LEVERAGING SOCIAL NETWORK DATA FOR ANALYTICAL CRM STRATEGIES - THE INTRODUCTION OF SOCIAL BI

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Abstract

The skyrocketing trend for social media on the Internet greatly alters analytical Customer Relationship Management (CRM). Against this backdrop, the purpose of this paper is to advance the conceptual design of Business Intelligence (BI) systems with data identified from social networks. We develop an integrated social network data model, based on an in-depth analysis of Facebook. The data model can inform the design of data warehouses in order to offer new opportunities for CRM analyses, leading to a more consistent and richer picture of customers’ characteristics, needs, wants, and demands. Four major contributions are offered. First, Social CRM and Social BI are introduced as emerging fields of research. Second, we develop a conceptual data model to identify and systematize the data available on online social networks. Third, based on the identified data, we design a multidimensional data model as an early contribution to the conceptual design of Social BI systems and demonstrate its application by developing management reports in a retail scenario. Fourth, intellectual challenges for advancing Social CRM and Social BI are discussed.

Keywords: Social Network, Business Intelligence, Social Business Intelligence, Data Warehouse, Conceptual Modeling
1 Introduction

Social networks are one of the most impressive landmarks in the history of both IS and marketing research. Facebook with over 800 million active members, Twitter with over 200 million members, and YouTube with over 48 million members provide a massive amount of potential customer data. Social media permeates nearly all activities of professional and social life. For instance, Facebook has recently announced its new timeline concept that organizes all personal data of a user along their entire membership in the network. Furthermore, a study with about 22,000 Myspace profiles (Thelwall 2008) has shown that only 27% of investigated profiles were private profiles.

Combining social network data with customer data as stored in common enterprise application systems would greatly enhance customer relationship management (CRM) and thus enable customer analysis on a much more detailed level. One manifestation is the access to a customer’s social ties in online networks. Knowledge about current life situations of customers might enable the offering of integrated and custom-fit product service bundles that benefit suppliers and customers at the same time. In addition, access to customer interests as well as group or event memberships might augment customer profiles in CRM systems, too.

The potential to capitalize on social networks has already been considered in the literature. In their paper on Digital Public Assets (DPA), Rosemann et al. (2011) conceptualized the potential of digital public goods such as social networks. In their view, DPA are goods that are characterized by non-excludability, non-rivalry, versatility, and positive network effects. Therefore, they differ significantly from common enterprise-wide systems that can be fully controlled by organizations. In this paper, we investigate the question of how data that is administrated on DPA can be utilized to augment the design of management reports as run in current business intelligence systems.

Four contributions are offered. First, we conceptualize Social CRM and Social Business Intelligence (Social BI) as emerging research phenomena in the IS discipline. Second, we discuss how data from social networks can augment CRM strategies by presenting a data model for the Facebook network. Third, by designing a multidimensional data model for structuring business reports, we inform the conceptual design of future Social BI systems. Fourth, privacy issues and real-time data analytics are presented as aspects to be investigated more thoroughly in future research.

The paper proceeds as follows. Related work on social media, Social BI and multidimensional data modeling is discussed in Section 2. Based on a review of the data requirements of analytical CRM strategies, we discuss the potential of including data from online social media to analytical CRM in Section 3. This is done based on re-engineering and analyzing a data model of Facebook as well as by designing a multidimensional data model for Social BI. The applicability and usefulness of the multidimensional data model is demonstrated by presenting business reports for a fictional retail company in Section 4. Based on a conclusion, potential for future research is offered in Section 5.

2 Related Work

2.1 Utilizing Social Media along the Customer Lifecycle

Kaplan & Haenlein (2010, p. 61) define social media as “a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user generated content”. In fact, the content users generate in social media becomes more and more relevant for product and brand marketing (e.g. Kaplan & Haenlein 2010; Thompson & Sinha 2008).

Referring to a four stage customer categorization in a customer’s lifecycle (prospects, responders, active customers, and former customers) (Rygielski et al. 2002), we further describe the potential benefits that social media contribute to each of these stages. Prospects: Prospects are potential customers that have no company contact yet. Marketing experts explicitly can use existing social networks in order to influence network members that might be potential customers. By engendering a
sense of loyalty, firms aim to increase the purchase likelihood of members (Thompson & Sinha 2008). 

