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Agent-based modelling and simulation in the analysis of customer behaviour on B2C e-commerce sites

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This paper examines the development and application of agent-based modelling and simulation in the analysis of customer behaviour on B2C e-commerce websites as well as in the analysis of the effects of various business decisions regarding online sales. 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 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. 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.

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1. Introduction

Electronic commerce has been expanding rapidly in the last 15 years and is now present in almost all sectors and in a majority of developed countries' markets. As a distributed environment, e-commerce involves a large number of market participants: customers, traders, intermediaries and other service providers who communicate, trade and collaborate among themselves using ICT-based applications. In the beginning of the e-commerce era, adoption of e-business applications provided companies with significant competitive advantage. It now may not be the case. A large number of companies are able to develop their e-commerce infrastructure relatively quickly and offer their services and products via the Internet. In order for e-commerce business to be successful, it is necessary to develop good business strategies and offer additional services to customers (Rosaci and Sarne, 2012).

Examining the behaviours of stakeholders in e-commerce has been the subject of numerous research studies. The academic literature often uses regression analysis as the most common approach for recognising the impact of key success factors of a considered e-commerce model (Kim *et al*, 2008). Besides, neural network-based models are increasingly developed (Pao-Hua *et al*, 2010). To improve the existing solutions and explore new means to support better business decisions, recent research has increasingly implemented agent-based models in the analysis of e-commerce models. Among the first to report such a model are Janssen and Jager, who investigated processes that lead to "lock-in" in the consumer market (Janssen and Jager, 1999). One of the best-known models used in practice was developed by North and Macal for the needs of Procter & Gamble (North and Macal, 2010). Tao and David Zhang used the agent-based simulation model to present the effect of introducing a new product on the market to serve as decoy (Zhang and Zhang, 2010). Although the authors confined themselves to only explaining the application of the mentioned effect, the model itself is far more comprehensive and deals with psychological mechanisms that govern customers in choosing a particular product. Okada and Yamamoto used the agent-based simulation model to investigate the impact of the eWOM effect upon the habits of customers purchasing on B2C websites (Okada and Yamamoto, 2009). Special attention is paid to the exchange of knowledge and information on the product between the buyers. Furthermore, the literature describes a large number of agent-based simulation models used in customer behaviour studies. An interesting example is the CUBES simulator (customer behaviour simulator), which studies mechanisms of customer interactions and their effect on different economic phenomena (Said and Drogoul, 2001). Liu *et al* used the agent-based simulation model to investigate the nowadays common continual price reductions on online markets (Liu *et al*, 2013). In recent years, this methodology has been 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).

The analysis of aforementioned research demonstrated that all papers addressed individual phenomenon in online purchasing. This paper examines the development and application of ABMS which offers a more comprehensive approach to the

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analysis of consumer behaviour and business strategies in B2C e-commerce sites. This simulation model analyses the impact of different variables in evaluation of consumer behaviour and different policies in management of e-commerce. It includes a wide variety of significant variables which model all relevant aspects of consumers' and managers' behaviour on B2C sites with the aim of establishing a realistic virtual market offering a basis for undertaking a large number of simulation experiments.

2. Research framework

The model presented in this paper includes a number of variables which aim to model all relevant aspects of consumers' behaviour and explain how they make decisions in online shopping. These variables are given in the form of a utility function which models buyers' behaviour while selecting a product. Elements of the utility function represent input variables of the simulation model. The simulation ensures that impact factors from the utility function, which affect the consumers' behaviour, can be observed separately.

The simulation model includes a number of agents which form a virtual market. All agents' characteristics shown in Tables 1 and 2 are considered to be input variables. Characteristics, such as product prices, and indicators related to technical characteristics of the website (quality of information of the site, perception of site design and technical characteristics, perception of the site design) may be altered in the course of the simulation experiment. Search weights for every seller agents are placed at the beginning of the simulation and can be changed during the simulation experiment.

Special attention was paid to the mutual interaction between the consumer agents in the trade that generates eWoM effects. In this paper, we describe online eWoM communication in terms of the consumer population, the number of interaction partners and their memory period. The basic indicators of B2C sales site business that were observed are market share and the number of visits on the website (surf share). They represent the output variables of this simulation model.

In the process of experimenting with the model, we varied a large number of business strategies of online sellers and a number of results obtained were analysed. Business policies included in this model were tested using the example of the existing business of B2C online sellers of computer components and children's apparel, namely the two websites www.eklik.rs and www.eporodica.rs websites.

