Evaluating the Effectiveness of Relational Marketing Strategies in Corporate Website Performance

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Abstract

The study aligns marketing intelligence approaches with website performance assessment for evaluating the effectiveness of a company's relational marketing strategies (RMS) in the performance of its corporate website. We develop a web mining based methodology that combines a classification procedure with discriminant analysis for analyzing click-stream data. Furthermore, we integrate managerial perspectives in investigating and interpreting customer website usage for determining RMS effectiveness. As a result, we are able to quantify the moderating effect of the website's structure and content on the effectiveness of Internet based relational marketing (RM) efforts. The applicability of this approach is demonstrated by investigating RMS effectiveness in the performance of a software developer's website. The results of our approach support website optimization and also enable customization for different relational marketing strategies.

1 Introduction

A critical concern of marketing has been how to initiate, customize and strengthen the relationship between a company and its customers, in order to increase customer satisfaction and to achieve a competitive advantage. This is reflected in a conception of relationship marketing (RM) that includes strategies for establishing, developing, and maintaining successful relational exchanges (Morgan & Hunt, 1994). RM has experienced considerable growth in the last few decades, both in business practice and as an object of academic research (Srinivasan & Moorman, 2005). Thus, the evaluation of RM effectiveness provides knowledge for increasing the return of a company's RM investment (Reinartz & Kumar, 2003). One of the most important relational exchange contexts takes place on the Internet, where a company's RM efforts are closely connected to the performance of its corporate website, particularly with respect to website structure, content provision, and quality of service (Palmatier, Dant, Grewal & Evans, 2006). Thus, the performance of a corporate website moderates the relationship between a company and its customers and thereby affects the strength of RM effectiveness. The question of how to quantify this moderating effect is the research objective of this study.

Marketing and information systems (IS) research addresses this in several ways: RM uses data intensive methodologies based on customer purchase behavior (*marketing intelligence*) to determine RMS effectiveness (Vercellis, 2009). In website performance assessment, RM outcomes such as web-customer satisfaction and loyalty are measured (i.e. Lee, Strong, Kahn & Wang, 2002; McKinney, Yoon & Zahedi, 2002). But IS also investigates website performance by analyzing customer-website interaction using clickstream data in web mining approaches (i.e. Senecal, Kalczynski & Nantel, 2005; Spiliopoulou & Pohle, 2001). Nevertheless, we observe only a small number of methodological approaches that link the evaluation of a company's RM effectiveness to website performance, based empirically on customer website usage.

We attempt to overcome this shortage by presenting a methodological framework that aligns marketing intelligence with web mining approaches. We model, analyze and predict the effectiveness of a company's RM effort in website performance by integrating managerial perspectives in the assessment of customer website usage. The knowledge gained supports website optimization and also enables customization for different relational marketing strategies.

The paper is structured as follows. After a summary of related research, we describe the developed methodology in detail. The practical relevance of our approach will be demonstrated by analyzing historical clickstream data of a corporate web site from the software development sector. Finally, we discuss our results and their limitations.

2 Related Research

Research investigating relational marketing strategy from a marketing intelligence perspective deals mainly with methodology improvement for relational marketing analysis that uses data mining techniques, the information infrastructure involved, and aspects of relationship economics such as customer lifetime value, acquisition, retention and cross-selling (i.e. Büchner & Mulvenna, 1998; Chi & Tavella, 2008).

Website performance assessment is a significant topic in marketing and IS research. Depending on the website type, different measures of effectiveness exist. For transaction-orientated websites in e-commerce, website effectiveness is determined in terms of revenue. Here, metrics are used that describe the customer lifecycle and customer web usage such as reach, acquisition, conversion, click through and look-to-buy (Lee, Hoch, Podlasek, Schonberg & Gomory, 1999; Teltzrow & Berendt, 2003). The effectiveness of information and service provision orientated websites is often measured by investigating customer web site usage in terms of implicit feedback (Stolz, Viermetz, Neuneier & Skubacz, 2005). In this case, web usage mining approaches are an adequate procedure (i.e. Bucklin & Sismeiro, 2003).

With regard to the research object of this study, only one web mining approach is known that estimates website performance in a corporate context using clickstream data (Hochsztain, Millán, Pardo, Pena & Menasalvas, 2003). Although customer value is estimated in this study from a website provider perspective, no clear conceptual linkage to relationship marketing (RM) and relational marketing analysis methodology is available. The study at hand will overcome this lack and directly integrate relational marketing analysis in an methodological web mining approach for determining the effectiveness of a company's RM efforts in its corporate website.

