A Methodological Approach for the Journey through Real-Time Marketing: From Customer Journey Analytics to Personalization Engines

Claudiu-Catalin Munteanu
Institute of Agricultural Economics, Romanian Academy, Bucharest, Romania
munteanu.katalyn@yahoo.com
Adina Cristea
Bucharest University of Economic Studies, Faculty of Marketing, Bucharest, Romania
adina.cristea@mk.ase.ro

Abstract

Many companies rely in practice on personalization engines and value co-creation in order to boost the efficacy of their one-to-one customer relationships. Real-time marketing (RTM) can increase the efficacy of marketing activities by taking advantage of technology, big data analysis, social media and constant connectivity. RTM fosters consumer engagement in value co-creation and in the personalization of products, offers and customer service. This paper suggests a methodology for implementing RTM by considering the main characteristics of customization strategies: novelty, serendipity and diversity. Based on the seven rules for RTM implementation, we propose and discuss the process of incorporating big data and customization strategies into a personalization engine driven by machine learning and big data analytics. We include in the personalization engine value co-creation drivers based on marketing drive value, customer lifetime value and strength and intensity of brand associations. The proposed process-based framework for RTM implementation integrates algorithms related to customer profile to calculate their future purchase probability, thus being a useful managerial tool for segmenting and targeting consumers in real-time. By adapting marketing communication patterns to these permanently 'evolving' segments, value co-creation and consumer satisfaction increase, while the AI algorithms also improve.

Key words: real-time marketing, personalization engines, big data marketing, customization strategiesm value co-creation
J.E.L. classification: M30, M31, C55, C81

1. Introduction

Real-time marketing (RTM) is an emerging, multi-disciplinary approach to relational marketing and services marketing which combines technology and management practice. The relational marketing paradigm focuses on the firm and the customer co-creating value, as defined by the customer and its expectations (Kao et. al., 2016). First introduced by Oliver, Rust and Varki (1998), RTM is conceptualized as a valid approach for continuous customer communication and for developing mass-customized offers that meet consumers' evolving needs. Thus, RTM offerings meet customers' current, individual needs (space) and are also able to adapt to their future needs (time) (Oliver, Rust and Varki, 1998).

The rapid rise of e-commerce has generated endless opportunities to create new value in the *online marketplace* (Suh et al., 2004). Mobile devices and services are becoming powerful channels for both distribution and marketing communication. This is a big paradigm shift from the classic relationship marketing and holistic marketing approaches to the network approach and big data marketing.

RTM makes personalized targeting possible by taking advantage of technology, social media and constant connectivity to foster organic consumer engagement and interactions towards co-creating personalized products, offers and customer service (Buhalis & Sinarta, 2019). For example, location-based advertising uses Google location-tracking technology in order to provide users with commercial information and ads which are specific to their current location. This is a simple example of service personification based on consent and preference management.

However, the practical implementation of RTM can be often largely problematic and unfeasible. First of all, customization strategies aimed at providing individually-tailored products fail to be customer-centered in a profitable manner for a business. RTM aims to increase customer participation and involvement in order to also increase their *perceived control* and thus to enhance their user experience and satisfaction (Stevens et al., 2017). By doing so, companies are also forced to focus on long-term one-to-one customer relationships. However, many companies often fail in practice to measure the efficacy of their one-to-one customer relationships and also of customers' satisfaction regarding their perception of control in co-production environments. Therefore, in order to properly implement a holistic marketing orientation, firms should first of all try to understand which components of their value-creation chain and service concept are most important to different subsets of customers (Munteanu et al., 2014).

Secondly, although companies are obviously benefitting from using a personalization engine on their Web site, social media accounts or in their digital products and services, customers are increasingly reluctant to be profiled in such a manner. Basically, customers have little or no control over the information that defines their customer profile, since user profiles are deeply buried in personalization engines. Furthermore, there is often no real incentive for a customer to take part in a personalization engine.

