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The Role of Individual Behavior and Social Influence in Customer Relation Management.

Jerzy Surma

Handbook of Research on Managing and Influencing Consumer Behavior

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Chapter 16

The Role of Individual Behavior and Social Influence in Customer Relation Management

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ABSTRACT

One of the crucial trends in business is to offer one-to-one personalized services. In this context, companies try to build customer relationship management systems based on the customer social relations and behavioral patterns. The key issue is predicting to which products or services a particular customer is likely to respond. Additionally, identifying peer-to-peer influence on social network sites is critical to a social media marketing strategies. That is why companies have to learn to understand their customer in the broader social context in order to build successful Customer Relationship Management (CRM) systems, which are described in this chapter. In those systems, the individual customer behavior patterns can be used to build an analytical customer profile. Based on the profile, a company might target a customer with a personalized message. In this chapter, the authors use four research studies in order to extensively present this issue.

INTRODUCTION

Living in contemporary world, we leave thousands of digital footprints behind us through usage of mobile phones, credit cards, electronic mail, browsing in social networks etc. Each footprint shows our real actions that we take in given time and place. The analysis of thousands of such footprints on large groups of people allow us to analyze human behavior on an unimaginable before scale in scientific studies concerning psychology and sociology (Lazer, 2009). The results of those analysis will have a significant influence on many disciplines such as medical prophylaxis, political elections or contemporary marketing in personalized customer relationship management. In this context it is interesting to look at the summary of historical development of customer management by Kumar (2008). It begins with direct relations with individual customers, then entire-market customers, segmented customers and finally the return to the initial idea of personalized service

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usage of interactive marketing (Deighton, 1996). Additionally in light of the current social media marketing challenges the focus switched to digital word-of-mouth (WoM) communication and/or consumer-to-consumer campaigns. Based on this interactive marketing should be extended to use social networks in order to support achieving marketing objectives through social influence (Trusov, Bodapati, & Bucklin, 2010).

According to Kumar, interactive marketing can be described as follows (Kumar, 2008):

1. **The Range of Decisions:** Identification of interested customers and assuring on-going relations or relations at proper time.
2. **The Range of Analysis:** Elaborating the complete characteristics of the customer.
3. **Value Building Factor:** Personalization and adapting proper service at a proper time.

The usage of customer behavior in marketing has a relatively long history. Analytical customer relationship management systems have been used in telecommunications and banking sector since the 90s of the previous century (Shankar & Winer, 2006). In this perspective, new type of data about diversified customer behaviors introduces new opportunities in contemporary marketing. This new potential, related to the development of Business Intelligence systems (Surma, 2011), has contributed to the development of personalized marketing concept based on profound analysis of history of contacts with customer[1].

It is important to underline an impact of social influence on the customer behavior. Identifying peer-to-peer influence on social network sites is critical to new social media marketing strategies (Aral & Walker, 2011). Social influence studies are described extensively in Cialdini and Goldstein (2004) paper, and a potential marketing application in on-line social networks are presented in Trusov (2010) research. Social influence mechanisms are widely deployed by companies to develop advertising messages for mass media. Showing people who somehow resemble the message's recipient, or on the contrary – members of a group to which the recipient aspires, can be perceived as an example of the use of social influence mechanisms. Currently, it is possible to customize advertising messages, based on the given consumer's level of susceptibility to social influence. Social relationships maintained by the users in on-line social networks to a large extent reflect their personal relationships maintained in the real world. Users perceive other participants as a source of information and aim at identifying with the group (Deutsch & Gerard, 1995).

CUSTOMER PROFILING

From Segmentation to Personalization

In order to understand properly new analytical opportunities in marketing, it is crucial to differentiate correctly the classic approach based on customer segmentation (see Figure 1) in comparison to personalized approach related to interactive marketing (see Figure 2). In case of segmentation, the division of customers is done usually on the basis of social-demographic characteristics (e.g., sex, age, education, place of residence) and the analysis of the purchase history, using the RFM[2] analysis. In this approach, the customer is classified to the segment as a similar object to other members (objects) of the segment[3]. All customers in a given segment, in a given marketing campaign receive the identical message, irrespective of the differences between them. The time and the method of delivering the message is chosen arbitrarily by the manager of marketing campaign and is the same for the whole segment. In this approach we usually don't reflect value changes of customer characteristics in time and we treat the whole segment as static and homogeneous group of objects.