3 Evaluating the Effectiveness of Relational Marketing Strategies in Corporate Website Performance

Corporate websites are an important channel for Internet based marketing communication in a company's multi-channel marketing efforts (Weinberg, Parise & Guinan, 2007). They support three relational marketing strategies (RMS) in particular: (1) the building of brand equity, which is the sum of the intangible assets of the corporate brand that are supported by factors such as name awareness, perceived quality and customer loyalty (Aaker, 1993); (2) the creation and maintenance of relationships at reduced costs (Shet & Parvatiyar, 2000); and (3) the creation of customer satisfaction by delivering superior products and services (Gale, 1994). Success in any of these strategies leads to an increase in repeat purchases, insulation from price increases and improved responsiveness to marketing communication by customers. Thus, a corporate website can maximize the impact of a company's RM efforts (Argyriou, Kitchen & Melewar, 2006). The strength of this contribution depends on how well the website performs with respect to customer information needs. Therefore it is necessary to develop metrics that evaluate the effectiveness in relation to customer website usage of the RM effort in website performance.

In the following, a general research framework is presented and operationalized that integrates RMS effectiveness determination in a web mining approach for modeling, evaluating and predicting RMS effectiveness in corporate website performance.

3.1 Corporate Websites and Relational Marketing Strategies

According to the functions a corporate website possesses, different relational marketing strategies (RMS) are supported, and different effectiveness metrics can thus be distinguished. Using the typology of website functions and metrics used by Booth & Jansen (2009), we specify firstly that a *commerce* orientation focuses on getting customers who visit the site to purchase goods or services directly from the website. The building of brand equity is the most important RMS here, because it addresses customer loyalty in terms of repeated purchases and perceived product quality. Clickstream-based effectiveness metrics for commerce emphasize transactions such as purchase or downloads. *Content and media provision* focuses on drawing in visitors and immersing them within the site. The relationship between a company and its customers can be strengthened as a result. Clickstream-based RMS effectiveness metrics are in this case concerned with visitor engagement, for instance a high number of visit actions indicating browsing, and long session duration. A *support and service* function helps users to find specialized answers for specific problems. This increases customer satisfaction at reduced external support costs. RMS effectiveness depends largely upon the provision of the searched information with regard to the structure of the website; thus, low page depth is a useful indicator in clickstream data.

3.2 The Evaluation Algorithm

The allocation of relational marketing strategies (RMS) to website functions is necessary for developing a web mining approach that integrates managerial perspectives in the investigation of customer-website interaction. Our approach proceeds in three steps: initially business experts perform a characterization and discrimination of RMS relevant effectiveness measures in historical click stream data; then we use a classification procedure for determining the values of the previously identified metrics in the historical clickstream data; and finally we evaluate RMS effectiveness and identify contributing factors by using discriminant analysis.

In the initial exploratory approach, a business expert identifies RMS relevant metrics for inferring customer behavior from the clickstream data. Here, typical RMS relevant visitor activities are identified, such as information gathering by browsing, fact-finding, and all possible transactions (Kellar, Watters & Shepherd, 2006). Browsing, as an expression of the RMS metric called visitor engagement, is usually defined by a high number of visit actions, and a long session duration in the clickstream data at the user session level. Fact-finding, on the other hand, is defined by a low page depth, which implies a low number of visit actions and a certain style of interacting with the structural elements of the website content (Bucklin & Sismeiro, 2003). Integrating a distinction of different page types, i.e.

into action/navigational and target pages (Spiliopoulou & Pohle, 2001), fact-finding is expressed in clickstream data by visiting only few navigational pages in order to find specific content.

Assuming that the corporate website supports different RMS, the identified visitor activities are then weighted by business experts according to their relevance for each available RMS (table 1). We express this formally, similar to Hochsztain et al. (2003):

Definition 1: The Strategy set $S = \{s_1, s_2, \ldots, s_n\}$ represents the relational marketing strategies of a company that are supported by the corporate website at a particular moment.

Definition 2: The Customer Website Usage set $U = \{u_1, u_2, \ldots, u_m\}$ represents different activities a visitor can engage in when interacting with the corporate website.

