Konzeption, Implementierung und Evaluation von automatisierten Ansätzen zur Analyse von Social-Media Inhalten

DISSERTATION

zur Erlangung des Grades eines
Doktors der Wirtschaftswissenschaft

eingereicht an der
Fakultät für Wirtschaftswissenschaften
der Universität Regensburg

vorgelegt von
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Tag der Disputation: 24.06.2020

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Abkürzungsverzeichnis

API	Application Programming Interface
BPI	Business Process Improvement
bzw.	beziehungsweise
CSF	Critical Success Factor
CRM	Customer Relationship Management
DF	Determining Factors
d. h.	das heißt
DS	Design Science
ESN	Enterprise Social Networks
GUI	Graphical User Interface
IS	Information System
IT	Information Technology
JSON	JavaScript Object Notation
KMU	Kleine und mittelständische Unternehmen
KPI	Key Performance Indicator
Mgmt	Management
MNB	Multi-Nominal Naive Bayes
REST	Representational State Transfer
S.	Seite
SMPM	Social-Media Performance Management
SUMI	Software Usability Measurement Inventory
u. a.	unter anderem
vgl.	vergleiche
VOC	Voice of the Customer
z. B.	zum Beispiel

1 Einleitung

Dieses Kapitel definiert den Rahmen und die Grundlagen der vorliegenden Dissertation. Dabei wird zunächst in Abschnitt 1.1 die grundsätzliche Thematik motiviert sowie die zugrundeliegenden Problemstellungen dargelegt. Anschließend werden in Kapitel 1.2 konkrete Zielstellungen definiert, aus welchen die acht Forschungsfragen der Dissertation hervorgehen, die im weiteren Verlauf der Arbeit adressiert werden. Die zur Beantwortung der Forschungsfragen angewendete Forschungsmethodik wird in Kapitel 1.3 behandelt. Abgerundet wird das Einleitungskapitel durch eine Beschreibung des Aufbaus der Arbeit in Kapitel 1.4.

1.1 Motivation, Problemstellung und Zielsetzung

> *„Social-Media geht nicht wieder weg; ist keine Modeerscheinung. Seien Sie dort, wo Ihre Kunden sind: in den sozialen Medien."*
>
> Lori Ruff, Social-Media Expertin

In den letzten Jahren stieg die Bekanntheit und Beliebtheit von Social-Media Plattformen im privaten Sektor rapide an (PWC, 2012, Statista, 2020b). In der Literatur ist der Begriff "Social-Media" als eine Gruppe internetbasierter Anwendungen definiert, welche auf Basis von Web 2.0 Technologien die Generierung und den Austausch von nutzergenerierten Inhalten ermöglichen (Kaplan and Haenlein, 2010). Abgesehen von dieser recht allgemeingültigen Definition zählen verschiedene Technologien wie soziale Netzwerke (z. B. Facebook und Twitter), Enterprise Social Networks (ESN, z. B. Yammer), Social-Networking-Anwendungen (z. B. MS Share Point) sowie auch Erweiterungen existierender Plattformen um soziale Komponenten (z. B. Blogs) zum Forschungsgebiet Social-Media (Heidemann et al., 2012, Turban et al., 2011). Laut aktuellen Studien nutzen 65% aller erwachsenen Personen in den USA soziale Netzwerke (Perrin, 2015, Statista, 2018). Schon 2021 werden soziale Netzwerke, wie Facebook oder Twitter weltweit bis zu 3,1 Milliarden Nutzer aufweisen, was im Vergleich zu den derzeitigen Nutzerzahlen einen Anstieg um 27% darstellt (Statista, 2020b). Allerdings betrifft der Trend der immer weiter steigenden Social-Media Nutzung nicht nur die Kommunikation von Privatpersonen, vielmehr ergeben sich dadurch auch neue Herausforderungen für Unternehmen. Kunden erwarten die aus dem privaten Bereich bekannten Kommunikationsformen und –kanäle nun auch bei der Interaktion mit Unternehmen (Berthon et al., 2012).

Ein wichtiges Anwendungsfeld ist in diesem Zusammenhang das Customer Relationship Management (CRM), da Unternehmen durch eine ausgefeilte Datenanalyse tiefere Einblicke in Kundenbedürfnisse und -verhalten erhalten (Kitchens et al., 2018, Schwaiger et al., 2017). Zu diesem Zweck ist es notwendig, die Meinungen und Vorlieben der Kunden auf möglichst direkte Weise kennenzulernen. In einer digitalisierten Welt eignen sich benutzergenerierte Inhalte wie Gästebewertungen, Beschwerden, Beiträge in Online-Foren oder sozialen Netzwerken usw. besonders gut für diese Aufgabe (Pinto and Mansfield, 2012, Sigala, 2012a, Sigala, 2012b). Vor allem Daten aus Social-Media Kanälen sind so eine wertvolle Quelle, da immer mehr Kunden ein Unternehmen bevorzugt über Social-Media kontaktieren, um Serviceanfragen und Reklamationen zu äußern oder Transaktionen abzuwickeln (Hanna et al., 2011).

Auffallend ist hier, dass neben großen Unternehmen auch immer mehr kleine und mittelständische Unternehmen (KMU) die Vorteile der Social-Media Nutzung realisieren und diese im Unternehmenskontext einsetzen (Meske and Stieglitz, 2013). Im Jahr 2013 waren 99,3% aller Unternehmen in diesem Bereich angesiedelt (Bundesamt, 2015). Daher spielen KMU eine wichtige Rolle innerhalb der deutschen Wirtschaft (Söllner, 2014).

Die Einbindung von Social-Media Technologien in die unternehmensinterne Kommunikation erleichtert die Identifizierung von Experten im Unternehmen, erhöht die Motivation der Mitarbeiter und verbessert das interne Wissensmanagement (van Zyl, 2009). Im externen Gebrauch, beispielsweise der Kommunikation mit Kunden, können durch direkte Kommunikation und Einbindung der Kunden in den Social-Media Kanälen (z. B. Feedback zu neuen Produkten) Kundenbeziehungen gefestigt und vertieft werden (Ramaswamy, 2010, Sigala, 2012b). Durch konkrete Reaktionen auf die Bedürfnisse der Kunden können langfristige Marken- und Kundenbindungen aufgebaut werden (Chikandiwa et al., 2013, Chua and Banerjee, 2013, Parveen, 2012). Ein weiterer positiver Aspekt bei der Einführung von Social-Media Technologie im Unternehmensumfeld ist der Zugewinn an Flexibilität durch kundenorientierte Angebote und Produkte (Mitic and Kapoulas, 2012, Ramaswamy, 2010). Aktuelle Wünsche und wichtige Themen der Kunden können so schnell aufgegriffen werden und in konkrete Produkte oder Services überführt werden. Diese Flexibilität ist gerade angesichts der steigenden Markttransparenz und den damit einhergehend schnelllebigen Kundenbedürfnissen immer wichtiger für Unternehmen (Goodrich and De Mooij, 2014, Sharma and Baoku, 2013). Aufgrund dieser positiven Auswirkungen investieren Unternehmen momentan sehr stark in die Integration von Social-Media Technologien in ihre bestehenden Geschäftsprozesse und IT-Landschaften (Trainor et al., 2014).

Die positiven Effekte bei der Nutzung von Social-Media im Kundenkontakt entstehen aufgrund eines tieferen Verständnisses von Kundenmeinungen und Kundenerwartungen (Ramaswamy, 2010, Sigala, 2012b). Posts und Kommentare auf den Social-Media Auftritten von Firmen repräsentieren die „Voice of the customer“ (VOC) und beinhalten die aktuelle Meinung der Kunden über Produkte, Dienstleitungen oder die Marke des Unternehmens an sich (Pande et al., 2000). In Meinungsäußerungen und intensiven Diskussion auf den Social-Media Kanälen geben Kunden aufgrund der gegebenen Anonymität meist deutlich mehr Informationen preis. Die Extraktion und Auswertung dieser Posts liefert wertvolle Kundeninformationen und dient als Ansatzpunkt für neue Produktentwicklungen oder Verbesserungsinitiativen. Im Gegensatz zu bisherigen Erhebungsformen, wie Qualitätsberichten und Kundenumfragen, sind Social-Media Posts sehr aktuell und liefern verzögerungsfreie Kundenmeinungen (Liu, 2012). Dies stellt einen erheblichen Vorteil dar, da die Daten immer aktuell ausgewertet werden können, keine Zeitverzögerung aufgrund nachträglicher Auswertungen besteht und aufgrund der größeren Datenmenge bessere und genauere Auswertungen möglich sind (Meran et al., 2013).

Allerdings ergeben sich durch rapide ansteigende Nutzer- und Postzahlen neue Herausforderungen für Unternehmen (Ramaswamy, 2010, Sigala, 2012a, Sigala, 2012b). Social-Media Daten enthalten meist große Mengen an unstrukturiertem Text, einschließlich mehrdeutiger Ausdrücke oder Grammatik- und Tippfehler. Dies erschwert die Analyse deutlich und verursacht enormen menschlichen Aufwand, welcher vor allem bei erhöhtem Postaufkommen auch direkt proportional den verwendeten Ressourcenaufwand erhöht (Stieglitz et al., 2014). Besonders bei KMU stellt dieser wachsende Aufwand, aufgrund begrenzter monetärer und personeller Ressourcen, ein Problem dar. Um dieses Problem zu adressieren, kamen in den letzten Jahren einige Softwarelösungen zur Auswertung und Überwachung von Social-Media Kanälen auf den Markt, welche direkte Verbindungen zu Social-Media Plattformen, wie Facebook und

Twitter, aufbauen und den manuellen Analyseaufwand ersetzen oder reduzieren sollen (Stavrakantonakis et al., 2012). Lösungen wie *Brandwatch*, *Radian6* oder auch *Social Bench* ermöglichen es, Kundenmeinungen, -beschwerden und -fragen in Echtzeit auszuwerten (Stavrakantonakis et al., 2012). Allerdings stellen diese Lösungen gerade für KMU meist keine Option dar, da die Kosten für geeignete Tools oft mehrere Tausend Euro pro Monat betragen und somit gerade für diese Unternehmen nicht erschwinglich sind (Kasper and Kett, 2011). Zwar gibt es teilweise freie Versionen der genannten Tools, jedoch sind diese meist minimalistisch und beinhalten keinerlei technischen Support, Mehrsprachigkeit oder Mehrkanalfähigkeit (Stavrakantonakis et al., 2012). Vor allem die fehlende Anpassung auf den deutschen Sprachraum stellt für kleine und mittelständische Unternehmen im süddeutschen Raum einen entscheidenden Schwachpunkt dar. Gerade KMU im süddeutschen Raum weisen meist eine starke regionale Bindung auf, woraus eine direkte und zielgerichtete Kommunikation zwischen Unternehmen und Kunden resultiert (Durkin et al., 2013, Lee et al., 2008). Daher beinhalten Social-Media Posts von KMU meist regionale, sprachliche Besonderheiten wie Slang sowie branchenspezifische Ausdrücke und Produktnamen (Laboreiro et al., 2010, Naaman et al., 2010, Petz et al., 2013). Aufgrund dieser sprachlichen Besonderheiten und der fehlenden Anpassung auf branchenspezifischen Wortschatz scheitern aktuelle, auf dem Markt erhältliche, kommerzielle Lösungen bei der Analyse und Überwachung von Social-Media Kanälen kleiner und mittelständischer Unternehmen (Waltinger, 2010).

Zudem konzentrieren sich vorhandene Social-Media Analysetools häufig auf einen allgemeinen Ansatz, bei dem entweder die Analyse der Semantik der Posts oder die Auswertung von strukturierten Daten (z. B. die Summe der Likes oder Shares) priorisiert werden (Wozniak, 2016). Beispielsweise beziehen sich Social-Media Daten, die von Diensten wie Google Analytics[1] oder Facebook Insights[2] gesammelt werden, hauptsächlich auf die Gesamtaktivität der Nutzer in Social-Media Kanälen, treffen jedoch keinerlei Aussagen zur Stimmung, Themenzugehörigkeit oder zu den inkludierten Emotionen der präsentierten Inhalte. Bei Ansätzen zur Priorisierung der Postsemantik (z. B. Sentiment Analyse oder Klassifizierung von Benutzerposts) wird dagegen meistens

[1] Google Analytics (kurz: GA) ist ein kostenloses, webbasiertes Tool von Google für die Webanalyse. Webmaster und SEOs können darüber wichtige KPIs und Website-Statistiken abrufen. (vgl. https://marketingplatform.google.com/about/analytics/)

[2] Facebook Insights ist ein umfangreiches Tool mit dem Seitenstatistiken zu den Facebook Fanpages abgerufen werden können. Diese Daten können Nutzer nicht nur als Facebook Administrator abrufen. Die Insights sind für alle Nutzerrollen bei Facebook, außer für Live-Beitragende, einsehbar. (vgl. https://www.facebook.com/business/learn/facebook-audience-insights)

die Gewichtung des gesammelten Feedbacks und dessen Einfluss auf andere Social-Media Benutzer vernachlässigt. Im Gegensatz dazu sind hybride Ansätze mehrstufig und kombinieren verschiedene Methoden der Datenauswertung (z. B. Analyse strukturierter & unstrukturierter Social-Media Daten), was zu einem Ansatz mit gemischten Methoden führt (Johnson et al., 2007, Johnson and Turner, 2003). Dies ermöglicht eine detailliertere und zielgerichtetere Analyse, die einen noch größeren Forschungswert verspricht als die isolierte Anwendung zuvor etablierter Methoden (Kitchens et al., 2018). Daher erscheint auch im Bereich der sozialen Medien eine Kombination verschiedener Forschungsmethoden vielversprechend und sollte in der Lage sein, die zugrunde liegenden Nachteile der einzelnen Verfahren zu kompensieren (Graffigna and Riva, 2015, Greene and Caracelli, 1997, Sidorova et al., 2016).

Zusammenfassend lässt sich also sagen, dass es derzeit in der Praxis keine effizienten Möglichkeiten gibt, Social-Media Inhalte von KMU mehrdimensional und automatisiert auszuwerten und daraus Handlungsempfehlungen für die Qualitätsverbesserung von Produkten und Dienstleitungen abzuleiten.

Aus diesem Grund ist die Konzeption und Entwicklung der hybriden Softwarelösung „**U**niversität **R**egensburg: **S**ocial-Media **A**nalysis **R**esearch **T**oolkit“ (UR:SMART), welche die mehrstufige Kombination verschiedener Social-Media Analysetechniken (Sentiment Analyse, Klassifikation von Posts, Clustering und quantitative Analysen) und verschiedene Datenformate (z. B. strukturierte bzw. unstrukturierte Daten) unterstützt, zentraler Bestandteil dieser Dissertation. Der zu entwickelnde, hybride Analyseansatz ermöglicht eine detaillierte, mehrstufige Untersuchung verschiedener Datenbasen, einschließlich Social-Media Posts oder Kommentaren auf der Fanseite oder Website eines Unternehmens. Somit kann ein breiteres Spektrum hochkomplexer Problemstellungen, auf Basis der Kombination verschiedener Analyseformen sowie der Integration neuer Analysetypen, gelöst werden (Sivarajah et al., 2017). Auf diese Weise kann ein Unternehmen, welches die hybride Analyse verwendet, beispielsweise direkt über die Gründe informiert werden, die zu einer positiven oder negativen Kundenerfahrung führen (z. B. Kundendienst, Produktqualität usw.). Solche Informationen stellen einen erheblichen Wissenszuwachs dar und können auf viele sinnvolle Arten genutzt werden, beispielsweise als verlässliche Entscheidungsgrundlage bei der Planung künftiger CRM-Kampagnen.

Zusammenfassend ergeben sich aus den erläuterten Problemstellungen drei konkrete Zielsetzungen:

> **Zielsetzung 1 (ZS1):**
> *Untersuchung der sprachlichen Besonderheiten von Social-Media Inhalten im süddeutschen Raum und Erhebung der Anforderungen an ein Social-Media Analyse Tool bei kleinen und mittelständischen Unternehmen im süddeutschen Raum.*

> **Zielsetzung 2 (ZS2):**
> *Identifikation, Implementierung und Evaluation geeigneter Algorithmen zur automatisierten Analyse von textuellen Social-Media Inhalten sowie deren Kombination zu einer hybriden Analyse.*

> **Zielsetzung 3 (ZS3):**
> *Entwicklung und Evaluation eines Softwaretools zur automatisierten Analyse von textuellen Social-Media Inhalten bei kleinen und mittelständischen Unternehmen im süddeutschen Raum, welches die zielgerichtete Kombination verschiedener Social-Media Analysemethoden unterstützt.*

1.2 Forschungsfragen

Ausgehend von der im letzten Kapitel beschriebenen Problemstellung und daraus hervorgehenden Zielsetzung, werden im Folgenden acht Forschungsfragen erarbeitet, welche die vorliegende Dissertation behandelt. Die Forschungsfragen werden dabei jeweils einer konkreten Zielstellung zugeordnet.

ZS1: Die ersten beiden Forschungsfragen befassen sich mit den sprachlichen Besonderheiten von Social-Media Inhalten bei KMU im süddeutschen Raum und der Erhebung von Anforderungen an ein Social-Media Analyse Tool bei KMU im süddeutschen Raum (*Zielsetzung 1*). Da vor allem bei KMU im süddeutschen Raum die Regionalität und damit sprachliche Besonderheiten eine große Rolle spielen, steht diese Unternehmensgruppe im Fokus des Forschungsvorhabens. Zunächst sollen auf Basis der Social-Media Auftritte von Partnerfirmen sprachliche Besonderheiten in den Posts (z. B. branchenspezifische Sprache oder Slang) identifiziert werden, welche potentiell erfolgskritisch für eine automatisierte Auswertung sind (*Forschungsfrage 1*). Im Anschluss sollen zum einen allgemeine Anforderungen an die zu entwickelnde Software erarbeitet und zum anderen zusätzlich spezifische Anforderungen an den Lösungsansatz, speziell bei KMU im süddeutschen Raum, identifiziert werden (*Forschungsfrage 2*). Beispielsweise ist es für diese Unternehmen sehr wichtig, auf bestimmte Probleme (z. B. fehlerhafte Produktbestandteile oder lange Servicezeiten) direkt einzugehen und Social-Media Posts spezifisch nach diesen Problemen auswerten zu können. Da sich diese, oft branchenspezifischen Probleme im Laufe der Zeit ändern können, ist zudem eine Anpassbarkeit der vordefinierten Problemstellung von Seiten des Unternehmens wünschenswert. Hieraus ergeben sich die folgenden Forschungsfragen:

Forschungsfrage 1 (FF1):
Welche sprachlichen Besonderheiten weisen Social-Media Posts bei süddeutschen kleinen und mittelständischen Unternehmen auf?

Forschungsfrage 2 (FF2):
Welche Anforderungen ergeben sich an eine Softwarelösung zur automatisierten Auswertung von Social-Media Posts speziell bei kleinen und mittelständischen Unternehmen im süddeutschen Raum?

ZS2: Nachdem die sprachlichen Besonderheiten von Social-Media Inhalten bei KMU im süddeutschen Raum sowie die Anforderungen an ein Social-Media Analyse Tool bei KMU im süddeutschen Raum identifiziert wurden, widmen sich die nächsten beiden Forschungsfragen der Identifikation, Implementierung und Evaluation geeigneter Algorithmen zur automatisierten Analyse von textuellen Social-Media Inhalten sowie der Kombination dieser zu einer hybriden Analyseform (*Zielsetzung 2*).