**Responders:** In order to increase the number of people who show an interest in a product or service, specific recommendation methods have been developed. For instance, Liu & Maes (2005) explored how a model of people can be built by capturing their web traces. They further used this model to generate interest maps of people. Another example is the investigation of the role of relationships between users for developing a track recommendation system for music platforms (Konstas et al. 2009). Through the recommendation of tracks that already have been listened to by a couple of friends, the likelihood to extend the number of responders for these songs can be increased. **Active Customers:** Social network activities aim to create a sense of “oppositional loyalty” (Muniz & O’Guinn 2001). Opppositional loyalty brings (potential) customers to an adversarial view of competing products. Companies hope to decrease the likelihood that social network members would buy products from competitors (Thompson & Sinha 2008). **Former Customers:** From a customer perspective, social media provide a powerful means to protest against a company’s behavior. Ward & Ostrom (2006) analyzed the behavior of unsatisfied customers on protest sites. They found that disgruntled customers might attempt to take revenge by negatively influencing other customers. Social networks empower customers to inform others to a much higher extent and much quicker than does offline word-of-mouth. On the other hand, organizations may use these platforms to identify the shortcomings of their goods and services and to react on emerging protest more quickly. In this way potential negative developments may be mitigated, while positive connotations may be fostered.

### 2.2 Introduction of Social CRM and Social BI

The area of CRM can be categorized into three distinct fields for research and management: Operational CRM, Analytical CRM and Strategic CRM (Iriana & Buttle 2006). In this article we contribute to the field of analytical CRM, which focuses “on the development and exploitation of customer data” (Reiny & Buttle, 2008, p. 25) in order to choose customer segments to be served, subject to the lifetime value of customers. In that way, analytical CRM aims to increase marketing and sales effectiveness by collecting and analyzing customer data regarding (1) actionable information, (2) offering appropriate products, and (3) selecting suitable channels (4) at the right time (Iriana & Buttle 2006). Business Intelligence (BI) is employed for analytical CRM, in that it “is used to understand the capabilities available in the firm; the state of the art, trends, and future directions in the markets, the technologies, and the regulatory environment in which the firm competes; and the actions of competitors and the implications of these actions” (Negash 2004, p. 189) (see Figure 1).

![Figure 1. Areas for research based on combining internal and external customer data](image-url)

Numerous articles discuss the usefulness of exploiting customer knowledge (e.g. Rowley 2002; Ryals & Knox 2001). These approaches are based on the assumption that the more information about the customers is known, the more support for decisions can be provided through CRM. However, traditional analytical CRM is restricted in that it applies Business Intelligence systems capable of
processing limited sets of internal customer data (e.g., name, address, bank account) and business transactions (e.g., offers, orders, invoices) only.

Motivated by the advent of huge amounts of user-generated content in social media, we conceptualize Social CRM as an emerging field of research and management that goes beyond traditional analytical CRM in that it is augmented with rich customer data to be identified from social media external of the organization (see Figure 1). Analogously, we conceptualize Social BI as the systematic approach of identifying, analyzing, and utilizing customer data that reflects this social context. Social BI systems are implementations of software that realize the concept of Social BI as IT systems (see Figure 1). They systematically integrate external social media data with customer information internal to the organization, offer analyses to interpret these data, as well as support management decision making.

The business value of Social CRM and Social BI is apparent when positioned into the context of social listening, social data analysis, and social engagement. First, organizations need to pay attention to what is being communicated by consumers on social media (i.e., social listening). For instance, discussion threads in technical customer forums for a specific car model can be observed by car manufacturers to discover shortcomings of their products. Second, the identified data have to be systematically analyzed. This is the central step for Social BI approaches, since customer data is not analyzed based on individual customers, but rather on the aggregated level (e.g., for customer segments). In the example of the car forum, all discussion threads could be analyzed by specific key word searches to identify common themes of technical issues. Third, analysis results can inform management decision making. For instance, the car manufacturer could choose to provide a solution for problems identified from analyzing conversation threads.