Figure 1. Classical marketing based on the customer segmentation: "Propose a customer to a product"
Source: Author.

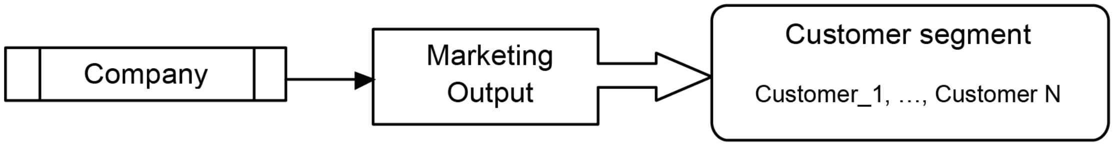
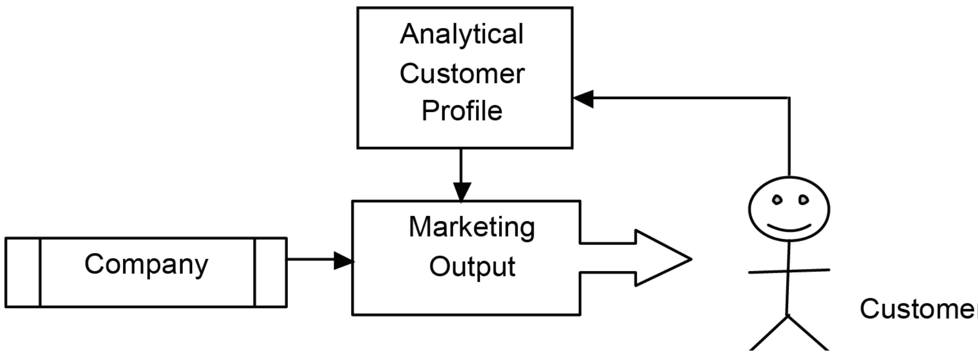


Figure 2. Interactive marketing based on the personalization: "Propose a product for a customer"
Source: Author.

