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Abstract

Social Media have emerged as an additional source of information for companies. Regarding an analysis of the huge data volumes within the Social Web, other approaches than manually analyzing social content are needed. Thus, Social Media Analytics (SMA) applications have emerged in recent years and have become inevitable for automatically generating valuable insights. However, these tools still suffer different shortcomings, which inhibit a deeper analysis and understanding of data. This research investigates and categorizes currently available analytics methods by outlining literature and analyzing practical applications. Furthermore, it draws a line between descriptive, predictive, and prescriptive analytics in the field of Social Media Analytics. As a result, this research complements existing research with strategic questions, possible outcomes of SMA applications, and enabling methods to compute these outcomes, and finally defines a research agenda.

Keywords: Social Media, Social Media Analytics, Business Analytics, Social CRM

1 Introduction

Within the last years, the use of Social Media has increased considerably. Social platforms, such as Facebook and Twitter, report more than one billion respectively 284 million monthly active users (Facebook 2015; Twitter 2015) and are thus connecting millions of consumers with their opinions worldwide. For example, every day there are more than 430,000 hours of new video material uploaded on the video platform Youtube (Youtube 2015), whereas in the same

time Facebook counts more than 55 million status updates (KISSmetrics 2015) and Twitter reports over 500 million tweets (Twitter 2014). Companies are thus increasingly confronted with a growing participation of internet users–and thereby potential consumers–within social networks. Regarding the customer lifecycle, a shift can be observed in the information and evaluation phases: consumers are no longer focusing on information given by a provider, but rather opinions on products or services shared by other consumers within social media. Therefore, social content is of high relevance for companies (Kaplan & Haenlein 2010; Heller Baird & Parasnis 2011; Woodcock et al. 2011; Mikalef et al. 2012) as they are able to gather additional insights into markets and consumer behavior. Those large volumes of social data match with the characteristic "3V" of Big Data–namely variety, velocity, and volume as summarized by Sagiroglu & Sinanc (2013)–and require automated analysis functionalities which are delivered through so called Social Media Analytics (SMA) applications. SMA applications are an integral part of a Social Customer Relationship Management (Social CRM) system as described in current literature (Sarner et al. 2010; Woodcock et al. 2011; Alt & Reinhold 2012). This has led to numerous SMA platform providers, while many of these tools are often easy to use and present qualitative results to obtain first insights into the market or the consumer base.

With respect to recent scientific literature on Social CRM and SMA software, there is no comprehensive understanding about analysis methods, analysis outcomes, and the enabling methods to compute certain outcomes. Therefore, this research aims at outlining literature and analyzing SMA applications in order to define the capabilities of SMA software for the analysis of unstructured content. The overall aim is to deepen insights generated through these applications and thereby to support decision making processes. In this context, this article formulates the following two research questions: First, are retrospective and prospective analytics supported by currently available SMA applications and are suggestions for the best possible actions provided based on these analytics in order to guide decision making? Second, which basic points can be derived from a tool analysis with regard to further research? A basic understanding based on business analytics is developed and, finally, a research agenda covering questions, enablers, outcomes, and a maturity level of SMA applications is defined. Finally, this article calls for further research, which helps driving analytics and decision making in an increasingly social environment.

2 Foundations

The following section clarifies the necessary foundations in the areas Social CRM and SMA, a general classification of SMA technologies as well as the SMA Process (also termed pipeline). Social CRM is regarded as the focused field of application of SMA, while SMA includes different technologies for analyzing unstructured data, such as user-generated content, in the frame of the SMA pipeline. A general classification of SMA technologies is used to identify the technological state-of-the-art and research gaps.

2.1 Social CRM and SMA

Although researchers may have a rough idea of what is meant by the term Social CRM, it is necessary to draw a line to the two related concepts it consists of: Social Media and Social CRM. Following (Greenberg 2010), Social Media is defined as web-based internet applications

that allow the creation, access, and exchange of user-generated content. Besides the well-known social networking sites, such as Facebook, there is a multitude of applications which can be classified according to (Kaplan & Haenlein 2010) into at least the following categories: social networking sites (e.g. Facebook), blogs and micro blogs (e.g. Wordpress, Twitter), collaborative projects (e.g. Wikipedia), and content communities (e.g. Youtube). With regard to a CRM system, these channels can be associated with a business's operational communication channels.