2.3 Multidimensional Data Modeling for Social BI Systems

For the conceptual modeling of BI systems, several modeling techniques were developed. They all refer to the basic constructs of data warehousing and reporting (Holten 2003). Reference objects are “measures, processes and states of affairs which can be object to arrangements or examinations on their own” (Riebel 1979, p. 869). Examples are master data like products, regions or customers. Particular reference objects like year 2010 or region Australia are conceptualized as instance objects. Hierarchically structured reference objects are conceptualized as dimensions. Reference objects may be leaf nodes in a hierarchical tree or as aggregation objects, the so-called inner nodes in the tree. Dimensional parameters are represented by (dimensional) attributes. The navigation through hierarchies is called roll-up for aggregation and drill-down for disaggregation. Other navigation operations exist for the detailed analysis of data. They are all summarized as online analytical processing (OLAP) operations (For OLAP details see Bulos, 1996). Ratios (or measures) reflect the value and performance of an organization. OLAP analyses are conducted based on ratios that are structured by dimensions. A data cube combines data in dimensions, measures and attributes to prepare multidimensional data analyses, such as OLAP.

Common modeling techniques for the conceptual specification of requirements for BI systems are Application Design for Analytical Processing Technologies (ADAPT) (Bulos, 1996), the Multidimensional Entity Relationship Model (ME/RM) (Sapia et al., 1998), the Dimensional Fact Model (DFM) (Golfarelli et al. 1998) and H2forReporting (H2fR) (Becker et al., 2012). Although these modeling techniques have in common that they support the modeling of basic data warehouse constructs, they differ slightly in their modeling constructs and notions. H2fR follows a target-oriented data warehouse design that is based on report definitions.

3 Design of a Multidimensional Data Model for Social BI

3.1 Identifying the Information Requirements of CRM Strategies

We build on the framework of CRM strategies as proposed by Kumar (2008) to identify the information needs of analytical CRM. The framework consists of eight strategies that are directed towards the central goal of measuring and maximizing customer lifetime value (CLV):
Customer selection: Companies need to focus on those customers that are most profitable. To inform the selection process, CLV is calculated for each customer. Moreover, different customer attributes are analyzed in order to set up homogenous groups of customers. Results might be customer segments in the form of ABC clusters that reflect distinct CLV segments.

Managing loyalty and profitability simultaneously: Not all loyal customers are necessarily profitable, and not all profitable customers are necessarily loyal (Reinartz & Kumar 2002). Customer segmentation helps to establish an effective loyalty program. To maximize profits, customers in each segment may be approached individually. The goal of this strategy is to assure the loyalty of the most profitable customers. Analyses for segmentation may include information about current revenues, margins, sold products, personal opinions, and service requests.

Optimal allocation of resources: Efforts need to be focused on those customers that are most profitable. In that way efforts for retaining non-profitable customers can be devoted to more rewarding customers. For preferred customers, the right mix of different contact channels has to be identified, along with an adequate contact frequency.

Pitching the right product to the right customer at the right time. In an ideal contact strategy, a company will deliver a sales message that offers the product to a customer who will likely make a near future purchase (Kumar 2008). This requires extensive information about customer’s preferences based on analyzing past interactions and his/her current situation. Only when the firm knows what customers need at a certain point in time and at a certain location, they are able to deliver a tailored product or service.

Preventing customer attrition: To avoid customer attrition, information about the past and current product or service satisfaction is required. On the basis of the probability of customer defection, decisions can be taken on whether, when and how to intervene. The CRM strategy aims at preventing a number of risks, such as loss of revenue, opportunity cost for re-acquisition of customers and negative word-of-mouth that might even affect other customers as well.

Managing multi-channel shoppers: Customers have constantly growing expectations towards the channels they want to be served with. These include channels for contacting the customers, channels for searching product information and purchasing, and channels for product and service delivery. From a company’s perspective, multi-channel strategies lead to higher revenue, increased sales share by single customers, and a higher likelihood to be chosen for future purchase (Kumar & Venkatesan 2005). In consequence, the company requires information on the channels available to and preferred by the customer, as well as information on channel integration.