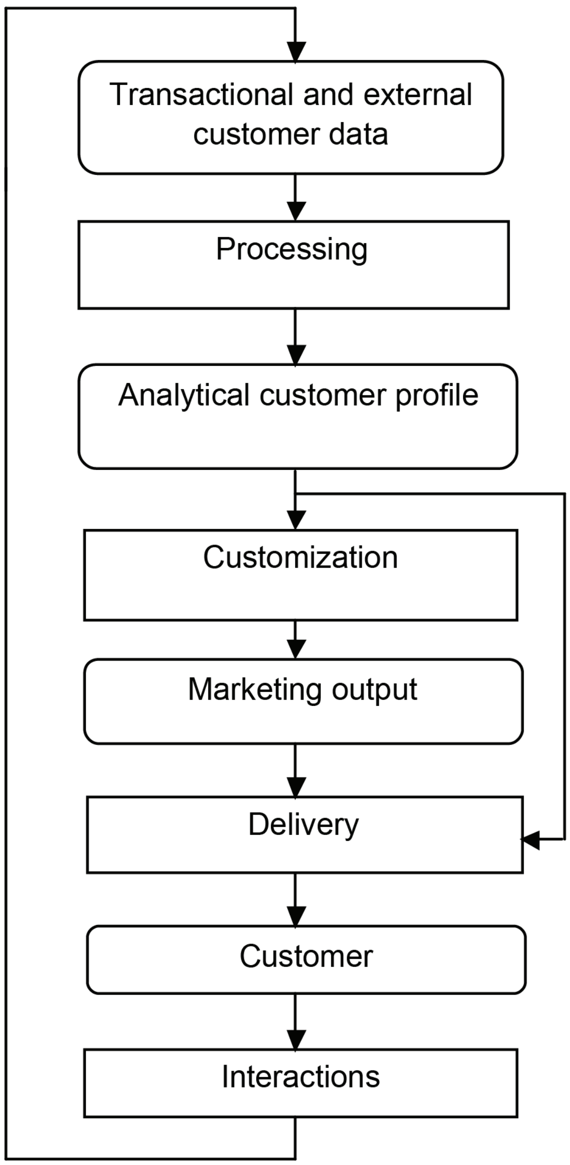


The interactive approach to customer management is significantly different (see Figure 2). Customer is treated as an independent person that has specific needs and preferences. The company wants to get to know the characteristics of the customer through conversations, maintaining the relationship (Kumar, 2008), as well as collecting and analyzing the digital footprints that customer leaves behind him in different interactions. It is well known that customer responds to a given marketing message is not happening in a vacuum. Many factors contributed to this decision, such as psychological variables (motivation, perception, learning, attitude, personality/lifestyle), social influence (family, social class, reference groups, culture), and purchase situation (purchase reason, time, surroundings) (Perreault, Cannon, & McCarthy, 2009). However, most factors that contribute directly to customer response cannot be captured and stored in corporate databases. The possible way to reflect these response factors is to relate them mainly to customer behavior patterns and available social relations data. As a result of this pattern analysis, it is possible to create the Analytical Customer Profile (Surma, 2012). On the basis of this profile, we can adjust the marketing offer to specific customer needs. The time and the method of delivering the message is determined by the customer preferences. As opposed to segmentation, the contact with customer is activated indirectly by the customer himself through the ongoing process of the prediction of his needs. In this approach, it is crucial to observe the behavior of the customer in time and to analyze the dynamics of the values of the characteristics represented in the profile. Next we will demonstrate the phases of contact personalization with customer and the idea of the customer analytical profile concept.

Personalization Process

The process of personalization, which is based on the analytical customer profile, is shown on Figure 3. The whole process consist of four phases (Versanen & Raulas, 2006):

Figure 3. The process of personalization
Source: Versanen and Raulas (2006).



1. **Processing:** Transform transactional and external client data into analytical customer profile. Customer profile is generated based on the econometrical and data mining methods (Chiu & Tavella, 2008).
2. **Customization:** Is the production of personalized marketing output due to:
   a. Selection of the proper product/service offer based on the customer needs (*hyle*),
   b. Development of the personalized marketing message, that is adequate to the customer preferences (*morphe*).
3. **Delivery:** Procedure how the personalized marketing output reaches the customer. During this phase an access channel and time of delivery is established. Those parameters are forecasting based on the customer preferences taken from customer profile.
4. **Interactions:** Recognized and registered customer behavior taken from two sources:
   a. **Internal:** Response for delivered marketing output, click stream on the company internet portal, personal data deliver into registration forms, contacts with call center, registered purchases, exchange opinion with others customers on the company blog, etc.
   b. **External:** Activities on the external online social networks [4], transactions in the loyalty programs with a business partners, customer data received from external marketing databases, etc.

The Structure of Analytical Customer Profile

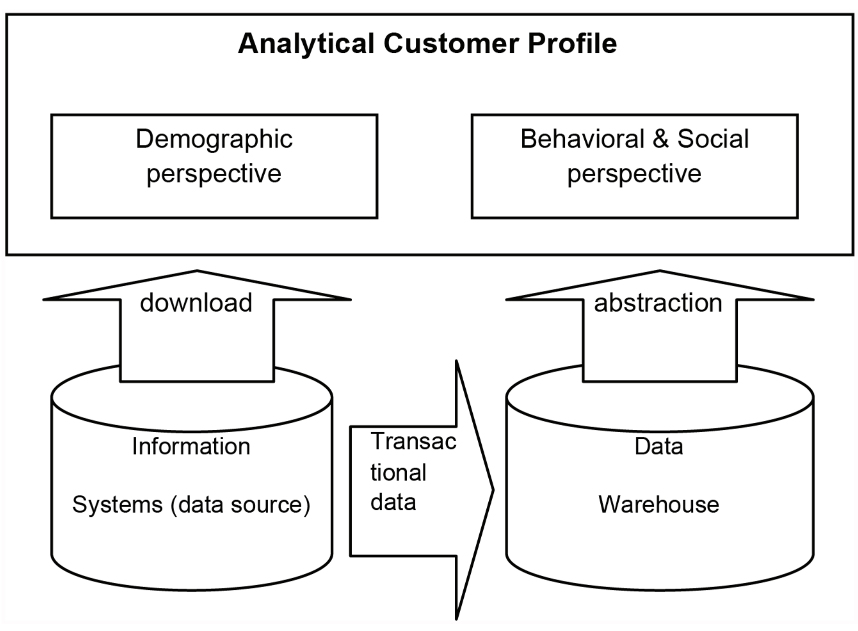
The main aim of personalization process (see Figure 3) is to deliver adequate marketing messages to the customer in proper time. We assume that it is possible to predict customer behavior on the basis of the history of his behaviors and social influence. It is crucial to established which variables describing the customer should be processed and whether there is appropriate transactional data available.