Ein wichtiger Punkt bei der Analyse der VOC ist das aktuelle Stimmungsbild der Kunden in Bezug auf bestimmte Themen wie Produkte, Kundenservice oder Prozesse. Dieses kann mit Hilfe der Sentiment Analyse, also der automatisierten Tonalitätsbestimmung und einer anschießenden Klassifizierung der Social-Media Inhalte zu vordefinierten Themenbereichen, bestimmt werden. Die automatische Auswertung der Tonalität von textuellen Inhalten ist ein breites Forschungsgebiet. Daher gibt es eine Vielzahl an Publikationen aus unterschiedlichen Bereichen wie Natural Language Processing, Text Mining, Web Mining und Information Retrieval (Liu, 2012). Ansätze zur Sentiment Analyse lassen sich grob in drei Teilbereiche untergliedern. Zum einen in dokumentbasierten Ansätzen, bei denen die Analyse von gesamten Dokumenten wie z. B. Zeitungsartikeln oder auch Produktbeschreibungen im Vordergrund steht, zum anderen die satzbasierten Ansätze, welche darauf abzielen das Sentiment eines einzelnen Satzes, beispielsweise in den Kategorien positiv, negativ oder neutral zu bestimmen. Des Weiteren lassen sich Aspekt basierte Ansätze nennen, welche sich auf bestimmte Aspekte/Attribute des Textes (z. B. Produktspezifika bei Reviews) fokussieren (Feldman, 2013, Liu, 2012, Vohra and Teraiya, 2013). Darauf aufbauend folgt die Klassifizierung der Social-Media Inhalte. Dabei sollen die zuvor hinsichtlich ihrer Tonalität ausgewerteten Social-Media Inhalte nun automatisiert zu bestimmten Geschäftsbereichen (z. B. Produkt- oder Servicequalität) zugeordnet werden. Bei Ansätzen zur automatisierten Klassifizierung von Social-Media Posts unterscheidet man vor allem zwischen überwachten und unüberwachten Ansätzen (Dayan, 1999). Weit verbreitet im Bereich der unüberwachten Ansätze sind vor allem das Clustering und das Topic Modeling (Aggarwal and Zhai, 2012a, Aggarwal and Zhai, 2012b, Aggarwal and Zhai, 2012c). Diese zielen auf die Zuordnung von Daten zu undefinierten, unbeschrifteten und automatisch aus der Struktur der Daten abgeleiteten homogenen Gruppen. Demgegenüber stehen überwachte Klassifizierungsverfahren, welche beschriftete Trainingsdaten nutzen, um Daten zu vordefinierten Kategorien zuzuordnen (Feldman and Sanger, 2007, Heyer et al., 2006). Sowohl bei der Sentiment Analyse als auch bei der Klassifizierung sollen zunächst geeignete Ansätze gefunden werden. Dafür soll eine Literaturrecherche durchgeführt werden, um Ansätze zu identifizieren und zu vergleichen. Im Anschluss werden geeignete Algorithmen prototypisch implementiert und iterativ evaluiert (*Forschungsfrage 3).*

Nachdem verschiedene Algorithmen zur Analyse von Social-Media Inhalten bei KMU im süddeutschen Raum identifiziert und evaluiert wurden, steht nun deren Kombination zu einer hybriden Analyseform im Vordergrund. Die Kombination von qualitativen und quantitativen Analysemethoden ist in der Forschung weit verbreitet, da die Verknüpfung dieser Methoden zu einer genaueren und vollständigeren Darstellung des untersuchten Phänomens führt (Johnson, 1995, Johnson and Christensen, 2000, Patton, 1990, Tashakkori and Teddlie, 1998). Daher soll die Kombination von Sentiment Analyse und Klassifizierung mit den zugehörigen Social-Media Metadaten (z. B. Likes und Shares) eine detaillierte quantitative und qualitative Auswertung von Social-Media Inhalten ermöglichen (*Forschungsfrage 4).* Beispielsweise sollen gezielte Auswertungen besonders negativer Social-Media Posts aus bestimmten Bereichen wie Service- oder Produktqualität möglich sein. Aus diesen Auswertungen sollen automatisiert Handlungsempfehlungen für Verbesserungsprojekte abgeleitet werden.

Vorhandene Tools können die oben genannten Herausforderungen jedoch nicht vollständig bewältigen, da sie beispielsweise keine Datenextraktion von mehreren Social-Media Plattformen enthalten oder hinsichtlich der Verfügbarkeit bestimmter Methoden (z. B. Sentiment Analyse, Klassifikation oder quantitative Analysen) eingeschränkt sind (Stavrakantonakis et al., 2012). Darüber hinaus konzentrieren sich die meisten Social-Media Analysetools nur auf einseitige Analyseansätze, welche entweder quantitative Methoden verwenden, z. B. die Anzahl der Fans, Likes und Shares, oder qualitative Methoden, z. B. die Analyse der Semantik der Posts (Wozniak 2016). Somit ergeben sich aus dieser Forschungslücke die folgenden Forschungsfragen:

Forschungsfrage 3 (FF3):
Welche Algorithmen zur automatisierten Sentiment Analyse und Klassifizierung von Social-Media Inhalten gibt es und welche sind für den gegebenen Anwendungsfall geeignet?

Forschungsfrage 4 (FF4):
Wie kann eine Kombination aus verschiedenen Social-Media Analyseformen (Sentiment Analyse, Klassifizierung, Clustering und quantitative Analyse) umgesetzt werden und welche Vorteile bietet die Kombination qualitativer Analyseverfahren mit quantitativen Social-Media Daten?

ZS3: Nachdem geeignete Algorithmen zur automatisierten Analyse von textuellen Social-Media Inhalten sowie ein Ansatz zu deren Kombination zu einer hybriden Analyse erarbeitet und implementiert wurden, befassen sich die verbleibenden Forschungsfragen mit der Entwicklung und Evaluation eines Softwaretools zur automatisierten Analyse von textuellen Social-Media Inhalten bei KMU im süddeutschen Raum, welches die zielgerichtete Kombination verschiedener Social-Media Analysemethoden unterstützt (*Zielsetzung 3*).

Um eine für KMU anwendbare Lösung für die beschriebene Problemstellungen bereitzustellen, wird das Softwareartefakt UR:SMART zur automatisierten Auswertung von textuellen Social-Media Inhalten entwickelt (*Forschungsfrage 5).* Die Software soll Unternehmen dabei unterstützen, Social-Media Inhalte bzw. die beinhalteten VOC auszuwerten und somit Probleme und Hinweise auf deren Ursachen (z. B. schlechter Kundenservice, Produktfehler etc.) zu identifizieren.

Um den tatsächlichen Nutzen der Software Lösung im Unternehmensumfeld zu bewerten, soll die Software bei Kooperationspartnern in die täglichen Geschäftsprozesse integriert und angewendet werden (*Forschungsfrage 6).* Dabei sollen sowohl auftretende Herausforderungen bei der Auswertung von Social-Media Posts identifiziert als auch die Anwendbarkeit der entwickelten Software im Unternehmensalltag aufgezeigt werden. Zudem soll die Softwarelösung hinsichtlich ihrer Genauigkeit evaluiert werden. Der Nutzen und die Usability sollen anhand eines konkreten Einsatzes im Unternehmen und mit Hilfe einer „Software Usability Measurement Inventory“[3] (SUMI) Studie gezeigt werden. Hieraus ergeben sich folgende Forschungsfragen:

Forschungsfrage 5 (FF5):
Welche Genauigkeit bieten geeignete Ansätze zur automatisierten Sentiment Analyse und Klassifizierung bei der Anwendung auf Social-Media Post von KMU im süddeutschen Raum?

Forschungsfrage 6 (FF6):
Welchen Nutzen und welche Usabilty bietet die entwickelte Softwarelösung für KMU im süddeutschen Raum?

Ergänzend wird im Rahmen des Social-Media Performance Management (SMPM) auf den zielgerechten Einsatz von Metriken sowie Social-Media Performance Messungen eingegangen, um mit dessen Hilfe die Interessen der Shareholder bzw. des Managements zu bedienen. Dabei wird sowohl auf Aspekte der Zielsetzung als auch auf den Grad der Zielerreichung Bezug genommen. Somit soll evaluiert werden, was konkret als Erfolg beim Einsatz von Social-Media klassifiziert werden kann und welche Konzepte es für einen ressourcengerechten Einsatz dieser Technologien gibt, um damit Wert generieren zu können. Ein zentraler Bestandteil ist dabei die Identifikation und Anwendung von relevanten Erfolgsfaktoren durch die eine Performancemessung anhand von Metriken ermöglicht wird (Bullen and Rockart, 1981).

Hierfür werden zunächst relevante Social-Media Erfolgsfaktoren anhand eines Literature Reviews (Cooper, 1988, Vom Brocke et al., 2009) identifiziert und konsolidiert, um diese anschließend anhand definierter Klassen zu kategorisieren. Durch die isolierte Betrachtung von Erfolgsfaktoren können zwar spezifische Eigenschaften von Social-

[3] Software Usability Measurement Inventory (SUMI) ist eine streng getestete und bewährte Methode zur Messung der Softwarequalität aus Sicht des Endbenutzers (vgl. Kirakowski, 1996).

Media näher untersucht werden, jedoch ist es damit noch nicht möglich, Performancemessungen anhand von Key Performance Indicators (KPIs) der Social-Media Aktivitäten eines Unternehmens durchzuführen. Um diese Lücke schließen zu können, wird ein bekanntes Konzept von (Bullen and Rockart, 1981) zu Grunde gelegt, welches ein Vorgehensmodell zur Messung anhand von drei Komponenten (Ziele, Erfolgsfaktoren, Metriken) darstellt und somit eine Grundlage für die Performance- und Erfolgsmessung von Social-Media Nutzung im Unternehmenskontext bietet. Zusammenfassend lassen sich aus dieser Problemstellung folgende Forschungsfragen ableiten:

Forschungsfrage 7 (FF7):

Welche Critical Success Factors (CSFs) von Social-Media für Unternehmen (B2C) können aus der Literatur identifiziert werden und wie können diese klassifiziert werden?

Forschungsfrage 8 (FF8):

Welche Social-Media Key Performance Indicators (KPIs) können mit den identifizierten CSFs abgeglichen werden?

1.3 Forschungsmethodik

Das Promotionsvorhaben beabsichtigt die Entwicklung einer Softwarelösung zur automatisierten Analyse von Social-Media Inhalten bezüglich ihrer Tonalität und Zugehörigkeit zu definierten Kategorien, und lässt sich daher klar dem konstruktivistischen Paradigma der Wirtschaftsinformatik zuordnen (Winter, 2008). In den letzten Jahren hat Design Science (DS) nach (Hevner et al., 2004) sowie (Peffers et al., 2007) eine hohe Popularität erlangt und sich zu einer legitimen IS-Forschungsmethode entwickelt (Alturki et al., 2011, Gregor and Hevner, 2013). Ein weithin anerkannter Ansatz zur Durchführung von DS-Projekten wurde von (March and Smith, 1995) vorgestellt, der eine Synthese der Aktivitäten "Build / Development" und "Justify / Evaluate" mit dem Ziel der Lösung eines organisatorischen Problems durch die Entwicklung eines IT-Artefakts, vorschlägt (Cleven et al., 2009). Daher folgt das Promotionsvorhaben, der in Abbildung 1 dargestellten DS Forschungsmethodik, um die Softwarelösung UR:SMART zur Analyse von Social-Media Daten zu entwerfen und zu entwickeln und jeden Teilschritt des Forschungsvorhabens iterativ zu evaluieren.

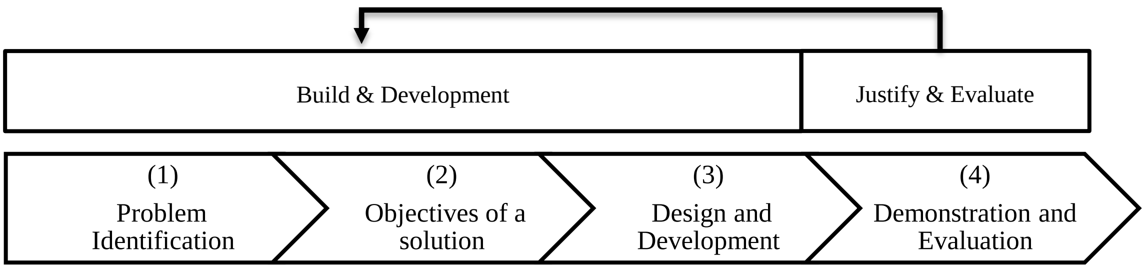

Abbildung 1: Forschungsmethodik der Dissertation

Zu Beginn der Arbeit erfolgt im ersten Schritt „**Problem Identification“ (1)** die Identifizierung und Formulierung der Problemstellung. Darunter fallen die auftretenden Herausforderungen hinsichtlich der spezifischen Charakteristika von textuellen Inhalten im Social-Media Bereich, die rasant steigenden Datenmenge innerhalb von Social-Media-Kanälen und die daraus resultierende Notwendigkeit der automatisierten Auswertung. Diese Problemstellungen wurden in Kooperation mit fünf KMU-Praxispartnern aus dem süddeutschen Raum erhoben und auf Basis der aktuell eingesetzten Anwendungen im Unternehmensumfeld sowie Interviews mit Social-Media Verantwortlichen bei den Kooperationsunternehmen evaluiert. Die aus der Problemstellung hervorgehenden

Zielsetzungen und Forschungsfragen wurden im vorausgehenden Kapitel 1.2 der Dissertation erläutert.

Im nächsten Teilschritt „**Objectives of a solution“ (2)** gilt es, mögliche Lösungsansätze zu der erläuterten Problemstellung zu entwickeln. Dabei werden zunächst die Anforderungen an die zu erstellende Softwarelösung festgelegt. Diese werden in Kooperation mit den bereits genannten fünf Kooperationspartnern erhoben. Zentrale Punkte stellen hier die automatische Extraktion von Social-Media Inhalten aus verschiedenen Social-Media Kanälen, wie Facebook oder Twitter, die kanalspezifische Aufbereitung der textuellen Social-Media Inhalte sowie die Analyse der Social-Media Inhalte dar. Dabei steht vor allem die Analyse der Stimmung innerhalb der Social-Media Inhalte (Sentiment Analyse), die Zuordnung der Inhalte zu bestimmten vordefinierten Themengebieten (Klassifikation), die Identifikation neuer Themengebieten innerhalb der Social-Media Inhalten (Clustering) sowie die Anreicherung der Analyseergebnisse mit quantitativen Social-Media Daten wie Reaktionszahlen (Likes, Shares etc.) im Vordergrund. Zudem soll eine zielgerichtete Kombination der verschiedenen Analysemethoden zu einem hybriden Ansatz möglich sein. Zur Identifikation geeigneter Algorithmen im Hinblick auf die Analyse der Social-Media Inhalte werden Literaturrecherchen zu den Bereichen Sentiment Analyse, Klassifikation und Clustering durchgeführt. Die identifizierten Algorithmen werden auf ihre Anwendbarkeit für die Analyse von Social-Media Inhalten bei KMU im süddeutschen Raum evaluiert.

Während der Phase „**Design- and Development“ (3)** erfolgt eine prototypische Umsetzung des Artefakts. Die Konzeption und Entwicklung der Softwarelösung wird in Kooperation mit fünf Kooperationspartnern aus dem süddeutschen Raum durchgeführt, um eine spätere Einsatzfähigkeit im Unternehmensumfeld zu gewährleisten. Hierfür erfolgt in der Designphase zunächst die Auswahl geeigneter Algorithmen für Sentiment Analyse, Klassifikation und Clustering basierend auf den durchgeführten Literaturrecherchen. Um einheitliche Datenformate und die freie Kombination der verschiedenen Analysemethoden sicherzustellen, wird als grundsätzliches Vorgehensmodell bei der Analyse der Social-Media Inhalte der generelle Ansatz zur Textanalyse nach (Aggarwal and Zhai, 2012a) angewendet (siehe Abbildung 2) sowie ein Gesamtdatenmodell für die zugrunde liegende Datenbank entwickelt.

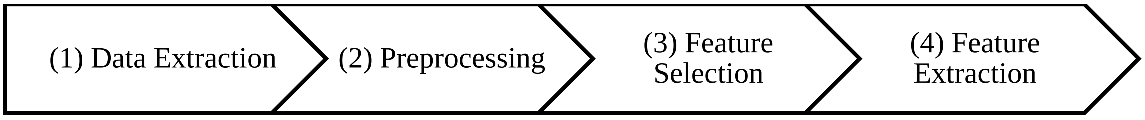

Abbildung 2: Genereller Ansatz zur Textanalyse nach (Aggarwal and Zhai, 2012a)

Als Ausgangspunkt werden während der (1) „Data Extraction“ Daten (z. B. Social-Media Posts oder Tweets) aus Social-Media Kanälen extrahiert und zur weiteren effektiven Verarbeitung in ein konsistentes Datenformat konvertiert (Akaichi et al., 2013, Feldman, 2013). Anschließend ist ein (2) „Preprocessing“ erforderlich, welches die verschiedenen Techniken wie Tokenisierung, Stoppwortreduktion, Stemming und Normalisierung umfasst (Aggarwal and Zhai, 2012a). Im nächsten Schritt erfolgt die (3) „Feature Selection“, die aus der Definition von Merkmalstypen und der Auswahl spezifischer Merkmale (z. B. Emojis, meinungstragende Ausdrücke oder Klassifikationsmerkmale) für die jeweilige Analyseform besteht (Selvam and Abirami, 2013). Abschließend erfolgt im Punkt (4) „Feature Extraction“ die Anwendung eines Algorithmus zur Extraktion der gewünschten Merkmale. Dieses Vorgehen wird auf alle Analyseformen der Social-Media Analysesoftware UR:SMART angewendet und sichert somit die Wiederverwendbarkeit und freie Kombination der verschiedenen Verfahren. Für diese frei kombinierbaren, hybriden Verfahren werden in Zusammenarbeit mit den Kooperationspartnern verschiedene Szenarien entwickelt, welche als Anwendungsbeispiele für hybride Analysen im Bereich der Social-Media Analyse dienen.

Ein weiterer wichtiger Punkt in der Designphase ist das Graphical User Interface[4] (GUI) von UR:SMART. Dieses wird auf Basis von Wireframes[5] entwickelt und bildet die Basis für die konkrete programmatische Umsetzung der GUI von UR:SMART (Garrett, 2010).

In der Development-Phase von UR:SMART steht die Implementierung der Datenextraktion und -aufbereitung sowie der ausgewählten Social-Media Analyse Algorithmen im Vordergrund. Hierfür wird die Programmiersprache JAVA sowie das Vaadin-Framework[6] zur grafischen Darstellung verwendet. Des Weiteren erfolgt die

[4] grafische Schnittstelle zwischen Computer und Benutzer

[5] Zeigt das Seitenlayout bzw. die Anordnung des Inhalts der Website, einschließlich der Oberflächenelemente und Navigationssysteme, und wie sie zusammenarbeiten (Garret, 2010).

[6] freies Webframework für Rich Internet Application unter der Apache-Lizenz 2.0 (vgl. www.vaadin.com)

technische Umsetzung der Applikations- und Datenbankarchitektur sowie die Implementierung der GUI.

Die Phase **„Demonstration and Evaluation“ (4)** zeigt auf, dass die entwickelte Software UR:SMART funktionsfähig ist und textuelle Social-Media Inhalte automatisiert auswerten kann. Hierfür wird die Software im Unternehmensumfeld der fünf KMU-Kooperationspartner im süddeutschen Raum aktiv eingesetzt, um die Funktionsfähigkeit zu demonstrieren. Im Teilschritt der Evaluation des Artefakts wird zum einen sichergestellt, dass das Softwareartefakt UR:SMART die eingangs definierten Anforderungen erfüllt. Zum anderen wird die Genauigkeit der entwickelten Algorithmen mit Hilfe der Metriken *Precision*, *Recall* und *F-Measure* dargelegt (Christen, 2012). Hierfür werden Social-Media Datensätze der Kooperationsunternehmen mit Hilfe von UR:SMART analysiert. Die Auswertungsergebnisse werden zum einen auf Basis manueller Auswertungen auf ihre Genauigkeit geprüft. Zum anderen erfolgt eine Evaluation und Plausibilitätsprüfung der Auswertungsergebnisse mit Hilfe von Interviews mit Social-Media Verantwortlichen der Kooperationsunternehmen. Zusätzlich wird durch eine SUMI Usability-Studie der Nutzen und die Einsetzbarkeit im Unternehmensumfeld betrachtet (Kirakowski, 1996).