The approach used in this paper is to consider the possibility of applying agent-based simulation models as a basis in B2C business models evaluation for the purpose of improving existing e-commerce strategies and obtain data that can be used in business decision analysis. Modelling and simulation based on autonomous agents and interactions among them are some of the more recent approaches in complex system simulation modelling (Macal and North, 2010). Agents' behaviour is often described by simple rules of behaviour (Palopoli *et al*, 2006) as well as by their interactions with other agents that consequently affect the behaviour of the observed agent(s). The reason for an increased use of these models is that they can easily describe real phenomena that are becoming ever more complex. In applying agent-based simulation models in the area of social processes, people are modelled as agents, while their social interactions and social processes are modelled as interactions among these agents (Gilbert and Troitzsch, 2005).

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. This research contributes to investigating how different consumer habits in purchase decision-

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		
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 rating	Input variable	Random (0–100)

making affect the complexity of consumer 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 strategies and track the behaviour of sellers, suppliers and consumers on the B2C electronic sales websites.

3. Consumer behaviour model

Customer behaviour on the Internet significantly differs from the traditional behaviour since Internet consumers have different habits and needs. Consumer analysis examines their needs and behaviours—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 (Engel, 1994): problem awareness, information search, evaluation of alternatives, decision on purchase and post-purchase evaluation. However, the manner in which they are carried out differs. The following text will further describe the impact factors in purchasing decision-making and links among individual consumer characteristics, website characteristics, the online seller business strategies and the purchasing decision-making process. According to Changa et al., the factors that affect the consumer's decision can be classified as perception of characteristics of the Internet as a sales channel, characteristics of the Internet site or product, consumer characteristics (Changa *et al*, 2005).

1. Perception of characteristics of the Internet as a sales channel
   The literature contains numerous models that take into account consumers' attitudes, perceptions and beliefs involved in the purchasing process. The best-known models dealing with this subject are the technology acceptance model (TAM) (Davis *et al*, 1998), the theory of planned behaviour (TPB) (Ajzen, 1985) and the theory of reasoned action (TRA) (Ajzen *et al*, 1980). Initially, these theories were not developed for the needs of online market; however, they are also applicable in this method of business.
2. Characteristics of the Internet site or product
   The aim of the Internet website is to turn general website visitors into buyers. According to the report on Internet business activities of a shopping centre (Dholakia and Lopo, 1998) and factors described by Chang, we can identify the following key attributes (Changa *et al*, 2005):
   - technical site characteristics (design, product information quality, interactive communication mode of payment—cash on delivery, credit cards, PayPall);
   - risk reduction measures (possibility of refund and/or exchange of goods), offer of well-known brands, guaranteed data security, sales at reduced price); and
   - product characteristics (price, quality).

4. Consumer characteristics

Consumer characteristics are demographic attributes (gender, age, education level, income), among which gender and age stand out as most influential (Riedl *et al*, 2010; Venkatesh *et al*, 2003). Besides demographic characteristics, the model addresses physiological aspects of decision-making and consumers' perception of Internet and browsed Internet sellers. The perception of the Internet as a sales channel is developed over time and depends on both positive and negative experiences the consumer gathers during the sales transactions.

Upon defining the factors affecting consumer behaviour in online purchasing, the next step in model building was to link consumers with sellers (Internet sales sites) and to determine the manner in which they communicate (Figure 1). In addition to the three described segments (consumers, sellers and communication), the model includes business strategies created by the seller, whose aim is to increase sales, profit and to build consumer trust. Hence, in this model we observe consumers with their social and cultural characteristics, on the one hand, and the market, namely online shops and mediators in sales with their e-business and e-marketing strategies, on the other.

5. Simulation model development

In the previous section, we identified the key entities of the model and elaborated on the fundamental theoretical concepts related to consumer behaviour. In order to build an *agent-based* simulation model, it is necessary that key entities of the logical model should be presented as agents and their interactions transformed into rules of behaviour. Consumers go through all the stages of online purchase. They first find the B2C online shops of interest, 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.