The term Social CRM is building upon these applications and describes a concept (Greenberg 2009). A broad base of research that covers various strategic and tactical elements in the application of social media to business purposes has developed. However, research focusing the integration of social media and CRM on the system and process level is still scarce (Lehmkuhl & Jung 2013; Alt & Reinhold 2012; Askool & Nakata 2011). This integration requires three additional components: an analysis layer for the identification of relevant content, an integration layer for interlinking CRM functionalities and processes with information from the social web, and an interaction layer for supporting the dialogue with the community (Alt & Reinhold 2012) to reduce the isolation of social media activities from the existing customer oriented business processes.

A key element of Social CRM is the integration of data from the social web. While traditional CRM systems are based on structured data in internal databases, the integration of social media introduces unstructured data and requires new techniques of data analysis. One potential pitfall is that unstructured data is not compatible with existing analytics software, such as Business Intelligence or SMA applications. Therefore, semantic mining methods (e.g. text or web mining) are applied in order to transform unstructured data into structured formats by adding missing meta-data or context, extracting meanings, and classifying postings (Reinhold & Alt 2011). In terms of Big Data and with regard to an integration of social media with CRM applications, social content has a high variety as it includes both structured data and unstructured elements, which may respectively may not conform to existing data fields in a CRM application. Data volumes are a further aspect which needs to be considered when analysing social content. Therefore, both analytical functionalities and data storage capabilities need to be adapted to the respective intent. Finally, the velocity of incoming data needs to be considered as SMA applications ultimately form an information base on which CRM processes should build upon.

However, referring to (Stieglitz et al. 2014), SMA aims at "*developing and evaluating scientific methods, technical frameworks, and software tools for tracking, modelling, analysing, and mining large-scale social media data*" and therefore bridges the gap between unstructured social media data on the one and structured CRM data on the other hand. This challenge was answered in the past by the development of new software applications such as Sysomos, Brandwatch, or Synthesio for assessing, analyzing and transforming such information (Rappaport 2010).

2.2 Classification of SMA technologies

As mentioned before, SMA is an integral part of Social CRM systems, which in turn may be regarded as a specialization of the more general research area business analytics (for a

description of analytics see Davenport & Harris 2007), which makes use of all forms of analytics to realize business outcomes. It emphasizes on actionable insights (Stubbs 2011) and thereby extends the existing understanding of analytics. As proposed by Davenport and Harris (2007) and refined by Lustig et al. (2010), three categories of analytics may be defined within business analytics: descriptive, predictive, and prescriptive analytics (Lustig et al. 2010). These categories can be adapted to the field of SMA to assess the necessity and potential of analysis methods. Figure 1 presents these categories, their enablers and outcomes according to Delen and Demirkan (2013).
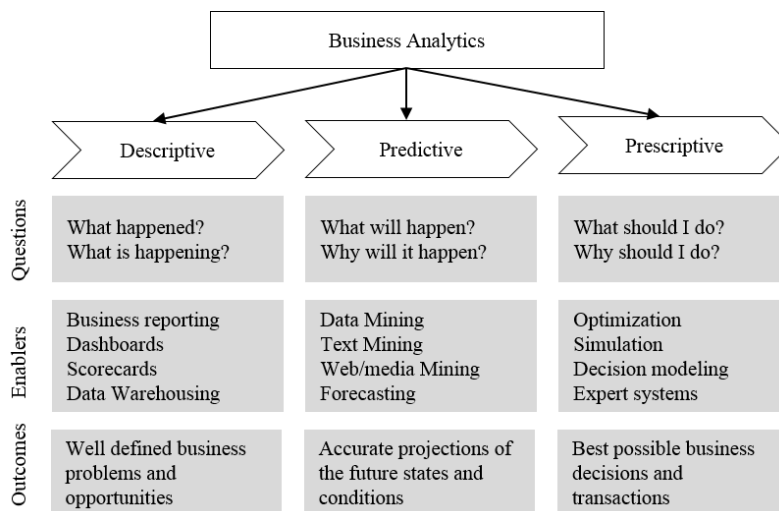