1.4 Aufbau der Dissertation

Zur Erreichung der erläuterten Zielsetzungen und zur Beantwortung der acht Forschungsfragen ist die Dissertation wie folgt aufgebaut: in Kapitel 1 (Einleitung) wird das Themengebiet der Dissertation, die automatisierte Analyse von Social-Media Inhalten, motiviert und die zugrundeliegenden Problemstellungen erläutert. Zudem werden die Zielsetzungen, die Forschungsfragen sowie die angewendete Forschungsmethodik Design Science (DS) zur Lösung der Forschungsfragen detailliert dargelegt. Die Kernergebnisse der kumulativen Dissertation sind in Kapitel 2 „Wissenschaftliche Beiträge“ zu finden. Dieses umfasst sechs wissenschaftliche Beiträge (Kapitel 2.1 bis 2.6), wobei je Beitrag eine oder mehrere der, in Kapitel 1.2 definierten, acht Forschungsfragen beantwortet werden. Auf Grundlage der erarbeiteten Ergebnisse wird in Kapitel 3 das im Rahmen der Dissertation entwickelte Software-Artefakt UR:SMART vorgestellt. Hierbei wird sowohl auf die Design- als auch auf die Entwicklungsphase des Software-Artefaktes detailliert eingegangen. Zudem erfolgt ein

Einblick in aktuelle Weiterentwicklungen sowie ein Ausblick auf zukünftige Funktionen und Erweiterungen der Software. Abschließend werden in Kapitel 4 die Kernergebnisse der Dissertation zusammengefasst und nochmals kritisch hinterfragt. Zusätzlich wird der Beitrag der Dissertation für Wissenschaft und Praxis erläutert und ein Ausblick auf weitere Forschungsfelder gegeben. Folgende Abbildung 3 gibt einen Überblick über den Aufbau der Arbeit:

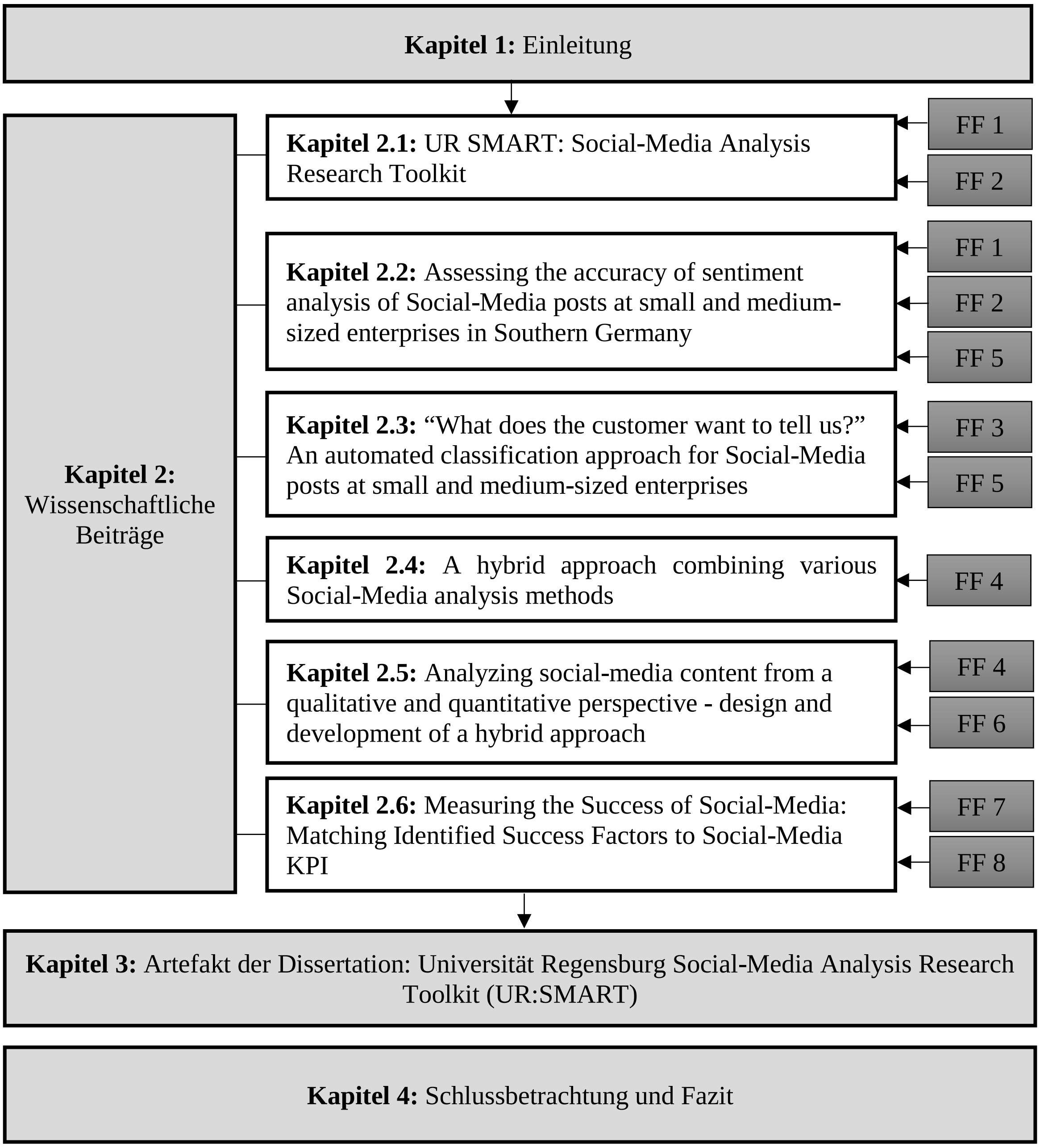

Abbildung 3: Aufbau der Dissertation

2 Wissenschaftliche Beiträge

In diesem Kapitel werden die einzelnen Forschungsbeiträge vorgestellt. Dazu wird zunächst ein Überblick über alle veröffentlichen Beiträge gegeben und anschließend jeder Beitrag ausgeführt. Folgende Tabelle 1 gibt einen Überblick über dieses Kapitel:

Kapitel	***Typ der Veröffentlichung***	***Status***	***Zitation***
2.1	Konferenzbeitrag	veröffentlicht	(Johannsen et al., 2016) Johannsen, F., Schwaiger, J. M., Lang, M., & Leist, S. (2016). *UR SMART: Social Media Analysis Research Toolkit.* In: International Conference on Information Systems (ICIS), Dublin 2016.
2.2	Konferenzbeitrag	veröffentlicht	(Schwaiger et al., 2016) Schwaiger, J. M., Lang, M., Ritter, C., & Johannsen, F. (2016). *Assessing the accuracy of sentiment analysis of Social Media posts at small and medium-sized enterprises in Southern Germany*. In 24th European Conference on Information Systems (ECIS), Istanbul, Turkey, 2016.
2.3	Konferenzbeitrag	veröffentlicht	(Schwaiger et al., 2017) Schwaiger, Josef Michael, Lang, Markus, Johannsen, Florian und Leist, Susanne (2017*) "What does the customer want to tell us?" - An automated classification approach for Social Media posts at SMEs.* In 25th European Conference on Information Systems (ECIS), June 5-10, Guimaraes/Portugal 2017.
2.4	Journalbeitrag	Under Review	(Schwaiger 2019) Schwaiger, Josef (2019), *A hybrid approach combining various Social Media analysis methods,* Electronic Markets Journal (EM) 2019
2.5	Journalbeitrag	Under Review	(Schwaiger et al., 2019) Schwaiger, Josef-Michael, Johannsen, Florian, Leist, Susanne, Hammerl, Timo und Falk Thomas (2019*), Analyzing social media content from a qualitative and quantitative perspective - design and development of a hybrid approach,* Business & Information Systems Engineering (BISE) 2019
2.6	Konferenzbeitrag	veröffentlicht	(Hammerl et al., 2019) Hammerl, T., Leist, S., & Schwaiger, J. (2019) *Measuring the Success of Social Media: Matching Identified Success Factors to Social Media KPIs.* In Proceedings of the 52nd Hawaii International Conference on System Sciences.

Tabelle 1: Übersicht zu den wissenschaftlichen Beiträgen

2.1 Beitrag 1: UR SMART: Social Media Analysis Research Toolkit

Adressierte Forschungsfrage	**Forschungsfrage 1:** Welche sprachlichen Besonderheiten weisen Social-Media Posts bei süddeutschen, kleinen und mittelständischen Unternehmen (KMU) auf? **Forschungsfrage 2:** Welche Anforderungen ergeben sich an eine Softwarelösung zur automatisierten Auswertung von Social-Media Posts speziell bei kleinen und mittelständischen Unternehmen im süddeutschen Raum?
Zielsetzungen	(1) Identifikation von Anforderungen an ein Social-Media Analyse Tool für KMU. (2) Identifikation von generalisierbaren Klassen für die Klassifikation von Social-Media Posts bei KMU. (3) Entwicklung eines Software-Prototyps, der eine automatische Sentiment Analyse und eine Klassifizierung von Kundenbeiträgen in Social-Media Plattformen, speziell auf die Bedürfnisse von KMU in Süddeutschland abgestimmt, ermöglicht.
Forschungsmethode	Design Science nach (*Hevner et al., 2004)* • Interviews & Workshop mit fünf Partnerunternehmen (KMU) • Allgemeine Methode der Textanalyse nach (*Aggarwal und Zhai 2012*)
Kernergebnisse (Überblick)	(1) Identifikation von 11 Anforderungen an ein Social-Media Analyse Tool für KMU. (2) Identifikation von 12 Klassen (z.B. Produkt, Service, Prozesse etc.) für die Klassifikation von Social-Media Posts bei KMU. (3) Speziell auf die Bedürfnisse von KMU in Süddeutschland abgestimmter Software-Prototyp UR:SMART, welcher die automatische Sentiment Analyse und Klassifizierung von Kundenbeiträgen in Social-Media Plattformen ermöglicht.
Publikationsort	37. International Conference on Information Systems (ICIS 2016), Dublin.
Ranking VHB JQ 3	A
Autor(en) und Anteile	Johannsen Florian 50% **Josef Schwaiger 20%** Markus Lang 20% Susanne Leist 10%

Tabelle 2: Fact Sheet Beitrag 1

UR SMART: Social Media Analysis Research Toolkit

Research-in-Progress

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Abstract

Social technologies have not only affected the way private persons communicate with one another, but also led to a shift of customer expectations regarding the communication channels offered by companies. Correspondingly, more and more customers preferably contact a company via social media channels to utter service requests, complaints or settle transactions. The posts capture valuable information about customers' concerns, moods and opinions amongst others. Therefore, social media analysis has increasingly been gaining importance for enterprises. However, the analysis of these posts is difficult, in case they are characterized by regional slang or a branch-specific language, which holds true for posts in social media channels of small-and-medium sized enterprises (SMEs) in special. As SMEs play a decisive role in the economy in southern Germany, we are developing a social media analysis tool, which matches the requirements of SMEs in that particular region and addresses the aforementioned challenges in addition.

Keywords: Social media, prototype, social media analysis

Introduction

The popularity of social media for private communication purposes has been increasing tremendously over the last decade (PWC 2012; Statista 2015). It is estimated that currently 65% of all adults in the United States are using social networking sites (Perrin 2015). Considering only those persons who claim to be active internet users, this number even rises to 76% (Perrin 2015). In that context, Facebook will have 2.44 billion users worldwide in 2018, which represents an increase of 37% as compared to current user numbers (Statista 2015). However, the use of social technologies has not only affected the way private persons communicate with one another, but also led to a shift of customer expectations concerning the communication channels offered by companies (Berthon et al. 2012). Accordingly, more and more customers preferably contact a company via social media channels to utter service requests, complaints or settle transactions (Hanna et al. 2011).

Against this background, companies strongly build on social technologies (e.g., Facebook, Twitter, Instagram, YouTube, etc.) to foster the external communication with customers (e.g., Stobbe 2010; Heidemann et al. 2012). Via social media channels, customer inquiries can be efficiently handled (e.g., Culnan et al. 2010), marketing material widely shared (e.g., Gallaugher and Ransbotham 2010) or complaints quickly solved (e.g., Pinto and Mansfield 2012) for instance. Accordingly, companies are heavily engaged these days in integrating upcoming social technologies with their business processes and their current IT-landscape (cf. Trainor et al. 2014). In that context, not only large companies invest into the adaption of social technologies but also small-and-medium sized enterprises (SMEs) become more and more engaged in the external communication via social media (e.g., Meske and Stieglitz 2013). In this regards, customer posts in social media channels open the opportunity to learn about current consumer needs and attitudes towards a company (e.g., Ramaswamy 2010; Sigala 2012). However, with the rising number of posts, a manual analysis is error-prone and a resource-intense process in addition. This is particularly crucial for SMEs, as these are characterized by limited staff resources amongst others.

Consequently, many social media analysis and monitoring tools for collecting and processing customer data directly from platforms like Facebook and Twitter have emerged in recent years replacing manual analyses efforts. Tools like Brandwatch[1], Radian6[2], Social Bench[3] etc. *"offer access to real customers' opinions, complaints and questions, at real time, in a highly scalable way"* (Stavrakantonakis et al. 2012, p. 53). Unfortunately, tool costs can go up to several thousand euros a month, which is not affordable for many SMEs due to tight budget limits (Kasper and Kett 2011). Although many tools are available as "free versions", these versions are mostly minimalistic and do not include technical support, sentiment analysis for languages other than English or functionalities for data extraction from multiple social media platforms (Stavrakantonakis et al. 2012). This is a tremendous drawback, especially for firms located in non-English speaking countries. Further, SMEs usually exhibit a limited regional presence, resulting in a direct and distinct communication between a company and its customers (e.g., Durkin et al. 2013; Lee et al. 2008). Thus, the corresponding customer posts are characterized by regional slang as well as branch-specific product names for instance (e.g., Laboreiro et al. 2010; Naaman et al. 2010; Petz et al. 2013). As a consequence, commercial social media analysis and monitoring tools fail in delivering acceptable accuracy levels regarding the analysis of social media posts at SMEs in particular (e.g., Waltinger 2010). To sum up, efficient means to automatically analyze social media posts in German language, adapted for the particular needs of SMEs, are still missing.

We address this gap by developing a software prototype that allows for performing a sentiment analysis and an automatic classification of customer posts in social media platforms. That way, a company may directly learn about reasons that lead to negative customer posts for instance (e.g., insufficient customer service). In this regards, our software is adapted to the needs of SMEs in southern Germany in special. For that purpose, we cooperate with five SMEs of different industries located in that geographic area. SMEs play a decisive role considering the German economy (cf. Söllner 2014). In 2013, 99.3% of all companies were declared as SMEs (Bundesamt 2015). However, southern Germany is also imprinted by a vast amount of rural regions (e.g., Bavarian Ministry of Agriculture and Forestry 2006). This makes the region of southern Germany particularly relevant for studies dealing with the application of social technologies at SMEs to increase value creation.

Our paper unfolds as follows: in the next section, foundations on social media analysis and monitoring tools as well as general requirements on corresponding software are presented. Afterwards, we introduce our collaborating partners and introduce their expectations regarding the tool. Then, the prototypical implementation is described and implications for management are presented. The paper ends with a conclusion and an outlook on future research.

Foundations

In literature, the term "social media" is defined 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*

[1] https://www.brandwatch.com/brandwatch-analytics/
[2] http://www.exacttarget.com/de/produkte/social-media-suite/radian6
[3] http://www.socialbench.com/social-media-analytics/

User Generated Content (UGC)“ (Kaplan and Haenlein 2010, p. 61). Despite this rather general definition, the “social media” phenomenon has not yet been fully understood (cf. Heidemann et al. 2012). This becomes evident as various technologies are ascribed to the field of social media, such as “online social networks (OSN)” (e.g., Facebook), “enterprise social networks (ESN)” (e.g., Yammer), “enterprise-owned social networks” (e.g., Dell’s IdeaStorm platform), existing communication applications enhanced by social functionalities (e.g., blogs), or tools supporting social networking applications (e.g., MS Share Point) (Turban et al. 2011). Using these social technologies to support the communication with internal or external customers (cf. Pande et al. 2000) leads to a huge amount of customer-related social media data. Efforts to analyze these data to learn about consumers’ opinions, complaints and questions in real-time are captured under the umbrella term “social media monitoring” (Stavrakantonakis et al. 2012). Against this background, several commercial tools were developed, as mentioned above, however, with shortcomings regarding their applicability for SMEs. Maynard et al. (2012) explicate general requirements on corresponding social media analysis and monitoring tools. Besides the ability to analyze the sentiment of customer opinions that may be posted in different languages, the functionality to separate relevant from irrelevant information as well as to aggregate the sentiment of single customers to an overall picture is decisive (cf. Maynard et al. 2012). Considering this, the tools must also be able to properly deal with the posts’ context information to recognize negations and to acknowledge common user reactions to particular events (e.g., product launch) (cf. Maynard et al. 2012). In case the posts are to be classified (e.g., product-related posts), the object addressed in a post needs to be precisely determined in addition (cf. Maynard et al. 2012). Besides these general requirements, a firm may pose individual needs on corresponding tools, such as for instance a customized design of the graphical user interface (GUI).

To develop a social media analysis and monitoring tool customized for SMEs in southern Germany, we follow the Design Science approach (cf. Gregor and Hevner 2013; Hevner et al. 2004). Accordingly, we impose requirements on our software that match the particular needs of corresponding SMEs. These requirements guide our prototypical implementation as well as the evaluation of the tool later on.

Development of a Prototype for Social Media Analysis at SMEs

Collaboration Partners for the Development

For the development of our tool called “UR SMART (University of Regensburg Social Media Analysis Research Toolkit)”, we first of all needed to gain valuable insights into the peculiarities of social media posts in social media channels of SMEs from a general perspective. Therefore, we contacted relevant firms and asked if they were willing to participate in our research. After conducting various interviews with SMEs from different industries, five companies decided to join our study (see Table 1).

Table 1. Participating Companies for the Development of UR SMART

Company	Industry/Description	# of fans & followers (approx.)
Company A	Market leader in fun sport equipment in the watersports industry	12.000
Company B	Online store for children's fashion, baby fashion, toys and children's furniture	85.000
Company C	Manufacturer and distributor of high-quality toys, games & room decor for kids of all ages	30.000
Company D	Leading manufacturer and distributor of equipment for daycare centers, kindergartens, and schools	2.500
Company E	Leading manufacturer of RVs, mobile homes and caravans	2.500

One of the main reasons of these companies to join our research was the vast amount of posts generated by the high number of followers on Facebook and Twitter. Correspondingly, the need for an automated analysis of the customer posts was given. As a starting point, we analyzed the social media presences of each company in detail. We focused their number of followers, each company’s online visibility, the topicality of the content and the target audience. All companies showed a clear commitment to social media, which became evident by linking the social media channels with the firm websites amongst others.

Company A is a well-known market leader for fun sport equipment in the watersports industry. The firm runs various social media channels including Facebook and Twitter pages for instance. The target audience of these pages is very homogenous, characterized by a strong interest in fun and watersport activities. Therefore, the language of the corresponding posts contains many specific expressions, leading to unsatisfactory accuracy levels when it comes to an unadjusted social media analysis. *Company B* is one of the top online stores for children and baby fashion, toys and furniture, heavily investing in its social media channels. As there are many divergent topics discussed, the target audience is heterogeneous, resulting in a high number of off-topic discussions. *Company C* is specialized in the area of B2C as well. The manufacturer and distributor of high-quality toys and games for kids has massively expanded its social media efforts over the last few years, resulting in a huge amount of posts that cannot be analyzed manually anymore. Hence, a tool for automatically assessing the topics of these posts was seen as a great benefit by *company C*. In contrast, *company D*, the leading manufacturer and distributor of equipment for daycare centers, kindergartens and schools, mainly operates in the B2B area. Therefore, the target audience is very professional and posts are strongly related to service and product offerings. An automated and accordingly adjusted analysis would definitely deliver important customer feedback in terms of both service and product quality. Finally, *company E*, a leading manufacturer of mobile homes and caravans, joined our study. Like the other collaborating partners, *company E* operates in a specific niche, resulting in unique and branch-specific language occurring in the posts. Because of that, a tool able to deal with this peculiarity in social media analyses was highly appreciated by the firm.