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 Moe's classification (Moe, 2003; Moe and Fader, 2002), and depending on their intention when visiting an online sales site:

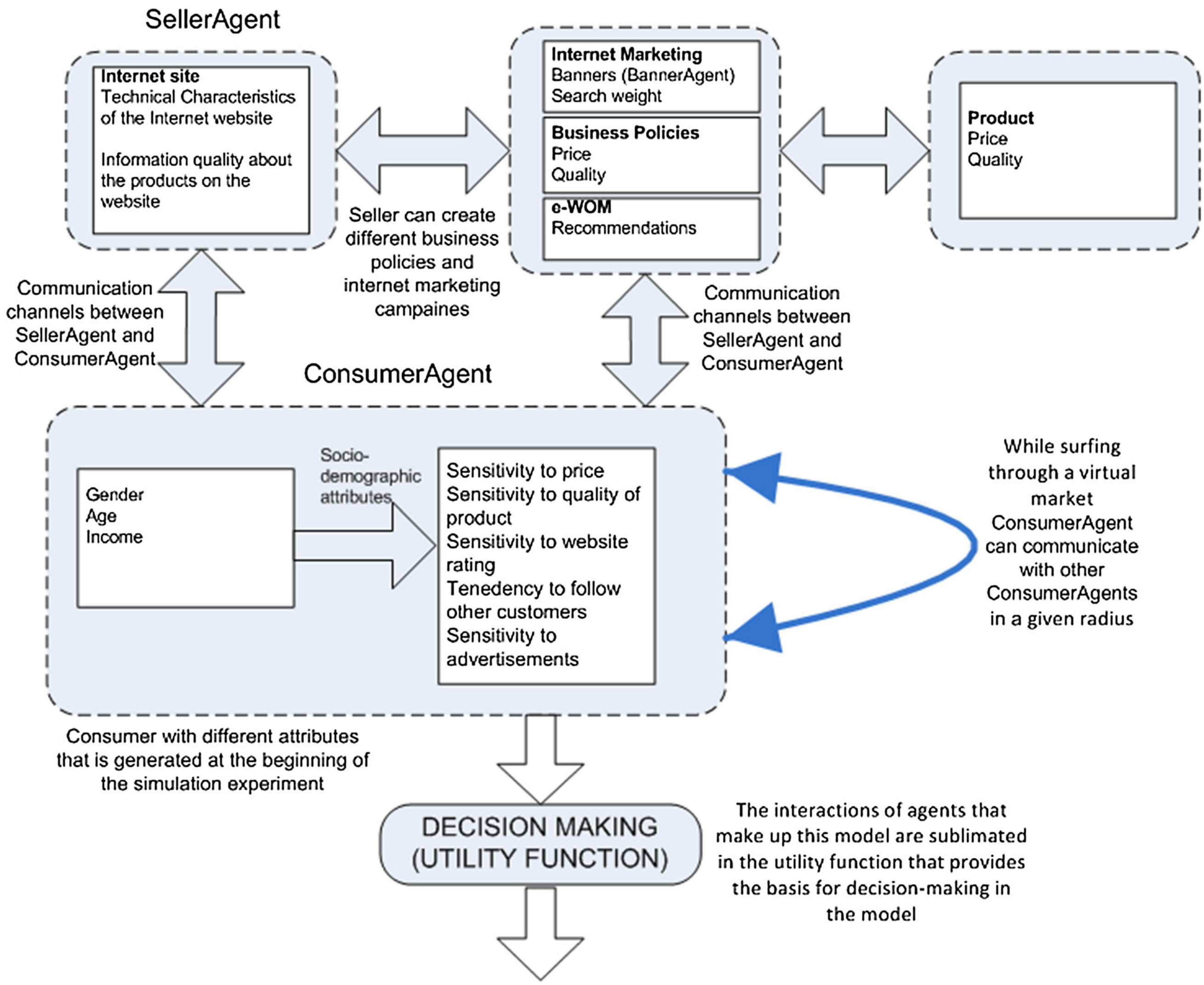

Figure 1 Consumer decision-making model in B2C electronic commerce.

1. Purchase the best offer—models a “rational” consumer who attempts to meet his needs, as fully as possible. These are marked yellow in the model.
2. Purchase the cheapest offer—the consumers that give priority to the lowest price when forming the product utility function on condition that the product attributes marked as imperative in the simulation experiment are satisfied. These are marked red in the model
3. Loyal consumers—the consumers with a high level of trust in certain sellers and who are satisfied with their services. In case of small differences in utility functions, these consumers choose the product from the seller from whom they have already purchased and to whom they trust more. They are marked blue in the model.

In generating ConsumerAgents, each agent is assigned characteristics as 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 generated at the beginning of the simulation, SellerAgents are randomly assigned attributes as shown in Table 2.

All attribute values in the model (Tables 1, 2) can be modified. In this paper, most of the attributes are illustrated for uniform distribution but the simulation model can easily deal with different distributions.

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.

