An Agent-Based Simulation of Payment Behavior in E-Commerce

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Abstract. The optimal configuration of an online store is a challenging task. Nowadays store managers decide on basis of their expert knowledge. This decision making is insufficient because their choices are often non-transparent and the effects of their decisions are difficult to predict. An example of this problem is the optimal configuration of payment methods that should be offered in an online store. In this paper, we focus on the problem of payment method configuration. We present an agent-based simulation that enables the simulation of the customer's payment behavior in order to support the decision-making process of store managers. We validate this simulation model by using data from real online stores and discuss the simulation results.

Keywords: Agent-Based Simulation, E-Commerce, Payment Behavior.

1 Introduction

The electronic commerce (e-commerce) on the Internet is for many enterprises an important channel of distribution in order to sell their products or to provide their services. Regarding the e-commerce between business and consumers (B2C), business transactions are typical realized by online stores (e-shops). The success of an online store depends among other on an optimal configuration of different aspects such as the shop layout, business processes, marketing activities, available payment methods, or the integration of third-party service providers.

The optimal configuration of an online store is a challenging task. The configuration requires precise knowledge about the interdependency between configuration parameters and the impact of these parameters within the e-commerce ecosystem. This interdependency is often multidimensional nature and includes dimensions such as technical, economics or social aspects. Today, store managers are responsibility for an online store and decide on basis of their expert knowledge about a configuration. Store managers have to configure in their (daily) business the store on basis of current trends or business objectives. Hence, they have to make decisions which might cause changes of the e-commerce system like pricing or marketing actions. These modifications directly influence the consumer

F. Klügl and S. Ossowski (Eds.): MATES 2011, LNAI 6973, pp. 41–52, 2011.

behavior and are reflected in key performance indicators such as conversion rate, business volume, or clickthrough rate. Due to numerous network effects, the store manager cannot forecast the consequences of his decisions. This is insufficient because their decisions are often non-transparent and the effects of their decisions are difficult to predict.

The shop configuration includes many aspects. Hence, we focus in a first step on the configuration of payment methods that should be offered in an online store. Today, there are a numerous payment methods. Out of these, a store manager has to identify the relevant ones that are accepted by the customers and suited for the business. Assuming the following scenario, a store manager wants to offer the possibility to pay with credit card. On the one hand, the credit card payment will attract new customers and thus, the sales volume will rise. On the other hand, regular customers will switch to the new payment method. This may have negative effects for other offered payment methods as they are mostly transaction-based. Hence, a lower number of transactions results in higher costs per transaction. After all, is it beneficial to integrate the credit card as an additional payment method?

An approach for the decision support is simulation. The simulation model represents the fundamental attributes of a system. This model is used to study the behavior of the system over time in order to draw conclusions about the behavior of the real system. As a result, different scenarios can be tested without changing the real system [1]. Since the customer acceptance is one of the critical factors for optimizing the payment methods, we want to develop a simulation model that forecasts the consumers' payment behavior according to the specific payment configuration. Typical question that we want to answer are, for instance: Does the integration of additional payment methods always result in new consumers? Are there payment methods that have a very high or very low consumer acceptance? Which is the configuration with the lowest dropout rate?

The paper is structured as follows. In the subsequent section, we describe our simulation model. We give first an overview of the entire simulation and present afterwards our agent-based payment simulation in detail. In Section 3 we calibrate and run our simulation in order to validate and evaluate the simulation results. In Section 4 we compare our simulation with other simulation approaches. Finally, we conclude in Section 5 with a discussion of our simulation approach and describe future work.