Requirements on a Social Media Analysis Tool for SMEs

We conducted several interviews with the social media representatives of our collaboration partners to assess their expectations on a social media analysis tool in more detail. Our aim was to enhance the list of general requirements as introduced in literature (cf. Maynard et al. 2012) by requirements particularly dealing with the needs of SMEs in southern Germany. As mentioned, social media data from SMEs may contain peculiarities such as regional slang for instance that are to be carefully handled in social media analyses (e.g., Laboreiro et al. 2010; Naaman et al. 2010; Petz et al. 2013).

From our interviewees we received multiple feedback unveiling that customers use a very specific language, e.g., branch-related expressions, as well as particular product and company names. The niche position of the companies in their markets was a major reason for that. In addition, there was a clear difference regarding the use of social media for the SMEs interviewed. On the one hand, some SMEs strictly used social media technologies as a marketing channel to present and promote new products or upcoming events, on the other hand, there were also SMEs involving users in general discussions (e.g., about their favorite vacation spots). Since currently available social media analysis and monitoring tools tend to support analyses that are more rudimentary in nature, such as counting the average number of posts per follower (e.g., Maynard et al. 2012), the aspired level of detail and diversity to trigger process redesign projects or marketing campaigns on the base of social media data is not achieved by these.

A central requirement mentioned by all collaborating partners (companies A to E) was the automatized analysis of customers' sentiment at a high level of accuracy *(requirement 1)*. Especially companies B (online store for children's equipment) and C (manufacturer and distributor of high-quality toys) had a large amount of followers on their Facebook and Twitter channels, eagerly posting requests, complaints or praise for instance. However, analyzing these posts manually and on a regular base was not possible due to limited personal resources. In that context, Twitter and Facebook were those channels that were intensively used by the companies for communicating with their customers. Thus, both channels were supposed to be the major sources for extracting customer posts, analyzing them and aggregating the findings subsequently *(requirement 2)*. Further, a high percentage of customers of company A (market leader for fun sport equipment in the watersports industry) were active users of public fan forums for kitesurfing or standup paddling. Accordingly, the ability to analyze and aggregate consumers' sentiment in freely accessible fan forums was an additional requirement that came up *(requirement 3)*. In that context, the analysis was supposed to be performed for German as well as English posts, as all companies operated on an international level *(requirement 4)*. More, a major requirement on the tool was the functionality to classify the customer posts according to predefined categories (e.g., product, service, partners, events, etc.) *(requirement 5)*. Especially at that point, the collaboration partners reported of tremendous drawbacks they had experienced when dealing with commercial social media analysis and monitoring tools. The classification should help employees to better assess the underlying reasons for particular customer moods, e.g., insufficient customer service, for being able to trigger improvement initiatives or marketing efforts for instance. In a conjoint workshop with all practice partners participating, the following classes to categorize customer posts were determined: (1) product, (2) service, (3) processes, (4) suppliers, (5) competitors, (6) retailers, (7) campaigns, (8) brand, (9) events, (10) User Generated Content (UGC), (11) contests and (12) topics related to provincial specifications.

Further requirements emerging were: the visual highlighting of extremely negative or positive customer posts *(requirement 6)*, the option to deactivate particular functionalities of the tool (e.g., spell checker) *(requirement 7)*, the ability to filter customer posts *(requirement 8)*, the option to manually change automatically generated analyses results *(requirement 9)*, the opportunity to define new classes for analyses *(requirement 10)*, and the implementation of a user management *(requirement 11)*.

Selection of Algorithms

The core functionalities of our tool refer to the sentiment analysis and classification of customer posts to match the requirements raised above. Generally, the classification and sentiment analysis of social media content are an interdisciplinary field, with relevant approaches potentially coming from the fields of Natural Language Processing, Text Mining, Web Mining and Information Retrieval (Liu 2012). Prior to implementation, a literature search on the databases ACM Digital Library, EBSCOhost, Emerald Insight, IEEE Xplore Digital Library, ScienceDirect and SpringerLink was performed (cf. vom Brocke et al. 2009) to find approaches and algorithms suitable to analyze the sentiment of customer posts at SMEs and to classify them accordingly. Regarding our search for sentiment analysis and classification algorithms, we placed our primary attention on sentence-based approaches, namely dictionaries, corpus-based approaches, syntactic patterns, artificial neural networks and treebanks (e.g., Medhat et al. 2014). In total, 196 promising publications were retrieved. However, we only focused on approaches that were evaluated and their applicability scientifically confirmed that way. In so doing, certain approaches came up in different publications and were thus only considered once further on. Additionally, we analyzed whether the functionality of an approach was described in sufficient detail to enable its implementation in the form of a tool or not. Eventually, we came up with 17 approaches that were categorized as "supervised" and "unsupervised" from a general perspective (e.g., Naive Bayes, Bayesian Network, Maximum Entropy, etc.).

Reflecting these approaches against the peculiarities of social media posts at SMEs, we decided that the implementation of a dictionary-based algorithm was the most promising solution for the sentiment analysis and the classification of posts accordingly. First, social media posts can be interpreted as a set compound of "fuzzy" text fragments, seldom characterized by correct grammatical structures (e.g., Laboreiro et al. 2010; Naaman et al. 2010; Petz et al. 2013). Algorithms that presuppose a correct grammar or orthography of the texts to be analyzed will thus not lead to convincing results in terms of the accuracy of an analysis. More, specialized or industry-related language occurs in social media posts at SMEs. Consequently, a suitable algorithm needs to take into account every single entity (e.g., word) of the post, a circumstance that makes it advisable to use a dictionary-based approach. Further, the dictionary-based approach offers an additional advantage because it can be customized to the specific needs of our cooperating partners by enhancing the dictionary by company-specific expressions (cf. Liu 2012). Considering this, a dictionary-based approach, building on SentiWordNet 3.0 (cf. Baccianella et al. 2010), was used for the implementation of the sentiment analysis.

Additionally, for the adequate classification of the numerous social media posts considering the above mentioned peculiarities, factors such as accuracy and processing speed of the algorithms as well as the ability to adapt them to deal with fast changing contexts (e.g., upcoming product trends) are essential (Read et al. 2012). Concerning the nature of data to be processed in our context, consisting of short, concise social media posts following no grammatical or other rules, the application of a dictionary-based approach is most promising for the purpose of classification (cf. Medhat et al. 2014). In this respect, posts are analyzed regarding seed words (e.g., Zagibalov and Carroll 2008), which enable their assignment to predefined classes.

Prototypical Implementation

For the implementation of our UR SMART prototype, we followed the general method of text analysis as shown in Figure 1 (cf. Aggarwal and Zhai 2012).

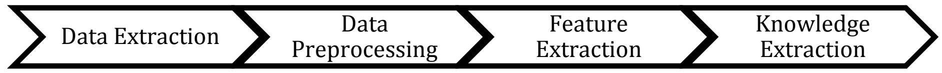

Figure 1. General Method of Text Analysis

The first step of the development of UR SMART was *Data Extraction*. Text data needed to be extracted from social media channels such as Facebook and Twitter and converted into a consistent data format for an effective further processing (Akaichi et al. 2013; Feldman 2013). Figure 2 shows a screenshot of the implemented prototype. In the extraction section, the user can choose a requested social media channel, until now Facebook and Twitter. Afterwards, a list of predefined Facebook or Twitter IDs is available, representing a user's social media presences. More, a timeframe is to be specified. The "start" button initiates the connection with the APIs (Application Programming Interfaces) of Facebook and Twitter, extracts all posts for the timeframe selected and stores the data in a database. In further developments, more social media channels, including blogs and open forums, will be added to the extraction section.

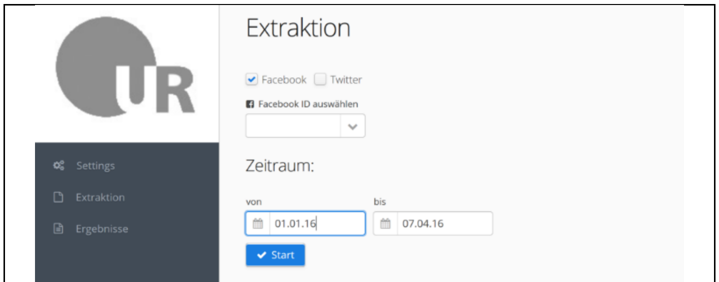

Figure 2. Prototype – Extraction of the Posts

Simultaneously, *Data Preprocessing*, including various techniques such as tokenization, stop word reduction, stemming and normalization, is performed to prepare the data for further analysis (Aggarwal and Zhai 2012). First, tokenization decomposes all posts into smaller parts, for example single words, and removes unneeded symbols and special characters (Carstensen et al. 2010). Additionally, stop word reduction eliminates words that do not carry opinions by using publicly available stop word lists (Angulakshmi and ManickaChezian 2014). Subsequently, a stemming process eliminates prefixes and suffixes, reducing all words to their stem or basic form (Akaichi et al. 2013). Finally, a normalization algorithm completes the step of *Data Preprocessing* and transforms all remaining text into lower case characters (Angulakshmi and ManickaChezian 2014).

After completing the steps *Data Extraction* and *Data Preprocessing*, the stored posts are further analyzed in the phases *Feature* and *Knowledge Extraction*. First, the sentiment of each post is determined by a sentiment analysis algorithm. Depending on the sentiment of each single token (e.g., word, emoticon) of a post, an aggregated sentiment-value is calculated with the value indicating a positive (> 0), neutral (0) or negative (<0) post (Feldman 2013).

As an example, we revert to a post extracted from the Facebook channel of company A:

"I have tested the board in France this week, it really is like that!!! Extremely manoeuvrable :-) Nice board...Yeeha"

After *Data Preprocessing* (including tokenization, stop word reduction, stemming and normalization) was performed, the algorithm assigns a value to each of the remaining tokens of the post. Thereby, the values assigned to each token are defined in the underlying dictionary and come from the interval [-2, 2]. Then, an aggregated sentiment-value for the complete post is calculated, which is *4.75* in our example (see Table 2). This value hints at a positive post (> 0). In Table 2, no negative values occur for the tokens, which, however, would generally be possible as well.

Table 2. Example for Determining the Sentiment of a Post

test	week	france	really	!!!	extremely	*manoeuvrable*	*:-)*	nice	*board*	*yeeha*
0	0	0	0.5	0	0	0.75	1	1.5	0	1

The post contains expressions that are specific for the watersports industry such as *"Yeeha"*, *"board"* or *"manoeuvrable"*. For more details on this particular issue, the reader is referred to Schwaiger et al. (2016).

Second, our prototype selects the class for each post by a corresponding classification algorithm. A list of classes, e.g., product or service, was predefined and specific seed words for every collaborating partner, pointing to a particular class, were identified, enabling a customized classification of social media posts for every partner.

As an example, we consider the class "product" for which two subclasses "quality" and "price-performance" are defined. The class "product" is generally characterized by the seed word *"product"* amongst others. For a more precise classification of posts, the following exemplary seed words are specified for the subclass "quality": *"condition", "damages"* and *"scratches"*. For the subclass "price-performance", the seed words *"expensive listing"* and *"discount"* shall be given. The post below (taken from the Facebook channel of company E) contains the seed word *"product"*, which allows a first allocation of the post to the superior class "product". Further, all aforementioned seed words of the subclass "quality" can be found. In contrast, none of those seed words specified for "price-performance" occur. Hence, the classification algorithm would unambiguously assign the post to the class "product" and the subclass "quality" correspondingly. In case the post would also contain seed words of the subclass "price-performance", the final assignment would be made by considering the total number of seed words found for each class. Principally, a double counting of the post for each category addressed may be implemented as well if desired.

"We bought the ***product*** *second hand, which was in a top* ***condition*** *despite its long use: almost no* ***scratches*** *or any noteworthy* ***damages****."*

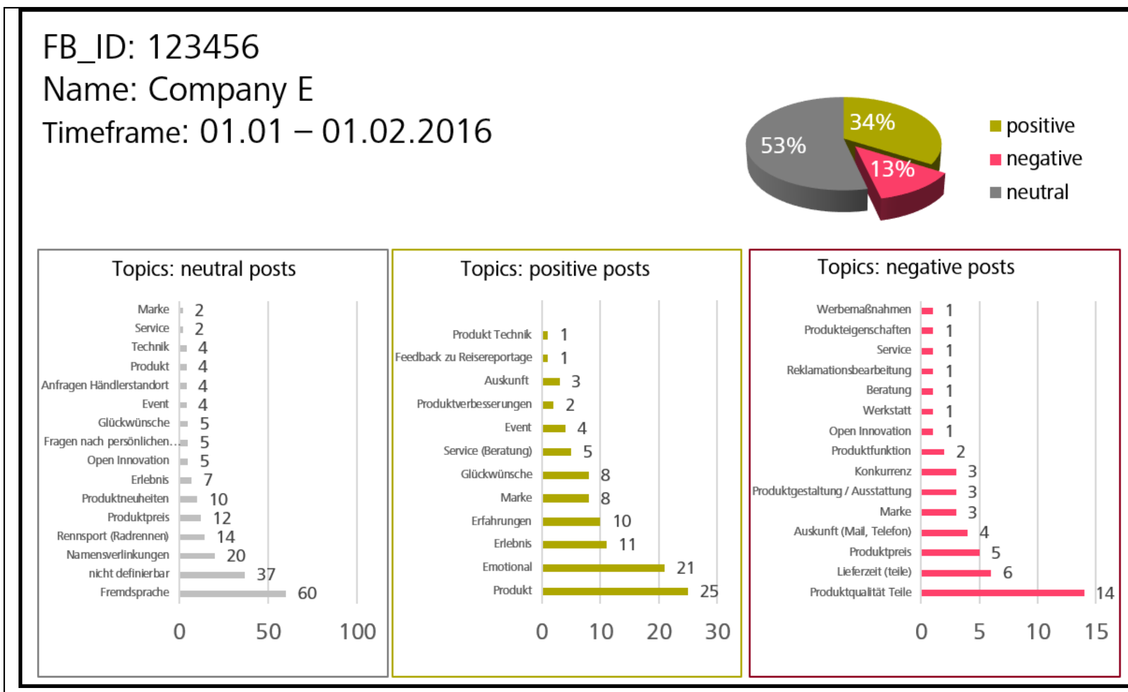

Figure 3. Report of the Analysis

All gathered data is presented with a table view and can be edited, deleted or exported. As a pure presentation of data in the form of a table view is often hard to understand, we designed a concept for presenting the results of the phases *Feature Extraction* and *Knowledge Extraction* in the form of reports. Each report is specific for a particular company and shows the analysis results for the time range as previously defined by the user. The results contain a pie chart presenting customers' sentiments, by differentiating between the number of "positive", "negative" or "neutral posts". Each of these categories is then further itemized, showing the contained classifications for every sentiment category. By that, the reasons for positive, negative and neutral posts become evident. For instance, 50% of all positive posts may be associated with matters of product quality and 20% of the negative posts with lacking customer service. An exemplary report is shown in Figure 3.

Validation

Currently, the accuracy of the prototype is validated using sample data extracted from the Twitter and Facebook channels of the five cooperation partners. For that purpose, we generated a sample set comprising 1.554 customer posts. These were reverted to for assessing the accuracy of the analysis in a first step, using the commonly accepted metrics *precision*, *recall* and *f-measure* (cf. Christen 2012). Non-German language posts or those created by the companies own social media teams were eliminated, resulting in 1.000 posts to be analyzed. Six researchers determined the sentiment of each post independently from one another with the results being discussed afterwards until a consensus was reached (402 positive, 455 neutral, and 143 negative) (cf. Schwaiger et al. 2016). The set of 1.000 posts and the corresponding manual sentiment assessment served as a base for judging the prototype's accuracy. We will briefly describe the results for *companies B and D* (see Table 1) in more detail and refer the reader to Schwaiger et al. (2016) for further information. As regards *company B*, an overall *f-measure* of 64%was reached, which is a significantly lower value as compared to all other companies. In this regards, a high level of off-topic discussion (e.g., *"our four-year-old still sleeps at our place and I´m appreciating it"*) not being associated with the product or service portfolio was given in the corresponding social media posts. During the manual analysis, the researchers agreed that these posts have a "neutral" sentiment whereas the algorithm analyzed each token of a post without knowing the context and, thus, classified them as "positive" or "negative". For *company D*, a considerably high overall *f-measure* of 88% was obtained. The posts were characterized by a structured clear and correct language, obviously because the addressees were business customers at large, which may serve as an explanation. Generally, considering the whole dataset, we found a significant amount of spelling mistakes in the posts across all companies, which prevented higher accuracy levels. Further, a lot of industry-specific language was observed (e.g., slang, jargon), especially for *company A* (e.g., *"already tried it, 9's at 32 knots: I´ve never jumped so high!!! Yeehaa!"*), which was used to enhance the existing feature libraries by corresponding expressions recently. Thus, to improve the accuracy of our prototype, further refinements in terms of a spell checking functionality and an enrichment of the dictionary by industry-specific expressions are currently being performed. At present, the classification of posts is validated by reverting to sample data and manually reflecting the classified posts against the categories as they were determined with the collaboration partners. The applicability and design of the prototype are so far assessed in workshops with the companies taking part, which enables discussions at regular intervals. For that purpose, various technologies to build a GUI (e.g., JavaFX, Vaadin, Java Server Faces) were evaluated prior to the implementation regarding "design" or "performance" amongst others and wireframes were used to match the design of the GUI with the partners' expectations. The feedback we received in our dialogue with the partner companies on the applicability and the design is very promising and encourages us to develop the tool further. In future, the tool will be subject to an evaluation in the partners' daily routines. Beneficial insights into the applicability will be gained to revise the tool, and usability studies are to be performed (cf. Bevan 1995). For instance, we plan to conduct a SUMI (Software Usability Measurement Inventory) study to receive valuable feedback on the tool's efficiency to perform the social media analysis, its learnability or its design to reach a positive emotional attitude from the employee side (cf. Kirakowski and Corbett 1993). In this regards, also a further refinement of the underlying dictionary, e.g., by the firms' terminology, expressions related to the product and service portfolio as well as customers' language will be pursued.

Implications and Discussion

Our prototype is currently being tested reverting to social media posts of our collaborating partners, and will be rolled out in these companies shortly. The prototype supports managerial decision making for SMEs based on social media data the following ways:

First, based on the reports, weaknesses in current business operations and processes become apparent. For instance, a large amount of negative posts regarding the customer service or the product quality is an indicator for problems in the production or the after-sales service process. Hence, business process improvement or reengineering projects may be triggered by an enterprise, with the tool supporting the selection of those processes to be improved (cf. Pande et al. 2000; Snee and Hoerl 2003). Generally, the selection of improvement initiatives is a challenging task for many firms (e.g., Thawesaengskulthai and Tannock 2008) and social media posts provide a valuable reference for decision makers in this respect. Further, via a filtering functionality of our tool, posts assigned to particular categories of the report (e.g., positive/negative posts on service) can be extracted and analyzed more profoundly, which helps to identify causes for insufficient process performance (e.g., lacking know-how of service employees). That way, the systematic derivation of suggestions to overcome process weaknesses is supported. Second, the effectiveness of the measures undertaken to optimize process performance can be monitored by the management because the tool allows to analyze social media posts in terms of different timeframes (see Figure 2). It can be checked whether the redesign of a process (e.g., the customer service process) affects the sentiment of social media posts uttered by customers for instance. A reduction of negative posts for particular categories (e.g., quality of service) or the increase of positive posts, respectively, would thus be an indicator for the success of process improvement initiatives. Third, the sentiment analysis across timeframes further allows to conduct longitudinal analyses of customer expectations because different topics may be the subject of consumer discussions, becoming apparent by the reports generated via our tool and the corresponding classification of posts. For instance, a suddenly rising amount of posts about a company's product portfolio may point to a change of consumers' needs in this respect (cf. Mukerjee 2013). Fourth, the management is made aware of particular critical issues (e.g., problems with product quality), since our algorithms take into account every single entity of a post during the sentiment analysis, which enables to filter exceptionally negative customer statements to be analyzed more closely. Fifth, customers' reactions to social media marketing or advertising campaigns become evident (e.g., Castronovo and Huang 2012). Hence, campaigns favorably received by consumers (e.g., prize competitions or special offers) often entail discussions in the social media channels. Based on the topics captured in these posts, which are recognized by our tool, SMEs may purposefully design and plan future campaigns to strengthen customer loyalty.