Figure 1: Basic theoretical understanding (according to Delen & Demirkan 2013)

Descriptive analytics thereby comprise a set of data processing technologies to understand and analyze business performance. Characteristic questions within this perspective are "What happened?" and/or "What is happening?", which in turn describes a predominantly retrospective view. Within SMA applications these questions are answered through simple standard and on-demand reporting, dashboards, and scorecards delivering insights like the number or fans, postings, and a distribution of conversations within different social media channels. The main outcome is the current business situation in terms of possible problems and opportunities. In contrast, predictive analytics use mathematical techniques to identify patterns (e.g. conversation volume per channel, the development of trending topics or user sentiments) and therefore answer questions like "What will happen?" and/or "Why will it happen?". Data, web, and text mining, as well as statistical time-series forecasting are the enablers of this view. The main outcome are future events and a reasoning why they may happen. Finally, prescriptive analytics include a set of mathematical techniques for determining a set of alternative activities (e.g. launching or re-adjusting a social marketing campaign) to improve decision making. This view focusses mainly on questions like "What should I do?" and/or "Why should I do?". Enablers of prescriptive analytics are among others optimization modelling, simulation modelling, and decision modelling, finally driving expert systems. The best course of action for a specific Social CRM scenario or a rich set of information leading to the best course of action are the main outcomes.

As business analytics may be regarded as a more general term of SMA, the given basic model will be applied to the conducted tool analysis. The functionalities of each SMA application will be clustered using the model. As a result, the state-of-the-art in analytics technologies and related deficits will be emphasized and points for a research agenda will be formulated.

2.3   SMA Pipeline

In the scientific literature, the analytics process, which may also be termed as analytics pipeline, consists of different phases and originates from the analysis of news media (Tenney 1912; Woodward 1934; Lasswell 1941). Current research presents several approaches with partially differing process steps. Below, a view on recent literature which describes automatable approaches is given. However, all processes require manual activities either by defining relevant source, configuring the search query, or by integrating results with third-party applications.

Following (Bengston et al. 2009) for the analysis of modern social media, the monitoring process encompasses the following five phases: the definition of the problem, the identification of online news sources that will be used to collect content, the development of search terms with respect to several strategies and the storage of search results, the analysis of textual content as the core phase of the analytics process, and finally the presentation of gained results. This analytics process approach is extensive as it includes strategic considerations with its first step and gives some relevant details. With regard to a Social CRM system, Reinhold & Alt (2011) propose seven "activities in an analytical Social CRM process", including monitoring, extraction, transformation, load, use, integration, and finally interaction regarding the subsequent interaction opportunities with a social community (Reinhold & Alt 2011, p.231). Another approach is proposed by (Bruns & Liang 2012) for the analysis of Twitter data. The authors suggest a three-step approach including data collection and storage in a first, data analysis in a second, and finally the publication of results in a third step. Stavrakantonakis et al. mention four relevant steps starting also with the collection of data, the establishment of a "listening grid" to store gathered data, followed by the actual analysis, and finally the generation of "actionable reports" in order to support decision-making (Stavrakantonakis et al. 2012, p.54). Finally, Ruggiero and Vos (2014) present a four-step approach. The following table summarizes relevant literature and gives a brief overview of considered process steps.

Author	Considered process steps
(Bengston et al. 2009)	• Define the problem • Identify online news sources • Develop search terms and download stories • Analysis • Presentation
(Reinhold & Alt 2011)	• Monitoring • Extraction • Transformation • Load • Use • Integrate • Interaction
(Bruns & Liang 2012)	• Data collection • Data analysis • Results publication
(Stavrakantonakis et al. 2012)	• Gather data • Establishing a listening grid • Analysis • Reporting • Insights
(Ruggiero & Vos 2014)	• Preparation • Data collection • Data analysis • Reporting