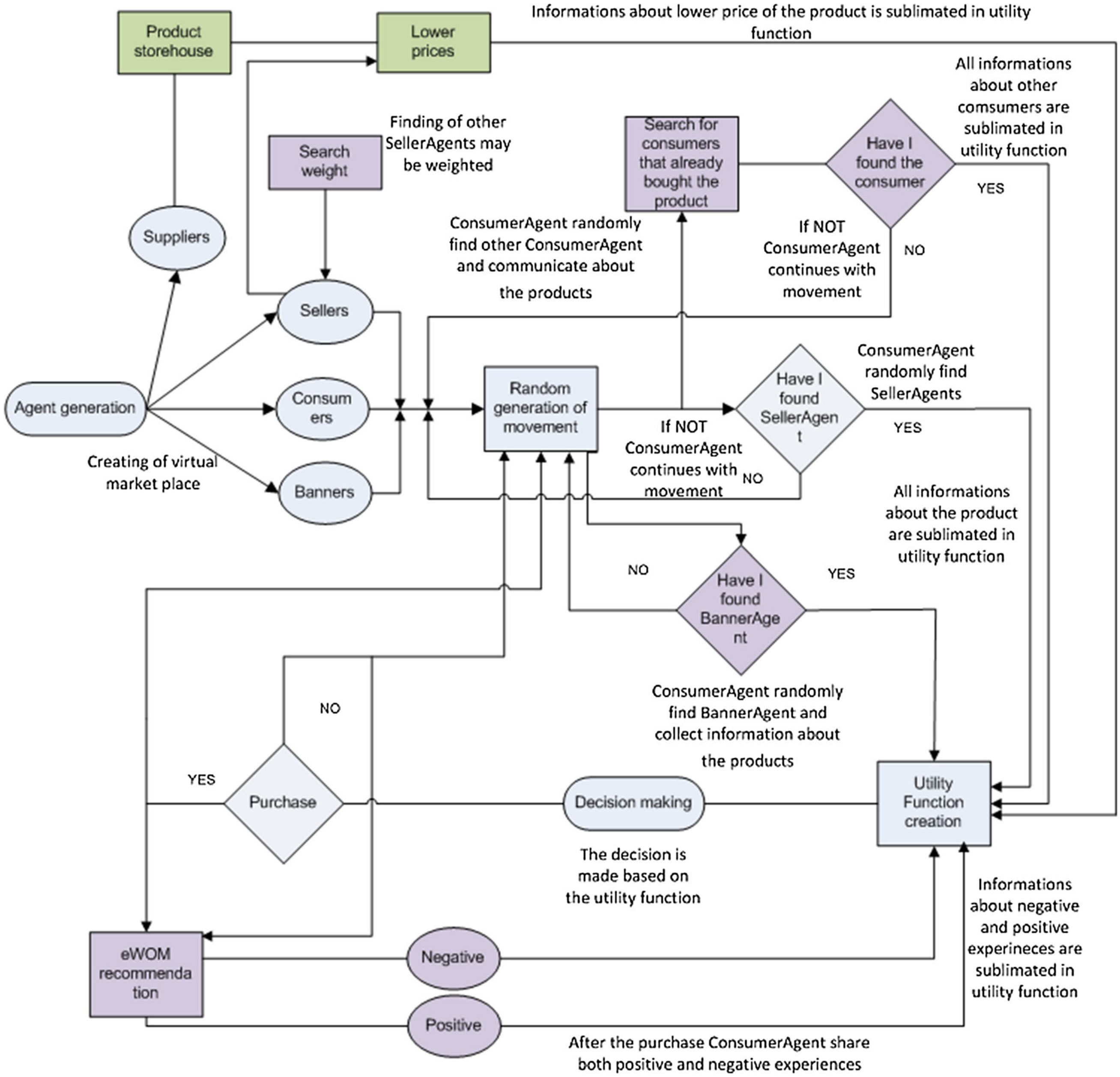

Figure 2 Graph of online purchase flow process in the simulation model.

The fourth type of agents is BannerAgents. They 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.

6. Agent interactions and rules of behaviour

In the first phase, 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 (Tables 1, 2). 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 the virtual market where they interact with other ConsumerAgents, SellerAgents and BannerAgents (Figure 2). Blue boxes in Figure 2 represent the basic simulation flow. Surfing on, the ConsumerAgent randomly finds Internet websites (SellerAgents) and form a utility function for all the products. All interactions between buyers' agents, sellers' agents and advertising agents are sublimated in the utility function. The utility function is formed in the evaluation and selection of products and represents the output variable of the simulation model. The consumer purchases the product that has maximum utility. The model allows for setting a utility function threshold so that the products that do not reach this threshold are rejected.