As regards the generalizability of our solution, it is to be considered that the adaption of the underlying dictionary is crucial to achieve a high level of accuracy in terms of the sentiment analysis and the classification of posts. While the dictionary-based algorithms that UR SMART builds on are generally valid, the design of the referenced dictionary needs to adequately consider peculiarities found in posts in social media channels of SMEs (e.g., regional slang and branch-specific expressions). For that purpose, we collaborated with five companies, analyzed the communication in their social media channels in detail – to uncover branch-specified expressions as well as slang – and adjusted our dictionary accordingly. More, company-specific features addressed in the posts, e.g., product lists, were provided by the SMEs and are currently used to further enhance the dictionary. While UR SMART may be applied at other firms straight away, the corresponding analysis will come at the expense of a decreased accuracy level of the results due to a lacking adaption of the dictionary. More, the categories for classifying posts may need to be revised in addition. In summary, the tool can be applied at firms from various branches and of different sizes due to the general validity of the algorithms used, however, a refinement of the underlying dictionary is a prerequisite for achieving high accuracy levels.

Conclusion and Next Steps

This paper describes our running research on the development of a social media analysis and monitoring tool "UR SMART", which is adapted to the particular needs of SMEs in southern Germany. While commercial tools exist in the field of social media monitoring and analysis, they fall short of the expectations of the SMEs in terms of their pricing policy and the ability to consider the peculiarities of customer posts properly (e.g., regional-specific slang, industry-specific expressions, etc.). Consequently, we address this gap by our prototype, which is developed in cooperation with five SMEs from southern Germany.

The implementation of the tool reverting to the requirements of five companies only surely is a restriction regarding the tool's general applicability. Nevertheless, this narrow focus allows for generating a prototype in a first shot, precisely addressing the major drawbacks of commercial software in regards to social media analysis at SMEs and for evaluating the tool in detail later on. Based on the specific results gained (e.g., specifically adapted dictionary, etc.), the tool will be customized to match the needs of additional partners as well and thus stepwise achieve greater practicality.

It is our declared aim to come to a generally valid dictionary applicable for social media analysis at SMEs in the region of southern Germany. Further, the fully automatized classification of customers' posts at SMEs is strived for, which is an under-researched topic yet. Applicable software solutions for that particular purpose are still missing. Our current work provides an important step towards closing this gap.

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2.2 Beitrag 2: Assessing the accuracy of sentiment analysis of Social Media posts at small and medium-sized enterprises in Southern Germany

Adressierte Forschungsfragen	**Forschungsfrage 1:** Welche sprachlichen Besonderheiten weisen Social-Media Posts bei süddeutschen, kleinen und mittelständischen Unternehmen auf? **Forschungsfrage 3:** Welche Algorithmen zur automatisierten Sentiment Analyse und Klassifizierung von Social-Media Inhalten gibt es und welche sind für den gegebenen Anwendungsfall geeignet? **Forschungsfrage 5:** Welche Genauigkeit bieten geeignete Ansätze zur automatisierten Sentiment Analyse und Klassifizierung bei der Anwendung auf Social-Media Posts von KMU im süddeutschen Raum?
Zielsetzungen	(1) Identifikation der spezifischen Eigenschaften von Social-Media Posts bei KMU. (2) Identifikation von Algorithmen zur automatisierten Sentiment Analyse von Social-Media Inhalten bei KMU. (3) Implementierung und Evaluierung eines geeigneten Algorithmus zur Sentiment Analyse bei KMU.
Forschungsmethode	Design Science nach (*Hevner et al., 2004)* • Literaturanalyse zum Thema automatisierte Sentiment Analyse *(Vom Brocke et al. 2009)* • Design und Development, Anwendung und Evaluation.
Kernergebnisse (Überblick)	(1) Identifikation von 17 potentiellen Sentiment Analyse Algorithmen aus der Literatur. (2) Verschiedene Besonderheiten von Social-Media Beiträgen bei KMU, z. B. spezielle Branchen- und Produktsprachen, themenfremde Diskussionen, branchenspezifische Komponenten (z. B. Slang, Jargon) und firmenspezifische Ausdrücke (z. B. Surferjargon im Fun- und Wassersport oder spezielle Fahrzeugteile). (3) Genauigkeit bis zu 88% bei der Anwendung eines Lexikon-basierten Sentiment Analyse Algorithmus, welcher speziell an die Charakteristika der jeweiligen KMU angepasst ist.
Publikationsort	24th European Conference on Information Systems (ECIS), Istanbul, Turkey, June 12-15, 2016
Ranking VHB JQ 3	B
Autor(en) und Anteile	**Schwaiger Josef** **50%** Markus Lang 25% Ritter Christian 15% Johannsen Florian 10%

Tabelle 3: Fact Sheet Beitrag 2

ASSESSING THE ACCURACY OF SENTIMENT ANALYSIS OF SOCIAL MEDIA POSTS AT SMALL AND MEDIUM-SIZED ENTERPRISES IN SOUTHERN GERMANY

Completed Research

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Abstract

In recent years, small and medium-sized enterprises (SMEs) have increasingly adopted Social Media technologies with the purpose of fostering the bidirectional communication with customers or to facilitate the collaboration between employees amongst each other. Thereby, customer posts in a company's Social Media channels capture consumers' current attitude towards product and service offerings or the enterprise as a whole. An automatic analysis of these posts does not only provide a firm with valuable knowledge on the customer relationship, but also frees up human resources in case the posts were screened by employees manually hitherto. However, posts in Social Media channels of SMEs are characterized by certain peculiarities such as regional slang or off-topic discussions amongst others. The study at hand investigates the impact of such characteristics on the accuracy of results received from an automatic sentiment analysis of corresponding posts. In this context, we revert to Social Media posts of five SMEs from southern Germany. The results show that an adaption of approaches used for sentiment analysis to the specific language of customers and firms is mandatory for achieving a high level of accuracy.

Keywords: Social Media, sentiment analysis, small and medium-sized enterprises.

1 Introduction

With affordable and reliable internet service for everyone and information technology evolving quickly, Social Media began to emerge massively at the turn of the millennium (Heidemann et al., 2012). According to current studies (cf. Statista, 2015a; PWC, 2012), the number of active Social Media users is estimated to be 2.44 billion worldwide in 2018. This is an increase of 37% compared to user statistics for 2015. In January 2015 alone, the social network Facebook had about 1.36 billion users and the microblogging service Twitter counted 284 million subscribers for instance (cf. Statista, 2015a).

As Social Media had developed into being a major part of communication in the private life of the majority of the young generation (PWC, 2012), many larger scale companies decided to join Social networks and microblogging platforms (cf. Gallaugher and Ransbotham, 2010). Literature presents a variety of benefits that companies may achieve by the purposeful introduction of Social Media technologies with either the individual, a team or the organization as a whole profiting (Lehner and Fteimi, 2013). For example, van Zyl (2009) points out that Social Media helps to find experts and business partners, to increase staff motivation, to accumulate organizational knowledge, to develop innovations, and to strengthen customer relationships. Further, the creation of customer adapted services and products is emphasized frequently (cf. Mitic and Kapoulas, 2012; Ramaswamy, 2010). This is particularly important as customer requirements are rapidly changing these days due to increased market transparency (cf. Goodrich and de Mooij, 2014; Sharma and Baoku, 2013). Social Media offers the opportunity to gain insights into customers' attitudes, supports brand building and thus contributes to establishing long-term customer loyalty (Chua and Banerjee, 2013; Chikandiwa et al., 2013; Parveen, 2012).

Lately, small and medium-sized enterprises (SMEs) have increasingly started to apply Social media, too (Meske and Stieglitz, 2013; Lee et al., 2008; Durkin et al., 2013). In this context, the improved bidirectional communication with consumers, the easy access to company knowledge, and a positive impact on the company culture are particularly accentuated (cf. Meske and Stieglitz, 2013; Lee et al., 2008). Besides these benefits, the introduction of Social Media in a company is reported to be comparatively easy (Bell and Loane, 2010), which increasingly tempts SMEs to apply corresponding technologies for supporting the day-to-day business.

Though, many of the benefits associated with the external use of Social Media (e.g., strengthened customer relationship, customer co-creation of services and products) (cf. Sigala, 2012; Ramaswamy, 2010) can be traced back to a deeper understanding of customer concerns and expectations gained by applying corresponding technologies. Social Media posts, e.g., on an enterprise's Facebook page, represent the "voice of the customer (VOC)" (cf. Pande et al., 2000) and capture current customer attitudes towards products, services or the company in general. The analysis of these posts can provide valuable information on consumers' behavior and serve as a base for triggering word-of-mouth (WOM) efforts (cf. Oh et al., 2016), product development projects or business process improvement (BPI) initiatives for example. As customer posts in Social Media platforms become visible without any delay, companies can immediately analyze them and retrieve a customers' current sentiment (cf. Liu, 2012). This is a clear advantage over the collection of secondary data (e.g., quality reports), which is often outdated, or the costly and elaborate conduction of customer surveys (cf. Meran et al., 2013).

However, to fully utilize the information captured in Social Media posts, all posts have to be analyzed and interpreted. Since the amount of posts quickly rises when a company establishes a Social Media strategy, enormous human efforts are required in case the analysis is performed manually. This is a major challenge for SMEs regarding limited human resources and the lack of time available to monitor Social Media channels besides the daily routines. Contrary to large enterprises that usually create own positions for Social Media responsibles, SMEs often charge employees of their operational divisions (e.g., marketing) with Social Media efforts. As a result, these employees cannot dedicate a lot of time into monitoring Social Media channels without sacrifizing their daily routine. Against this background, the necessity for an automated sentiment analysis of Social Media posts becomes evident. Several approaches (cf. Liu, 2012) and tools have been developed to fulfill this purpose in recent years (e.g., Brandwatch, SocialBench, etc.), anyway, it is a market still in the process of maturation (cf. Paltoglou, 2014). Additionally, customer posts in Social Media channels of SMEs are characterized by colloquial language, consumers' regional dialects and an industry-specific terminology amongst others. What is missing yet are profound insights regarding the accuracy of automatic approaches for conducting sentiment analyses in comparison to manually performed analyses of corresponding posts at SMEs. Due to the lack of grammatical structure and industry-related language encountered in Social Media posts we consider dictionary-based approaches as particularly well suited for the analysis. We thus post the following research questions:

- RQ1: What accuracy does an automatic sentiment analysis using a dictionary-based approach provide for posts in SMEs' Social Media channels in southern Germany in comparison to the results of a manual classification?
- RQ2: What peculiarities of the customer posts can be reverted to for explaining a potential inaccuracy of the analysis results?

By the first research question, we aim to provide a better understanding for the capabilities of established approaches for the automatic sentiment analysis to correctly assess customers' current attitudes towards a company. In this context, we investigate Social Media posts of five SMEs from southern Germany. Generally, SMEs play a decisive role in the German economy (cf. Söllner, 2014) with 99.3% of all companies being assigned to this enterprise category in 2013 (Statistisches Bundesamt, 2015a). Especially in southern Germany, SMEs employ a majority of the workforce (cf. Söllner, 2014; Handelskammertag BW, 2015); e.g., in Bavaria 99.6% of the employees in the private sector work for SMEs (Statistisches Bundesamt, 2015a, 2015b). Neverthless, from an economic perspective, southern Germany is also characterized by a vast amount of underdeveloped rural regions (cf. Bavarian Ministry of Agriculture and Forestry 2006). Consequently, the region of southern Germany is particular interesting for studies dealing with the application of information technology at SMEs to raise business performance. The second research question aims to uncover deficiencies of the automatic sentiment analysis and to investigate the causes for these drawbacks reverting to the characteristics of customer posts. These insights help SMEs to decide whether an automatic sentiment analysis is worth the investment of resources. Therefore, our findings are particulary interesting for practitioners disussing the potentials of Social Media introduction.

The paper unfolds as follows: in section 2, foundations on Social Media, sentiment analysis and peculiarities of customer posts at SMEs are introduced. Afterwards, the procedure of our research is presented (section 3). Section 4 highlights the result of the investigation. The results are discussed and interpreted in section 5. The paper is rounded off with a conclusion, limitations and an outlook.

2 Foundations

2.1 Social Media and Peculiarities of Posts in SMEs

Social Media entails *„…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“* (Kaplan and Haenlein, 2010, p. 61). These Internet-based applications incorporate blogs, social networking sites, collaborative projects, content communities, virtual social worlds as well as virtual game worlds (Kaplan and Haenlein, 2010). At first, Social Media was used as a way for individuals, mostly students, to maintain long-distance friendships or relationships. Many social networking sites like Six Degrees (founded 1997), Friendster (2002), MySpace (2003) and Facebook (2004) emerged by providing a solution for this need to its users. Microblogging platforms like Twitter (2006) provided additional ways to inform your friends or “followers” about your daily life events.

In today’s market, Social Media technologies are increasingly adopted by enterprises integrating them with their business processes to support value-creation. SMEs can easily engage in Social Media as costs are minimal and the level of IT skills needed is low (Abed et al., 2015). For example, SMEs can benefit from using social networks like Facebook to gain positive impact, e.g., by reducing costs for customer service, by improving customer relations, or by improved information accessibility (Ainin et al., 2015). Alongside, recent studies revealed that one of the main strategic goals of German SMEs is to improve customer service (Statista, 2015b). To support this goal, direct access to customer data is required and *“…social media usage has a positive influence on information accessibility. Organizations can get information about their potential customers, their tastes, their wants easily from the conversations in the social media sites such as Facebook pages, twitter sites etc.”* (Parveen et al., 2015, p. 11). However, the use of Social Media in SMEs is very diverse since the owner-managers are a heterogeneous group, e.g., in regards to their preference for face-to-face interaction with customers, or the knowledge and skills in the e-Business context (Derham et al., 2011). A major driver for Social Media adaption in organizations is identified as institutional pressure from the external environment, e.g., customers, or competitors (Parveen et al., 2015). Especially for customers Social Media is a quick and easy channel of communication that enables them to interact with a company publicly.

Social Media data commonly consists of the following elements: a username, the shared content, the time and date of the post, the self-reported location of the user, references to other users or sites, and the network of the user (Murphy et al., 2014). Posts in Social Media distinguish from other communication in three points. First, the posts are by default either accessible by the public or at least by several members of a personal network. Hence, Social Media posts usually address more than one person. The second characteristic of Social Media posts is the shortness of the post, triggered by either technical limitations of the platform (e.g., 140 characters on Twitter) or by constraints of the user (e.g., typing a post on a mobile device on the subway). In either case posts need to be concise (Zhao and Rosson, 2009). Consequently, text economy increases, e.g., whitespaces are spared as well as words are replaced by numbers of similar pronunciation (Laboreiro et al., 2010; Petz et al., 2013). Additionally, there is a high usage of emoticons to express emotions (Pak and Paroubek, 2010; Petz et al., 2013). A third differentiation point of Social Media posts results from the meshed structure of a social network. Posts reflect this structure by adapting it, for example by allowing users to provide direct feedback to other users' posts or by offering the possibility to add references into posts (Naaman et al., 2010).

Aside from these aspects, Social Media posts show several specifics in regards to the language used. Especially non-standard language elements like emoticons (see section 4.2), "internet slang" (e.g., the expression "4u"), multiple languages within one posts, or spelling errors (e.g., "Helllllooooo") typically occur and should thus be regarded (Laboreiro et al., 2010; Petz et al., 2013). As Social Media posts can be created on many different devices without the ability of spellchecking, an increase of spelling mistakes can be observed (Laboreiro et al., 2010; Naaman et al., 2010).

Beside these general characteristics of Social Media posts, there are some additional peculiarities of posts relating to SMEs in southern Germany that influence the content and structure of the posts. SMEs usually show a limited regional presence (Durkin et al., 2013; Lee et al., 2008). This typically results in a more direct communication between the companies and their customers and employees (Durkin et al., 2013). This stronger relation can also be observed in corresponding Social Media posts, which often address specific products, services or local events hosted by the companies. While little research has been focusing on this topic, we were able to retrieve some peculiarities by interviewing several Social Media representatives of SMEs in southern Germany. We received multiple feedback from our interviewees that pointed out that their target audience uses a very specific language. As SMEs tend to be niche players in their industries, their customers tend to use very special language and expressions as well as product and company names. Additionally, customers may use the Social Media channel as a first approach for complaints and customer service requests since SMEs usually do not maintain call centers or local service centers. Thus, we expect a lot of posts carrying service requests and therefore have a rather negative annotation. Furthermore, we identified a difference in usage of Social Media among the SMEs interviewed. While some use Social Media channels strictly as a marketing channel to present new products or upcoming events, others try to involve their users in general discussions. We also identified open innovation as a potential usage scenario of Social Media for SMEs. As SMEs account for the majority of companies in a nation, the individual companies differ vastly in size and public recognition. As a result, we also expect customer involvement in Social Media channels to be very heterogeneous and very dependent of the popularity of the product or service offered.

2.2 Approaches for Sentiment Analysis in Social Media

Automated sentiment analysis of specific text is an interdisciplinary research field. In consequence, there are a variety of publications in the areas of Natural Language Processing, Text Mining, Web Mining and Information retrieval (Liu, 2012). Sentiment analysis consists of different subareas, such as subjectivity detection, sentiment classification and opinion summarization (Kumar and Sebastian, 2012).

Approaches with reference to sentiment analysis can be categorized into three different classes. At first, document-based approaches aim towards the classification of the sentiment of a whole text corpus, for example newspaper articles. The second category focuses on sentence-based approaches, which analyze whether a single sentence can be classified as having a positive, negative or neutral sentiment. The third category considers aspect-based approaches which focus on entities and their aspects. For example, in product reviews the attributes (aspects) of the reviewed products (entities) could have different characteristics (Vohra and Teraiya, 2012; Feldman, 2013; Liu, 2012).

Considering the research questions, the focus of the study was to analyze Social Media posts in SMEs. Accordingly, we focused on sentence-based approaches, namely *dictionaries, corpus-based approaches, syntactic patterns, artificial neural networks* and *treebanks* (Medhat et al., 2014). When using *dictionaries,* the sentiment of each entity (e.g., each word) from a text is classified into a positive or negative class using dictionaries. The dictionaries annotate opinion carrying words. The sentiment of the whole text is determined by considering the sum of the combined scores of all its entities (Turney, 2002; Kundi et al., 2014). *Corpus-based approaches* determine the sentiment based on a domain specific text corpus regarding the context of the sentence, which can be recognized by particular adverbs (Liu, 2012). *Treebanks* disassemble the sentence into a hierarchical grammatical structure (tree). With respect to the purpose of sentiment analysis, this structure could be used either to identify recursively restraining negations or to determine the semantic orientation of the sentence by means of adverbs and adjectives (Turney, 2002; Sadegh et al., 2012). *Artificial neural networks* consist of parallel operating units (neurons) to classify the sentiment of a sentence. The words that need to be classified traverse the network through weighted branches. The network can be trained by adjusting the weights of the branches (Sebastiani, 2002).