Finally, as RTM is inherently associated with the rise of e-commerce, it is also associated with the rise of a new global market and thus of fierce competition. While firms are competing in delivering targeted, personalized online offers, consumers are faced with advertising fatigue. Thus, consumers are increasingly trying to resist many of the online RTM methods used for targeting them by using ad-blockers, unsubscribing to newsletters and by minimizing any unsolicited communication. Therefore, offering highly relevant offers and content proves crucial first for moving through the advertising clutter and being noticed and then for remaining relevant and engaging, in order to establish a long-term customer relationship.

Considering these issues, we propose a methodological approach for RTM implementation. We focus on co-creating value as a main approach for customer relationship management (CRM), while also proposing measures to incentivize customer participation.

2. Theoretical background

RTM can be regarded as a network structure consisting of multiple interacting actors that perform interdependent actions (Miles, 2018). Each of these actors is supported in practice by core technologies to collaboratively provide mutual offerings. For example, a public forum such as Quora or Reddit developed their own app for mobile users in order to better integrate them into their ecosystem. The purpose of such integration is to facilitate the use of techniques for online marketing. These integration techniques include the use of tools such as database marketing, one-to-one marketing and target marketing (Ha & Park, 2002). Therefore, RTM needs to consider the ever-evolving role of technology in building customer relations.

Traditionally, relationship marketing emphasizes the mutuality of relationships in value co-creation (Anker et al. 2015). However, value co-creation is mainly conceptual and anchored in service marketing rather than in the broad marketing theory and practice. Therefore, it lacks *empirical evidence* in two important directions: 1) the appropriate contexts and conditions for collaborative co-creation; 2) the effects of value co-creation on firms and customers (Alexander et al., 2012).

Studies have suggested that consumers use relationships with companies to *satisfy their self-definitional needs* (Bhattacharya & Sen, 2003). Whether a customer perceives his relationship with a company or brand as a mutually beneficial relationship or not determines the efficacy of value co-creation. For example, efficacy may be boosted by using on the company website a collaborative filtering module that identifies customers whose interests are similar to those of a given customer and recommends products this given customer previously liked.

In practice, narrow-minded personalization can create such called "filter bubbles" that present themselves as invisible and personal universes of information that might trap users into a relevance paradox (Pariser, 2011). The problem with "filter bubbles" is that they confine customers to isolated information neighborhoods and restrict them from seeing or exploring the vast array of other purchase possibilities (Nguyen et al. 2014).

In order to avoid this problem, personalization techniques should be based on novelty, serendipity and diversity (Matt et al. 2014). *Novelty* is based on bringing forth items, facts, services or information not previously known by the consumer and is important because it drives user engagement. *Serendipity* is based on unexpectedness, surprise and awe and is important because it fosters a positive emotional response. *Diversity* is based on variety and is critical to maintain relevance and to prevent boredom or disengagement. In practice, only a combination of personalization and diversification can improve competitive performance in value co-creation (Ranjan & Read, 2016). As a result, RTM can simultaneously improve the baseline, plain personalization and plain diversification approaches in terms of both efficacy and accuracy.

However, as they focus on the relevance of suggestions for their customer base, most common personalization techniques tend to disproportionally consider and amplify the popularity of available choices and options (Hamedani & Kaedi, 2019). As a result, most common personalization techniques tend to guide our choices towards common and frequent consumption patterns, but those patterns are subject to a concentration bias, especially for already popular choices. For example, if a product has a sufficient number of popular, detailed, positive reviews, these will generate the consumption trends (Su & Niu, 2021; Jimenez & Mendoza, 2013). Consumers will ignore negative reviews for that same popular product or ignore similar products with neutral or less reviews. In a similar fashion, personalization algorithms recommend products based on prior sales and ratings, thus creating a rich-get-richer effect for popular products and negate the growth opportunities for new or unpopular products (Hamedani & Kaedi, 2019). As a consequence, narrow-minded personalization techniques such as online recommendation systems can have detrimental effects, such as arbitrarily deconstructing non-prevailing views. Moreover, they can alienate consumers more highly oriented towards diversity and novelty.