Table 1: Approaches to the definition of the SMA pipeline

Summarizing the existing approaches of an analytics pipeline, four main steps are suggested as displayed in Figure 2. First, the definition of media sources and appropriate search terms. Second, the pre-processing of data for integrating and aligning the heterogeneous data from different sources as well as the application of various analysis techniques. This paper focuses mainly on this step. Third, the presentation and interaction of users with the results. Fourth, the use of results, which is the only manual task. Each steps yields requirements for and influences the outcome of the other steps.
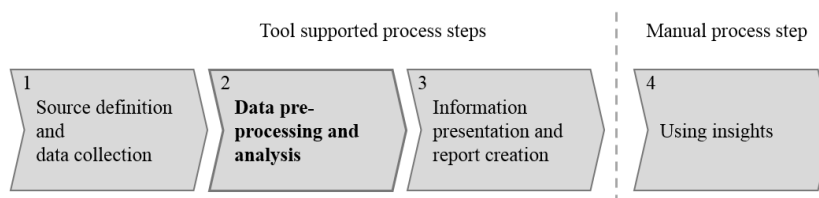

Tool supported process steps   Manual process step

| 1 Source definition and data collection | 2 **Data pre-processing and analysis** | 3 Information presentation and report creation | 4 Using insights |

Figure 2: Social Media Analytics Pipeline

The definition of media sources that are used to extract the social web content will influence all future outcomes as well as the configuration of the pipeline. It is essential to choose relevant channels carefully, because this step defines the ability to use historic data.

Each SMA application also covers different social media channels and those even in different degrees, which may require the use and integration of different applications. Furthermore, it is a crucial step to select the search terms that are relevant for the analytics scenario. Those terms generally define the dataset from which results can be obtained in the next steps. If the search phrase is too narrow, methods can produce only results within this scope. If the search phrase is too broad, the volume may be overwhelming and noise will influence the applied methods.

The step of analysis itself builds up on the data basis, requires a pre-processing, applies the analyzing methods (e.g. web, text, and data mining) and aims at generating domain insights. Data analysis is thereby a core element of the analytics pipeline and influences the necessary pre-processing (e.g. data aggregation, data fusion). The main task within this process step is to calculate information based on unstructured data, such as social media content and the quality of data as well as the algorithms define the outcome (e.g. sentiment, precision). The last step presents the results in the form of interactive visualizations, input into other systems or reports. Usually, SMA applications provide several presentations in the form of e.g. dashboards, diagrams, and charts, or support export functionalities, but the ability to refine search terms or to drill down depends on the applied methods and the user interface. Exemplary results that are displayed are the volume of postings per channel over time, demographic aspects of the posting writer, the overall tone of the postings based on their content, and the relevance of a media channel based on the volume posted on it. Because of its central role within the SMA pipeline, the step of data analysis and the available methods are the focus of the following sections.

3 Analysis methods and basic outcomes

Several approaches for the extraction of information from social media have evolved yet. Stieglitz et al. (2014) summarize these methods as "Social Media Analytics", a term which encompasses the extraction of raw data from social media and their transformation into insightful and useful information. Following (Zeng et al. 2010) SMA "is concerned with developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data (…) to facilitate conversations and interactions (…) to extract useful patterns and intelligence". Hereby, methods like text mining are subjected to an often complicated task. Major challenges are (1) the automated analysis of contained information within unstructured texts, (2) the automated recognition of patterns within texts, and (3) the aggregated presentation of gained information. Following Stieglitz et al. (2014), in the context of SMA three main analysis methods have evolved: text analysis/mining, social network analysis, and trend analysis (Stieglitz et al. 2014). For descriptive analytics the first methods commonly comprise tasks of data gathering and extraction, text categorization and clustering, as well as summarization and visualization methods (Zanasi 2007). Methods of data mining are partially overlapping with those from text mining as they comprise classification and clustering of texts, as well as affinity grouping and profiling (Berry & Linoff 2004). As a second method, social network analysis includes data aggregation and mining, network modeling, user attribute and behavior analysis, interaction analysis, recommender system development, and finally link prediction and entity resolution (Golbeck 2013).