Although sentiment analysis is a lively discussed field of research, the available approaches and solutions do not reach satisfactory accuracy levels for practical applications yet (Collomb et al., 2014). This is particularly true when it comes to German Social Media posts. The German language contains a vast amount of complex language-specific grammatical rules and thus many approaches initially designed to interpret English fail in delivering acceptable accuracy levels (cf. Waltinger 2010). Challenges for the approaches especially occur in case the posts capture regional slang or irony. For the purpose of irony detection, knowledge about the topic addressed, the events related to ironic statements (e.g., special incidents), and correctly identified emotions, e.g., expressed by emoticons, are important factors (Carvalho et al., 2009; Davidov et al., 2010; Derks et al.,2008; Gonzales-Ibanez et al., 2011). To identify slang, current sentiment analysis approaches build on dictionaries covering branch-specific or topic-related expressions for instance (Asghar and Zubair, 2014; Nielsen 2011). However, generally valid cross-industry dictionaries do not exist yet. Accordingly, a case-dependent adaption of current approaches for sentiment analysis or a value-adding combination of them is required in practice (cf. Gonçalves et al., 2013). To sum it up, sentiment analysis research still is in a maturing phase with commercial social monitoring tools requiring further improvements to be beneficially applied at SMEs (cf. Sponder, 2010).

3 Procedure of the Research

For answering the research questions, we followed the procedure as shown in figure 1. The steps are part of a larger Design Science project (cf. Hevner et al., 2004), aiming at the development of a Social Media monitoring tool adapted to the needs of SMEs in southern Germany in particular.

Figure 1. Procedure of the research

To identify existing approaches for sentiment analysis, the first step was to *review the state of the art*. For this purpose, we examined 196 relevant publications resulting in 17 identified approaches potentially suitable for automatic sentiment analysis of textual elements. Social Media posts represent a specific area of application, for which only a limited number of algorithms are applicable. Thus, a main task was to identify a suitable approach for the given area of application.

Within the *construction of the scenario,* we cooperated with five SMEs from southern Germany. Each company operates at least one Facebook page and is heavily engaged in the field of Social Media. In a discussion with representatives of the five companies we defined the further elements of our scenario (e.g., languages analyzed, timespan of the data extraction).

For the next phase, the *application of the approach*, we used a well-established text-mining procedure (cf. Aggarwal and Zhai, 2012). Its first step is the extraction of the Social Media data from every company's Facebook page. For this objective, we developed an extraction tool based on public API libraries. Our extraction tool connects to existing Facebook and Twitter developer interfaces and stores the extracted data in a universal file format. The extracted data is then used for further data preprocessing and analysis. Due to the linguistic and structural characteristics of Social Media posts, we had to adjust the existing sentiment analysis algorithms to fit our specific requirements. Aside from customizing the algorithms for the shortness of Social Media posts (Zhao and Rosson, 2009), we focused on the integration and detection of emoticons, media-specific words and multiple languages in a single text (Laboreiro et al., 2010). As a result, we created a software application that can automatically conduct a sentiment analysis on Social Media posts in German language, specifically aimed at the peculiarities of SMEs.

The last step of our research procedure is the *presentation and interpretation of the results.* For the evaluation of the results generated by the automated application, it was necessary to first assess the test data manually. For this purpose, the sentiment of every single extracted post was determined by a group of six researchers and discussed with at least one representative of each participating company. The agreed-upon sentiments served as a comparative value for our automatic sentiment analysis. As we eliminated subjectivity as much as possible, we considered the manual sentiments identified as "reality". To determine the accuracy of the automated analysis, we used the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). The results were then discussed and evaluated at a workshop with representatives of all participating companies.

4 Identification of Peculiarities in the Application of Sentiment Analysis in the Context of SMEs in Southern Germany

4.1 Construction of the Scenario

As mentioned earlier, we generally considered 17 algorithms for sentiment analysis as appropriate for our research. With regards to the stated peculiarities of Social Media posts in the context of SMEs (see section 2.2), the implementation of a dictionary-based algorithm was seen as the most promising approach for multiple reasons: first, Social Media posts do not provide a precise grammatical structure; much more they often contain a set of "fuzzy" text fragments. Second, we expected a lot of specialized resp. industry-related language to occur in Social Media posts of SMEs. Hence, algorithms for sentiment analysis requiring a correct grammar or orthography of the texts to be analyzed will not achieve a convincing classification. Therefore, the algorithm to be selected needs to be able to cope with these circumstances by taking into account every single entity (e.g., word) of the post. Additionally, the dictionary-based approach allows for a simple customization and thus enables its application for the different requirements of the cooperating companies (Liu, 2012).

After selecting the approach for further evaluation regarding the quality of the sentiment analysis, we defined a structured evaluation scenario. To gain valuable insights into the specifics of Social Media posts in SMEs in general, we selected the Facebook sites of five SMEs for our data collection. For this purpose, a company search was performed. Freely available online databases with addresses of German companies and the internet were analyzed in that context. The search was directed at enterprises of small and medium sizes across all industries, openly declaring their commitment to Social Media. The commitment could be shown by a link to Social Media channels on the firm's website, by inviting visitors to become "fans" on Facebook, or by encouraging them to follow the company's Twitter account.

The Social Media presence for each firm identified was then analyzed to see whether up-to-date content was regularly pronounced by the company (e.g., announcement of events, etc.) or not. Further, the number of followers of a company's Social Media channels was drawn upon to judge its online visibility, and only those enterprises that continuously updated their Social Media presence were further considered. In these cases, the companies' dedication to Social Media could be acknowledged from an external perspective making them potential candidates for our evaluation. Relevant firms were then contacted and asked if they were willing to participate in our evaluation. A total of five companies from various industries and different target audience decided to join our study (see table 1). The companies mentioned the vast amount of posts generated by the high number of followers as their main reason for the need of an automatic analysis and thus for joining our study. To generate comparable results for all companies, we agreed on only analyzing the companies' Facebook pages and focusing on posts in German language.

Company	**Industry/Description**	**# of Employees (approx.)**	**# of FB fans (approx.)**
Company A	Market leader in fun sport equipment for watersports	80	4,000
Company B	Online Store for children's fashion, baby fashion, toys and children's furniture	400	85,000
Company C	Manufacturer and distributor of high-quality toys, games & room decor for kids of all ages	1,200	30,000
Company D	Leading manufacturer and distributor of equipment for day-care centers, kindergartens, and schools	200	2,000
Company E	Leading manufacturer of RVs, mobile homes and caravans	1,200	1,500

Table 1. Participating companies in our evaluation

First, we extracted all posts from the Facebook pages for a ten week timespan (July 25th to October 6th 2015), providing us with a total of 1,554 initial posts (see table 2). However, the extracted posts also entailed posts by the companies' own Social Media teams as well as posts in non-German languages. Thus, we had to eliminate these from our dataset which subsequently shrank to exactly 1,000 posts to be analyzed. We continued our research by conducting a workshop with Social Media representatives from the five companies. In this workshop, we selected approx. 40 eye-catching posts per company and discussed the specifics of these in regards to special expressions and meanings of the corresponding industries. After this valuable input from practice, six researchers were able to determine the sentiment for each of the 1,000 posts individually. The results were then discussed and aggregated to the sentiment agreed upon (402 positive, 455 neutral, and 143 negative). The resulting list of 1,000 posts and their corresponding sentiment were the foundation for the evaluation of the algorithm in regards of its accuracy to estimate sentiments in Facebook posts for SMEs in German language.

company	**# of extracted posts**	**# of relevant posts**
Company A	325	125
Company B	416	260
Company C	351	316
Company D	90	34
Company E	372	265
total	**1,554**	**1,000**

Table 2. Number of extracted and relevant Facebook posts per company

4.2 Application of the Approach

For the evaluation of the approach for analyzing the sentiment, the application follows the general method of text analysis as shown in figure 2 (cf. Aggarwal and Zhai, 2012).

Figure 2. Selected approach for sentiment analysis

As a starting point, data (e.g., posts or tweets) is extracted from Social Media channels and converted to a consistent data format for further effective processing (Akaichi et al., 2013; Feldman, 2013). Even though we focused on the companies' German Facebook pages, one of the main problems during our evaluation was the mixture of English and German language in the extracted Social Media posts. As many of the preprocessing techniques are language dependent and we focused on posts in German only (see section 4.1) this issue needed to be addressed. Thus, we implemented a language detection prior to the other steps to determine the language of every single post and eliminated non-German posts.

Subsequently, data preprocessing, including various techniques like tokenization, stop word reduction, stemming and normalization, is required (Aggarwal and Zhai, 2012). Tokenization describes the decomposition of posts into smaller parts, e.g., single words. Additional symbols, punctuation and special characters are removed (Carstensen et al., 2010). Afterwards, stop word reduction is performed. Hereby, words that do not carry opinions are removed (Angulakshmi and ManickaChezian, 2014). To identify these, publicly available stop word lists are applied. The next preprocessing technique used is called stemming. During the stemming process, prefixes and suffixes are eliminated and words are reduced to their stem or basic form. For example, the verb "walking" is stemmed to its base form "to walk" (Akaichi et al., 2013). Normalization is the last of the mentioned preprocessing techniques. Thereby, all remaining text is transformed to lower case characters (Angulakshmi and ManickaChezian, 2014).

Despite the mentioned preprocessing techniques, most approaches for sentiment analysis cannot handle some special content immediately. Therefore, a feature extraction composed of defining feature types and selecting specific features (e.g., emoticons, part of speech, sentiment carrying expressions) is necessary (Selvam and Abirami, 2009). Due to the frequent occurrence of these features in our dataset, we integrated particular dictionaries to meet this specific characteristic of Social Media posts. To establish a proper feature resource, we examined our dataset and extracted the most common features. A collection of examples is presented in table 3.

<table>
<tr><th>Features indicating a positive sentiment</th><th>Features indicating a negative sentiment</th></tr>
<tr><td>(y) | :-) | ;-) | =) | :-D | XD | (x | (=| ^^ | *O* | :-* :') | <3 | :-P | :o)
„Yeeha“| „rock&roll“| „Bang!“ | „wow“</td><td>:-(| /: | :' | :'(| :_(| T_T | ;-; | Dx | 'n' | :\ | :/ | >:o D:
„#soEinShice“ | „das macht betroffen“</td></tr>
</table>

Table 3. Examples for features found in our dataset

After completing the steps data extraction, data preprocessing and feature extraction the act of *knowledge extraction* follows. As presented in section 2.2, a variety of algorithms for conducting this task exists. Due to the emphasized characteristics of Social Media posts, as mentioned, dictionary-based approaches represent a generally accepted approach for the automated sentiment analysis of such textual content. Dictionaries represent lexical resources with annotated words (Feldman, 2013). Depending on the sentiment of each word, the annotated value is either positive, neutral or negative. It is expressed by a number within a predefined range (a higher value is more positive) (Feldman, 2013). For example, given a value range of [-2;+2], the word "fantastic" would be annotated with a value close to +2, while the word "horrific" would be annotated with a value close to -2.

A widely accepted implementation of a dictionary-based approach is SentiWordNet 3.0. SentiWordNet 3.0 represents a lexical resource for automated sentiment classification (Baccianella et al., 2010). However, SentiWordNet 3.0 only provides a lexical resource for English. To support German Social Media posts as well, we used SentiWS, a German language resource for analyzing the sentiment of German texts (Remus et al., 2010). As SentiWS did not match the structural requirements of the SenitwordNet 3.0 approach, we adapted SentiWS by converting the structure of the German dictionary to fit the one of SentiWordNet 3.0 (Remus et al., 2010). Both resources contain lists of positive and negative opinion carrying words.

For acknowledging irony and slang the dictionary was extended with expressions pointing to special events (e.g., product launch) of the branches considered. Also we classified the appearing emoticons into positive and negative ones to identify the expressed emotions within the posts. Further, a manual screening of posts on the companies' Facebook sites was performed to extend the dictionary by words capturing slang expressions.

4.3 Presentation and Interpretation of the Results

To measure the accuracy of our approach, we used the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). To calculate these metrics, we had to define the underlying variables. The approach allocates the analyzed posts to three different sentiments (S), namely positive, negative, or neutral. For each sentiment we thus needed to define a differentiation between the two categories for the true and false allocation of the relevant posts. Consequently, we identified six categories which oppose the results of the automated approach to the real world data mentioned earlier (see table 4). Based on these categories, the accuracy of the implemented approach could be measured.

Sentiment (S)	Category	Description
Positive	true positives	posts, which are correctly assigned to the sentiment *positive*
	false positives	posts, which are assigned to the sentiment *positive*, but are not positive in real world data
Negative	true negatives	posts, which are correctly assigned to the sentiment *negative*
	false negatives	posts, which are assigned to the sentiment-category *negative*, but are not negative in real world data
Neutral	true neutrals	posts, which are correctly assigned to the sentiment *neutral*
	False neutrals	posts, which are assigned to the sentiment *neutral*, but are not neutral in real world data

Table 4. Sentiments and related categories

The metric *precision* focuses on the implemented approach. It calculates the amount of correctly assigned posts in relation to all automatically classified posts for a given sentiment S:

$$\text{precision}(S) = \frac{|\text{true }(S)|}{|\text{true }(S)| + |\text{false }(S)|}$$

For example, a high value for *precision* (e.g., close to 1) predicates that a very high number of posts that are assigned to the sentiment S by the algorithm are classified correctly. Contrary, a low value of *precision* (close to 0) indicates that a high number of posts are not classified correctly. When looking at our dataset (see table 5), 48 posts of company A were classified positive by the algorithm, but only 45 of them are truly positive and thus classified correctly. Consequently, the *precision* for the sentiment *positive* for company A is 45/48 = 0.94, resulting in a *precision* of 94 percent.

In comparison, the metric *recall* calculates the amount of correctly assigned posts in relation to all posts classified in the real world data for a given sentiment S.

$$\text{recall}(S) = \frac{|\text{true }(S)|}{\text{all posts classified in the real world data for }(S)}$$

Hence, a high value (close to 1) for *recall* for positive posts indicates that most of the truly positive posts are also classified correctly as being positive. A low value for *recall* indicates that the share of the automatically and correctly classified posts for a sentiment in relation to all posts of this sentiment is low. For example, the *recall* for the sentiment *positive* for company A in our dataset in table 5 is calculated by dividing 45 correctly classified positive posts by all 52 positive posts in the real world (0.87).

Since *precision* and *recall* aim at different objectives, there is a third metric called *f-measure*. It merges *precision* and *recall* to their harmonic mean and gives an overall view of the accuracy of the used approach (Makhoul et al., 1999; Hripcsak and Rothschild, 2005).

$$\text{f} - \text{measure }(S) = \frac{2 * \text{recall }(S) * \text{precision}(S)}{\text{recall}(S) + \text{precision}(S)}$$

In our example, *f-measure* of company A for the sentiment *positive* is 2*0.94*0.87/0.94*0,87 = 0.90.

The following table 5 shows all results of our application of the dictionary-based approach on the extracted dataset provided by the five Facebook pages of the cooperating companies.

The first column ("real # of posts") represents the number of positive, neutral and negative posts, agreed upon by the six independent researchers and verified with the responsible experts from each company. The second column ("classified # of posts") represents the number of automatically classified posts into positive, neutral and negative sentiments. The numbers for true positive, true neutral and true negative posts are written in bold. Consequently, the other numbers in this column represent the false positive, false neutral and false negative numbers of posts. For example, company E has a total of 95 positive posts in the "real world". The dictionary-based approach classified a total of 89 posts as positive, whereas 70 were true positive (classified correctly) and 19 were classified incorrectly (false positive).

		real # of posts			classified # of posts				precision			recall			f-measure		
		+	o	-	+	o	-	∑	+	o	-	+	o	-	+	o	-
company A	+	**52**			**45**	1	2	48	0.94			0.87			0.90		
	o		**64**		6	**61**	2	69		0.88			0.95			0.92	
	-			**9**	1	2	**5**	8			0.63			0.56			0.59
	∑				52	64	9								Ø 0.80		
company B	+	**73**			**58**	37	10	105	0.55			0.79			0.65		
	o		**135**		13	**78**	9	100		0.78			0.58			0.66	
	-			**52**	2	20	**33**	55			0.60			0.63			0.62
	∑				73	135	52								Ø 0.64		
company C	+	**165**			**140**	14	4	158	0.89			0.85			0.87		
	o		**124**		22	**101**	3	126		0.80			0.81			0.81	
	-			**27**	3	9	**20**	32			0.63			0.74			0.68
	∑				165	124	27								Ø 0.79		
company D	+	**17**			**17**	1	1	19	0.89			1.00			0.94		
	o		**12**		0	**10**	0	10		1.00			0.83			0.91	
	-			**5**	0	1	**4**	5			0.80			0.80			0.80
	∑				17	12	5								Ø 0.88		
company E	+	**95**			**70**	9	10	89	0.79			0.74			0.76		
	o		**120**		20	**107**	16	143		0.75			0.89			0.81	
	-			**50**	5	4	**24**	33			0.73			0.48			0.58
	∑				95	120	50								Ø 0.72		
total	+	**402**			**330**	62	27	419	0.79			0,82			0.80		
	o		**455**		61	**357**	30	448		0.80			0.78			0.79	
	-			**143**	11	36	**86**	133			0.65			0.60			0.62
	∑				402	455	143								Ø 0.74		

Table 5. Results of the application

As the results shown in table 5 demonstrate, the implemented dictionary-based approach achieved an aggregated *f-measure* of 74 percent. Although, the particular results for the different companies and sentiments vary significantly. Most of these differences can be explained by the peculiarities of Social Media posts for SMEs as described earlier in section 2.1.

For example, there are consistently high *f-measure* values (avg. 88 percent) for company D, the leading manufacturer and distributor of equipment for daycare centers, kindergartens, and schools. These high values can be explained by the very structured, clear and correct language within the posts of company D (e.g., see table 6 example #1). We see the fact that the target audience are mainly business customers as the underlying reason for this observation.

However, we also identified cases where the application of the automatic approach resulted in indifferent values. Considering company B, an Online Store for children's fashion, baby fashion, toys and children's furniture, the *f-measure* for positive posts is 65 percent and the *f-measure* for neutral posts is 66 percent, both significantly lower compared to all other companies. We analyzed the respective posts and noticed a high level of off-topic discussions that do not relate to the company's products or services (see table 6 example #2). During the initial manual classification, the researchers agreed upon that these off-topic discussions belonged to the *neutral* sentiment. In contrast, the automatic approach processes all posts word by word without knowing the context of the post. Thus, it classified these posts *positive* or *negative*, based on the annotation of the containing words.

Another peculiarity of Social Media posts we observed in the posts of company A is industry-specific language. As company A is a market leader in fun sport equipment in the watersports industry, we noticed industry-specific components (e.g., slang, jargon) to be commonly used in positive posts of our dataset (see table 6 example #3). Based on these observations, we enhanced the existing feature libraries and included several generally known expressions of the fun- and watersports industry. After integrating these industry-specific items, we achieved a recognition rate of about 90 percent for positive posts.

A lot of times Social Media posts demonstrate a network character by addressing more than one person, for example when fans congratulate a company for winning a certain award or when they provide general feedback to certain events, e.g., sweepstakes or giveaways (see table 6 example #4). This could be repeatedly observed in the posts of company C, a manufacturer and distributor of high-quality toys, games & room decor for kids of all ages.

Generally, it is noticeable that positive posts are classified very well. Especially companies whose posts are written in a certain language that is typical to the relevant industry or region (company A / company E) or directly address specific products or services (company C) achieve high values for *f-measure* for positive posts. Additionally, the frequent use of emoticons to express sentiment within Social Media posts contributes to a higher accuracy of the algorithm (see table 6 example #5). We see these two reasons as a main driver resulting in an aggregated *f-measure* value of 80 percent for all positive posts.

However, there is a discrepancy in negative posts. The classification of negative posts resulted in an aggregated *f-measure* of 62 percent for all posts, which is significantly lower than the average *f-measure* value of positive posts. This gap can be explained by two factors. On the one hand, several customer complaints about malfunctions contain company-specific expressions and are written in a neutral way, which makes it impossible for the approach to identify them as negative posts (see table 6 example #6). This results in low *f-measure* values of 59 percent for company A and 58 percent for company B. On the other hand, we identified a number of posts that contain negation and irony, which results in comparatively lower *f-measure* values for negative posts.