Purple boxes in 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, 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) and advertisements with banners (BannerAgents).

During their surf through the virtual market, ConsumerAgents “look for” BannerAgents in a certain radius surrounding them (input variable with the semantics of number of banners the ConsumerAgent sees during his search), thus simulating the impact of different marketing policies upon consumers’ attitudes when choosing a product on the Internet. Bearing in mind that not every consumer reacts to banners in the same way, one input parameter of each ConsumerAgent is sensitivity to marketing campaigns. Thus, the consumer’s inner sensitivity (perception) to the offered product is modelled. Each ConsumerAgent “memorises” a number of reviewed BannerAgents, that is, brands they represent.

Surfing on, a ConsumerAgent randomly finds Internet websites (SellerAgents). Finding different sellers may be entirely random or affected by a seller-paid banner on browsers to which the ConsumerAgent reacted. In the model, this is achieved by setting weights on certain SellerAgents (input parameter of the model) so that SellerAgents with higher weight values are more likely to be visited. However, it is also possible to generate a number of SellerAgents for different brands. Hence, the model allows for simulating a better “visibility” of the website on the Internet. The larger number of SellerAgents of a particular colour, the higher likelihood of finding a website selling a particular type of product becomes.

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 in Figure 2). Promotional prices are among the most important attributes affecting a consumer’s decision to purchase online. Although promotional campaigns of reduced 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.

7. 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. 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:

$$U_i = C_i + A_i + D + T_i, \tag{1}$$

where U_i is function of ConsumerAgent as regards product i ($i = 1$ to N), C_i is ConsumerAgent rating of the i-th product price, A_i is effect of i-the product marketing campaign on ConsumerAgent, D is factors related to demographic attributes of ConsumerAgent and T_i is ConsumerAgent rating of the i-th online website (SellerAgent).

The model observes price as a product attribute. 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, 2010):

$$C_i = -\alpha P_{\mathrm{ri}} - P_{\mathrm{ei}} + K, \tag{2}$$

where α is consumer’s rating ($\alpha > 1$) versus the real price of the observed product; P_{ri} is price of the i-th product; K is constant for ConsumerAgent which depends on socio-economic attributes (better-off consumers are less price-sensitive); P_{ei} is 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}

$$P_{\mathrm{ei}} = P_{\mathrm{ave}} = \frac{1}{n}\sum\nolimits_i^n P_{\mathrm{ri}}, \tag{3}$$

so that after the replacement we obtain

$$C_i = -\alpha P_{\mathrm{ri}} - P_{\mathrm{ave}} + k. \tag{4}$$

The next element of utility function regards the consumer–agent sensitivity to eWOM effect can be expressed as (Jager, 2008)

$$A_i = \alpha_i W_i + \beta_i B_i, \tag{5}$$

where A_i is effect of i-th product marketing campaign on ConsumerAgent, α_{i} is ConsumerAgent’s sensitivity to positive and negative recommendations for product i, W_i is effect of positive and negative recommendations on the decision to purchase i-th product, β_i is Consumer agent’s sensitivity to brand i marketing (value ranging between 0 and 1) and B_i is number of banners for brand i ConsumerAgent sees during his Internet surf. The effects regarding positive and negative recommendations after purchasing may be calculated in the following manner (Aggarwal *et al*, 2012):

$$W_i = \frac{E_p^2 - E_p E_n}{(E_p + E_n)^2}, \tag{6}$$

where E_p is number of positive rates of interaction and E_n is number of negative rates of interaction. 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:

$$B_i = \frac{R_i}{R}, \tag{7}$$

where R_i is number of BannerAgents of brand i in the BannerAgent's surroundings and R is total number of BannerAgents in the ConsumerAgent's surroundings.

The following set of impact parameters in the utility function is related to the consumer attributes. As stated above, the two most influential parameters are the consumer's gender and age.

$$D = \alpha A + \beta P, \tag{8}$$

where D is factors related to demographic attributes of ConsumerAgent; α is sensitivity of ConsumerAgent's age; A is ConsumerAgent's age; β is sensitivity of ConsumerAgent's gender to the choice of product; P is ConsumerAgent's gender.

The final member of the utility function comprises parameters related to consumers' attitudes and beliefs and to their perception of the website quality. It takes into account the perceptions of the quality of information on the products the consumer finds on the website, the quality of payment and ordering of goods, perceptions concerning the website design and advantages offered by online shopping. The last attribute of this member of the utility function describes the risk perception and trust of the website and the Internet as a shopping channel.

