E-CRM Success Factors as Determinants of Customer Satisfaction Rate in Retail Website

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Abstract: Electronic Customer Relationship Management (E-CRM) is a marketing strategy that integrates all business activities for attracting and retaining customers over the internet to consolidate retention, cross-buying, brand loyalty and customer satisfaction. E-CRM features influencing customer satisfaction in retail website have not been well researched and analyzed through online customer experience. This study, which is an extension of work originally presented in the International Conference on Soft Computing and Pattern Recognition [1] attempts to uncover the presence of E-CRM features on retail websites, affect values and determine weights importance of these features over the customer satisfaction rate based on customer click stream and online reviews data. This paper makes a theoretical and methodological contribution for managers of online service industry in improving their E-CRM performance according to the online customer behavior and satisfaction level.

Keywords: navigational data, fuzzy logic, weight establishment, multi criteria analysis decision making, satisfaction rate, class prototype, relevant index.

I. Introduction

Learn more about customer’s characteristics, needs and behavior is central to e-CRM. This research presents a comprehensive approach to design, develop and improve e-CRM implicitly based on online customer’s behavior. E-CRM system enables companies to collect massive amount of data to manage every changing needs of online customers. From the architecture point of view, the CRM framework is classified into analytical, operational and collaborative. Analytical CRM relies on the production, storage and analysis of data generated by operational and collaborative CRM. Based on these data, the various analysis tools are used for extracting knowledge that serves as a support for decision-making, and in particular for improving processes of operational CRM. Collaborative CRM is considered as a tool to directly contact customers. An organization strategy needs to set out these objectives before embarking on e-CRM strategy. This requires identifying the key strategic issues that relate to its proposed e-CRM initiatives: 1. Specifying critical factors and measures that have the most impact on E-CRM system for a specific retail website. 2. Presenting e-commerce website as alternative to the critical factors. 3. Applying E-CRM to support e-customer satisfaction survey. In order to achieve the best solution for these considerations, we have benefited from online customer behavior to affect scores to different E-CRM features according to the customer satisfaction level. Measure of these scores has been deduced from mining customer’s reviews and in-store navigational click stream. Next, we have used these data as inputs of the proposed MCDM method which is performed by weighting method and ordering preference using similarity and dissimilarity to ideal satisfaction class prototype. The remainder of this study is structured as follows: First, a fuzzy framework based on customer navigation is developed and adopted for data collection. Evaluation criteria are divided into effective factors regarding customer relationship management principles. Next section describes the theoretical proposed method. How the proposed model is used on a real example in order to compare and rank E-CRM indices is also explained. In final Section conclusions and suggestions are discussed.

II. Existing Related Bibliography

A. E-CRM Antecedents

Any variable that have possible impact toward customer satisfaction will also give a strong impact on E-CRM performance. Customer satisfaction is one of the major dimensions in E-CRM performance. Various studies have been done before by a number of researchers as far as the quality determinants of E-CRM strategies are concerned. The main objective of the study proposed by Wong Ke Er [2] was to examine the relationship between CRM and customer satisfaction on Taobao website. In this study, CRM was discussed by using four dimensions, which are e-service quality, website design, employee behavior and relationship development. The research [3] aimed to investigate the micro-

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linkages between E-CRM and electronic loyalty of customers, through electronic banking satisfaction as a mediator variable. Specifically, the neglected roles for expected security and convenience of website design.

H. Al-Dmour et al. [4] provided researchers with an integrative framework, which linked ECRM success factors with customers’ satisfaction, trust and retention. This research aimed to investigate the impact of ECRM success factors (process fit, customer information quality and system support) on the facilitation of the ECRM process. The study of Archanakumari and V. Selvan [5] was based on 150 respondents and analysis confirmed the conceptual model that convenience, trust and security have significant effect on customer satisfaction. This study enabled managers and marketers to implement the e-CRM in the best shape and match it with current needs and requirements of consumers.

The work proposed by authors of the paper [6] discussed how e-commerce companies improved its competitiveness in the retail industry through innovative CRM. The company provided training for its staff, managed the staff and style properly. For the work of E. Ardyan and G. Sugiyarti [7], co-information sharing activity and product competitiveness positively influenced ECRM performance. According to authors of [8] [9] [10] [11], a set of e-crm antecedents that positively influence consumer’s satisfaction (Efficiency, content and logistics of order processing, customer payment and billing) have arisen.