The analytical customer profile is a result of abstraction (generalization[5] and aggregation[6]) of interactions (time series of customer transactional data, as well as other social-demographic data) in order to generate adequate marketing messages[7]. The characteristics (variables) stored in analytical profile generally belong to one of two perspectives (see Figure 4):

- **Demographic Perspective:** Built on the basis of data declared by customer and received from official contacts with customer. This data is mainly statistics (e.g., place of birth). However some of them are subject to change in time (e.g., place of residence, education).
- **Behavioral and Social Perspective:** Build on the basis of behavioral data left by customer during interactions with the company, other customers, and social environment. This data is mainly dynamic.

The successful prediction of customer behaviors is possible only when analytical profile really reflects motivations and attitudes that determine customer decisions. Those motivations and attitudes result from a human nature of analyzed person and are in reality responsible for her actions (Nisbet, Elder, & Miner, 2009). The interactions reflected in transactional data can be compared to shadows (*σκιά*) of Plato in the cave (Plato, 2007). If we continue this metaphor, the analytical profile is built on the basis of "shadows" and as defined it is rather imperfect attempt to model human behavior. However, we have to underline three conditions that are favorable to build profiles. First of all, transactional data represents real actions, as opposed to declared information. Secondly, it is the long term, often longstanding abstraction of transactional data that is the key of analytical profile. In this context, the level of credibility of knowledge about customer is increasing according to the length of data collecting period. Finally, the wide range of collected transactional data is also important: from the data available inside the company, through the public data available e.g., on on-line social networks, to data retrieved from customer profiles from other companies.

Figure 4. The structure of analytical customer profile
Source: Author.



Profile Analysis

The business dimension of personalization requires a proper analysis of client profitability in time, i.e., the calculation of profits from sale per customer in comparison to average costs spent on his service. When every customer is unequivocally identified and monitored with the usage of analytical profile, it is possible to calculate the indicator of past customer value and to estimate the indicator of customer lifetime value (Kumar, 2008). The indicator of past customer value allows among others the precise monitoring of customer profitability, in which we can compare the positive cash flows earned thanks to the knowledge from analytical profile and the individual costs of building and maintaining the analytical profile. The usage of analytical profile allows us to calculate the indicator of lifetime value, which is related to prediction of future customer margins and future costs (taking into account changes in time value of money). The prediction of "what and when" customer is willing to buy is in this context a key element[8].

Prediction models determine which characteristics (variables) should be represented in analytical profile. This set of variables can differ according to type of products or sector etc. The usage of models that suggest a given customer the most probable purchase and its time allow the personalization management system (after the update of analytical profile) to pass on to customization phase. Afterwards it is possible to activate automatically the phase of delivering the marketing message to customer at proper time [9]. In this context we can talk about the activity of analytical profile whether the process was automatic or was directly monitored by marketing department. In this approach, the analytical profile (as a real customer representation) generates declaration of realization of personalized, 1-to-1 marketing campaign. Everyday management of large volume of unique declarations is a new and nontrivial management problem, i.e., event driven process management.

RESEARCH STUDIES

In this chapter four research studies are presented. Those projects were carefully selected in order to present the recent research in customer profiles analysis and the social influence (see Table 1).

Proactive Customer Relationship Management

We have already shown the trend to transform customer relationship management activities from campaign-centric (static and old fashion approach) to customer-centric, where the company needs to develop detailed knowledge about customers. This approach requires the continuous development of customer profile, and then to apply marketing interventions that are relevant to the status and preference of each individual customer. In this context Sun, Li, and Zhou (2006) proposed the framework of proactive CRM based on the

Table 1. Research studies characteristics

Study	Social Influence	Customer Profile Management	Source
Proactive Customer Relationship Management	No	Yes	Sun, Li, and Zhou (2006)
Social influence in on-line social networks: Cyworld	Yes	No	Raghuram, Han, and Gupta (2009)
Social influence in on-line social networks: Facebook	Yes	No	Aral and Walker (2012)
Customer referrals in financial services	Yes	No	Kumar, Petersen, and Leone (2010)

Source: Author.