Acquiring profitable customers: Long-time relationships to new, potentially profitable customers have to be established, whereas ties with recently inactive but potentially profitable customers may be strengthened. To that end, customer information like shopping history, product or service preferences, and intentions of purchase are needed to decide whether investments in customer acquisition and retention would pay off in the long run. Again, distinct segments may be identified (e.g. easy to acquire but not profitable customers vs. hard to acquire but profitable customers) and served individually, or discontinued to be served by future marketing activities.

Customer referral strategies: The goal of this strategy is to save customer acquisition and retention costs. A significant amount of research is devoted to better understanding causes and consequences (business value) of customer referrals (Kumar et al. 2007; Reichheld 2003). From a company’s perspective, information on the social network of individuals is essential for these considerations.

3.2 Systematizing the Available Data in Social Media

Traditional BI systems offer abundant data to analyses customer data. The question of who the most profitable customers are or which regions generate the most profit can be answered by such systems, based on processing transaction data in ERP systems, such as SAP. In social media, these questions cannot be answered in the same way for various reasons, such as the fragmentation of data across various social media. Therefore, the data administrated on social networks must be described first, in order to identify and prepare relevant data prior to their use in BI systems. In line with literature on data schema integration (Batini et al. 1986), we develop an abstract model for data stored in social networks (see Figure 2), based on analyzing the Facebook network (www.facebook.com).
The data model contains some entity types for data that might already exist in internal BI systems. Such overlapping entity types, like product, profile or affiliation, are shaded in grey. At the heart of social networks is the individual member, represented by a profile. The profile contains all personal information such as name, age, location, or interests. A subset of these data like the name, address or age might as well be stored in traditional master data records kept in CRM systems and extracted to BI systems for further analysis. On social media, each profile is associated with one or more affiliations, subject to a validity period. An affiliation may be either an educational institution or a workplace. Moreover, locations can be tracked by implementing a tertiary relationship that adds a location type to a profile-location relationship. A location type might be the current location, the hometown or a home address. A profile contains a personal blog which, depending on the privacy setting, is accessible by anybody. This blog acts as a kind of news station where any event (status change) of other members and all events are published automatically. Depending on the platform, these public messages may be augmented through rich content, such as photos and videos.

![Abstract social network data model](image)

Each profile is linked to \( n \) other profiles where each relationship is of a certain relationship type. Examples for relationship types may be friend, spouse, or in terms of business networks, business partners. Relations in social networks are undirected. The relations themselves contain the relationship start date and possibly historical information about cancelled relationships. The relationship relation is one of the most powerful sources of information contained in social networks because it enables the formation of both the individuals’ ego networks and the social network as a whole. Network analysis techniques focus on the analysis of such relationships. They can be categorized into sociocentric and egocentric approaches (van der Aalst 2004). Both categories contain metrics to measure a multitude of network properties, such as the centrality of particular members (egocentric, ego) or of the network as a whole (sociocentric). Typical network metrics include, for example, the Centrality Degree (distribution of the number of links to other network members), Centrality Betweenness (intermediary node location), or Centrality Closeness (minimal distance of an indirect path between two members) (Freeman 1979).

Besides the direct and indirect relationships of members, social networks offer the ability to initiate and participate in special groups and events, where members may communicate with other members with the same interest. The relationship between one member profile and a group or event is tertiary because each relation is coupled with a certain role type like group initiator, fan or group member.
Facebook enables its members to send messages to each other. Messages may be private or public. Private messages will be sent to a closed group of recipients. Public messages may either be comments on other members’ blog entries, group or event messages which appear on a blog, group or event page, where virtually anybody is able to read the message. In particular, Facebook offers the ability of a so called I-like-button, which refers to a like-comment on other messages. We express this special feature through an m-n relation between a profile and a public message. Furthermore, all interests can be “liked”. To express the interests of a certain person, social networks enable the selection of activities, sports, entertainment, or products. In business networks, members can express whether they are currently in the need for a new job and state their abilities, which in business networks are referred to as skills. So far, in our data model we only express the like-relationship. Table 1 categorizes data that might be used for analyses on the individual level and data that might be used for analyses on a network level and expresses example attributes and metrics.