Patterns extraction and trend analysis as mentioned by Zeng et al. (2010) and Stieglitz et al. (2014) indicate the necessity of predictive methods. Predictive analytics are considered as a further necessary view (Sussin et al. 2015) and comprise a collection of computer-based methods from the research fields text mining (Weiss 2005), data mining and statistical methods. Text Mining may contribute to this task through categorization and clustering techniques whereas data mining contributes to predictions in the same way and adds specific methods as for example estimation based on regression models and prediction. Computational intelligence may also contribute to predictions as its specific methods like artificial neural networks have been applied to classification, pattern completion, and times-series modelling tasks (Engelbrecht 2007). Currently under development are for example methods of sentiment analysis based on machine learning (Stieglitz et al. 2014) and–following the practical example of Brandwatch–based on complex rules instead of simple word lists (Brandwatch 2012). Budak et al. propose coordinated and uncoordinated trend detection as a means to detect emerging topics among highly clustered and distributed users (Budak et al. 2011) and Kasiviswanathanet al. (2011) propose a dictionary learning-based framework for the detection of emerging topics (Kasiviswanathan et al. 2011). Finally, Mathioudakis et al. (2010) define a method for the early identification of items with high attention in social media (Mathioudakis et al. 2010). From a research perspective, a basic set of methods for predictive analytics is given, but no prescriptive methods in the field of social media analytics were found in the related literature.

Using scientific literature on social media analytics and monitoring, a set of basic outcomes–merely in the field of descriptive analytics–can be defined. These outcomes represent exemplary insights, which are generated by applying e.g. text and data mining methods to social content. Reinhold and Alt (2012) instance the definition of relevant content, the identification of opinion leaders, and the presentation of relationships between actors as basic outcomes (Alt & Reinhold 2012). Stieglitz et al. (2014) extend this view and further instance the analysis of posting sentiments, trending topics, as well as relevant communities. Zhang et al. (2014) contribute to these examples with the analysis of spread patterns (Zhang & Vos 2014). The following table summarizes recurring analysis results within literature. The results will further structure the analysis and represent outcomes to be observed.

Author	Examples for analysis outcomes
(Alt & Reinhold 2012)	• Relevant content • Opinion leaders • Relations between actors
(Stieglitz et al. 2014)	• Posting sentiments • Trending topics • Relations between actors • Opinion leaders • Relevant communities
(Zhang & Vos 2014)	• Posting sentiments • Spread patterns

Table 2: Example results of social media analytics

4 Analysis of current SMA applications

The following chapter builds up on the proposed classification of SMA technologies (Figure 1) and the analytics pipeline with its respective analytics outcomes (Table 2) and aims at structuring the associated analysis of SMA applications. While literature defines a myriad of SMA technologies for at least descriptive and predictive analytics, it is supposed that currently available SMA applications lack rich functionality in the field of predictions and prescriptions. Therefore, the following research questions are formulated: Are descriptive, predictive, and prescriptive analytics offered by current SMA applications? Which basic points can be derived for a research agenda? The analysis aims at answering these research questions. Following on this, a technological gap is explained in more detail and a research agenda for SMA applications is defined.

4.1 Structure of the analysis

To conduct the analysis it is first necessary to create the analysis structure referring to an analysis concept. This concept is deduced from the introduced analytics categories and the exemplary outcomes as mentioned above.

Based on this simple structure the tools are assessed with respect to the delivery of the given result within each analytics category. This articles goal is not the determination of the best application available as this depends strongly on the respective underlying business scenario and other influencing variables. Instead, the contribution of the analysis lies in a formative evaluation of the tools functionalities. The resources of this analysis were trial and full versions of the tools. All tools were configured with the same input and used in practice in order to verify the availability of relevant features within the analytics process. In addition, white paper and provider information were used if provided. However, it seems obvious that marketing material of providers is biased and needs to be considered critically.

4.2 Selection of applications

In the present paper, a list of seven social media analytics applications forms the basis of the analysis: Sysomos, Brandwatch, Viralheat, Social Mention, Talkwalker, Synthesio, and Trackur. Although this list does not claim to be exhaustive, it represents a selection that was based on the following criteria (Stavrakantonakis et al. 2012):

1. Applications need to cover multiple business functions, e.g. market research, customer support, marketing, and trend identification;
2. Applications need to offer a rich set of functionalities, e.g. dashboards, crawlers, and sentiment analysis;
3. Applications need to have a considerable presence in the market, i.e. they are amongst the most relevant tools on the market;
4. Applications need to have technical information and trial accounts available.