adaptive learning. Adaptive learning offers the company the opportunity to learn about customer preferences in an uncertain environment and adapt its strategies in a real-time fashion. Formally they formulate CRM intervention decisions as a solution to a stochastic dynamic control problem under demand uncertainty with built-in customer reactions. The adaptive learning component allows to derive an integrated sequence of CRM decisions about *when* to contact *which* customer with *what* product using which communication channel (*how*). This approach was empirically tested on the cross-selling campaign management for a retail banking services in a national bank (Li, Sun, & Montgomery, 2005). The data set consist of monthly account opening and transaction histories, cross-selling solicitations about the type of product promoted, communication channels, and demographic information of a randomly selected sample of 4000 households for 15 financial product groups during a total of 27 month.

The effectiveness of a cross-selling campaign was improved from 5,6% to 11,2%. The return on investment on performed campaigns was improved by 40,8%, and demonstrate the increase of long-term profit when the company shifts its cross-selling strategy from campaign centric to customer centric. This research justifies the approach in which the company is able to maximize long-term profit based on the dynamic and customized decisions generated from time series of information about the customer.

Social Influence in On-Line Social Networks: Cyworld

Cyworld[10] is a South Korean social network service operated by SK Communications. With over 18 million users out of a 48 million population (with 33 million Internet users) Cyworld is South Korea's leading social network. Created in 1999 when the online advertising market was not enough to sustain a website, and when valuations of online communities was unheard of, Cyworld had to come up with innovative business models, services and pioneered many functions which are gradually being "rediscovered" elsewhere. Raghuram, Han, and Gupta (2009) performed the research on Cyword with three questions (a) do friends influence purchases of a user in a social network ? (b) which users are more influenced by social pressure ? and (c) what is the impact of this social influence in sales and revenues. To address these questions they developed a quantitative model that capture the effect of social influence on a member's decision purchase. The Cyworld users can decorate their own mini-home pages by purchasing virtual items[11]. Based on that the transactional (purchasing) data for building the model was taken by monitoring behavior of over 200 users for several months.

The final results show that there is a significant and positive impact of friends purchases on the purchase probability of users. They found significant heterogeneity among users. Deep examination reveals differences across three user groups: positive (40%), negative (12%), and zero (48%) social effect. Users who have limited connection to other members are not influenced by friends purchases. Positive social effect, translated into a 5% increase in revenue, was observed in moderately connected users. These users are imitating others behavior. In contrast to this group, highly connected users tend to reduce their purchases of items when they see their friends buying them. This negative social effect reduces the revenue for this group by more than 14%. These empirical results are relevant for social networking sites. The members in high status group have an influence on those in the middle status group for the diffusion of a new product.

Social Influence in On-Line Social Networks: Facebook

The econometrical identification of social influence is a difficult problem, especially in the case of which separation of correlation from causation in networked data is complicated (Aral, 2011). In the mentioned research on Cyworld this problem is not solved. Aral and Walker (2012) research based on experiments give an opportunity to identify influential and susceptible individuals in large social networks with a clear separation causation from correlation. They proposed an experiment on Facebook that was conducted over a 44-day period. At the beginning of the experiment, they ran an advertising campaign to recruit a representative population of Facebook users to the experimental application. Advertisements were subsequently displayed to users through advertising space within Facebook and within existing Facebook applications in such a way as to maximize the likelihood that representative proportions of the demographic characteristics of Facebook users were captured. The campaign was conducted in three waves throughout the duration of the experiment to recruit a population of experimental subjects that consisted of 7730 application users (continued to fully install and use the application sufficiently to grant permission for the application to send notifications on their behalf) and 1.3M distinct peers, resulting in 976 peer adoptions.

The main results were as follows: younger users are more susceptible to influence than older users, men are more influential than women, women influence men more than they influence other women, and married individuals are the least susceptible to influence in the decision to adopt the product offered. Additionally experimental results show that the joint distributions of influence, susceptibility, and the likelihood of spontaneous adoption in the local network around individuals together determine their importance to the propagation of behaviors.