According to mathematical model presented in (Forsythe *et al*, 2006), we can define the ConsumerAgent's rating for the i-th online site (SellerAgent):

$$T_i = \beta_1 I_i + \beta_2 P_i + \beta_3 B_3, \tag{9}$$

where I_i is quality of information on i-th site; P_i is perception of site design and technical characteristics for i-th site; T_i is perception of the site design of i-th site; β_1, β_2, β_3 are parameters of sensibility (weights) generated in a random manner in the range from 0 to 1.

8. Simulation runs and results analyses

The observed simulation model is implemented in the NetLogo software. It was subjected to a number of experiments and data were 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).

The aim of the first simulation experiment (Figure 3a) was to show how each member of the utility function affect the basic indicators of B2C sales, market share and surf share. In the first stage of simulation experiment, all types of products have the same initial conditions for business. In Figure 3a (phase 1) we see that, after an initial oscillation, the SellerAgents' market share stabilises as well as surf share (Figure 3b, phase 1).

In the next phase of the simulation experiment, we observed the effect of eWOM on the output variables of the model. The graph in Figure 3a (phase 2) shows that the sales of best-selling products (yellow and blue) increased most rapidly. The increase in sales is expected market behaviour. The price of the products remains the same; however, consumers most often "comment" the best-selling products, which further improve 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

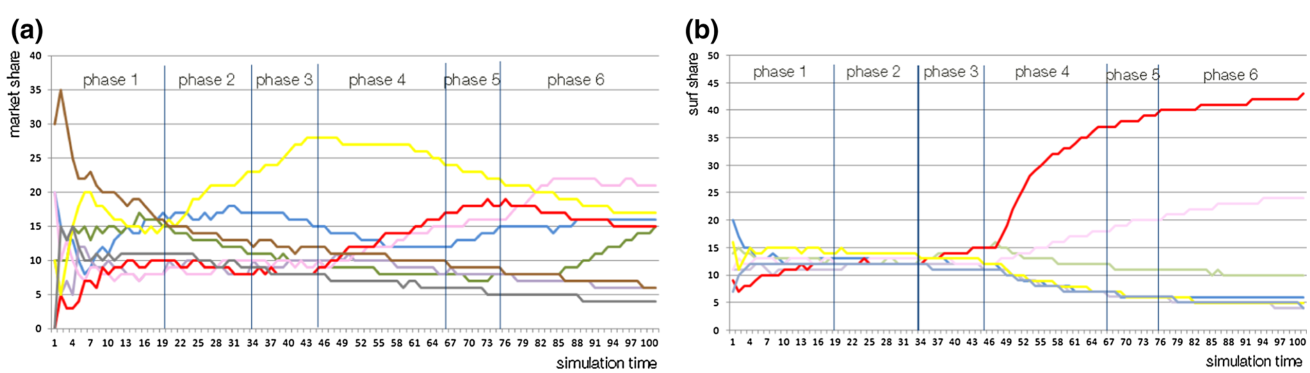

Figure 3 **a** Market share in the various stages of the simulation experiment. **b** Surf share in the various stages of the simulation experiment.

ConsumerAgents who have already purchased the observed product. The broader the radius, the more powerful the eWOM effect on the utility function becomes.

In the next stage of the simulation experiment, we include the effects of product marketing through BannerAgent generation. In this iteration, twenty "red" and fifteen "pink" BannerAgents were generated. Now we notice that the surf share on websites that sell the "red" and "pink" products has increased significantly. However, this type of advertising had very low effect on the increase in product sales Figure 3a, b, phase 3. This can be explained by the fact that the "red" and "pink" products have a very small market share; hence the eWOM effect on those products was modest, and the applied level of marketing has not been powerful enough to alter the situation to a more significant extent.

In the subsequent phase, the experiment continues to test the effect of increasing the "visibility" of the website. The "visibility" of SellerAgents with the lowest sales will be increased by generating additional five "pink" and "red" SellerAgents. We can also increase the "visibility" of SellerAgents by assigning search weights for "red" and "pink" SellerAgents. Thus, in their surfing through the Internet, the ConsumerAgents will encounter these SellerAgents more frequently, which will lead to a significant increase in the number of visits to these websites (Figure 3a, b, phase 4). The increased number of visits does not automatically mean the increase in sales. We can see in Figure 3a that the sales on the observed websites increase, however, far more slowly in comparison with the number of visits. 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. This should be taken into consideration when planning the site promotion costs.

