices are among the most important attributes affecting a consumer's decision to purchase online. Although investments into promotional campaigns of reducing prices have a positive effect on the increase in sales, they can in turn reduce the company's profits to a significant extent (Bailey, 1998; Michael and Sinha, 2000). When consumers expect price reductions and promotional campaigns to become a usual practice, they are reluctant to purchase goods that are not on promotional sales.

3. Components of utility function

The consumer's utility function is created on the basis of information the ConsumerAgent collects on a product and in interactions with other consumers. At the beginning of a simulation it is possible to define the lowest utility function value below which the ConsumerAgent never makes a pro-purchase decision. Suppose that N brands were present at a virtual market. If we view incentives as independent variables, and character traits as coefficients of these independent variables, we can define the function in the following manner:

$$U_i = P_i + A_i \qquad (1)$$

where:

U_i - function of ConsumerAgent as regards product *i* (*i* = 1 to *N*).

P_i - ConsumerAgent rating of the *i*-th product price and quality.

A_i - effect of *i*-the product marketing campaign on ConsumerAgent.In product rating consumers usually compromise between what they get by purchasing the product and how much money they give in return. The model observes price as one product attribute and product quality as the other, integrating all the aspects of product quality.

$$P_i = C_i + EQ_i \qquad (2)$$

where:

P_i - ConsumerAgent's rating of the *i*-th product price and quality.

C_i – ConsumerAgent's sensitivity to the *i*-th product (brand) price.

EQ_i – ConsumerAgent's sensitivity to the *i*-thproduct (brand) quality.

The value of coefficient C_i shows the effect of product price on the ConsumerAgent's attitude towards purchasing the given product. As a rule, higher prices tend to have a negative effect on consumers' motivation to buy a certain product. The distributed model of sensitivity to price (Kim et.al 1995) suggests that a lower price of a product generates a lower sensitivity to product price in a ConsumerAgent. Sensitivity to price can be expressed as follows (Zhang and Zhang, 2007):

$$C_i = -\alpha P_{ri} - P_{ei} + k \qquad (3)$$

where:

α – consumer's rating ($\alpha > 1$) versus the real price of the observed product;

P_{ri} – price of the *i*-th product;

k – constant for ConsumerAgent which depends on socio-economic attributes (better-off consumers are less price-sensitive);

P_{ei} – expected price of *i*-th product; this parameter is difficult to define so it will be replaced by a mean value of all the products in the observed category P_{ave}

$$P_{ei} = P_{ave} = \frac{1}{N}\sum_{i}^{N} P_{ei} \tag{4}$$

So that after the replacement we obtain:

$$C_i = -\alpha\, P_{ri} - P_{ave} + k \tag{5}$$

The next key attribute the consumer-agent rates is the product quality. The coefficient Q_{ij} denotes the coefficient of *i*-th consumer-agent sensitivity to *j*-th product price. Sensitivity to quality is a multidimensional variable since the brand, that is, the product may have a number of quality aspects. Assuming that product *i* has *m* quality aspects, and on the basis of model shown in (Jager, 2008), ConsumerAgent's rating of *i*-th brand can be calculated as follows:

$$EQ_i = \sum_{j=1}^{m} \beta_{ij} Q_{ij} \tag{6}$$

where:

Q_{ij} – *j*-th quality aspect for brand *i*;

β_{ij} – weight of *i*-th quality aspect for brand *j* (value ranging between 0 and 1).

The next element of utility function regards the consumer-agent sensitivity to eWOM effect as well as sensitivity to marketing campaigns. Analytically, it can be expressed as:

$$A_i = \alpha_i\, W_i + \beta_i\, B_i \tag{7}$$

where:

A_i – effect of *i*-th product marketing campaign on ConsumerAgent.

α_i – ConsumerAgent's sensitivity to eWOM effect for product *i*;

W_i– effect of other ConsumerAgents on decision to purchase *i*-th product.