The customer journey is based on consumer brand associations and inferences that are highly dependent on the semantics of the information (Wu et al. 2019) and anchored in the context of location-based information (Lemon & Verhoef, 2016). As a result, this journey is not necessarily related to commonalities in exposure, experiences, and selected choices among the different users. With a variety of systems using personalization engines, there is a lot of data being collected about users as they interact with social media, the web and tracking software. Each personalization engine independently builds up user profiles and can use this information to personalize the system's content and service offering, but they cannot accurately map the customer journey (Wu et al. 2019).

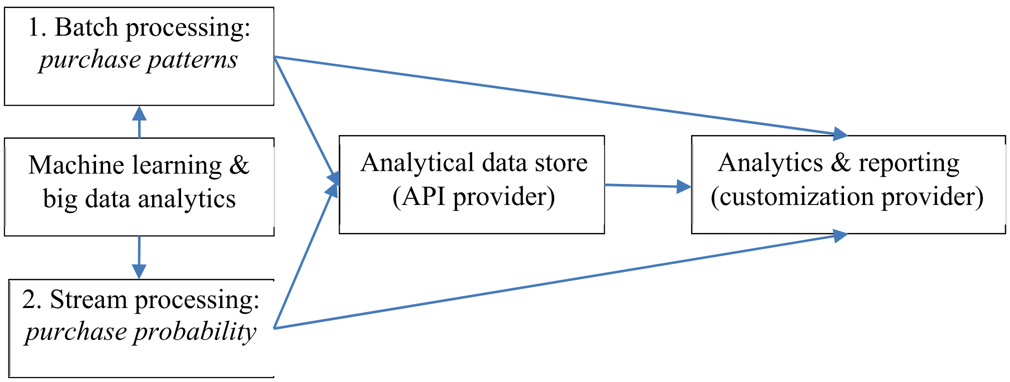
Therefore, we postulate the following seven customer-centered rules for RTM implementation:

1. Consumers find meaning in a customer relationship that creates a positive sense of self;
2. A meaningful customer relationship determines the customer purchase pattern;
3. A purchase pattern that is repeated and validated forms the *customer journey* and provides customer insight;
4. Customer insight can be generalized by discovering associations between customers that share the same journey, thus forming a consumer ecosystem;
5. The consumer ecosystem is based on their primary need, which is best satisfied by a basic service, and on further personalized needs, which require personalized services;
6. As the precision of satisfying personalized needs increases by using a combination of individual and multi-lateral services, the efficacy of the personalization engine also increases;
7. Personalization engines must avoid the formation of "filter bubbles" and map the consumer journey accurately.

3. Research methodology

This paper suggests a methodology for implementing RTM that can use customer analytics for a personalization engine. The role of the engine is to apply a marketing action to any potential customer by extrapolating from previous purchasing patterns and purchasing probability for a given product. As real-time online marketing requires simplicity, speed, and accuracy, a classic relationship marketing customization approach is not adequate, therefore data mining must be combined with a big data structure into a neural network (Cheng et al., 2020). The process-based framework for RTM implementation is depicted in figure 1. The first step involves batch processing, namely simultaneously data mining a number of available cases regarding the customer profile to unveil relevant purchase patterns. The second step involves stream processing, the high-speed analysis of online data resulted from using the mining algorithm defined in the previous step, in order to evaluate purchase probabilities.

Figure no. 1. The process-based framework for real-time marketing implementation



Source: Authors' own contribution

3.1. Batch processing

The first step of the RTM implementation process is to select the most relevant information from each ***category of big data*** required for RTM. The big data categories most used in marketing applications include behavioral, attitudinal and transactional metrics. Each category of data is subject to batch processing based on *association rule mining*. Association rule mining identifies correlations between sets of items and thus possible patterns and causal relations (Zhao & Bhowmick, 2003). Because association rule mining usually generates too many redundant rules (Chen et al., 2006), it is somewhat difficult to find important rules that give essential information about customers while also remaining relevant in a marketing context.