<table>
<thead>
<tr>
<th>Examples for data that can be identified on social media</th>
<th>Individual Level of Analysis</th>
<th>Network Level of Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Profile</strong></td>
<td><strong>Group</strong></td>
<td><strong>Message</strong></td>
</tr>
<tr>
<td>Name</td>
<td>Group name</td>
<td>Message headline</td>
</tr>
<tr>
<td>Gender</td>
<td>Group members</td>
<td>Blog length</td>
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<tr>
<td>Age</td>
<td></td>
<td>Own interests</td>
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<tr>
<td>Location</td>
<td></td>
<td>Search interests</td>
</tr>
<tr>
<td>Affiliation</td>
<td></td>
<td>Own interests</td>
</tr>
<tr>
<td>Last visit</td>
<td>Creation date</td>
<td>Event name</td>
</tr>
<tr>
<td></td>
<td>Creation date</td>
<td>Event members</td>
</tr>
<tr>
<td></td>
<td>Last update</td>
<td>Event date</td>
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<td></td>
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<td>Event location</td>
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<tr>
<td></td>
<td></td>
<td>Betweenness centrality</td>
</tr>
</tbody>
</table>

Table 1. Social network data categorization and examples

3.3 Matching of Information Needs and Social Network Data

The data identified from social media (section 3.2) may be employed in manifold ways to augment analytical CRM strategies (section 3.1). While we cannot discuss the value of each data item for each analytical CRM strategy in detail here, we emphasize the following observations.

Online social networks offer supplementary details for customer selection. The long tail effect (Anderson 2006) enables suppliers to build meaningful customer segments of virtually any size, even on an individual level. To that end, data from customer profiles, memberships in groups, events, certain interests, or even in a person’s relationship status (e.g., singles) can be considered for forming the segments. Since customers have multiple interests and properties, they can be added to multiple segments. On a network level, cluster analyses have the potential to analyses relationship networks that go beyond the size of ego networks. This fine-grained data can then be used to run market segmentation and customer lifetime value computations at a very detailed level of analysis.

With respect to managing loyalty and customer profitability simultaneously, data from online social networks can be used to add information on customer loyalty to traditional market analyses. Online social network data such as profiles, group memberships, messages, or blog entries might be analyzed in order to identify a customer’s satisfaction with the goods or services offered by the supplier. Disgruntled customers might use a social network as communication channel to share their bad experiences with other consumers. On the other hand, satisfied customers would perhaps click the like button to become followers of the firm. However, customer profitability needs still to be calculated based on transaction data (such as orders or invoices), which are traced by traditional CRM systems.

Regarding the optimal allocation of resources, companies should focus on keeping their most important customers satisfied, while reducing expenses for low value customers. New ways of data segmentation enable companies to contact customers individually, at lower cost and with comparatively higher chances of success. In addition, customers who frequently use online social networks can be expected to have a comparatively high willingness to share and co-create information. Therefore, they might be more willing to accept self-service technologies, purchase goods and services online more often, and might be more responsive to commercial offerings provided online. This increases resource efficiency related to acquiring new customers.

All of the information offered on online social networks can help companies to pitch the right products or services to the right customer at the right time. An exhaustive and consistent amount of
online activity with many “likes”, comments, and participation in events would suggest that the information available in social media reflects an individual’s “true” social circumstances. This is important for companies to reason about the preference functions of their customers and offer tailored product and service offerings. For instance, location-based services can help to identify value propositions in line with the current location, messages, and events of customers.

Preventing the attrition of customers is based on calculating the probability of defection for each customer and deciding if at all, when and how to intervene (Kumar 2008). If a customer is not satisfied with a product or service, the company might detect this information through analyzing profiles, groups, events, or Blog entries. For instance, “likes” of competitors’ products might be good indications for an increasing likelihood to defect.

Managing multi-channel shoppers depends on integrating information that stems from interactions with customers on various channels. Whereas internal CRM systems are restricted to track a company’s traditional interaction channels, online social networks constitute a new way for tracking interactions that individuals perform with other actors on social networks. Therefore, an analysis of data such as profiles, messages, or blog entries, as well as recognizing the embedding of the communication into the customer’s ego network provide rich ways to improve the quality and accuracy of customer data, in case this information is available.