B. Usage of Fuzzy MCDM Methods for E-CRM Strategy

Study of Rouyendegh, B.D. et al. [12] presented a hybrid framework of Analytic hierarchy process and Intuitionistic Fuzzy Technique for Order of Preference by Similarity to Ideal Solution for the assessment and evaluation of E-commerce web site performance. The proposed hybrid model enabled decision makers to assess and efficiently used intuitionistic fuzzy numbers. In addition, human judgment can effectively be incorporated in the evaluation process. The research lead by Heidary Dahooie, J. et al. [13] developed a multi-attribute-decision-making technique rely on Step-Wise Weight Assessment Ratio Analysis and hesitant fuzzy weighted geometric Heronian mean decision-making methods, for evaluating e-government websites. The proposed framework overcome the limitations of previous investigations such as the possibility of aggregation of expert opinions using group decision-making and modeling the hesitancy of the experts. The focus of paper [14] was to consider Search Engine Optimization (SEO) criteria evaluation as a MCDM problem in which the criteria are in different priority levels and the criteria values take the form of hesitant fuzzy linguistic term sets to facilitate the elicitation of information in hesitant situations. A three-step solution approach was developed: (i) determination of 21 SEO criteria, such as page loading time, page size and meta-keyword (ii) prioritizing the criteria using hesitant fuzzy analytic hierarchy process, and (iii) ranking 70 Turkish websites of the industrial engineering departments using Technique for Order Preference by Similarity to Ideal Solution. Thus, this study assessed and prioritized factors for designing a successful B2C e-commerce website. The study of Li, R. and Sun, T. [15] conducted a thorough literature survey to screen important factors reported in past studies. Five main factors and nineteen sub-factors were selected for further prioritization. Later, FAHP prioritized factors based on their importance. Finally, based on the FAHP results, TOPSIS-Grey ranked five alternatives (e-commerce websites).

The article of Negi et al. [16] proposed a method to preprocess web services using the various classification technique. After that, a hybrid weight evaluation mechanism was employed to obtain the weight values of each nonfunctional parameter. In the end, the web services that were near to user expectations were selected out using the ranking method.

Assigning the relative importance of each attribute with an overall ranking can be done through the use of many pairwise comparisons based methods such as AHP (Analytic Hierarchy Process) which was applied to establish a set of all judgments based on decision-makers specific requirements in the comparison matrix to obtain a local weight of each criterion and sub criterion. With the objective of exercising judgment upon the ranking of the e-commerce sites, research of Sharma K. et al. [17] used AHP method to assign the criteria weights which in turn assist in generating the ranking of the web sites. AHP and ANP have also been extended to their fuzzy version by several researchers. Other classical multi criteria methods such as DEMATEL, MACBETH, CORPAS and MAUT have been extended under fuzzy environment [18] [19]. Negative and positive ideal solutions based methods TOPSIS and VIKOR have been developed under fuzziness and applied to many MCDM problems [20].

Only few applied MCDM algorithms consider quantitative, qualitative, imprecise and inconsistent information inherent in the evaluation data. In relation to the above-mentioned problem, it is suggested that the type of evaluation criteria should be increased and a dynamic customer-based MCDA method to evaluate online shops ought to be applied. Approaches mentioned above required the real level of the e-crm factor’s importance, which in turn helps to improve the website quality without considering implicit consumer perceptions of e service he receive. The areas where sequence of web events generated by each user should be required to assess the online service quality.

III. E-CRM Evaluation Data

A. Candidate Attributes

The entire dimensions used are adapted from the background research. The present study uses 5 criteria with 30 sub criteria in the proposed analysis of e-CRM. Fig. 1 shows the complete list of features which are described below:

Usability: is defined as the degree to which a user can complete tasks effectively and efficiently. Usability is concerned with functionality/usefulness, ease of learning, ease of use, aesthetics, user satisfaction and quality of enormous amounts of information available in the internet. Therefore, sites offer efficiency feature to allow the user to filter the content they see and to suit his tastes and preferences. User friendliness feature acts as self-help for customers looking for answer to their queries. This feature allows the company to collect personal information from users, when the user registers for the membership. It also allows them to track the customer’s behavior at the site over time.