β_i – ConsumerAgent's sensitivity to brand *i* marketing (value ranging between 0 and 1);

B_i – number of banners for brand *i* ConsumerAgent sees during his Internet surf.

Effect of the exchange of knowledge and information on the product between the on ConsumerAgent can be calculate as:

$$W_i = N_i/N \tag{8}$$

where:

N_i – number of ConsumerAgents in the ConsumerAgent's surroundings who use product *i*;

N – the total number of ConsumerAgents in the ConsumerAgent's surroundings.

Effects regarding positive and negative recommendations after purchasing is possible to be calculated in the following way (Aggarwal et.al., 2012):

$$W_i = (E_p^{\,2} - E_p\, E_n) / (E_p + E_n)^2 \tag{9}$$

where:

E_p – number of positive rates of interaction.

E_n – number of negative rates of interaction.

ConsumerAgents rate their interaction with seller-agents following each purchase made. The percentage of negative comments is an input parameter into a simulation model and is a subject of calibration in the simulation experiment.

The model also observes the interaction between ConsumerAgents and BannerAgents that represent banners on the Internet. ConsumerAgent's sensitivity to marketing campaigns (banners) can be determined as follows:

$$B_i = R_i / R \tag{10}$$

where:

R_i - number of BannerAgents of brand *i* in the BannerAgent's surroundings.

R - total number of BannerAgents in the ConsumerAgent's surroundings.

Simulation model uses utility function as basis for the purchase decision making. All the incentives in the model are viewed as variables that can be changed with every other experiment. The process of evaluation of all impact parameters and their ranking for the purpose of purchase decision making is modelled by the utility function. In the simulation experiment it is possible to consider or exclude each of the four members of the utility function. In this way it is possible to test all influential factors separately or in any mutual interaction.

4. Simulation experiment

The observed simulation model is implemented in the NetLogo software. It was subjected to a number of experiments and data are collected for an analysis of the behaviour of B2C *online* sales system. The basic indicators of B2C sales site business that were observed are market share and the number of visits on the website (surf share). At the beginning of simulation ConsumerAgents, ConsumerAgents and BannerAgents are generated, as described earlier in the paper. The simulation ensures that impact factors from the utility function, which affect the consumers' behaviour, are observed separately.