Data from social network sites can augment strategies for acquiring profitable customers. Whereas the traditional approach to acquire new customers would be to place commercial ads in order to establish ties with entirely new customers, online social networks complement this approach. Data from social networks can augment traditional strategies for getting in touch with potential customers at a much more detailed level of analysis.

In terms of referral marketing strategy, companies might want to access additional customers who obtain a central position within their ego networks as well as in the overall online social network. Based on sufficient network data, these authoritative persons can be discovered with network analysis techniques as hubs (i.e., the people that know many other influential people) and authorities (i.e., the influential people who are known by many other people) (Kleinberg 1999). Based on this information, a supplier can identify well-networked people who can share their thoughts with other people in far less time than can poorly networked people. Moreover, these people might span structural holes (Burt 1995) in the network, such that they can diffuse positive (as well as negative!) word of mouth into separate sub-communities very quickly.

3.4 Introducing a Multidimensional Data Model for Social BI Systems

In order to design OLAP reports for the support of decisions regarding analytical CRM strategies, data dimensions, hierarchies, and measures are essential elements that need to be specified before designing the actual reports. Based on the identified information needs from CRM strategies and the data systematized in the abstract social network data model (see Figure 2) we derive dimensions and measures available to create business reports.

One challenging technical task in order to combine internal CRM data schemata and social network schemata is managing the integration process itself (Batini et al. 1986). While this issue can be quite challenging in real-world settings, we abstract from this issue by assuming that customer information from social media can be matched with the customer entity type contained in the BI data schemata. The profile contains master data that might be used as primary key, for instance, e-mail address, phone number or address (or combinations of them). In this way a reliable link between internal BI datasets and social network datasets can be established. Having this profile-customer-connection in mind, we are now able to link transaction data such as sales quantity, turnover or return rates with the rich data identified from social networks.

In terms of CRM strategies and data that social networks may deliver, group and event memberships, personal interests and sociocentric network analyses seem particularly relevant. Based on this data subset we define the following six dimensions: Event, Home location, Realtime Location, Interest,
Affiliation and Group. All proposed measures and dimensions, as well as the hierarchies and instance objects are depicted with the H2fR language in Figure 3.

Events can be aggregated among two different nested hierarchies. First an event takes place at a certain location. Thus, a location hierarchy consisting of country, region, city and event was modeled. Second, an event takes place on a date at a certain time. Consequently, a hierarchy for the event date was modeled. Most companies do not track all former locations of a customer which brings us to the modeling of the dimensions Home and Realtime Location. Both dimensions can be derived from the entity types location and location type (see Figure 2). They contain one hierarchy starting with the hierarchy level country and ending with the home location(s) of a customer. Regarding the Interests of a customer, we identify one hierarchy that contains three hierarchy levels, starting with the interest type and ending with one particular interest. We distinguish the two interest types of professional interest and personal interest. The next level distinguishes interests in categories like sport, entertainment or leisure activities. The final hierarchy level contains one specific interest. The Affiliation, as another component of the profile, is refined to the hierarchy level affiliation category (workplace or education). Subordinate to that, the dimension is disaggregated by location-based characteristics, ending with the affiliation itself. Finally, each social network enables the formation of Groups. These groups enable the creation of a small network, which contains more than one subject. We use these subjects to build up categories of groups like work groups, fun groups, product groups, or location-based groups. Within the group dimension, we additionally model a second hierarchy that aggregates through the membership role of a customer within a particular group.

Besides the definition of dimensions, we use measures from internal BI Systems and combine them with measures available from social network analysis. Network analyses measures are manifold and cannot be exhaustively described here. We pick the centrality measures Betweenness, Degree, and Closeness (Freeman 1979; van der Aalst 2004) as they are amongst the most prominent measures for sociocentric and egocentric network analysis. In addition, we propose measures regarding the messages sent in the social network. The number of blog, event or group messages, their average and sum helps to identify the strength of relation between active social network customers along with their consumption behavior. We assume that customers who post many messages would be more interested in joining a certain group, too.
4 Demonstration

We now apply the multidimensional data model, including measures and dimensions, by designing management reports for a retail company (e.g., Walmart or Tesco). As depicted in Figure 4, we define a Social BI data cube (A) and two management reports (B and C) which provide views on this cube. Both reports are tailored to the CRM strategy information requirements. Retail companies offer loyalty cards or online apps to their customers to increase loyalty and turnover. One of the most prominent examples is Payback (www.payback.in). According to Payback’s statistics, 59% of German households use payback cards. Similar rates might be reached for retailer-specific loyalty cards. We expect that it is possible to track shopping carts and have access to personal customer information, presupposing the permission of the customers. Integrating this massive amount of data into a BI system and match it with social network data would open up new analysis potential.