Content Adequacy: This feature allows the visitor to quickly locate the required content on the web site where is looking
for a specific piece of information. As sub criteria, we consider electronic bulletin which allows visitors to share information with others. A visitor can post a message or can respond to a posted message on a special web page. This interaction, over time, creates a community of users around the company's service or product. Product highlights feature allows the company to highlight products or services that may be relevant in a particular context.

**Reliability:** This feature contains shipping policies, return policies, warranty, guarantee and other company commitments. Customers are more likely to feel satisfied if they know of the status of their order than if they do not. Most of customers use customer service to find out when they can expect delivery of their order. This feature depends also on privacy policy. Today, most sites have a privacy policy and post it on their web site. This not only assures the customer that his information is protected, but will also protect the company from violations.

<table>
<thead>
<tr>
<th>Goal</th>
<th>Aspects</th>
<th>Criteria &amp; Objectives</th>
<th>Sub Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-CRM Strategy</td>
<td>Usability</td>
<td>Efficiency</td>
<td>• Accessibility, Site map, Time behavior, Purchase process performance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>User Friendliness</td>
<td>• Communication facilities, Forms of payment availability, Shopping cart metaphor, Chat, FAQs, Alternative channels, Membership</td>
</tr>
<tr>
<td></td>
<td>Content Adequacy</td>
<td>Readability</td>
<td>• Correctness, Clarity, Local search engine</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Easy of Manipulation</td>
<td>• Updated content, Product information availability, Product comparison, Product highlights, Electronic bulletin, Promotion, Recommendation</td>
</tr>
<tr>
<td></td>
<td>Reliability</td>
<td>Functionality</td>
<td>• Accuracy, Information delivery, Order status</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Security</td>
<td>• Purchase condition, Payment system security, Site authentication, Confidentiality, Privacy</td>
</tr>
<tr>
<td></td>
<td>Order Fulfillment</td>
<td>Delivery Time</td>
<td></td>
</tr>
</tbody>
</table>

**Usability, Content Adequacy and Reliability** which are considered as fuzzy attributes.

**B. Navigational Data Collection**

Fig. 2 shows the OOHDM navigational schema for an online store. We have partitioned the navigational design space between navigational nodes and activity nodes; we use UML stereotypes <<entity>> and <<activity>>, to indicate which partition an item belongs to. Thus, on the top side of the Figure 2 you find activities and the corresponding process and entity nodes (bottom). Typically, a business process like CheckOut is composed of several activities like Login, ConfirmItems, and so on. The composition is represented by an aggregation relationship. A basic activity such as Login collaborates with application entities such as Customer to create an output page that lets the user enter or modify data. A business process defines the sequence in which its child activities should be executed, that is, the control flow among these activities. For example, the CheckOut process defines a strict one-way sequence for the activities that comprise it.

**Figure 1.** Census of e-CRM Attributes

The proposed data preprocessing model for customer analysis tracks various online activities of customers to construct logical user sessions and affect values to relevant entries variables for our proposed e-CRM system which takes into account new set of variables; categorical, continuous and fuzzy variables for evaluating online service quality. After the customer’s order is shipped, we detect its feedback information to assign values to Order Fulfillment as a categorical variable and Delivery Time which is numeric one. According to the Fig. 1, we have three other variables: Usability, Content Adequacy and Reliability which are considered as fuzzy attributes.

**Figure 2.** Object-Oriented Hypermedia Design Method (OOHDM) Navigational Schema

To emphasize the separation of concerns between process execution and navigation, we add a UML activity diagram (Figure 3) to the conceptual schema to describe the data flow [21]. From the navigational schema viewpoint, the Checkout parent activity first starts the Login child activity, which returns control to CheckOut after the user completes or cancels it. After a successful login, CheckOut starts the ConfirmItems child activity and passes control to it until that activity returns control, and so on. A composed activity is responsible for passing control among its child activities;
Select Delivery Options and Select Alternative Payment activity for buying.

The timeout threshold $t_0$: time period for website access without discovering product(s).

The timeout threshold $t_0'$: time period before the current time without adding any product to the basket.

Time period $t_p$: is the length of product consultation time.