2 Simulation Model

2.1 Overview of the Shopping Simulation

The simulation of the payment behavior is part of a larger simulation chain. Before presenting the payment simulation in detail, we give a general overview of this simulation chain. We can essentially differentiate two parts: the customer group and the e-commerce system (see Fig. 1). The customer group represents people participating in online business as consumers. They have specific properties and a certain behavior. These customers can interact with the e-commerce

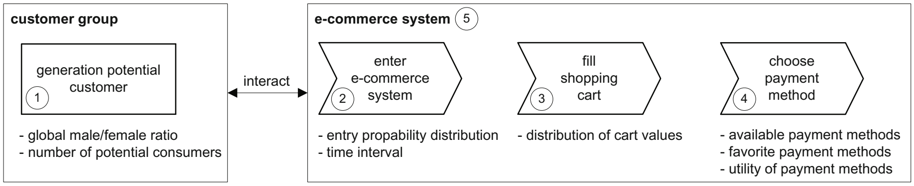

Fig. 1. Overview of the simulation components

system. The e-commerce system has also a specific behavior and is also described by abstract properties. The system behavior is defined by a process consisting of different activities. Each activity represents a point of interaction between the customers and the e-commerce system. Thus, each interaction point can be realized by an encapsulated simulation. This encapsulation enables the reuse or replace of individual simulations.

The complete simulation chain consists of five parts. (1) The first part generates the set of potential customers with a specific gender (female or male). Input parameters are the share ratio of gender and the number of customers who can participate in online business. (2) The second part simulates the shop entry of customers. Since from the potential customers, only a small number visits the shop. The entrance mainly depends on the gender and the time of entrance. Thus, we can define as input parameter the probability in dependency of the gender and time. This time differentiation enables the simulation of typical seasons such as Christmas or Easter. (3) The third part simulates the filling of the cart with a customer-specific cart value. The distribution of the cart values serves as input for the simulation and differentiates between male and female consumers. The cart values can be used to calculate economic key data according to the offered payment types. Moreover, it is possible to model a dependency between the cart value and the available payment methods. (4) The fourth part simulates the payment behavior of the customers. Input parameters are the preferred payment method of the customers, the available payment types, and the utility of the available payment methods. We provide a more detailed presentation of this simulation in the next section. (5) The fifth part of the simulation is the e-commerce system that serves as container for the aforementioned simulations two, three and four.

2.2 Simulation of the Payment Behavior

The objective of this simulation is to reproduce the payment behavior of customers in an online store in order to find the optimal payment configuration. The input of this simulation is a set of customers with a gender and a cart value. The output is customers with a certain payment method or a cancel of buying.

The assumed behavior of a typical customer is shown in Figure 2 as an UML activity diagram. A customer prefers to pay with her/his favored payment method and checks for the availability of this method. If the method is

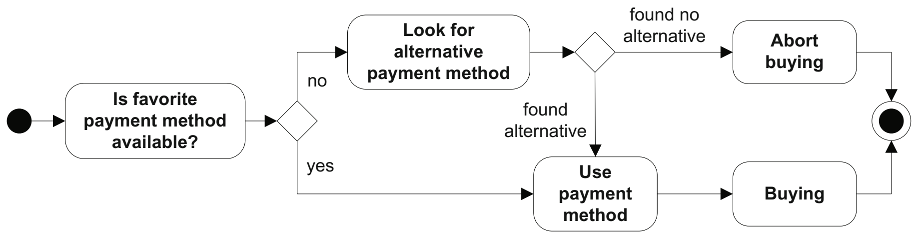

Fig. 2. Model of the payment behavior

available, then the customer will use this method and the payment process is finished. Otherwise the customer will cancel the buying or look for an alternative payment method in the shop. We define the function fav that yields the probability for a certain payment method Z_i (e.g. invoice, credit card, prepayment or cash on delivery) to be the favorite type of payment

$$fav : Z \rightarrow [0,1] \in \mathbb{R} \ . \tag{1}$$

Based on studies [2,3] and the evaluation of real payment data, we identify a dependency between the favorite payment method and the gender. For instance, credit card is preferably used by men and invoice is preferably used by women. Hence, we distinguish between the functions fav_m and fav_f for men and female, respectively. As the two functions fav_m and fav_f cannot be determine directly from the shop data, we have to derive these functions from the gender-neutral function fav. We assume the following two conditions. First, the gender-neutral favored payment method is the male-specific favored payment method times the probability that a consumer is male $P(male)$ plus the female-specific favored payment method times the probability that a consumer is female $P(female)$. Formally, this is defined as:

$$fav(Z_i) = fav_m(Z_i) \cdot P(male) + fav_f(Z_i) \cdot P(female) \ . \tag{2}$$

Second, the ratio $r(Z_i)$ of the payment method Z_i is specified as the quotient of $fav_f(Z_i)$ and $fav_m(Z_i)$, formaly defined as:

$$r(Z_i) = \frac{fav_f(Z_i)}{fav_m(Z_i)} \ . \tag{3}$$

Based on equation (2) and (3), we derive the favorite payment method for men and women as follows:

$$fav_m(Z_i) = \frac{fav(Z_i)}{P(male) + r(Z_i) \cdot P(female)} \tag{4}$$

$$fav_f(Z_i) = fav_m(Z_i) \cdot r(Z_i) \ . \tag{5}$$

If the favored payment method is not available, then the customer will look for an alternative payment method in the shop or cancel the buying. The customer decides on basis of a certain probability for an alternative payment method. This decision essentially depends on the utility of a payment method which is gender-neutral and described by the following function:

$$utility : Z \rightarrow \mathbb{R} \ . \tag{6}$$

In the literature, there are different approaches for modeling the consumer specific decision process using a utility for each alternative. We use the so-called Luce model [4] which is defined as follows:

$$P(Z_i) = \frac{utility(Z_i)}{\sum_{i=1}^{n} utility(Z_i)} \ . \tag{7}$$

Finally, if the customer finds one or more alternative types of payment, then he will choose those alternatives with the specific probability and the purchase process will end. In case she/he does not find an appropriate alternative, this will lead to the abort of the purchase and the termination of the payment process.

2.3 Agent-Based Implementation of the Shopping Simulation

In the course of time, several simulation techniques have been developed. A relatively new method is multi-agent simulation which has become a common approach for simulation in social science [5]. This technique uses intelligent agents for the modeling of complex systems. Agents are entities in a certain environment with a limited perception of their environment. They are capable of doing autonomous actions and interactions with other agents in order to delegate their objectives [6].

Multi-agent systems are widely-used in the field of retailing. The heterogeneous behavior of the customers and their several interactions are well supported by the agent-based paradigm. The underlying bottom-up approach allows for a realistic modeling of consumer behavior. Furthermore, the approach enables the usage of user-specific information collected from real systems such as Customer Relationship Management (CRM) or e-commerce systems.

We apply the agent-based approach for modeling the heterogeneous payment behavior depending on specific attributes. The implementation of a multi-agent system is usually done by means of agent-based modeling platforms. Today, there is a large number of such platforms available, see [7] or [8] for an overview of various toolkits. We use SeSAm (Shell for Simulated Agent Systems) to implement the different parts of our shopping model. This open source tool supports a visual programming of the implementation. The behavior of the agents is specified using an activity graph derived from UML [9].

The customers are modeled as agents. We specify the general class customer and derive two special classes thereof. One represents male consumers, the other characterizes the female consumers. The e-commerce system and its relevant attributes are modeled as the environment of the agents. Resources are not used within the model. The information exchange between the different parts of the shopping simulation is realized via comma-separated files.

3 Validation of the Payment Simulation

3.1 Calibration

In order to run and validate the payment simulation, we have to calibrate the input parameters with initial values. These values based mainly on German studies about the payment behavoir and real data from available online stores.

First, our model contains the four payment methods: invoice (Z_1), prepayment (Z_2), credit card (Z_3), and cash on delivery (Z_4). These types of payment are widely-used in Germany. Furthermore, we set the number of customers to 100.000. In order to study the gender-specific payment behavior, we use the following gender ratio female/male: 23/77 and 77/23. Next, we define the function fav by the co-domain shown in Table 1. The values are adopted from the study [2]. Based on these gender-unspecific values, we calculate the function values for men (fav_m) and women (fav_f). For calculating these values, we need the ratio r of the favored payment methods in dependency of the gender. The ratio is shown in Table 2 as the result of an analysis of real shop data. Further, we need the *utility* function as an input parameter. The values of the distinct payment types are defined in Table 3. These values are derived from a study [3]. In this study customers evaluated different payment methods with the grade 1 (very well) till 5 (bad). The utility value is the percentage rate of the customers who gave a grade better than average grade 2.6.