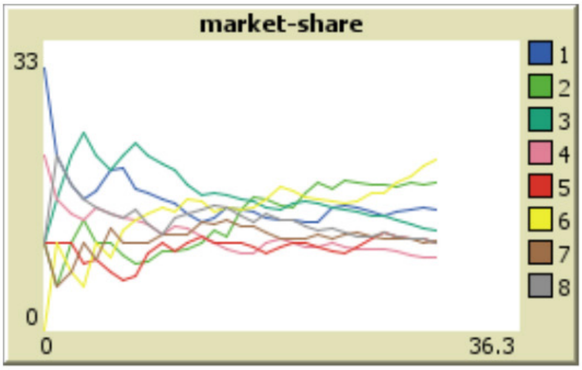

Figure 3-a: GraphvOM effect on market share

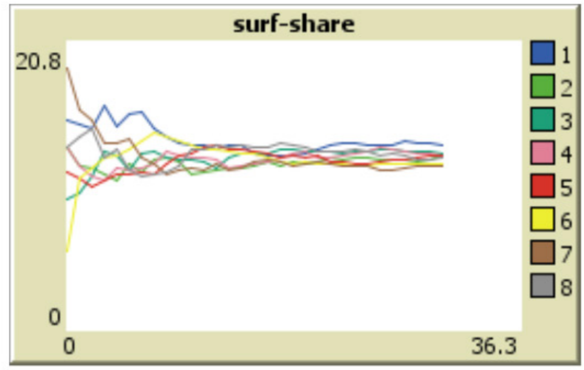

Figure 3-b: Graph: eWOM effect on surf share

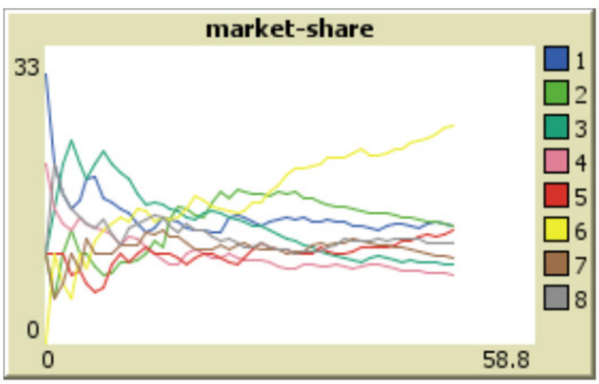

Figure 4-a: Graph: BannerAgent effect on market share

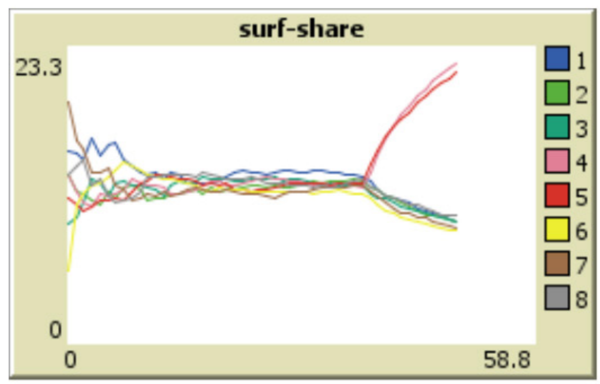

Figure 4-b: Graph: BannerAgent effect on surf share

In the initial simulation experiment all types of products are assigned the same price in the amount of 100 monetary units, as well as the same quality level. Thus all the Internet sites have the same initial conditions for business. For every purchase the ConsumerAgents contact four websites (SellerAgents) in their surroundings. This number is an input parameter and can be changed depending of the scenario we wish to test. After an initial oscillation, the SellerAgents' market share stabilizes and that both visits and sales are almost evenly distributed across SellerAgents. This is an absolutely expected result given equal initial business conditions set in the model and, in a certain way, may be used in model verification.

In the next stage of the simulation experiment we observed the effect of eWOM on the output variables of the model. The graph in Figure 3-a[1] shows that the sales of, in that time, best-sold products (yellow and green) increased most rapidly. The price of the products remains the same and so does the quality, however, consumers most often "comment" the best selling products, which further improves their sales. The intensity of the eWOM effect, depending on the selected scenario, can be adjusted through the "choice-neighbours-buyers" input parameter that determines the radius in which ConsumerAgents follow other ConsumerAgents who have already purchased the observed product. The broader the radius, the more powerful the eWOM effect on the utility function. In case of eWOM effect on increase of surf share, it can be concluded that this effect is of minimum importance, as shown in the graph in Figure 3-b.

In the following stage of the simulation experiment we include the effects of product marketing through BannerAgent generation. In this iteration, 20 banners were generated for pink and red products, and the click-through-rate (CTR) was set at 10%. The 10% coefficient for CTR is unrealistically high (in practice, this coefficient normally amounts to 4%), however, we did this to illustrate the sensitivity of the model to an abrupt rise of this coefficient (Figures 4-a and 4-b).

Now we notice that the surf share on websites that sell the "pink" and the "red" products has increased significantly in comparison with the competition (Figure 4-b). However, even though the sales of the "red" product increased slightly, this type of advertising had no effect on the increase in the "pink" product sales. This can be explained by the fact that the "pink" product has so far had

[1] Colours are visible only in the internet version of the paper at http://dx.doi.org/10.1515/orga-2016-0010