The next member in the utility function refers to the technical characteristics of the Internet site and the consumer perception of the Internet site. Each of the quoted parameters is multiplied by weights whose values are set as input values into the model. As the experiment continues, weights are set on these parameters on the "blue" site. The results show (Figure 3a, b, phase 5) that as of that moment, the sales of blue product increase slowly, although the number of visits to this website does not change significantly.

In the final phase of the observed simulation experiment, we test the effect of the product price on the online sales. The prices of the best-selling "yellow" and the second best "blue" products increased by 5 and 3%, respectively, whereas the price of the "green" and "pink" brand decreased by 5%. Effects of these changes can be seen in the graphs in Figure 3a, b, phase 6. We can see from the graphs that these relatively small changes in prices do not have an immediate effect on the sales of the product; however, sales improve over time.

In the second simulation experiment, the idea was to observe the model's behaviour in the conditions where every SellerAgent conducts a different business strategy of participation on the B2C *online* market as shown in Table 3.

Table 3 SellerAgents input parameters

Type of SellerAgent	*Price*	*BannerAdvertising*	*Search weight*	*Visibility*	*Product information*	*Design and technical characteristics*	*Website trust*
Blue	100		5		10	10	10
Green	100			5	10	10	10
Turquoise	100	10			10	10	10
Pink	100		5		10	10	10
Red	95				10	10	10
Yellow	100	15			12	12	12
Brown	100			7	10	10	10
Grey	100	20	5		10	10	10

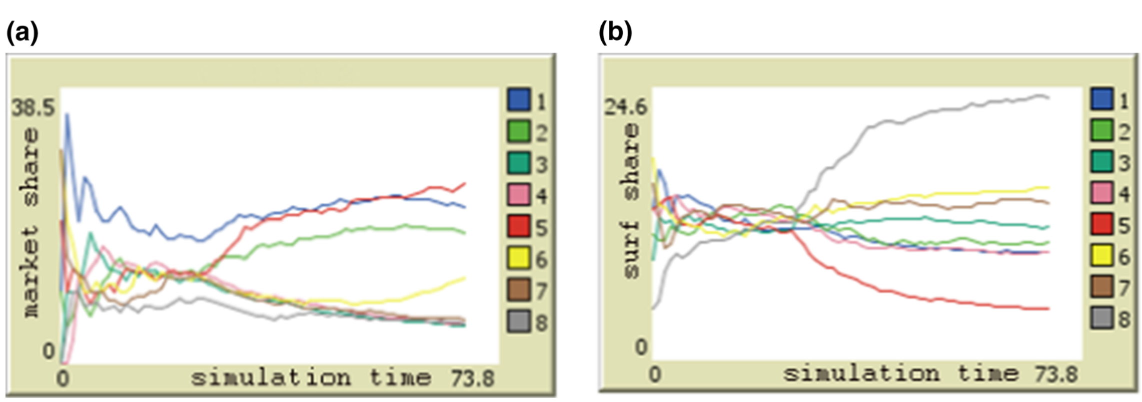

Figure 4 **a** SellerAgents market share. **b** SellerAgents surf share.

This experiment shows that the proposed simulation model can successfully simulate different business strategies and their effects on the market B2C online sales.

The data presented in Table 3 show that the "red" brand SellerAgent invested assets into a promotional campaign, the effect of which was price reduction. The SellerAgent who offers the "blue" product on the market invested in the website visibility on the Internet. The seller of the "green" product had similar investments. The SellerAgents of "turquoise", "yellow" and "pink" products invested their assets in online marketing, whereas the seller of the "yellow" product invested in the website quality and consumer trust. The "grey" seller invested substantial capital in marketing; however, he did not change the price of the product.

The key indicators of the online market behaviour, after the simulation experiment was completed, are presented in the graphs in Figure 4a, b.

We can see in the graph in Figure 4a that the sales of the "red" product is characterised by a continual growth and that, in time, this brand becomes the best-selling brand. Such a market share of the "red" product is consistent with the initial expectations that the most important impact factor affecting the market share of the online brand is the (low) price of the product. As the cheapest on the market, this product is attractive to all ConsumerAgents, especially to the red ConsumerAgents, who are most sensitive to product price. If we look at the graph in Figure 4b, we see that the surf share for the SellerAgent who sells the "red" product is extremely low. Such a low number of visits to the website in comparison to the other observed websites is probably a result of lower investments of this seller into other forms of marketing campaigns.

If the sales of the "red" SellerAgent are compared with those of the "blue" and "green" SellerAgents who also have high market shares, then there is a problem of justification of marketing campaigns based solely of the "low price" policy. The results show that the "blue" SellerAgent who invested substantially to increase the visibility of the site achieved a negligibly lower market share in comparison with the "red" SellerAgent.