3.2 Simulation Run and Validation

We run the simulation experiment 30 times with the input parameters described in the section above, ten with a gender ratio of 23/77, ten with 50/50, and ten with 77/23. Due to the lack of space, we only show the simulation results produced with a gender ratio 23% female and 77% male. In our evaluation (see Sec. 3.3), we also include the inverse and fifty-fifty gender ratio and. The average of the simulation results is shown in Table 4. We validate the results by using the values from this study [2] and real store data. The study includes seven configurations of payment methods that are shown in Table 5. If we compare the results of the study with the results of the proposed simulation model, then four configurations exactly coincide and only three configurations have differences. A detailed comparison shows in Table 6 the absolute and relative errors.

Table 1. Probability distribution of the favorite payment method depending on the gender

Gender	Invoice (Z_1)	Prepayment (Z_2)	Credit Card (Z_3)	Cash on Delivery (Z_4)	Cancel
neuter	0.65	0.04	0.23	0.03	0.05
male	0.62	0.04	0.26	0.03	0.05
female	0.77	0.03	0.13	0.02	0.05

Table 2. Ratio r between $fav_f(Z_i)$ and $fav_m(Z_i)$ of the several payment methods

Invoice (Z_1)	Prepayment (Z_2)	Credit Card (Z_3)	Cash on Delivery (Z_4)	Cancel
1.20	0.66	0.52	0.53	1

Table 3. Utility of payment methods ($utility(Z_i)$) based on [3]

Invoice (Z_1)	Prepayment (Z_2)	Credit Card (Z_3)	Cash on Delivery (Z_4)	Cancel
0.96	0.09	0.29	0.12	0.3

The maximum of all absolute errors is three percentage points (see Tab. 6, Z_2, Config. 3) and the maximum of all relative errors is 18% (see Tab. 6, Z_2, Config. 9). The payment method with the biggest relative errors is prepayment with three relative errors more than ten percent (see Tab. 6, Z_2, Config. 3, 9, and 13). All other types of payment have a relative error that is less than five percent. In summary, one can state that the presented simulation has a high conformity with the results of [3]. If we involve the rounding error, then we can substantiate this statement. The values of the study are rounded on two decimal places and the absolute error can be as minimum 0.01. For instance, this can be in the case of payment Z_2 a reason for the high relative error. In general, we conclude that our model is correct.

3.3 Evaluation of the Simulation Results

In this section, we analyze the simulation results of Table 4 with regard to the questions of Section 1. First, the results show, if more payment methods are offered, then the dropout rate is lower. On average, if only one payment type is available, then 50% (see Tab. 4, Config. 2–5) of the consumers cancel the payment process. If two payment methods are offered, the average dropout rate is 26% (see Tab. 4, Config. 6–11). For three offered types the value is 13% (see Tab. 4, Config. 12–15) and if all payment methods are available the dropout rate is only 5% (see Tab. 4, Config. 16). The values remain constant if the rate of female customers is raised. Moreover, the table shows that every payment method is accepted by at least 24% if it is the only one offered.

Furthermore, the results indicate that the purchase on invoice has the highest rate of acceptance. More precisely, if purchase on invoice is offered, then the dropout rate is with less than 15% small (see Tab. 4, Config. 2, 6, 7, 8, 12, 13, 14, and 16). The other types of payment cannot replace purchasing on invoice, even if all alternatives are available the dropout rate is 29% (see Tab. 4, Config. 15). If the rate of female consumers is increased, then this observation is strengthening. If 77% of the customers is female, then the dropout rate for purchase on invoice is only 10%. The dropout rate in case that all other alternatives are available is 32%.