Therefore, we recommend the association rule mining should be calibrated in accordance to the customer-centered rules, in order to unveil the commonalities in different types of customer journeys. Additionally, to select the most relevant rules, we advocate for the use of resource-based theory (Kozlenkova et al., 2014) in a big data context for deciding on the volume, variety and velocity of processed data. Specifically:

- The overall *volume* of processed data should be proportional with the *marketing decision value*, thus with the importance of marketing benefits than can be obtained for processing the data.
- The *variety* of data - consisting from the number of different data entry points regarding a particular customer -, should be determined by analyzing *customer lifetime value*. Valuable customers in terms of purchased volumes, purchase frequency and brand interactions during their lifetime relation with the brand should be profiled in more depth, to enhance personalization and co-creation value.
- The *velocity* of data – defined as the time between two successive actualizations of client data - should be determined by analyzing the strength of *brand associations*. Consumers with less strong brand associations may change their preferences and purchase patterns much easier, thus require a more frequent calibration of delivered content to retain and engage them.

Based on these parameters, a purchase pattern should be determined for each possible customer. All determined purchase patterns will be discarded in the absence of associated financial metrics, while only the relevant ones will be integrated into the analytical data store via the API provider.

3.2. Stream processing

The second step is to predict the ***purchase probability*** for each possible customer. Each purchase probability is subject to stream processing based on decision tree and logistic regression models. In order to accomplish this task, the data set from the mining algorithm used in the first step will be modified, selecting the most relevant data.

A hybrid approach based on artificial intelligence (Chen et al., 2006) must be used to predict the weight of each parameter in the model: marketing drive value (*MDV*), customer lifetime value (*CLV*), strength and intensity of brand associations (*SBA, IBA*).

In the hybrid-based approach, in step 1 we first compute the *accuracy* of Φ as an independent classifier. Φ will always be trained for each of the above model parameters based on regression weights from a multiple regression model including purchase intention as a dependent variable and marketing drive value, customer lifetime value, strength and intensity of brand associations as independent variables.

Secondly, in step 2 we *independently* predict the *purchase probability* for each parameter based on the customer decision tree. Finally, in step 3 we train λ as a dummy variable to avoid misclassification. For each step, a large-scale deep learning algorithm that has already been tested and corrected for web scraping must be used. The resulting function is described in equation 1.

$$Min \sum_{i}^{n} \Phi\lambda\overline{\mathrm{T(i,j)} \oplus \mathrm{M(i,j)}} \quad (1)$$

Φ = independent classifier;

λ = dummy variable;

i = customer *i*;

n = the maximum number of potential customer for the product *j*;

j = the given product for which we make the analysis;

T (i,j) = calculates the *purchase pattern* for customer *i* and product *j* (presented as a "fail or no fail to purchase" index), by using the batch processing of consumer data (Step 1).

M (i,j) = calculates the *purchase probability* for product *j* regarding customer *i* (presented as a probability distribution), by using stream processing (Step 2);

$M(i,j) = \int_{-\infty}^{\infty} x_i f(x)dx$, where:

$x_i = MDV \circ CLV \circ SBA \circ IBA$ and

$f(X) = \sum_{i=1}^{n} x_i p_i$

$\oplus$ = exclusive OR function that encapsulates the threshold or critical value for each given parameter and its regression weight as a classifier.