Time period $t_p'$: a time spent before purchase that must not be greater than the timeout a threshold $t_0''$.

$P_s$ is the set of consulted product(s) and $P_s - P_s'$ the consulted product(s) not added to basket. $P_s' - P_s''$ represents products added and then deleted from the online basket and the set of purchased product(s) is denoted by $P_s''$.

For each user, perform the following:

1. Find the time difference between the website access and abandonment.

C. Fuzzy-Based Preprocessing

1) Considered Measures

Clicks: the interaction between the user and the web server; is measured by the click of mouse.

Visits: the number of times a user visits a specific web site. Every new session is counted as a new visit.

Exists: counted by site inactivity for more than a specific period.

Repeated visitor: the average number of times a user returns to a site over a specific time period.

Session: a sequence of internet activity made by one user during a period of time.

Page views: the view of any page by user

Page view per visit: average number of page views per visit.

Page views per session: average number of page views per session

Click per session: average number of clicks per session.

Figure 3. Object Activity Diagram of Data Flow
b. If this difference exceeds the threshold \( t_0 \), assign a session ID \( S_v \) to the user.

c. If \( t_p \) exceeds \( t_0' \), assign consultation sessions \( S_c \) to user who consults product(s) without any placement to online basket.

d. Assign the session basket \( S_b \) to the user who adds items to his online shopping cart, but exits without completing the purchase.

e. Sessions of purchase \( S_p \) have an end when user pays consulted product(s).

2) Preliminaries

Let A be a fuzzy variable and X the range of its values. Fuzzy sets are characterized by a membership function, which is also called the degree or grade of membership. One suggestion is to ask the experts to assign a real number from the interval \([0, 1]\) for each relationship and then calculate the average. However, it is difficult for the experts to assign a real number in order to express their beliefs with regard to the strength of relationships. This is the reason why partially ordered linguistic variables such as "weak", "medium", etc.

The membership function defined as: \( f_0: X \rightarrow [0,1] \), this function maps X into real numbers defined in the interval \([0,1]\). Subsets present expression to evaluate e-commerce websites fuzzy criteria using five basic linguistic terms, as "very weak", "weak", "medium", "strong", and "very strong".

3) Fuzzy Inference

The proposed fuzzy-based framework searches membership functions suitable to mining click stream data for E-CRM strategy implementation.

The proposed framework first collects customer’s navigational data to automatically derive the resulting membership functions by computing possible values of click stream data according to the possible online customer actions, initializing membership threshold until a good set of membership functions has been obtained and transforming each set of membership functions into linguistic representation on the universe of E-CRM features.

Values of the inferior and superior limits of the triangle base is based on formulas mentioned thereafter to depict the domain of mapping for the membership function (MF) for five linguistic terms: VW (Very Weak), W (Weak), M (Medium), S (Strong) and VS (Very Strong). (See Figure 5).

Here an algorithm used to generate triangular membership function on numerical data. Assume the fuzzy attribute has numerical value \( x \). Each linguistic term \( T_i \) has a triangular membership function, \( m_i \) represents scale values of the X axis:

\[
(x) = \begin{cases} 
1 & \text{if } x \leq m_1 \\
(m_2 - x) & \text{if } m_1 < x < m_2 \\
(m_2 - m_1) & \text{if } x \geq m_2 
\end{cases}
\]

The Fuzzy values of usability \( V_U \), content adequacy \( V_CA \) and reliability \( V_R \) are based on e-commerce website’s visit, consultation, basket and purchase session. More details in our previous work [22].

Equation (1) refers to the value of the website’s usability \( V_U \) is based on values of \((t_0, \psi(s)\) and \(\Phi(s)\) which depend on the time of website’s consultation and product discovering.

\[
V_U = \frac{1}{\text{card}(S)} \sum_{s \in S} (\psi(t_s) \psi(s) + \Phi(s)) \quad (1)
\]

\[
\psi(t_s) = \begin{cases} 
1 & \text{if } t_s < t_0 \\
0 & \text{else} 
\end{cases}
\]

\[
\psi(s) = \begin{cases} 
1 & \text{if } s \in S - S_v \\
0 & \text{if } s \in S_v 
\end{cases}
\]

\[
\psi(s) = \begin{cases} 
-1 & \text{if } s \in S_v \\
0 & \text{if } s \in S - S_v 
\end{cases}
\]

For the equation (2), \( \psi(t_p) \), \( \psi(p) \) and \( \Phi(p) \) are related to the consultation time of product and product added to the basket to calculate value of website’s content adequacy \( V_CA \).
IV. Proposed Fuzzy Weighting Model

A wide variety of e-CRM attributes requires that customer satisfaction measurement is a multivariate evaluation problem which depends on alternatives assessed on the basis of attributes [23].