Table 4. Simulation results of the several configurations of payment methods (payment methods: Z_1=Invoice, Z_2=Prepayment, Z_3=Credit Card, Z_4=Cash on Delivery; payment configuration: 0=off, 1=on)

Config.	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4	Cancel
1	0	0	0	0	-	-	-	-	1.00
2	1	0	0	0	0.88	-	-	-	0.12
3	0	1	0	0	-	0.24	-	-	0.76
4	0	0	1	0	-	-	0.59	-	0.41
5	0	0	0	1	-	-	-	0.28	0.72
6	1	1	0	0	0.84	0.06	-	-	0.10
7	1	0	1	0	0.69	-	0.24	-	0.07
8	1	0	0	1	0.84	-	-	0.05	0.11
9	0	1	1	0	-	0.13	0.52	-	0.35
10	0	1	0	1	-	0.19	-	0.23	0.58
11	0	0	1	1	-	-	0.52	0.14	0.34
12	1	1	1	0	0.67	0.04	0.23	-	0.06
13	1	1	0	1	0.81	0.05	-	0.04	0.10
14	1	0	1	1	0.67	-	0.24	0.03	0.06
15	0	1	1	1	-	0.11	0.47	0.13	0.29
16	1	1	1	1	0.65	0.04	0.23	0.03	0.05

Finally, we close the evaluation with the following observations. The results of Config. 6 and Config. 13 illustrate that the adding of additional payment methods does not always lead to new consumers. In this case the type cash on delivery is added but the dropout rate remains with 10% constant. The configurations 12 and 14 show that one payment method can substitute another. In this example, prepayment and cash on delivery are able to replace each other. Similar effects appear if the rate of male and female consumers is changed. If half of all consumers is female and purchase on invoice and credit card are offered, then cash on delivery can be omitted without raising the dropout rate. Furthermore, prepayment and cash on delivery will replace each other if purchase on invoice

Table 5. Reference values [2] (payment methods: Z_1=invoice, Z_2=prepayment, Z_3=credit card, Z_4=cash on delivery; payment configuration: 0=off, 1=on)

Config.	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4	Cancel
1	0	0	0	0	-	-	-	-	1.00
3	0	1	0	0	-	0.21	-	-	0.79
6	1	1	0	0	0.84	0.06	-	-	0.10
9	0	1	1	0	-	0.11	0.53	-	0.36
10	0	1	0	1	-	0.19	-	0.23	0.58
13	1	1	0	1	0.80	0.06	-	0.04	0.10
16	1	1	1	1	0.65	0.04	0.23	0.03	0.05

Table 6. Absolute and relative error of the several configurations (payment methods: Z_1=invoice, Z_2=prepayment, Z_3=credit card, Z_4=cash on delivery; payment configuration: 0=off, 1=on; error: Δ=absolute error, δ=relative error; direction: ↓=simulation value < reference value, ↑=simulation value > reference value)

Config.	Z_1	Z_2	Z_3	Z_4	Z_1 Δ	Z_1 δ	Z_2 Δ	Z_2 δ	Z_3 Δ	Z_3 δ	Z_4 Δ	Z_4 δ	Cancel Δ	Cancel δ
1	0	0	0	0	-	-	-	-	-	-	-	-	0	0%
3	0	1	0	0	-	-	0.03	14% ↑	-	-	-	-	0.03	4% ↓
6	1	1	0	0	0	0%	0	0%	-	-	-	-	0	0%
9	0	1	1	0	-	-	0.02	18% ↑	0.01	2% ↓	-	-	0.01	3% ↓
10	0	1	0	1	-	-	0	0%	-	-	0	0%	0	0%
13	1	1	0	1	0.01	1% ↑	0.01	17% ↓	-	-	0	0%	0	0%
16	1	1	1	1	0	0%	0	0%	0	0%	0	0%	0	0%

is the only alternative. If 77% of all consumers is female, then similar effects can be observed.

4 Related Work

Multi-agent models are widely-used to simulate customer behavior. Moreover, agent-based computational economics is a separate research field which uses agent-based systems to study economies that are emerge from individual decisions of autonomous agents and their interactions [10]. In the following, we discuss four approaches for model consumer behavior.