Considering the information offered by the software vendors, tools were selected that correspond to the first two criteria. Covering the third criterion, tools were selected that are mentioned by market research companies, such as Forrester Research and Gartner (Smith 2014; Hopkins et al. 2014). Regarding the third criterion, only tools which offer a trial version to prac-

tically analyze the functionalities were chosen, in order to enrich information given in vendor's marketing material.

5 Findings

According to the above mentioned approach and by applying the constructed model, the analysis was conducted. Appendix A gives a complete overview of the results table and shows that descriptive analytics are mostly covered through the considered outcomes (Table 2), whereas predictive analytics are only partially covered within SMA applications. This result is even emphasized with regard to prescriptive analysis methods implemented in recent applications as there were no related functionalities found within the applications. These results are staying in contrast to the introduced literature and answer the first research question: descriptive, predictive, and prescriptive analytics are not evenly distributed in the investigated SMA applications.

Looking back at the basic model (Figure 1), the conducted tool analysis and scientific literature lack sufficient evidence of enablers in the three discussed categories. Consequently, based on research from IBM in the field of descriptive, predictive, and prescriptive analytics, the following enablers may be defined for each category and are proposed for the adaption to SMA applications (IBM Corporation 2013):

- Descriptive analytics: reports, dashboards, business intelligence
- Predictive analytics: alerts, predictive models, forecasts, scorings
- Prescriptive analytics: business rules, organization models, comparisons, optimizations.

Descriptive analytics are included in all of the analyzed applications and therefore form the methodological basis of the performed analytics. Methods of Business Intelligence are the enablers of a retrospective analysis of social content, presenting results mainly in dashboards and reports. These results are suitable for describing the current business situation and possible problems.

Regarding predictive features, only few outcomes are delivered. In the case of conversation volume and sentiments this is mainly because of alerts, which can be defined by a user and help identifying an ongoing development. With regard to trending topics, alerts and simple forecasts are offered, but are less distributed among the applications. Opinions leaders are predicted only by one application, whereas this result is computed through an alert, too. In summary and in addition to the use of analysis methods as mentioned before, it is observed that the proposed enablers are not used to their fully extend. Outcomes hereby aim at predicting future events and developments.

Finally, prescriptive features were not identified within the chosen applications, although providers of specialized tools are already providing optimization features. In this context, RiteTag helps a twitter user to complement a tweet with the most appropriate hashtags, for example. However, this tool does not belong to the class of SMA applications and requires the user to switch between multiple applications. Taking this into account, it offers a simple optimization feature and thereby contributes to answering the question of the best possible actions. Pre-

scriptive analytics are expected to indicate the best possible activities and decisions within a Social CRM environment. In summary, the assessed maturity level of the three analytics categories may be divided into high for descriptive, middle for predictive, and low for prescriptive analytics.

With regard to a Social CRM system, prescriptive analytics generally represent a high level of marketing optimization as they answer the above mentioned question "Which actions are appropriate?". It allows marketers to go even further than predicting user sentiments or campaign developments by considering predictions and highlighting fields of action. Given this tool set, marketers may be able to drive customer engagement and increase revenue. The current analytics pipeline encompasses the process steps as shown in Figure 2, but, however, needs to be enhanced. Recent analysis technologies (e.g. computational intelligence, graph analysis, and graph mining) may facilitate higher quality of outcomes and provide additional insights. As the analysis step is influencing the entire pipeline and the named potentials need to be leveraged, research in the following areas is necessary (Table 3). The listed points are sorted by the affected pipeline steps, beginning with the first step.