Definition 3: We define w_{ij} as the weight to each relational marketing strategy, where i represents the i^{th} visitor activity and j the j^{th} relational marketing strategy. It is assumed that business experts assign weights differently for each visitor activity in every relational marketing strategy. The weight function has the following properties:

$$0 \leq w_{ij} \leq 1 \text{ where } s_i \in S, u_i \in U \text{ with } \sum_{i \in S, j \in U} w_{ij} = 1.$$

For each RMS the sum of all visitor activities is always 1; when an activity possesses no weight, then it is not relevant for this RMS from a managerial point of view. Table 1 displays an example of such a relevance weighting of customer behavior RMS specific.

		RMS for website functions		
		Commerce	Content/media	Support /service
RMS effectiveness metric	Customer website usage	Brand equity (s_1)	Relationship maintenance (s_2)	Customer satisfaction (s_3)
Visitor engagement	Long session duration (u_1)		0.5	
	Browsing (u_2)		0.3	
Page depth	Finding (u_3)	0.1	0.1	0.9
Transaction	Buy, download (u_4)	0.9		0.1

Table 1: Example of relevance weightings for customer behavior in RMS

This is relevant for the following steps, where we deploy a statistical classification method (decision tree) for inferring visitor activities in the clickstream data (Fox, Karnawat, Mydland, Dumais & White, 2005). Further, the expert discrimination of user activities and their defined thresholds are used for identifying and selecting visitor activity representing nodes of the decision tree. Integrating the RMS weighting for calculating an overall RMS effectiveness value then extends the so enriched classification results. Here, we apply an effectiveness heuristic that determines the number of user sessions with RMS relevant customer behavior, using a linear equation *L*: if the user session contains any RMS relevant activities, then the website successfully moderates a company's RM effort; if the user session does not contain any RMS relevant activities, than the website fails to moderate the RM effort. This is formally expressed by:

$$L_1 = s_1 u_1 + s_1 u_2 + \cdots + s_1 u_j$$

$$L_i = \sum_{j=1}^{m} s_i u_j$$

- If RMS effectiveness in a user session is determined to be $L > 0$
- If RMS failure in a user session is determined to be $L <= 0$

This dichotomous RMS effectiveness value is necessary for the last step of our analysis, where discriminant analysis depicts the relative contribution of the modeled and classified visitor activities to overall RMS effectiveness.

For an overview of the developed methodology see figure 1.

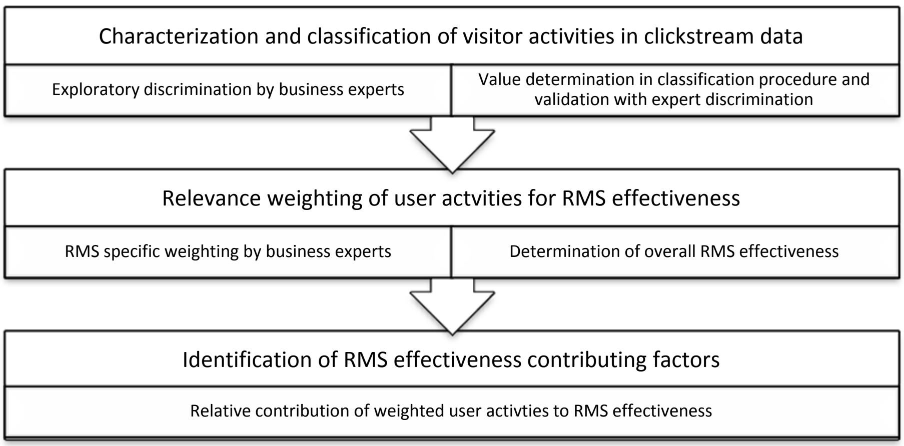

Figure 1: Developed methodology for RMS effectiveness evaluation

4 Implementation and Empirical Results

The developed approach was applied for evaluating the effectiveness of the relational marketing strategies (RMS) in the website of a German software developer. The website is dynamic and contains over 25 billion distinct URLs for content generation. The website offers a commerce function (shop), content and media provision (product catalogue, media center, company, community) and service and support (support). Relevant RMS that are moderated by website performance are: (1) building of brand equity, which refers to the shop area; (2) relationship maintenance in all content providing areas; and (3) creation and increase of customer satisfaction in the service and support area.