![Figure 4. Social CRM Data Cube and Conceptual Report Models](image)

Report B refers to the CRM strategy of an optimal allocation of resources. It provides marketing managers with information on changes of revenue and number of customers for certain customer segments (A, B, or C segments, with a certain interest, e.g., football, soccer, or tennis) on a monthly basis. In the rows, users can drill through the dimension customer category. The columns allow drilling through into time to identify the measures average revenue, and number of customers. Both measures were taken from internal BI systems, whereas the interests were identified from social networks. The use of such a report provides an insight into current revenues of customers who are categorized into more valuable customers (A customers) and less valuable customers (B and C customers). Marketers may now analyses the differences and develop their marketing decisions based on this information. If most valuable customers would be more interested in Tennis than in Football, marketing campaigns might be more efficient if focusing on this sport.

The second report example (C) focus on the CRM strategy of pitching the right product to the right customer at the right time. It provides information on the number of customers that have been at a certain place and participated in a particular event on Facebook. Assume a Facebook member that attends the event “Madonna Concert” and logs in via a mobile phone application in Paris. Now we aggregate all members that are currently located in Paris and attend the Madonna concert event. If there is a large enough number of profitable customers, marketers may directly inform the local branch in Paris to prepare a promotion on Madonna CDs. They may inform the customers via Facebook and thus offer the right product to the right customer at the right time.
5 Conclusion

In this paper, we introduced the area of research and management of Social CRM, which builds on internal customer data enriched with information retrieved from external social network sites. We then argued that BI systems, as a major information source, need to be systematically extended to the inclusion of customer data available on social network sites. To elicit the information needs of analytical CRM, we referred to the eight CRM strategies of Kumar (2008). Based on the analysis of Facebook, an abstract social network data model was developed, which formally describes the data that is available on typical social network sites. We then matched the information needs with the provided data and developed a multidimensional OLAP cube, especially for customer selection and product placement strategies. To demonstrate the feasibility of the approach, we elicited a fictive case of a retailing company.

Several contributions to the IS discipline are offered. From the outset of theoretical considerations on the business potential of Digital Public Assets, we introduced Social CRM and Social BI as emerging phenomena for IS research. Second, we demonstrated how CRM strategies would benefit from incorporating data from social network sites into BI systems, based on developing a data model for Facebook, as well as a multidimensional data model for designing reports in Social BI systems. Third, we demonstrated the applicability and utility of this multidimensional data model by designing a particular Social BI data cube for a retail company.

A limitation is the restriction of analysis to the data offered on Facebook as one, however dominant, example for social networks. The model could be advanced based on the analysis of other social networks. The restriction on current CRM strategies leaves room for designing particular strategies that require processing social network data in the first place. In addition, the feasibility of the proposed approach for Social BI needs to be thoroughly evaluated in real world scenarios to assess its real business value.

We understand our paper as an early contribution in the field of Social BI. While we focused on the perspective of information needs from the viewpoint of analytical CRM, a multitude of related issues remain to be explored. Primarily, privacy issues will be of major importance since the analysis of data we proposed in this paper has to be in line with the privacy policy required by legal regulation. IS researchers and managers are faced with the need to design and deploy new business models based on which companies may process social data, while customers might benefit as well, such as from lower prices or more elaborate offers. Moreover, with the expected advent of in-memory computing, research on utilizing data from social media for real-time BI is needed. An example is matching customers and product offerings based on events that occur based of real-time information that is issued via mobile phone applications or tablet PCs. From a marketing perspective, further research might focus on innovative CRM strategies that presuppose processing huge amounts of social network data. A related specific issue is the question on which consequences arise for customer segmentation from the availability of social media data.

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