It must be noted that if the critical value for each given parameter is greater than 0.5, the hybrid approach will predict if the customer will buy the product in any given setting. Therefore, detected purchasing patterns are not only used as input data for step II, but also as a marketing customization tool. Afterwards, the prediction model extracts target customers from the pool of potential customers and classifies them throughout the purchasing probability. It is important to find viable target customers because only those customers are susceptible to be influenced by brand positioning and can be directly related to company revenue. If a potential customer is a valid target customer, the target value is 1 for purchasing the product; otherwise, the target value for purchasing the product is 0. All target fields should be binary (0 or 1) in order to obtain a nominal type of data sequence.

The decision tree should use the chi-square method as splitting criterion with at least a 0.2 significance level because in a marketing setting, purchasing a product is built upon customer engagement (Calder et al. 2016). A significance level below 0.2 can indicate insufficient engagement and is rather specific to purchasing non-differentiated products such as vegetables at a grocery store.

There are no specific requirements for building the neural network linked to marketing activities, therefore the standard Multiple-layer perceptron algorithm can be used for building the neural network. It is important for the hybrid model to be the best prediction model possible (this is assured by selecting the model with the minimum possible misclassification rate). In practice, a lift chart can be used to measure the performance of the prediction models. In this context, the lift value from the chart explains the ratio of customers who actually buy in reality the product (within a predetermined time interval such as one month from the prediction) to the total number of purchasing customers (in a month).

Analyzing the lift chart of a mining model can provide further insights into customer segmentation. A *lift chart* illustrates the improvement provided by a mining model when compared against a random guess, measuring this improvement through a *lift* score (Microsoft, 2021). By dividing sections of the lift chart by *sorting target customers in an ascending order of purchase probability*, managers can employ a micro perspective on customer value co-creation. By specifically targeting each customer segment from the lift chart in different periods of time (e.g. via personalized emails or browser ads), purchase probability helps digital marketers to establish a one-to-one marketing action plan that is personalized for each customer and is an automated process. Because the API provider manages product recommendation solely based on real customer behavior, marketers gain full control towards the inducement of product purchases in a real-time manner.

4. Conclusions and managerial implications

Central to RTM logic is the proposition that the customer has the center role in value co-creation. Previous approaches for RTM implementation are based on customer profile and purchasing information. But the limitation of this approach is that the marketing strategy becomes reactive rather than proactive. We provided a practical solution to eliminate these limitations by proposing a methodology for RTM using purchasing patterns through *associations rule mining* and *purchase probability prediction*. In a practical setting, incorporating purchasing probability into the process-based framework for RTM can help better targeting customers and provide valuable information for marketing strategy based on offer personalization. Also, the use of purchasing patterns into the personalization framework has macro marketing implications such as increased customer satisfaction, more efficient marketing expenditures and a higher probability for marketing actions to induce purchase. Our proposed RTM framework creates the premises for offering a highly personalized and relevant content to consumers. Thus, their skepticism towards the online use of personal data and annoyance towards commercial messages unsuited for their needs should greatly decrease.

Our methodology has clear advantages for RTM implementation. First, our methodology requires a short processing time to calculate purchasing probability because it is based on machine learning. Therefore, it uses a small amount of data compared to classical customization strategies that usually require customer-based marketing research. Secondly, detected purchasing patterns can be used both as input data, but also as a marketing customization tool. Thirdly, a RTM personalization engine build upon the proposed methodology will amplify the salience of various available choices and options, not only the most popular ones. The salience of these choices will be based on the consumer profile generated through association rule mining, in a consumer ecosystem that is controlled by the company. The association rule mining will be based on our seven customer-centered rules for RTM implementation. As a result, consumers are empowered to bypass "filter bubbles" with each interaction with the services or products of the company.

From a theoretical standpoint, we think that the original contribution of this paper is to suggest a methodology for RTM implementation based on predicting the value of the anonymous customer. Further research should focus on testing this methodology in a real-case scenario. Future case studies should be built for products, services, but also for corporate brands.

From a managerial standpoint, the proposed framework for RTM implementation represents a useful tool for managing the process of value co-creation in a highly competitive business setting, by integrating various diverse customization strategies and relationship marketing methods.

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