Let $(C_i)_{j=1...5}$ the consumer’s satisfaction level, which are represented by five classes: "very satisfied" $(C_1)$, "satisfied" $(C_2)$, "moderately satisfied" $(C_3)$, "somewhat satisfied" $(C_4)$, and "not satisfied" $(C_5)$.

$(A_j)_{j=1...p}$ denotes the finite set of p e-CRM criteria that may influence consumer’s satisfaction as shown in figure 1. $V_{q,j}^i$ represents the possible value of criterion $A_j$ given by clients of category $C_i$. We denote by $(C_j^i)_{j=1...p}$ the prototype of the attribute $(A_j)_{j=1...p}$ for category or class $C_i$.

The weight $a_j^i$ denotes the relevant indicator or the importance of attribute $A_j$ to determine the class $C_i$.

In the prototype algorithm, one prototype is built for each class from the input vectors with three types: numeric, nominal and fuzzy ones. The class of a new input is then predicted as the class of the prototype which is closest to this input.

A. Numeric Criteria

The prototype $C_j^i$ of numeric criterion $A_j$ is the average of its values given by all members of class $C_i$ (6)

$$C_j^i = \frac{\sum_{q=1}^{n} V_{q,j}^i}{n}$$

The weight $a_j^i$ (7) of numeric criterion $A_j$ is the standard deviation of its values given by all members of class $C_i$ compared with the average:

$$a_j^i = 1/\sqrt{1 + \sum_{q=1}^{n} (V_{q,j}^i - C_j^i)^2} \in [0,1]$$

B. Nominal Criteria

For the class $C_i$, the prototype $C_j^i$ of nominal criterion $A_j$ is the value that has a high frequency among all possible values $(V_{q,j}^i)_{q=1...m}$ of this criterion. $m$: number of possible values for nominal attribute $A_j$. The relevance indicator of nominal criterion $A_j$ is calculated by: $a_j^i = f(C_j^i) \in [0,1]$.

C. Fuzzy Criteria

The dissimilarity $d(V_1, V_2)$ between any two values $V_1$ and $V_2$ for the fuzzy attribute $A_j$ can be computed by:

$$d(V_1, V_2) = \left(\sum_{i=1}^{5}(V_{1i} - V_{2i})^2\right)^{1/2}$$

The proposed formula to calculate the dissimilarity is a Euclidean distance where $V_1$ and $V_2$ represent the vector of belonging to fuzzy objects $\{a_1, ... a_i, ..., a_5\}$ which are represented by functions mapping the fuzzy attribute scale (See Figure 5) $V_i = v_{1i}, v_{12}, ... v_{15}$.
The similarity \( s(V_1, V_2) \) between any two values \( V_1 \) and \( V_2 \) for the fuzzy attribute \( A_j \) can be computed by:

\[
s(V_1, V_2) = \frac{1}{1+\delta(V_1, V_2)} \tag{9}
\]

The prototype \( C^*_j \) of fuzzy criterion \( A_j \) is the most typical value of \( A_j \) which is very similar to values of members of the class \( C_i \) and very different from members of other classes. We use functions of similarity and dissimilarity to calculate the typicality of different values of fuzzy criterion \( A_j \) for the class \( C_i \).

Let \( (v_{ki})_{k=1...5} \) be the value of the criterion which may be represented by five fuzzy sets called "very weak", "weak", "medium", "strong", and "very strong". \( v^i_{qj} \) be the possible value of criterion \( A_j \) given by member of the category \( C_i \).

\[
D_{kj} = \frac{1}{n} \sum_{q=1}^{n} \delta(v_{kj}, v^i_{qj}) \quad \text{(10)}
\]

\[
S_{kj} = \frac{1}{n} \sum_{q=1}^{n} s(v_{kj}, v^i_{qj}) \quad \text{(11)}
\]

The typicality of \( v_{kj} \) is defined by \( T_{kj} = \frac{(S_{kj} + D_{kj})}{2} \). The prototype \( C^*_j \) of the fuzzy criterion \( A_j \) is the value that has the maximum typicality: \( C^*_j = v^i_{qj} \) where \( T_{qj} = \max_{k=1...5} (T_{kj}) \).