A relevant contribution to our work has come from Rigopoulos et al [11]. The authors describe a multi-agent system for the acceptance of payment systems. The customer decision process of choosing a payment method is also simulated using the utility theory. The consumer calculates the utility of each available payment method resulting in a probability vector including an adopting probability for each payment method. In opposition to our model, the utility of a payment method depends on several consumer-specific attributes. Another difference is the application area. Rigopoulos et al. focus on digital retail payments in general, whereas our model addresses the payment process in online stores. Since the model described in [11] is developed to support the strategic decisions of banks and other payment service providers, it is also possible to forecast the success of new payment methods. Our model considers the most widely-used payment methods of the German market.

The agent-based simulation technique is also used to model the behavior of customers in a supermarket [12]. In conformity with our approach, the authors characterize every customer agent with specific attributes such as gender. Additionally, each consumer is characterized by a set of feature agents. Every feature agent represents a single parameter of the consumer's behavior and is modeled as an autonomous agent. The interaction of the feature agents yields the shopping behavior of the customer. Consequently, the utility theory is not used within this model. Another difference is in the modeling of the shopping process. The model presented in [12] addresses the purchasing behavior in general, whereas we primarily focus on the payment process.

A multi-agent system for optimization of promotional activities is described in [13]. Using this simulation, the effects of different points in time and target groups can be studied for the market penetration of new products. Each consumer is represented by an agent. Furthermore, the decision of adopting a new product is modeled by using the utility theory, analogous to the simulation model presented in this paper. In [13] the utility of a new product consists of an individual preference and a social influence whereas the second factor is not considered for choosing the preferred payment method.

Another example of modeling consumers as autonomous agents within a multi-agent system is described in [14]. The authors propose a model which can be used by sellers to determine the optimal mail-in rebate for different products depending on their prices. In contrast to our model, the model in [14] does not include the payment process. A special feature of their work is the fact that the agents gain experience about the used mail-in rebates and take this into account for future decisions. Such learning effects are currently not implemented in our approach.

5 Conclusion and Future Work

5.1 Summary

Multi-agent simulation is a technique that uses the bottom-up approach to model complex systems. Hence, multi-agent simulations are widely used to model customer behavior. We propose an agent-based model for the simulation of the shopping process in online stores. The developement of the model based on the expert knowledge from shop managers, past payment data from real online stores, and several studies. Our description focus on the forecasts of the consumers payment behavior in order to support store managers in their decision making process. We use five parts to model the shopping process. This modularity simplifies the adaptability to other e-commerce systems. For instance it is possible to add additional components that are relevant for modeling the consumer behavior. In some cases the customers have to register in the e-commerce system in order to use additional types of payment.

Further, we have validated the simulation results and have shown the correctness of this simulation. Only the method prepayment shows a high relative error in some configurations. From the viewpoint of a shop manager, we evaluated the simulation results and derived some regularity in the payment behavior. We point out that the behavior of the consumers is based on data of the German market. Since the payment behavior differs greatly between countries, the applicableness of e-commerce systems outside the German market has to be checked.

5.2 Future Work

The proposed simulation focuses on the consumers' payment behavior. Nevertheless it is possible to calculate the business volume of a certain time interval according to different payment configurations because the entering in the online store and the filling of the shopping cart are also parts of the model. In order to forecasts the profit of different scenarios the shopping simulation has to be extended. Hence, one of our next steps is the integration of the specific costs (fixed costs and transaction costs) of each payment method. We intend, further, to develop an additional module that simulates the customer-specific risk of non-payment.

The presented model considers only four payment methods namely purchase on invoice, prepayment, credit card and cash on delivery. Thus, the adding of further payment methods is an essential task for future modeling. Moreover, there are various aspects that need refinement of the consumer behavior. Our initial model differentiates between male and female customers. The distinction with respect to additional attributes like age, salary or order frequency is future work. Moreover, modeling the experience of customers and the influence of selecting a payment method is also a future task.

We model the process of choosing an alternative payment method by using a general utility for every type of payment. We intend for every attribute that affects the decision process of a consumer (e.g. security, speed or consumer-specific costs) to use several utility functions. The refinement of the utility function belongs also to our future work.

Acknowledgments. The work presented in this paper is undertaken as a part of the SimProgno project (01IS10042C). SimProgno is funded by the German Federal Ministry of Education and Research.

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