The SellerAgent of the "grey" product, who invested the largest amount into marketing but did not reduce prices of the product, managed to considerably increase the surf share. However, he failed to increase the market share, i.e. the sales of his product, to the same extent. Similar behaviour can be found in the case of the "brown" seller.

It is interesting to analyse the behaviour of the "yellow" and the "green" sellers. The "yellow" seller invested in improving the site quality and consumer trust in the site, information quality and the technical characteristics of the site. The results show that this seller records a small but steady growth of market share throughout the simulation experiment.

We can conclude that, apart from investing in marketing, which increases the site visibility and pursuing the policy of "low" prices, online sellers have to invest in the development of the site and the services available on the site, thereby increasing consumer trust and satisfaction.

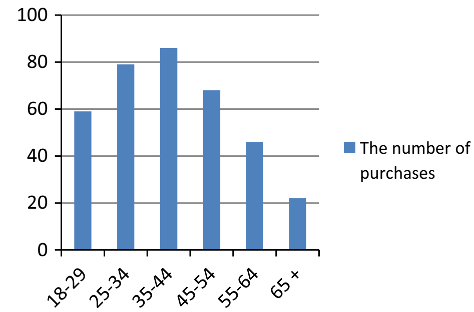

Figure 5 Consumer age structure diagram.

In addition to the results related to the sellers' market share and surf share discussed so far, the simulation model generates data related to consumers who purchased on the virtual market. The data on generated sales are collected in.txt files and, after the simulation, are available for analysis and further processing.

Figure 5 shows the consumer age structure in the observed simulation experiment. On the basis of data generated at the eklik.rs and eporodica.rs websites, we established the gender distribution of customers which demonstrates the equal number of female and male visitors to the website. The same applies to age structure of agent buyers. Depending on the type of the online market (type of products) we observe, it is possible to experiment with different demographic attributes of the consumers.

9. Conclusion

This paper addresses the analysis of consumers' behaviour and sellers' business strategies on B2C e-commerce systems by developing and applying agent-based modelling and simulation (ABMS). The continuous development in the field of e-commerce requires applications of advanced decision-making tools due to the large amount of data generated. Those tools should be able to process those data to enable easier and more efficient decision-making. An agent-based simulation enables the development of sophisticated models, which includes all relevant factors and key determinates of e-commerce systems behaviour. The simulation model examined in this paper can be used as a tool for evaluation of most common B2C online e-commerce systems. It allows evaluation of consumer behaviour and consequences of different e-business strategies.

The model includes a broad range of impact variables used to model all the relevant aspects of online consumer behaviour. 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. 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 based on the conceptual model of consumer behaviour established on research and theoretical grounds provided by a body of research in the areas of marketing, psychology, philosophy, management, economics and other related disciplines.

The simulation model enables the monitoring of all interactions between the SellerAgent, ConsumerAgent and BannerAgent by generating the indicators of B2C site business performance such as 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 results obtained in the simulation experiments can be successfully used to analyse the behaviour of B2C markets and to monitor the effects of different business strategies of online sellers.

It can be concluded that the designed e-commerce simulation model can be used as a powerful tool capable of gaining a better insight into consumers' behaviour on the Internet and behaviour of companies engaged in B2C e-commerce.

As shown in the paper, consumer decision-making on the Internet should be a continuous subject of research and study. Therefore, new insights and approaches open promising avenues of further research. With a number of important exceptions, the role of ethics, social responsibility and altruism on both the consumer and seller side, which are as a rule ignored in the models and theories discussed here, may also be a future research area in the elaboration of the existing model.

Statement of contribution This paper addresses the behaviour of consumers and business strategies of sellers in B2C e-commerce systems by applying the agent-based modelling and simulation (ABMS). It contributes to the theory and practice of simulation modelling by building the agent-based simulation models which could act as a tool supporting decision-making in electronic commerce. By linking the areas of modelling based on agents and electronic commerce, this paper addresses the new opportunities for a quality of assessment of consumer behaviour and reasons explaining this behaviour in e-commerce. 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 and is the original contribution of this work. 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 comprises four components. The first component relates to the price 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 third component takes into account the demographic characteristics of consumers in making a purchase decision. The fourth component takes into consideration a site visitor perception of a product which is based on the information available at the website. The simulation model implemented in the software NetLogo enables the monitoring of all interactions between the SellerAgent, ConsumerAgent and BannerAgent by generating the indicators of B2C site business performance (market shares, surf share and profitability). This model represents the original contribution of this paper. 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.

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