Research area	Examples	Affected pipeline steps			
		1	2	3	4
Adaption of the analytics pipeline	An adaption of the analytics pipeline may lead to better analysis results. Therefore, the following adaptions are proposed: • Dictionaries such as taxonomies or ontologies can be derived from enterprise databases and may simplify the source definition as explained above and may even provide query suggestions (Alt & Wittwer 2014) • Construction of hypotheses within the analysis step of the pipeline may lead to new insights • Rule engines offer the ability to define business rules for alerts and therefore enable better predictions • The users' opportunity of influencing the presentation of results (e.g. the manual editing of incorrect computed sentiments or the adoption of dashboards) need to be increased User-friendly and simple description languages may improve both querying social data (e.g. XML-based formats) and defining rules for decision making (e.g. decision modeling languages)	●	●	●	(●)
Implementation of advanced analysis methods	Regarding the enablers of descriptive, predictive and prescriptive analytics, it is necessary to determine, which *underlying analysis techniques* are relevant. Therefore, research on recent analysis techniques is necessary. Following		●	(●)	(●)

Table 3: Research agenda

Research area	Examples	Affected pipeline steps			
		1	2	3	4
Interactive visualization	The improvement of visualizations leads to a better us-ability of applications and improved understanding of present data. Therefore the following is proposed: • *Improved presentations* of results with recent ap-proaches (e.g. hyperbolic search tree, graphs and in-teractive dashboards) may even raise intelligibility of data • *Time lines* order data by publication time and deepen understanding of developments • The application of *predictions variants* (e.g. linear and non-linear regression models) • *Responsive visualizations* as known from Business Intelligence applications (e.g. drill down) need to be adopted to the field of SMA User-defined *combination of results* (e.g. the combina-tion of sentiments and channels, cf. Sussin et al. 2015) as possible through Online Analytical Processing (OLAP) techniques may also raise intelligibility and lead to new, case-specific insights		(•)	•	
Domain of application	The following functionalities would improve predictive (e.g. alerts) and prescriptive analytics: • *Recommendations* are a means to improve decision making and successful activities (e.g. rule-based ac-tions, alerts, and the suggestion of similar successful marketing activities) • *Time planning* (e.g. the best point of time to release a posting on social media) • *Suggestions* (e.g. posting, text, tweet, next best ac-tion) *Simulation* (e.g. influencer fit, channel strategy, inquiry prediction)		•	(•)	
Systems integration	Research is needed in the field of systems integration as companies need to decide between a *best-of-breed approach* (using isolated, specialized applications) and an *integrated systems approach* (e.g. integrated Social CRM systems). Regarding the use of analyzed data re-search is needed in the following areas: • Integrated systems may provide *automated interac-tions* with consumers (e.g. automated answers after a complaint was detected) Research on *decision support* based on social content needs improvement regarding reliable and robust meth-ods			(•)	•
•	Directly affected pipeline step				
(•)	Indirectly affected pipeline step				

Table 3 (continued): Research agenda

The adapted model (Figure 3) summarizes the proposed enablers for the realization of descrip-tive, predictive and prescriptive analytics in the context of SMA as well as an assessment of the maturity level of these analytics. Based on these results, a basic set of research areas is formu-lated and thereby answers research the second question.
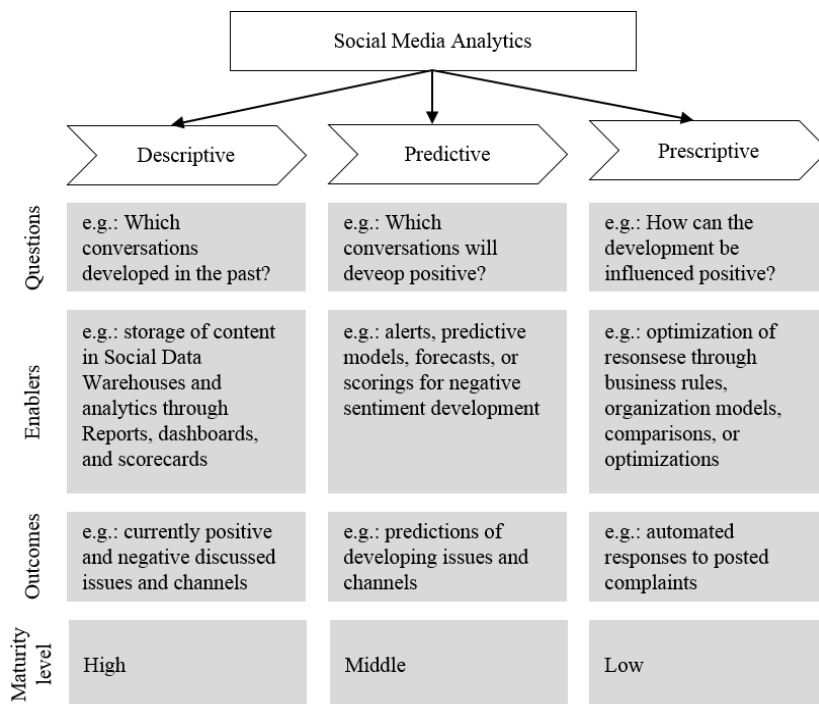
Figure 3: Adapted theoretical model