#	Example (in German language)	Translation to English / Explanation
1	*Es wäre schön wenn es auch was für die unterstützte Kommunikation nicht sprechender Kinder gäbe, solche Kinder gibt es ja auch in Kindergärten und Krippen.*	It would be nice if you offered products to support the communication of not speaking children, as they also visit kindergartens and nurseries.
2	*Unser 4-jähriger schläft immer bei uns und ich genieße es. Vergeht ja viel zu schnell die zeit.....*	Our four-year-old still sleeps at our place and I´m appreciating it. Time is running too fast…
3	*Schon ausprobiert, 9er bei 32 Knoten: So hoch war ich noch nie!!! Yeehaa*	Already tried it, 9’s at 32 knots: I´ve never jumped so high!!! Yeehaa
4	*Wann erfährt man denn, ob man dabei ist, wenn schon die erste Spielefamilien testen können? Hatte mich am 10. September schon beworben.*	When do I get informed if I´m involved, since the first families are already testing the products? I already applied on September the 10th.
5	*:D*	:D
6	*An wen wende ich mich, wenn mein Van einen Konstruktionsfehler hat bezogen auf die Scheibenwischer.*	Who should I contact if my Van has construction errors concerning its windshield wipers.
7	*gefelt mir*	Spelling error (correct would be “gefällt”)

Table 6. Examples for peculiarities identified

Additionally we identified that spelling mistakes are widely spread in our dataset. Due to the diversity of users within social networks, spelling mistakes reoccur constantly in Social Media content (Agichtein et al., 2008). This fact also lowers accuracy as misspelled expressions cannot be identified by the approach (see table 6 example #7).

In summary, regarding research question 1 (RQ1), the highest value for the *f-measure* received was 88 percent for company D while the lowest value was 64 percent for company B. Correspondingly, dictionary-based approaches provide a high level of accuracy in case the Social Media posts have a structured, clear and correct language. With an increase of off-topic discussions, slang, spelling errors or industry-specific expressions the accuracy decreases which clearly becomes evident in table 5. Considering our second research question (RQ2), we observed a strong variation among the investigated companies' posts. This is justified through several peculiarities of Social Media posts in SMEs: by specialized industry- and product-specific language, by off-topic discussions that do not cover company-specific topics, by industry specific components (e.g., slang, jargon) and company-specific expressions (e.g., surfer jargon in fun- and watersports or dedicated vehicle parts). It also is notable that the correct classification is highly influenced by the usage of emoticons to express sentiment.

5 Discussion

Generally, the sentiment analysis as performed above provides valuable insights into customers' current attitude towards a company. For example, a high number of posts classified as "negative posts" can be seen as an indicator for consumer dissatisfaction requiring a firm to trigger corresponding countermeasures such as product or service campaigns. Further, a high number of positive posts may indicate a generally optimistic mood amongst customers, positively shaping the company image. From that point of view, the sentiment analysis serves as a valuable indicator as to whether a company's efforts to meet customer requirements (e.g., by the current product and service portfolio, etc.) are successful or get out of hand. All participating SMEs of the study agreed that the automatic analysis will lead to a tremendous cutback of human efforts as the assessment of the posts' sentiment was usually done manually by the companies hitherto which is a time-consuming and error-prone task. As shown in table 5, the accuracy of the analysis varies for different companies, but the f-measures generally were above the expectations of the firms participating *(see RQ1)*. In this regard, the data also confirmed the strong use of Social Media channels for the bidirectional communication between SMEs and customers as described in literature (cf. Meske and Stieglitz, 2013) because a large number of company posts (e.g., answer to requests, support for common problems) mixed with posts from the customer side.

Nevertheless, the study also showed that the accuracy of the sentiment analysis at SMEs, using a dictionary-based approach, strongly depends on a proper extraction of features inherent to consumers' Social Media posts as well as a decent adaption of the dictionaries regarding the terminology used by enterprises and their customers *(see RQ 2)*. Accordingly, slang as well as industry- and product-specific expressions need to be adequately considered for instance as shown in section 4.3.

From this point of view, our investigation does not only provide beneficial insights for SMEs using Social Media, but also contributes to the current body of knowledge on sentiment analysis. In our study, we used a dictionary-based approach, which is widely established in literature (e.g., Turney, 2002; Kundi et al., 2014). Many freely available lexical ressources for automatic sentiment analysis exist (e.g., SentiWordNet 3.0). However, these are not customized for certain industries or types of companies in the region of southern Germany. Furthermore, the amount of lexical resources in German language is limited. Thus, for raising the accuracy level of dictionary-based approaches, the lexical ressources need to be translated from English into German and enhanced by the peculiarities of Social Media posts at corresponding companies.To our best knowledge, a systematic uncovering of such characteristics for firms in southern Germany has not been performed yet.

Language-specific peculiarities that could be deducted from research refer to expressions capturing slang at first. These can be used to revise existing dictionaries. Further, we were able to identify expression related to special events (e.g., new product launch) for the branches considered, which is a prerequisite to unveil irony (e.g., Davidov et al., 2010). Thereby, the selection of companies was helpful for finding expressions related to slang and irony, since the customer base of the five different SMEs was rather diversified. Contrary to a very homogeneous customer group, e.g., as given for direct banks, a strong variation in the use of language was observed. This positively affected the extraction of a set of expressions supporting irony and slang identification (e.g., ‘incredible customer service ;)’). Additionally, a large set of branch-specific jargons was identified, with detailed findings for the toy, children fashion and child equipment industry as companies B, C, and D came from that particular field. By enhancing existing dictionaries accordingly, the accuracy of the sentiment analysis could be further improved significantly. The results as presented are the base for the development of a dictionary for SMEs in southern Germay, which we will pursue in future work.

More, six researchers were engaged in assessing the sentiment of the posts in our database to mitigate subjectivity and conduct the assessment. In practice, such a use of human resources is unrealistic, especially for SMEs with a limited number of employees. Thus, an automatic sentiment analysis with adapted dictionaries, leading to precise results, is a great support for SMEs as confirmed by the participating companies.

6 Conclusion and Outlook

In the research at hand we conducted an automatic approach for sentiment analysis using Social Media posts from five SMEs. Therefore, posts from the companies’ Facebook sites were extracted with help of a prototype, preprocessed and then classified using SentiWordNet 3.0 and SentiWS as a combined dictionary. The results show that a considerable level of accuracy was reached. Nevertheless, to receive results that are more precise, an adaption of the dictionaries to the specific terminology of a company and its customers alike is required.

By the sentiment analysis as described, practitioners are given means to determine consumers’ current attitude by an automatic approach. This is highly beneficial for SMEs who usually do not have the resources to monitor their Social Media channels on a regular basis besides the day-to-day business. Based on the insights into customers’ mood, a company may start initiatives to clarify misunderstandings or to restore customer satisfaction for example.

The findings of this study are also beneficial for research as the impact of peculiarities of customers’ Social Media posts at SMEs are investigated more profoundly. There still is a vague understanding of how the characteristics of Social Media posts influence the accuracy of the automatic analyses using dictionary-based approaches. The research at hand addressed this gap by explicitly focusing on SMEs in southern Germany. Thereby, the peculiarities of according posts were uncovered in detail. It became evident, that adapting the dictionary to a firm’s terminology – determined by the product and service portfolio – as well as customers’ language use is mandatory to receive a high-level of accuracy.

There are some limitations to this study: at first, we focused on SMEs from southern Germany which is a restriction in terms of the generalization of the results. Though, the focus on a particular geographic region allows to draw more detailed results for that particular area. Second, the number of SMEs participating in the study is limited to five. Considering additional enterprises might have provided further peculiarities of posts not explicated yet. Third, the manual sentiment analysis which was used to judge the accuracy of the automatic approach underlies subjectivity to a certain degree. We mitigated this by having six researchers perform the analysis and consolidate the results. Posts were further discussed with representatives of the affected companies. However, complete objectivity cannot be assured.

As this research is part of a larger Design Science project, we will further develop the aforementioned prototype to better match the requirements of SMEs in future work. This includes the company-specific adaption of freely-available dictionaries amongst others. Thereby, based on the findings, mechanisms to identify slang and irony more precisely will be pursued reverting to the knowledge gained on industry-specific topics for instance. Further, the creation of algorithms for automatically clustering customer statements, e.g., based on keywords identified within posts, is to be done. Currently, such in-depth insights are usually gained by manually screening data collections of customer statements, using techniques such as the CTQ-Matrix for example (cf. George et al., 2005), which is time-consuming and resource-intense revealing the necessity for automatic clustering approaches.

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2.3 Beitrag 3: "What does the customer want to tell us?" An automated classification approach for Social Media posts at small and medium-sized enterprises

Adressierte Forschungsfrage	**Forschungsfrage 3:** Welche Algorithmen zur automatisierten Sentiment Analyse und Klassifizierung von Social-Media Inhalten gibt es und welche sind für den gegebenen Anwendungsfall geeignet? **Forschungsfrage 5:** Welche Genauigkeit bieten geeignete Ansätze zur automatisierten Sentiment Analyse und Klassifizierung bei der Anwendung auf Social-Media Posts von KMU im süddeutschen Raum?
Zielsetzungen	(1) Identifikation von Algorithmen zur automatisierten Klassifikation zur Analyse von Social-Media Inhalten bei KMU. (2) Implementierung und Evaluierung eines geeigneten Algorithmus zur Klassifikation-Analyse bei KMU.
Forschungsmethode	Design Science nach (*Hevner et al., 2004)* • Literaturanalyse zum Thema automatisierte Klassifikation *(Vom Brocke et al. 2009)* • Design und Development, Anwendung und Evaluation
Kernergebnisse (Überblick)	(1) Identifikation von 9 potentiellen Algorithmen zur Klassifikation von Social-Media Inhalten bei KMU aus der Literatur. (2) Das Zielstellung des Social-Media-Kanals des Unternehmens spielt eine entscheidende Rolle bei der Klassifizierung von Social-Media Beiträgen. (3) Die unternehmensspezifische Anpassung der wichtigsten Kategorien ist entscheidend für ein hohes Maß an Genauigkeit (4) Insgesamt liegt der Mittelwert für die Präzision (53,28%) unter dem Mittelwert für den Recall (80,45%), Genauigkeit 62,75%
Publikationsort	25th European Conference on Information Systems (ECIS), Guimarães, Portugal, 2017
Ranking VHB JQ 3	B
Autor(en) und Anteile	**Schwaiger Josef 35%** Lang Markus 35% Johannsen Florian 20% Leist Susanne 10%

Tabelle 4: Fact Sheet Beitrag 3

"WHAT DOES THE CUSTOMER WANT TO TELL US?" AN AUTOMATED CLASSIFICATION APPROACH FOR SOCIAL MEDIA POSTS AT SMALL AND MEDIUM-SIZED ENTERPRISES

Research paper

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Abstract

Social media posts created by customers capture a lot of business relevant information for decision-makers, e.g., current consumer expectations on products and services. For that purpose, the social media posts need to be analyzed thoroughly. In this respect, a topic-related classification facilitates managerial decision-making because business relevant topics, social media users discuss about, immediately become obvious and the need for action can be derived. For instance, it may get obvious that the majority of a company's negative customer posts refers to a particular product or a specific campaign. However, such a classification of social media posts is particularly challenging for small and medium-sized enterprises (SMEs). This is because human resources for a manual examination of posts are missing and an automatic analysis is error-prone due to particularities of customer posts such as the occurrence of regional dialect or branch-specific expressions. We thus develop a tool, which enables the automatized topic-related classification of social media posts and matches the particular requirements of SMEs in southern Germany. Our solution is evaluated by using a data set stemming from three collaborating companies.

Keywords: Social Media, Classification, Small and Medium-Sized Enterprise.

1 Motivation

The number of active social media users has been steadily increasing over the last couple of years (e.g., Chaffey, 2016). It is estimated that 90% of all American young adults (18-29 years) use social media for private communication purposes while even the number of elderly users (above 65 years) has tripled since 2010 (currently 35%) (Perrin, 2015). Social media user records are equally high for Europe, with 63.2% of Internet users participating in social media networks on an average (eMarketer, 2016). According to current studies, Facebook counts 1.6 billion users worldwide and the microblogging service Twitter has 313 million subscribers for instance (Statista, 2016a; Statista, 2016b). In this regards, the wide dispersion of social media has not only influenced peoples' private communication behaviour but also the way customers interact with enterprises (Hanna et al., 2011). Hence, a lot of consumers are contacting firms via social media these days shifting away from traditional communication channels such as telephone, email or fax (cf. Hanna et al., 2011). Besides large companies, also small and medium-sized enterprises (SMEs) have increasingly begun to use social media, e.g., to improve the bidirectional communication with consumers or to positively impact the company culture amongst others (Meske and Stieglitz, 2013; Lee et al., 2008; Durkin et al., 2013).

In that context, customer posts in social media platforms (e.g., a company's Facebook page) contain a lot of information about current expectations regarding products, services or a company in general (cf. Sigala, 2012a; Sigala, 2012b; Hienerth et al., 2011). The expectations – also entitled as "voice of the customer" in literature (e.g., Lunau et al., 2008) – capture the current assessment of the "value" (cf. Womack and Jones, 1996) consumers ascribe to a firm's offerings (cf. Keil, 2010) and point out *"what's important to customers"* (Pande et al., 2000, p. 190), e.g., an innovative product design. A topic-related classification of corresponding posts facilitates managerial decision-making because business relevant topics, social media users discuss about, immediately become obvious and the need for action can be derived. For instance, it may get clear that the majority of a company's negative customer posts refers to a particular product or a specific campaign. Management may then trigger according initiatives to counteract reasons for consumer dissatisfaction (e.g., product redesign) and increase customer loyalty (e.g., Chua and Banerjee, 2013). Such countermeasures may comprise process improvement projects (cf. Thawesaengskulthai, 2010) or the specification of new products and services (cf. Sigala, 2012a) amongst others. The classification of customer posts thus is a helpful means to systematically structure a disorganized set of posts extracted from social media channels and to prepare the ground for management decisions (cf. Huang et al., 2013).

However, due to lacking resources, the classification of social media posts is challenging for SMEs in case it is performed manually and a large amount of data is to be analyzed (cf. Capgemini, 2015). Employees at SMEs often do not find the time to screen the social media channels besides their daily routines. Although several social media analysis tools are available on the market (e.g., Brandwatch, Radian6, etc.), none of them support a topic-related and company-specific classification of posts (cf. Wozniak, 2016). Further, commercial tools are not affordable for many SMEs due to a restricted IT-budget (cf. Kasper and Kett, 2011; Stavrakantonakis et al., 2012). Some tools are available as "free versions" but these do not include technical support, multilingual analyses for languages others than English or functionalities for data extraction from multiple social media platforms (cf. Stavrakantonakis et al., 2012; Wozniak, 2016). Hence, their applicability in an entrepreneurial context is limited. This holds particularly true for applications at SMEs located in non-English speaking countries. Further, because of the limited regional presence of SMEs (cf. Durkin et al., 2013), customer posts in the corresponding social media channels are usually characterized by regional slang as well as branch-specific product names and expressions amongst others (e.g., Laboreiro et al., 2010; Naaman et al., 2010; Petz et al., 2013). Such peculiarities are not considered by current commercial tools leading to a low accuracy of social media analysis results (e.g., Waltinger, 2010; Wozniak, 2016).

SMEs play a pivotal role considering the German economy. In 2015, there were about 3.62 million SMEs in Germany and, currently, more than 60% of all people in paid work are being employed by this company type (Söllner, 2014; Statista, 2016c). Especially in southern Germany, a large majority of employees is engaged at SMEs (cf. Söllner, 2014; Handelskammertag BW, 2015). In Bavaria this number even amounts to 99.6% of the employees in the private sector (Statistisches Bundesamt, 2015). However, southern Germany is also imprinted by a lot of underdeveloped rural counties (cf. Bavarian Ministry of Agriculture and Forestry, 2006), which makes this region highly interesting for analyzing the impact of information technologies on business performance.

Against this background, the paper's aim is to design, implement and evaluate a social media analysis tool, which considers the peculiarities and specific needs of SMEs. Building on a prior work of ours (cf. Schwaiger et al., 2016), which focuses on the sentiment analysis at SMEs in particular, the main emphasis of this research is on the automatized topic-based classification of customer posts. Hence, the contribution of the paper is as follows: first, we provide a solution – consisting of a classification approach and a corresponding tool – that explicitly takes into account the characteristics of social media posts at SMEs (e.g., regional dialect, slang, etc.), which is a prerequisite to receive high accuracy levels for social media analysis. Existing tools show drawbacks in this respect (cf. Wozniak, 2016) and our research strongly contributes to the field of social media analysis at SMEs paying attention to their particular requirements, which is an under-researched topic yet. Second, our research provides a starting point for the development of generally valid dictionaries enabling social media analyses at SMEs. Hence, we pose the following research question (RQ):

How can an approach for classifying social media posts at SMEs, considering the inherent characteristics of these posts, look like? How can the approach be realized in form of a software tool?

The structure of the paper is as follows: in section 2, foundations on social media and peculiarities of posts at SMEs are presented. Afterwards, the procedure of the research is described. Section 4 deals with the development and evaluation of a social media analysis tool for SMEs. The tool development follows the Design Science (DS) approach (Peffers et al., 2007; von Alan et al., 2004). Subsequently, the benefits of the research are emphasized. The paper is rounded off with a conclusion and an outlook.

2 Foundations

In literature, social media is described 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 (UGC)"* (Kaplan and Haenlein, 2010, p. 61). Examples for internet-based applications entail blogs, social networks (e.g., Facebook or Twitter), enterprise social networks (ESN) (e.g., Yammer), collaborative projects (e.g., Office 365) as well as tools supporting social networking applications (e.g., MS Share_Point) (Turban et al., 2011). In its early stages, social media was used as a solution for individuals, mostly students, to maintain long-distance friendships or relationships. Many social networks like MySpace (2003), Facebook (2004) and Twitter (2006) emerged, providing a simple and direct way to communicate and to inform friends and "followers" about your daily life activities.

Aside from private usage, social media technologies are also increasingly adopted by enterprises integrating them for supporting value-creation. In this regards, not only large enterprises invest into the adaption of social media technologies but also SMEs become more and more engaged (e.g., Meske and Stieglitz, 2013). Especially when it comes to SMEs, the introduction of social media technologies is quite simple as costs are minimal and the required level of IT-expertise is low (Abed et al., 2015). Against this background, companies are becoming more and more engaged in using social technologies like Facebook, Twitter, Instagram or YouTube to strengthen the customer relationship, to support communication with consumers (e.g., Heidemann et al., 2012; Stobbe et al., 2010) and to integrate upcoming social technologies with their business processes and the IT-landscape (cf. Trainor et al., 2014). With the help of social media channels, companies can easily and efficiently handle customer inquiries (e.g., Culnan et al., 2010), share marketing material widely (e.g., Gallaugher and Ransbotham, 2010) or solve customer complaints quickly (e.g., Pinto and Mansfield, 2012). However, with the extended usage of social media channels, the number of posts is also rising quickly and to fully utilize the information captured in social media posts, all data has to be analyzed and interpreted. Particularly at SMEs, which are characterized by limited financial and human resources, an error-prone and a resource-intense manual analysis process is often found.

Besides the general characteristics of social media posts, as described by *Laboreiro et al.* (2010), *Naaman et al.* (2010) or *Zhao and Rosso* (2009), there are some additional peculiarities which are particularly evident at SMEs in southern Germany. Usually SMEs show a limited regional presence, which typically implicates a more direct communication between company employees and their customers (Durkin et al., 2013; Lee et al., 2008). Hence, also corresponding social media posts reflect this tight relation and often address specific products, services or local company-hosted events. By interviewing several social media representatives at SMEs in southern Germany, we were able to retrieve further characteristics. Thus, SMEs tend to be niche players in their industries, which results in a very special language that includes specific expressions as well as product-related and company-related terms. Furthermore, we perceived different aims of using social media among the interviewed SMEs. Some SMEs use social media channels exclusively for marketing campaigns to emphasize new product launches or upcoming events. Additionally, some SMEs strengthen their customer loyalty by offering prize competitions and free product trials. In contrast, others try to involve their users in general discussions and, by doing so, keep their social media channels populated and vivid.