Customer Referrals in Financial Services

The social influence effect investigated in Cyworld and Facebook is crucial in a proper understanding of referral marketing. Referral marketing is a method of promoting products or services to new customers through referrals, usually word of mouth. Kumar, Petersen and Leone (2010) examined the monetary value of word of social relations, referral behavior and their role in consumer decision making and purchase behavior. The main research hypothesis was whether it is possible to predict customer's indirect impact (through referral behavior) on the firm's future profits. This hypothesis was empirically verified on the basis of data collected from 14160 customers in four years period. The data was obtained from the financial services company (ranks high among the global Fortune 1000 firms), and was related to a wide range of products and services, including banking, insurance, and investments. The data included each customer's own purchase behavior and the estimated marketing costs. The data set included also the findings from a survey given to each of the 14160 customers that provided information on their "willingness to refer" to new customers. In this sample 9492 of customers stated that they are intended to make referrals, however only 4204 actually made attempts at referrals.

The efficiency of the performed campaign management was measured by means of CLV (customer lifetime value) and CRV (customer referral value). For CLV, the average in performed experiments in the test group customers was $274 before and $291 after (the same for the control group is significantly lower and was respectively $270 and $271). For CRV, the average in performed experiments in the test group customers was $145 before and $164 after (the same for the control group is significantly lower and was respectively $145 and $146). The results show that each of the performed campaigns was successful in significantly increasing the average customer's CLV and CRV. Based on this research we can see that building a social network can be a long-term competitive advantage for both the customer and the firm because it enables the firm's relationship with each customer to evolve over time (Ganesan, 1994).

FINAL REMARKS

In order to build a successful customer relationship management systems companies must learn to understand their customer in a social context. The crucial problem is to the predict a customer response based on a behavioral modeling. To predict the action of customer response we must model human nature based on behavioral patterns and social relations. In this context we presented a model of an active analytical customer profile. In four research studies we showed the current research in this field.

The presented results are promising but showing a lack of models that integrate customer behavior and social influence. Nevertheless the question, what exactly does it mean for someone to influence or be influenced by their peers is an open and difficult research problem. The experimental approach is the best research framework available, but it is seems almost impossible to detect all factors in observational data in order to get a proper flow of influence.

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KEY TERMS AND DEFINITIONS

Analytical Customer Profile: A result of abstraction of interactions (time series of customer transactional data, as well as other social and demographic data) in order to generate adequate marketing messages.

Customer Relationship Management: The principles, practices, and guidelines that an organization follows when interacting with its customers.

Interactive Marketing: An identification of interested customers and elaborating the complete characteristics of the customer in order to achieve personalization and adapting proper service at a proper time.

Personalization: A process of analyzing (processing) customer data, customization and delivery of marketing output, and interactions with customers for increasing their lifetime value.

Social Influence: Occurs when one's emotions, opinions, or behaviors are affected by others.

ENDNOTES

1. The representative publications in this area are: presentation of the idea of Customer Intelligence (Kelly, 2006) and introducing "N=1" concept by Prahalad and Krishnan (2008).
2. RFM stands for Recency - How recently a customer has purchased ?, Frequency - How often does he purchase ?, Monetary Value - How much does he spend ?
3. Usually it is segmentation a priori, in which market segments are determined arbitrarily on the basis of expert knowledge. The usage of data mining techniques allows segmentation post-hoc in which thanks to clustering algorithms, it is possible to discover real customer segments on the basis of the analysis of available transactional and social-demographic data.
4. See as an example functionality of the Open Graph protocol for Facebook: developers.facebook.com/docs/opengraph [2014.04.21].
5. An example of generalization would be defining customer interest on the basis of books purchased and viewed by him. Generalization requires defining and implementing the appropriate ontology model of the chosen field.

[6] Aggregation is a standard procedure in data warehouse, it requires performing appropriate procedures on quantitative data such as sum or average.

[7] The idea of abstraction of time series was presented by Haimowitz and Kohan (1996) as well as Wijsen (2001).

[8] Exemplary purchase prediction models are logit models (Knott, Hayes, & Neslin, 2002), probit models (Shibo, Sun, & Wilcox, 2005), or Bayesian models (Venkatesan, Kumar, & Bohling Venkatesan, 2007). The studies of these models have shown that despite the limited access to transactional data, it was possible to achieve statistically accurate improvement of customer purchase prediction compared to expert prediction.

[9] Of course it is also possible to stop delivering message to customer e.g. in case of negative prognosis in analyzed future.

[10] http//:global.cyworld.com. [2014.04.21].

[11] In 2007 Cyworld generated $65 million or almost 70% of its revenue from selling virtual items. The remaining revenue was generated from advertising and mobile services.