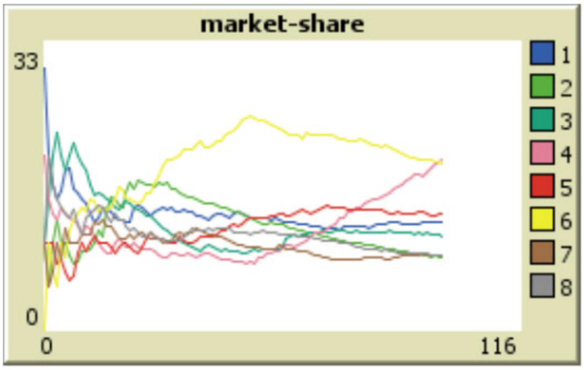

Figure 5-a: Graph: SellerAgent search weights effect on market-share

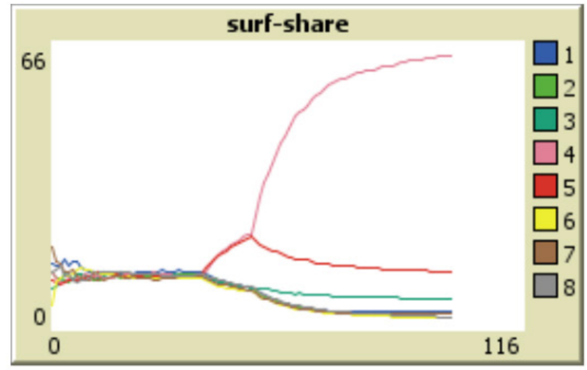

Figure 5-b: Graph: SellerAgent search weights effects on surf-share

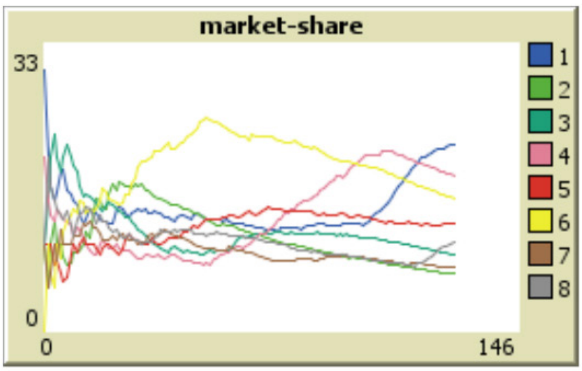

Figure 6-a: Graph: Effect of price and quality change on market share

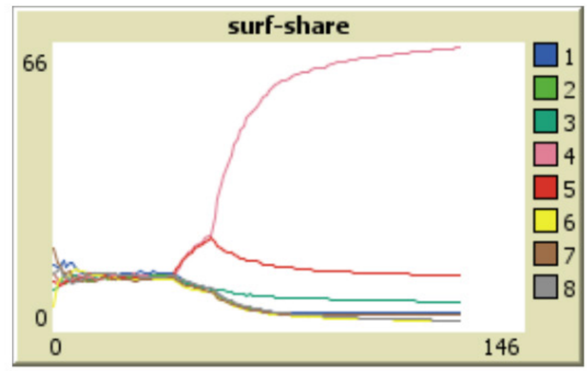

Figure 6-b: Graph: Effect of price and quality change effect on surf-share

the smallest market share (Figure 5-a), hence the eWOM effect on it was modest, and the applied level of marketing has not been powerful enough to alter the situation to a more significant extent. In this way it is possible to test different business policies related to the effects of internet marketing by way of banners.

Upon discontinuing the simulation, the experiment continues to test the effect of increasing the "visibility" of the website through increasing the ratings on the browsers. We will increase the "visibility" of SellerAgents by assigning weights for their search. At the same time we define the number of websites randomly searched with these weights. We will now assume that a majority of consumers browsing the Internet will check a certain number of top-ranked sites from the list of offered sites (in this experiment we will choose three), while in further browsing they choose the remaining sites randomly. The number of websites browsed on the basis of search weights and of those browsed randomly are input variables into the simulation model.