6   Conclusion and outlook

This research presents an analysis of currently available methods for SMA. It illustrates that SMA may be clustered into three categories, namely descriptive, predictive, and prescriptive. Based on business analytics, a model is provided and adapted for the research field of SMA. For each analytics category it shows basic questions and outcomes, and reveals necessary methods to compute those outcomes. Each part of the model is explained by simple examples. Based on an analysis of SMA applications, a maturity level in practice is deduced and, finally, points for a research agenda within the field of SMA are defined. These results are based on scientific literature and on a tool survey.

In detail the findings show that the maturity level of descriptive analytics is rather high, which is supported by current literature. Compared to predictive analytics features in practice, where maturity level is rather medium, literature shows first approaches for each analytics category. A low maturity level is observed for prescriptive analytics features, which are the least cov-ered–in literature and practice. Following this idea, this requires an adaption of the proposed analytics pipeline, which is differently defined by current scientific literature. The formulated points for a research agenda reflect this adaption, providing more detail for concrete research activities (see Table 3Table). The suggestions for the adaption of the pipeline are a first ap-proach that needs more elaboration. However, this framework reveals an approach for the first time.

Limitations arise considering the number of analyzed SMA applications. The study examined seven applications, but, of course, there are numerous applications in the market.

Although the study cannot be regarded as representative, tools were chosen, which are recommended by Gartner and Forrester. Furthermore, some potentially relevant applications could not be considered as there were no trial versions available. Lastly, this article focuses on SMA applications, but with regard to a Social CRM system there are more classes of applications identified, e.g. in the field of social media management. These tools aim at planning and publishing postings across multiple social media channels (e.g. Twitter, Facebook) based on the division of labor. Following this idea, possible prescriptive technologies, such as suggestions for the most appropriate hashtags or keyword within a social media posting, may be spread wider.

Acknowledgements

Appendix A

Application outcomes	Sysomos			Brandwatch			Viralheat			Social Mention			Talkwalker			Synthesio			Trackur		
	Descriptive	Predictive	Prescriptive	Descriptive	Predictive	Prescriptive	Descriptive	Predictive	Prescriptive	Descriptive	Predictive	Prescriptive	Descriptive	Predictive	Prescriptive	Descriptive	Predictive	Prescriptive	Descriptive	Predictive	Prescriptive
Relationsips between actors	◐	○	○	◐	○	○	○	○	○	○	○	○	●	○	○	○	○	○	○	○	○
Relevant communities	●	○	○	●	○	○	●	○	○	●	○	○	●	○	○	●	○	○	●	○	○
Conversation volume	●	●	○	●	◐	○	●	○	○	○	○	○	●	◐	○	●	◐	○	○	◐	○
Sentiment	●	○	○	●	◐	○	●	●	○	●	○	○	●	○	○	●	◐	○	●	◐	○
Trending topics	○	◐	○	◐	◐	○	◐	○	○	○	○	○	○	○	○	●	○	○	○	○	○
Opinion leaders	●	○	○	●	◐	○	●	○	○	●	○	○	●	○	○	●	○	○	○	○	○

●	Feature is available
◐	Feature is partially available
○	Feature is not available

Table 4: Results of the analysis of SMA applications

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