The relevance indicator of the criterion \( A_j \) is the average of the differences between the maximum typicality for category \( C_i \) and the typicality of other possible values for this criterion:

\[
\alpha_j = \frac{\sum_{k=1}^{5} (T_{k} - T_{qj})}{4} \in [0, 1].
\]

On one hand, these weights help to identify central individuals in a group. On the other hand, they can be used in various applications such as classification by prototypes. The principle is to deduce a system of weights associated with various criteria of an e-commerce website within each class of satisfaction customers.

V. Prototype Classification for E-customer Satisfaction Survey

The block diagram mentioned in Figure 6 provides a better understanding of the process of prototype classification in data stream scenario, particularly focusing on the mathematical foundations of classifying customers taking into account weights of continuous, categorical and fuzzy criteria.
VI. Findings

A. Case Study

We choose reviews and click stream data from TMALL as the data source. TMALL is an important business unit of Alibaba Group which is known as the top one B2C platform in China. The user’s behavior of browsing TMALL reflects their preference of items. This data set contains 25432915908 records of user-item interactions. Features of each row are listed as below:

<table>
<thead>
<tr>
<th>Item</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>User_id</td>
<td>A string as &quot;u9774184&quot;, denoting an unique user</td>
</tr>
<tr>
<td>Item_id</td>
<td>An integer in[1, 8133507], denoting an unique item</td>
</tr>
<tr>
<td>Action</td>
<td>Type of behavior, a string like &quot;click&quot;, &quot;collect&quot;, &quot;cart&quot;, &quot;alipay&quot;, represents for 'click', 'add to favorite', 'add to cart' and 'purchase', respectively</td>
</tr>
<tr>
<td>Vtime</td>
<td>Timestamp of user’s behavior</td>
</tr>
</tbody>
</table>

Table 1. User-Item Interaction.

Review data is available for partial "user-item" pairs, which contains the review and rating on the item/merchant/logistic. This data set contains 241919749 rows, corresponding to 241919749 reviews:

<table>
<thead>
<tr>
<th>Item</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item_id</td>
<td>An integer in[1, 8133507], denoting an unique item</td>
</tr>
<tr>
<td>Feedback</td>
<td>A string containing multiple key words, separated by ' '. There words are extracted from the raw title by an NLP system</td>
</tr>
<tr>
<td>Rate_Pic_url</td>
<td>An URL linked to corresponding image online</td>
</tr>
<tr>
<td>Gmt_create</td>
<td>Timestamp of the review, A string as &quot;yyyy-mm-dd hh:mm:ss&quot;</td>
</tr>
</tbody>
</table>

Table 2. Online Customer Reviews.

<table>
<thead>
<tr>
<th>Item Id</th>
<th>Item Id</th>
<th>User Action</th>
<th>VTime</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>u41</td>
<td>i161</td>
<td>Click</td>
<td>30/09/2014</td>
<td>★★★★</td>
</tr>
<tr>
<td></td>
<td>i534</td>
<td>Alipay</td>
<td>15:19:00</td>
<td>★</td>
</tr>
<tr>
<td>u57</td>
<td>i135</td>
<td>Cart</td>
<td>26/09/2014</td>
<td>★★</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>02/09/2014</td>
<td>★</td>
</tr>
<tr>
<td>u1641</td>
<td>i109</td>
<td>Alipay</td>
<td>11:50:52</td>
<td>★★</td>
</tr>
</tbody>
</table>

Table 3. Tmall Data Sampling.

<table>
<thead>
<tr>
<th>Item</th>
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<tbody>
<tr>
<td>Item_id</td>
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</tr>
<tr>
<td></td>
<td>i534</td>
<td>Alipay</td>
<td>15:19:00</td>
<td>★</td>
</tr>
<tr>
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<td>i135</td>
<td>Cart</td>
<td>26/09/2014</td>
<td>★★</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>02/09/2014</td>
<td>★</td>
</tr>
<tr>
<td>u1641</td>
<td>i109</td>
<td>Alipay</td>
<td>11:50:52</td>
<td>★★</td>
</tr>
</tbody>
</table>

Table 3. Tmall Data Sampling.