Figures 5-a and 5-b show that in this case, again, the number of visits to sites increases, as well as their sales after a certain time. We can draw a conclusion that investment into a better visibility of a site on the Internet increases the number of visits and sales to a larger extent in comparison with marketing via banners, which should be taken into consideration when planning the site promotion costs.

In the final stage of the observed simulation experiment we test the effect of the product price and quality change on the online sales. The prices of the best-selling "pink" and the second best, "yellow" products increased by 5% and 3%, respectively, whereas the price of the worst-selling, "grey" brand decreased by 5%. Simultaneously, the quality of the "blue" product improved by 5%, and that of the "red" product improved by 3%. Effects of these changes can be seen in the graphs in Figures 6-a and 6-b.

We can see from the graphs in Figures 6-a and 6-b that these relatively small changes in prices and quality do not have an immediate effect on the sales of the product, however, sales still improve over time. The increase in sales of the "red" product on the basis of improved quality is somewhat slower, though. This may be a result of relatively slack marketing activities of the observed Internet seller, but also of the time required that the improvement of the product quality on the market should have a beneficial effect on sales.

The analysis of the obtained results proves that the model is capable of simulating various business policies and market effects on online B2C sales. We began the first simulation experiment with equal conditions of sale for all online shops, whereby we achieved a market balance with similar numbers of visits and sales for all SellerAgents. We continued the experiment to test the business policies of on-line promotion, product price variations, product quality variations and variations in the quality of the Internet site.

5. Conclusion

The research proves that the methodology of agent-based simulation and modelling can be successfully implemented in modelling and simulation of processes on online markets. It also shows that the results obtained can be successfully used to analyse the behaviour of such markets and monitor the effects of different business strategies of online sellers on generated sales, site visits and other success indicators in doing business in the e-commerce domain.

For the needs of this research a simulation model was developed in the NetLogo, software that enables us to monitor the key interactions of the core players on the online market. The generated agents who present the dynamic entities of the model are assigned attributes based on empirical and theoretical data retrieved from the B2C online market. Thus the online market managers are provided with the tool to investigate into the impacts and effects of implementing their own business strategies and strategies to the market flows.

The interactions of agents that make up this model are sublimated in the utility function that provides the basis for decision-making in the model. The rules of behaviour and interactions, included in the model through the utility function, denote the complexity of the decision-making process which occurs in evaluation and purchase of products in the part of B2C e-commerce. The utility function is comprised of two components. The first component relates to the price and the quality of the product. The second part implements the effects of different marketing activities of agent-sellers on B2C markets, whereby special attention is devoted to eWOM effects. The simulation model enable to monitor all interactions between the SellerAgent, ConsumerAgent and BannerAgent by generating the indicators of B2C site business performance (market shares and frequency of sites visits). It enables the model users to test different business decisions and monitor the behaviour of sellers, suppliers and consumers on sites dealing with B2C e-commerce.

The rules of behaviour and interactions included into the model stress the complexity of the decision-making process in product evaluation and purchase in the B2C e-commerce segment. The observed simulation model includes a broad range of impact variables whose aim is to model all the relevant aspects of consumer behaviour and explain their method of decision making when purchasing on-line. Of course, as well as any other model, the observed model does not pretend to take into consideration all the real components affecting the consumer choice, however, a careful choice of the utility function components provides for summing up all the key elements that can significantly affect consumers' attitudes and decisions. Such an approach to consumer behaviour modelling is founded on the conceptual model of consumer behaviour established on research and theoretical grounds provided by numerous works in the areas of marketing, psychology, philosophy, management, economics and other related disciplines.

We can conclude that the designed e-commerce simulation model is a tool that ensures a better insight into the question of consumer behaviour on the Internet, and the companies engaged in e-commerce in the B2C segment now have a tool that can help them better understand their consumers, improve market segmentation, improve the business profitability and test their business strategies. As shown in the above discussions, consumer decision making on the Internet is the subject of continual study, therefore, new insights and approaches are certainly out there, waiting to be explored, which opens a broad area for further study.

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