4.1 Clickstream Data Collection and Data Preparation

For investigating RMS effectiveness in website performance, we collected server log files of the clickstream over a period of four weeks (6.5 GB). In the following data preparation and transformation process, according to Cooley, Mobasher & Srivastava (1999), and Markov & Larose (2007), data was cleaned and sessionized using MySQL 5.5.9. In total, we identified and prepared for statistical analysis 1,389,413 sessions with a session duration longer than 10 seconds and containing two or more visit actions. Additional data was collected by using a crawler to distinguish navigational and content page view objects. The crawler requested the HTML page title, which offers information about the website area for all included URLs and parsed each URL as navigational or content objects. To this end, we deployed a decision heuristic: page view objects with more than 30 links are navigational; those with less than 30 links are content objects. This classification was successfully evaluated and validated by comparing the mean of session duration values (Spiliopoulou & Pohle, 2001). In total, we identified 143,546 distinct navigational, and 11,075,070 content objects in our data set.

For applying our developed web mining approach, we generated four data sets that allocate user sessions according to their clicks in a website area such as products, shop, community and support (multiple response possible). In further data quality monitoring, outliers were identified and removed using the interquartile range method (Larose, 2005) for the ratios of visit actions and session duration in each data set.

Table 2 displays the data set after outlier removal.

	Means of session ratios per website area			
	Products	Shop	Community	Support
N of sessions	114,264	158,529	20,052	184,626
Session duration per website area (SD)	20.11	156.36	277.14	146.80
Session duration per navigational object (SD_Nav)	14.86	18.82	21.40	33.52
Session duration per content object (SD_Con)	5.25	137.55	255.74	113.28
Visit actions in website area (VA)	2.85	3.85	3.98	3.42
Visit actions navigational objects (VA_Nav)	2.06	0.59	0.56	0.80
Visit actions content objects (VA_Con)	0.79	3.26	3.41	2.62

Table 2: Mean of session ratios per website area

4.2 Data Analysis and Results

Statistical analysis was performed using PASW Statistics 18 and PASW Modeler 13. Data analysis proceeded according to the developed approach.

Initially, the expert executed characterization and discrimination of RMS relevant visitor activities in the sessionized click stream data. It defined the thresholds for the ratios visit actions (VA) and session duration (SB), and the values of the indicator variables that were used for describing visitor activities. In the subsequent classification procedure, a C&RT regression tree was used for predicting the values of the visitor activities browsing and fact-finding, and for classifying visitor activities within the whole data set. The Gini-index was used as a measure of impurity and a test-sample cross validation for tree-selection. Two models for each activity were calculated and compared, using one dependent (DV) and one or more independent variables (IV). For model comparison and evaluation, the model with the lower standard error of the estimate (*s*) was preferred. For each activity an indicator variable was created (Breiman, Friedman, Stone & Olshen, 1984).

Table 3 displays the regression models, and the results of the model evaluation that prefers model 1, as well as the predicted values of the ratios used for model 1.

		Regression tree				Model evaluation	
		C&RT model 1		C&RT model 2		*s* C&RT 1	*s* C&RT 2
		DV	IV	DV	IV		
Products	Browsing	VA >3.5	SD>12.5	SD	VA	0.02	4.34
	Fact-Finding	VA<3.5	SD_Nav<0.5, SD_Con>12.5	SD	VA-Nav. Con	0.01	4.33
Shop	Fact-Finding	VA <3.5	SD_Nav<0.5, SD_Con >2.5	SD	VA_Nav, VA_Con	0.03	167.44
Comm-unity	Browsing	VA >3.5	SD >39.5	SD	VA	0.10	1836.77
	Fact-Finding	VA<3.5	SD_Nav<0.5, SD_Con> 31.5	SD	VA_Nav, VA_Con	0.10	1790.04
Support	Fact-Finding	VA <3.5	SD_Nav<0.5, SD_Co>14.5	SD	VA_Nav, VA_Con	0.02	7196.89

Table 3: Classified user activities

The identified user activities were then relevance weighted as presented in table 4.