Table 4. Descriptive Example of Used Training Data
Customers who don’t describe their feedback were chosen as testing set as mentioned in Table 5.

<table>
<thead>
<tr>
<th>Item</th>
<th>Item</th>
<th>User</th>
<th>VTime</th>
</tr>
</thead>
<tbody>
<tr>
<td>u39</td>
<td>i46</td>
<td>Click</td>
<td>03/09/2014 21:01</td>
</tr>
<tr>
<td>i53</td>
<td>Cart</td>
<td>29/09/2014 11:17</td>
<td></td>
</tr>
<tr>
<td>i366</td>
<td>Alipay</td>
<td>04/09/2014 19:23</td>
<td></td>
</tr>
<tr>
<td>u3286</td>
<td>i52</td>
<td>Collect</td>
<td>27/09/2014 0:28</td>
</tr>
<tr>
<td>u2984</td>
<td>i41</td>
<td>Cart</td>
<td>24/09/2014 21:36</td>
</tr>
</tbody>
</table>

*Table 5. Tmall Testing Data*

Data in Table 4 present the processed original data (Table 3) used as training data to learn the model and to adjust weights. Test dataset is used for assessing model performance on future data. However, in many applications only two sets are created, training and test. Table 4 describes used training and test data where class is deduced from online reviews which are filtered by 5 starts referring to customer satisfaction rate. C1: Very Satisfied, C2: Satisfied, C3: Moderately Satisfied, C4: Moderately Satisfied, C5: Not Satisfied. For each class of each customer, restrictions can be placed on E-CRM features values to define their possible changes based on e-customer behavior during navigation sessions. These features will be classified into 5 linguistic terms. e.g. (0.0/VW Very Weak + 0.0/W Weak + 0.5/M Medium + 0.5/S Strong + 0/VS Very Strong).

**B. Results and comparison**

For the purpose of the current study a performance assessment model for e-commerce is proposed including criteria, indicator weights, and evaluation method. The model designs prototype to understand customer satisfaction trends. For this process, the related attributes weights are identified to assist in understanding customer needs.

<table>
<thead>
<tr>
<th>Class</th>
<th>Usability</th>
<th>Content Adequacy</th>
<th>Reliability</th>
<th>Order Fulfillment</th>
<th>Delivery Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td>Available-To-Promise</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>1.042</td>
<td>0.901</td>
<td>1.180</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C2</td>
<td>M</td>
<td>M</td>
<td>S</td>
<td>Available-To-Promise</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>0.968</td>
<td>0.886</td>
<td>0.905</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C3</td>
<td>W</td>
<td>M</td>
<td>M</td>
<td>Not Available-To-Promise</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>0.965</td>
<td>0.986</td>
<td>1.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C4</td>
<td>W</td>
<td>S</td>
<td>M</td>
<td>Not Available-To-Promise</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>0.820</td>
<td>0.869</td>
<td>0.742</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C5</td>
<td>W</td>
<td>W</td>
<td>VW</td>
<td>Not Available-To-Promise</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>0.865</td>
<td>1.033</td>
<td>1.190</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Table 6. Class Satisfaction Prototype Based on Typicality as a Relevance Index Using Training Dataset.*

Table 6 depict the prototype showing the profile of online customer and display pertinent information from the customer point of view like e-CRM factors interestedly encourage participation of customer as frequent buyer. Attribute of "Order Fulfillment" and "Reliability" have the high rank among the effective factors, it is recommended that accessibility of customer knowledge information about order status should be made possible for the entire staff, a positive view should be created on change of customer relation. The usability and delivery time factors are rated second. The feature "Content adequacy" is identified as the factor with least priority of effect.

![Figure 7. ECRM Attributes Weights Based on Prototypes Calculated in Table 6](image)

Results show that the proposed model gives label correctly predicted respecting the three types of features, e.g: the customer u4 is affected to the class C1 (Very satisfied) with a maximum membership degree equals to 0.752.

We give a broader comparison in tabular from the existing MCDM methods for ECRM implementation and the proposed method under fuzziness (Table 7). Comparison results show that the e-commerce is not an area frequently researched by using fuzzy sets with categorical and numeric data as evaluation criteria. Existing approaches realize customer’s attitudes towards the preferred online service characteristics without prior knowledge about the E-CRM criteria weights in the customer’s viewpoint. Our proposed approach can evaluate E-CRM system by capturing the precise and uncertainty of vague and imprecise information based on customer click stream data record.
<table>
<thead>
<tr>
<th>Analysis Method</th>
<th>Problem Definition</th>
<th>Considered Criteria</th>
<th>Measures of Goodness of split</th>
<th>Decision Rules and Class Assignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision Tree</td>
<td>Customer profiling</td>
<td>Continuous data</td>
<td>Usage of Golden-section search (GSS)</td>
<td>Identifying a group of customers who have the same preferences and predict the set of customers with highest probability to accept the offer based on their personal characteristics</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Numeric and categorical criteria</td>
<td>Entropy Information Metric (TEIM)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Continuous valued (real and integer)</td>
<td>K-ary partition discretization</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Fuzzy criteria</td>
<td>Combined fuzzy C-means and ID3, Order-Neuro- Fuzzy Decision Tree, or multilabel fuzzy decision tree</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Analysis Method</th>
<th>Problem Definition</th>
<th>Considered Criteria</th>
<th>Weighting Attributes</th>
<th>Aggregation of Preferences and Class Assignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Envelopment Analysis (DEA)</td>
<td>Measuring e-commerce efficiency</td>
<td>Inputs, outputs should reflect an analyst’s or manager’s interests</td>
<td>Weights are determined using linear programming to maximize the ration of outputs to inputs</td>
<td>A gray relational coefficient is built to know which alternative should be improved to come close to the aspiration level.</td>
</tr>
<tr>
<td>Grey Analysis Method (GRA)</td>
<td>Improve e-store business</td>
<td>build an influential network relationship map(INRM) of quantitative criteria</td>
<td>Weights based on face-to-face questionnaire administered to 10 frequent shoppers who are e-store experts</td>
<td></td>
</tr>
<tr>
<td>Or VIKOR Method</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOPSIS Or PROMETHEE Or ELECTRE</td>
<td>Ranking B2C e-commerce Website</td>
<td>Subjective or vague data must be considered during the process</td>
<td>AHP, LINMAP, ANP methods are performed according to the decision-makers preference</td>
<td>The preferences of decision-makers are indentified using Saaty scale.</td>
</tr>
<tr>
<td>Quality Evaluation Method (QEM)</td>
<td>Website quality evaluation</td>
<td>Measurable criteria: Aesthetic, Ease of use, multimedia, rich content, reputation</td>
<td>Weights depend mostly on expert’s judgments using website quality metrics (QCF score)</td>
<td>Assessment of partial and total quantitative quality preferences regarding the experts standpoints.</td>
</tr>
<tr>
<td>PROPOSED APPROACH</td>
<td>Customer Satisfaction and Strategic analysis of electronic service quality</td>
<td>Use numeric, nominal and fuzzy evaluation criteria. Possible to add different types of other evaluation criteria</td>
<td>Assign weights of evaluation criteria based on customer’s opinions. Weights must denote the importance of the criterion to determine different e-customer’s satisfaction levels</td>
<td>Aggregation preferences based on normalization weights of numeric, nominal and fuzzy evaluation criteria according to each customer satisfaction level.</td>
</tr>
</tbody>
</table>

Table 7. Comparative Study of MCDM methods and the Proposed Model.
VII. Conclusion and Implications

The results of this study give several implications for online service providers and marketing managers with regard to how to plan and market services that will be considered valuable by customers. Furthermore, the present study considered as important grounds for implementing e-CRM performance in assessing service providers to achieve sustainable customer satisfaction based on customer navigational data. Concerning the factors that influencing E-CRM performance. The present research suggests five factors as important determinants of E-CRM performance. A MCDM method has been proposed to carry out factors weights in accordance with customer satisfaction level.

Further study can expand the proposed method with other more objective criteria analysis methods to increase its accuracy and robustness by expanding the framework across industries and integrating more important factor that may influence E-CRM performance.

References