	Website area	Products	Shop	Community	Support
	RMS	Relationship maintenance	Building of brand equity	Relationship maintenance	Create customer satisfaction
Weights of RMS relevance	Long session duration	0.5		0.5	
	Browsing	0.2		0.3	
	Fact-Finding	0.2	0.1	0.1	0.9
	Download	0.1	0.1	0.1	0.1
	Purchase		0.8		

Table 4: Relevance weighting of visitor activities

Then, overall RMS effectiveness was calculated, using the weighted activity indicator variables (table 5). Results demonstrate that the company's RM effort was moderated differently in each website area: for relationship maintenance in the product area, only 45 % of all user sessions were determined as effective; whereas in the community area, which provides an exchange forum between customers, a high effectiveness of 77% was achieved. For the building of brand equity in the shop area, the website performed moderately efficiently, with 48% of RMS user sessions effective. The creation of customer satisfaction displays the highest RMS failure, including 75% of all user sessions.

Website area	Products		Shop		Community		Support	
RMS	Relationship maintenance		Building of brand equity		Relationship maintenance		Create customer satisfaction	
Statistics	N	%	N	%	N	%	N	%
RMS failure	62956	55.1	83891	52.9	4473	22.3	138251	74.9
RMS effectiveness	51308	44.9	74638	47.1	15579	77.7	46375	25.1
Total	114264	100	158529	100	20052	100	184626	100

Table 5: Results of RMS effectiveness determination

Finally, discriminant analysis determined the relative relevance of the weighted activities. The assumption of homogeneity of variance was fulfilled; analysis was thus conducted. The quality of discrimination was very high, as shown in high eigenvalues and low values of Wilk's Lambda (eigenvalues between 5.04 and 8.84; Wilk's Lambda between 0.10 and 0.17 with p = 0.00)

Table 6 presents the average discriminant values. Table 7 shows the relative importance of the weighted visitor activities for RMS effectiveness.

	Group centroids	
	RMS effectiveness	RMS failure
Products	-2.68	3.29
Shop	-2.24	2.52
Community	-4.19	1.20
Support	-1.31	3.91

Table 6: Average discriminant values

	Structure matrix of standardized discriminant coefficients				
	Website area	Products	Shop	Community	Support
	RMS	Relationship maintenance	Building of brand equity	Relationship maintenance	Create customer satisfaction
RMS relevance weighted visitor activities	Long session duration	0.17		0.88	
	Browsing	0.65		0.46	
	Fact-Finding	0.09	0.36	0.12	0.71
	Download	0.11	0.08	0.09	0.15
	Purchase		0.30		

Table 7: Relative importance of user activities for RMS effectiveness

Classification results for the predicted group membership (RMS failure/effectiveness) are good with 95.3 % (products), 95.8 (community), 99% (support), and 100% (shop) for the correct prediction assumed a priori probability.

Results of the discriminant analysis indicate that the contribution of visitor activities to RMS effectiveness varies in the different website areas: for relationship maintenance, visitor engagement is the greatest contributing factor, which is characterized by browsing in the product area and by long session duration in the community area. Effective building of brand equity in the shop area is determined by low page depth, indicating fact-finding as a prominent activity besides purchase. The effective creation of customer satisfaction in the support area is also affected most by low page depth due to fact-finding.

Integrating overall RMS effectiveness into this perspective, our study finally demonstrates that the website moderates the company's overall RM effort differently: It moderates it particularly well for relationship maintenance in the community area, where a high visitor engagement supports the strength of the company-customer relationship. In the product area, the company's RM effort is less effective for relationship maintenance. Further, the website is not successful in moderating the RM effort in terms of customer satisfaction in the support and service area. Fact-finding, the user activity which contributes most to effectiveness, is not supported, indicating that the website does not provide a quick and efficient information provision in this area. Thus, the website needs optimization in navigational aspects, content access and presentation in the support and service area in particular.

5 Discussion

The developed methodology has several implications for practitioners and researchers. For practitioners, a RM effort orientated investigation of website performance using customer web usage data was provided, and knowledge of RM effort orientated website customization and optimization is generated. Further applications of this methodology support online analytical processing by providing user model development, identification and classification. Implications for researchers include the extension of existing approaches for determining website effectivity. We provided a comprehensive methodology for interpreting implicit user data, combining expert discrimination and data mining techniques. Furthermore, this methodology unites marketing and IS research by aligning marketing intelligence with advanced web mining techniques.

The main drawback of the method is the characterization and discrimination of user activities by business experts, which determines the quality and quantity of the activities modeled in the subsequent classification procedure. Further, the selection and weighting of activities of RMS relevant visitor activities may not be adequate and exhaustive for the RMS in a company's multi-channel marketing strategy.

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