The term "classification" is defined as the assignment of data towards a predefined set of categories (Feldman and Sanger, 2007). Because of the abovementioned various types of social media usage an approach for an automatic classification of social media posts needs to be highly customizable. Social media posts need to be classified in a company-specific way (e.g., product-related or event-related posts) and the object addressed in a post needs to be precisely determined (cf. Maynard et al., 2012).

3 Procedure of the Research

To develop a tool, called "UR SMART (UR Social Media Analysis Research Toolkit)", for the automated classification of social media posts, which is customized for SMEs in southern Germany, we follow the Design Science (DS) approach (Peffers et al., 2007; von Alan et al., 2004). DS has gained high popularity and has become a legitimate IS research method (Alturki et al., 2013; Buckl et al., 2013; Gregor and Hevner, 2013). A widely recognized suggestion on how to conduct DS projects was introduced by *March and Smith* (1995) and *Peffers et al.* (2007). In this respect, DS research represents a synthesis of the activities "build/development" and "justify/evaluate" with the main goal of developing an IT-artifact to address an organizational problem (Cleven et al., 2009; von Alan et al., 2004).

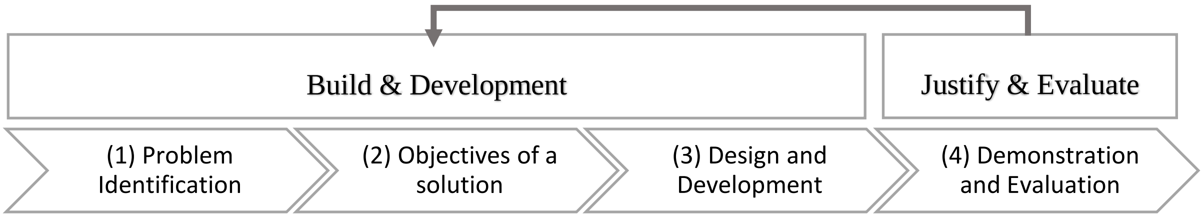

Figure 1. Procedure of the research

As a first step (1), we **identified the problems** in analyzing social media posts at SMEs by choosing three cooperating partners located in southern Germany, which openly declared their commitment to social media and provided us with detailed problem descriptions. Based on that, we derived the need to develop a software solution, which considers the peculiarities and specific needs of SMEs and enables an automatized sentiment analysis and classification of customer posts. Second (2), we **defined the objectives of a solution** by collecting requirements on a corresponding tool via several interviews with business intelligence managers, social media managers, online marketing managers as well as marketing staff of our collaborating partners. In this regards, the technical realization of the sentiment analysis was done in a previous work of ours (cf. Schwaiger et al., 2016), while the focus of this paper is on the realization of the classification functionality to provide a more detailed perspective on customer attitudes. Hence, for the identification of existing approaches aiming at the automatized classification of customer posts, we conducted a literature review. For this purpose, we examined 130 relevant publications leading to 20 approaches that are potentially suitable for the automated classification of textual social media content. The next step was the **design and development (3)** of our IT-solution. In this regards, we conceived and developed a web based tool enabling the sentiment analysis and classification of social media posts in close cooperation with our collaborating partners. For the **demonstration and evaluation** (4) of our artifact, we chose the combined evaluation method "prototype and action research", as suggested by *Peffers et al.* (2007). The evaluation was realized by a real world deployment of the artifact at our collaborating partners. Additionally, we assessed the accuracy of the developed tool in terms of classifying posts by reflecting the results of an automatized classification against the outcomes of a manually performed classification of a specific data set, which was provided by our cooperating partners. To reduce subjectivity, the manual classification was performed by three researchers. To measure the accuracy of our artifact, we applied the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). Conclusively, the results of the evaluation were **communicated and discussed** at workshops and audio conference with representatives of all participating companies.

4 A Tool for the Automatized Classification of Customer Posts

4.1 Selection of collaborating partners

For the development of our tool, we collaborated with three partners as indicated in Table 1. For that purpose, a company search was performed in a prior step. We focused on SMEs across all industries who were openly committed to social media usage, e.g., by presenting a link to social media channels on their website or by suggesting visitors to become followers on Twitter or fans on Facebook. In this context, online databases with addresses of German companies and the internet were drawn upon to delimit our search to those companies located in the region of southern Germany. The social media presence of potential candidates was closely investigated to see whether the content was updated on a regular base (e.g., product launch) or not. For our study, only SMEs that were actively engaged in social media use and continuously shared new content were further considered. More, the number of followers on Twitter and Facebook was used for judging the online visibility of a firm. Three firms finally decided to join our study and the conjoint development of a social media analysis tool. By the tool, the SMEs expected to get more profound insights into customers' attitudes by the analyses of posts.

Company	Industry/Description	# of employees (approx.)	# of Facebook fans (approx.)
Company A	Market leader in fun sport equipment for watersports	80	89000
Company B	Online Store for children's fashion, baby fashion, toys and children's furniture	400	85000
Company C	Manufacturer and distributor of high-quality toys, games & room decor for kids of all ages	1200	38000

Table 1. Collaborating partners

4.2 Collection of requirements

To identify existing problems within social media analysis, we conducted several interviews with our collaborating partners. Thereby we identified their requirements on a tool supporting the analysis of social media posts, which guided its development. To get an overall view, we interviewed business intelligence managers, social media managers, online marketing managers as well as marketing staff. That way, specific expectations from various representatives of SMEs in southern Germany were uncovered supplementing commonly established requirements from literature (cf. Maynard et al., 2012).

The interview partners reported that users of their social media channels used a very specific language imprinted by slang and branch-related expressions due to the niche position of the companies in the market. Some companies exclusively used social media as a communication path to reach customers ("megaphone perspective", e.g., to pronounce campaigns and product launches) whereas others actively invited customers to engage in a bidirectional dialogue ("magnet perspective", e.g., to solve complaints, identify their personal preferences or answer service requests) (cf. Gallaugher and Ransbotham, 2010). In this respect, the monitoring of customer-to-customer dialogues and the automatized classification of posts was strived for, to unveil business relevant topics of great interest to customers (e.g., design of products) and to react quickly ("monitor perspective") (cf. Gallaugher and Ransbotham, 2010). Nevertheless, the analyses supported by available commercial tools tend to be more rudimentary in nature, e.g., number of followers reached by a post, and the required level of detail to trigger improvement or redesign initiatives is not reached by these (cf. Wozniak, 2016). In addition, more nuanced and localized analyses to adequately consider local "slang" or topics of "regional interest" are required to meet the particular needs of SMEs in southern Germany, which however are not supported by the standard functionalities of common tools yet (cf. Wozniak, 2016).

General requirements on the tool to be developed were the ability to extract data from Twitter and Facebook *(requirement 1)* and the automatized sentiment analysis of each customer post *(requirement 2)* at first. As the partners operated on an international level, the tool was supposed to support the analysis of English and German posts *(requirement 3)*. Particular negative or positive posts were to be highlighted by the tool separately *(requirement 4)*, while the user should be able to disable additional functionalities (e.g., spell-checker) upon request *(requirement 5)*. For example, – regarding *requirement 4* – one interview partner (company C) stated *"it would be important to recognize negative developments by help of the posts immediately"*. The ability to filter customer posts (e.g., by creation time) *(requirement 6)*, to modify automatically generated reports *(requirement 7)* and the implementation of a user administration *(requirement 8)* were demanded by our partners as well. More, a key requirement on the tool was the option to automatically classify customer posts *(requirement 9)* and to define new categories on demand *(requirement 10)*. All these requirements were rated as equivalent in importance.

Considering *requirement 10*, the general categories as shown in Table 2 were principally considered to be promising for classifying customer posts and were worked out in a first conjoint workshop with all practice partners participating. Hence, posts should be allocated to the most appropriate category:

No.	Category	Description
1	Product	Praise or complaints about the company's products
2	Service	Remarks about the service portfolio
3	Processes	Posts concerning processes, e.g., the handling of orders or claims
4	Suppliers	Information about the delivery (delayed shipment…)
5	Competitors	Information about goods and services from competitors
6	Retailers	Information about retailers
7	Campaigns	Feedback about campaigns, e.g., raffles
8	Brand	Verdicts about the company
9	Experience / event	Posts about experiences at events
10	User generated content (UGC) / emotional post	Videos, pictures or other content created by users
11	Contests	Posts sharing emotions about contests
12	Topics related to provincial specifications	Posts capturing experiences about provincial specifications

Table 2. Proposed categories

However, to quickly receive a first version of the tool for the collaborating partners, the participants prioritized these categories and only those with the highest priority were supposed to be implemented in a first shot. For that purpose, the partners selected those categories in a follow-up workshop, which best matched with their major aims for using the social media channels. For instance, companies applying social media to support "product advertisement" considered the categories "campaigns" and "experience/event" as most important. The suitability of the chosen categories was validated by reflecting them against a sample set of representative posts gained from the social media channels of each collaboration partner in addition. The categories to be realized in the first version of the tool thus were: "product", "service", "campaigns", "processes", "experience/event" and "UGC/emotional post".

4.3 Approaches for classifying social media posts

To identify objectives of a solution, we conducted a literature review on social media analysis. The automated analysis of textual data is a widely distributed research field. In general, the computer-assisted analysis of text documents to identify specific patterns within large collections of data is described as *text-mining* (Feldman and Sanger, 2007; Heyer et al., 2006). A main field of text mining is defined as Machine-Learning (ML). ML characterizes a set of approaches and algorithms to identify the earlier mentioned specific patterns to predict future data (Murphy, 2012). When it comes to the automated grouping of large data sets, different research areas can be found in literature. To identify suitable approaches for the automatized classification of customer posts, a literature search on the databases ACM Digital Library, EBSCOhost, Emerald Insight, IEEE Xplore Digital Library, ScienceDirect and SpringerLink was performed (cf. vom Brocke et al. 2009). For this purpose, we examined 130 relevant publications leading to 20 identified approaches potentially suitable for the automatic clustering or classification of textual social media content. On the one side, there are unsupervised approaches which focus on the assembly process of data to achieve automatically defined homogenous groups by identifying statistical structures and patterns (Dayan, 1999). The best-known techniques in the field of unsupervised ML are *clustering* and *topic modeling*, which both aim at different objectives (Aggarwal and Zhai, 2012b). *Topic modeling* approaches like “probabilistic latent analysis” (pLSA) (Hofmann, 1999) or “latent dirichlet allocation” (LDA) (Blei et al., 2003) try to identify specific topics within huge sets of textual data by reducing the dimensionality and attaching different weights to the specific data set (Crain et al., 2012). *Clustering* approaches like k-means (MacQueen, 1967), expectation maximization (Dempster et al., 1977) or agglomerative hierarchical clustering (Tan et al., 2005) renounce a reduction of dimensionality and try to group matching elements of the dataset on base of their structure (Feldman and Sanger, 2007; Heyer et al., 2006). In contrast to unsupervised approaches, which focus on the assembly of data to come to automatically defined, unlabeled and homogenous groups, there are also supervised ML techniques that provide the automated mapping of data. These techniques are summarized by the term *classification* and use labeled training data to determine the affiliation towards previously defined categories (Feldman and Sanger, 2007; Heyer et al., 2006). Considering the aim of this research, namely the development of a solution for the automated classification of posts, which focuses on the assembly of data towards predefined classes (Feldman and Sanger, 2007; Heyer et al., 2006), 11 of the earlier mentioned 20 approaches were not further considered because they only support an unsupervised clustering. So consequently, we ended up with a total of 9 potentially suitable approaches. Typical approaches in the research field of *classification* are k-nearest-neighbor (Cover and Hart, 1967), naïve bayes (NB) respectively multinomial naïve bayes (MNB) (McCallum and Nigam, 1998; Tuarob et al., 2014) or support vector machines (SVM) (Gunn, 1998). Especially when it comes to textual data, SVM and NB/MNB deliver convincing results (Jin et al., 2013). Hence, we focused our research on 4 remaining approaches in this field. NB assumes that every categorizing attribute is equally consequential and independent from one another (Feldman and Sanger, 2007). A special variant of NB, which implements the NB Algorithm for multinomial spread data, is MNB. It is often used when it comes to textual data like social media posts and delivers better outcomes than NB, particularly for large data sets with specialized event models (McCallum and Nigam, 1998; Tuarob et al., 2014; Kibriya et al., 2004). As the simultaneous analysis of English and German posts is one of the requirements of our cooperating partners, we choose a multilingual supervised classification approach (e.g. Giannakopoulos et al., 2012) to be most suitable for our research.

4.4 Design and development of a supervised classification approach

As mentioned, we focus on the automated classification of social media posts for SMEs in southern Germany in this research, to provide more substantial insights into posts that were already classified by help of a sentiment analysis (positive, negative, neutral, etc.). In this respect, the ability to adapt the classification algorithm to fast changing contexts (e.g., upcoming product trends) is crucial (Read et al., 2012). Especially in terms of sectoral characteristics, several statements can have a meaning which is different to the “common sense”. An example for such sectoral characteristics are first names (female or male) occurring in social media posts. Considering company “A”, posts including first names like “Clara” unambiguously address human beings, while for companies “B” and “C” such posts may also refer to “dolls” that are retailed by them. In addition, the structure of the investigated posts is decisive. Two aspects need to be considered: at first, social media posts are usually written in a short, succinct way (Zhao and Rosson, 2009). Many social media posts are thus created without a circumscription of the expressed statement. For instance, a typical product review is usually articulated as a combination of the reviewed product and the experiences or feelings associated with it. An exchange of a single entity (e.g., name of the product) may lead to a completely different classification. Consequently, the meaning of every single entity (e.g., word) of the post is relevant for a correct classification. Second, social media posts typically do not follow grammatical rules (e.g., Laboreiro et al., 2010). As a consequence, approaches presupposing correct grammatical structures are not applicable at hand. While these content-related issues are important in terms of the classification, also a company’s purpose of using social media needs to be considered. Due to dissimilar target groups (e.g., customers or fans), the appearance of company-specific or branch-specific issues in social media posts may differ massively. In this regards, company “A” mainly aims at relating its products with joyful emotions by publishing many posts including photos or event reports. In contrast, company “B” intends to maintain a sense of “togetherness” by fostering discussions about topics of interest for their target group.

Considering this, we chose an approach, which combines MNB with a dictionary-based seed word library. Posts are analyzed regarding these seed words (e.g., Carroll, 2008), which allows to assign them to predefined classes. Furthermore, as an additional advantage, the dictionary-based approach enables to customize the classification of posts considering the specific needs of our cooperating partners by enhancing the seed word dictionary by company-specific expressions (cf. Liu, 2012).

Our classification approach is based on the general method of text analysis by *Aggarwal and Zhai* (2012a). Subsequently to the pre-processing step, which uses several techniques like tokenization, stop word reduction as well as normalization to eliminate irrelevant parts, the data is categorized by help of a dictionary. The dictionary contains the most frequently used and relevant seed words (up to 4000 pre-trained words) to enable the assignment of a post to the specific categories of our cooperating partners (see section 4.2). To trigger the classification of a post its core entities (so called tokens) are drawn upon. At first, these tokens will be processed by a stemming algorithm, which transforms the entities to a normative shape, e.g., by cutting designated word endings (Porter, 2001). Afterwards, matching word candidates from the post are being identified and reflected against the seed words from the dictionary. If an entity matches with a seed word from the dictionary, the post will be assigned to the designated category. This task is iterated until all matching word candidates are identified. For example, the post *“wow! Eine Kullerbühkugelbahn*[1]*!! ”* (company “C”) is reduced to *“wow! ~~Eine~~* ***k****ullerb****ue****hkugelbahn”*. During pre-processing, the language “German” is detected by identifying typical German language features, e.g., umlauts. Afterwards, all letters are transformed to lower case. Subsequently, all umlauts are exchanged. Finally, appropriate word candidates for the entities *“wow” (UGC/emotional post)* and *“kullerbuehkugelbahn” (product)* are searched for. As a result, the post is classified according to the categories “UGC/emotional post” but also “product”.

A classification of posts, according to the process as described, highlights those topics customers are vividly discussing about in the social media channels. In combination with a sentiment analysis of the posts their tonality gets evident as well. Hence, conclusions can be drawn whether customers have a positive attitude towards particular issues (products, campaigns, services, etc.) or not. This prepares the ground for management decisions (e.g., product redesign initiatives). While the main focus of this paper is on the classification of posts – after a sentiment analysis was already performed – the sentiment analysis functionality of our tool was realized and validated in a previous work (cf. Schwaiger et al., 2016).

4.5 Demonstration and evaluation

In the following, the realization of the major requirements on our tool “UR SMART”, as introduced in section 4.2, is briefly described. Considering *requirements 1 and 2* the ability to extract data from Twitter and Facebook as well as the sentiment analysis of customer posts, were implemented (see Figure 2). The ability to analyze German as well as English posts was realized by including a language detection functionality as part of the pre-processing phase *(requirement 3)*. During sentiment analysis, the tonality of posts is determined by the detection and reconciliation of specific words with annotated features (seed words, smileys, etc.). Particular negative or positive posts are highlighted separately *(requirement 4)*. Additional functionalities (e.g., spell-checker) can be enabled or disabled upon request *(requirement 5 – lower check box in the right graphic of Figure 2)*. A filtering function for customer posts *(requirement 6)* by features like category, message, score (sentiment analysis) or timestamp is implemented as well. To manage user access a user administration *(requirement 8)* was realized. The ability to automatically classify customer posts *(requirement 9)* is described in this paper in detail. Figure 3 shows an exemplary

[1] The expression refers to the wooden marble run “Kullerbüh“, which is offered by company “C”.

classification of posts for company “C” (within an observation period of three months). It gets obvious, that the topic-related classification of posts further details the results of the sentiment analysis. For instance, it gets obvious that 263 negative customer posts refer to the category “product”, whereas also 547 positive posts exist in this respect. (see Figure 3)

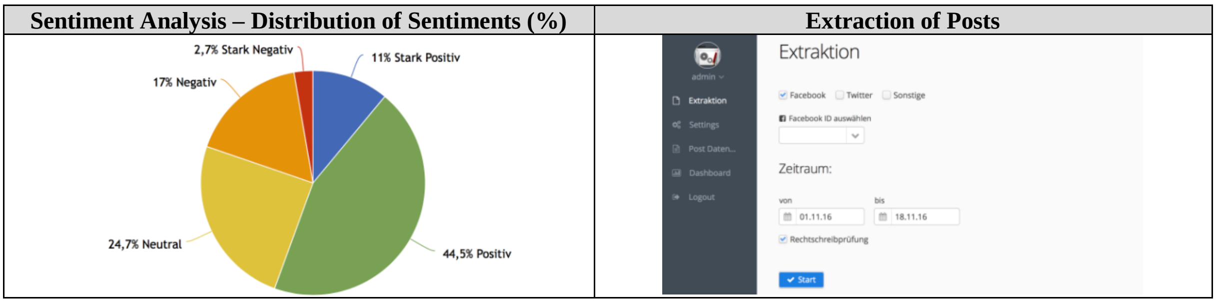

Figure 2. Sentiment analysis and extraction of posts

Because of that, the classification of posts specifies the results gained via the sentiment analysis in more detail. While the sentiment analysis only indicates whether posts have a “positive”, “negative” or “neutral” tonality, the classification allows to uncover those topics, the customers are actually discussing in a positive, neutral or negative way. In Figure 3, the sentiment analysis of our tool distinguishes between “strong positive”, “positive”, “neutral”, “negative” and “strong negative” posts.

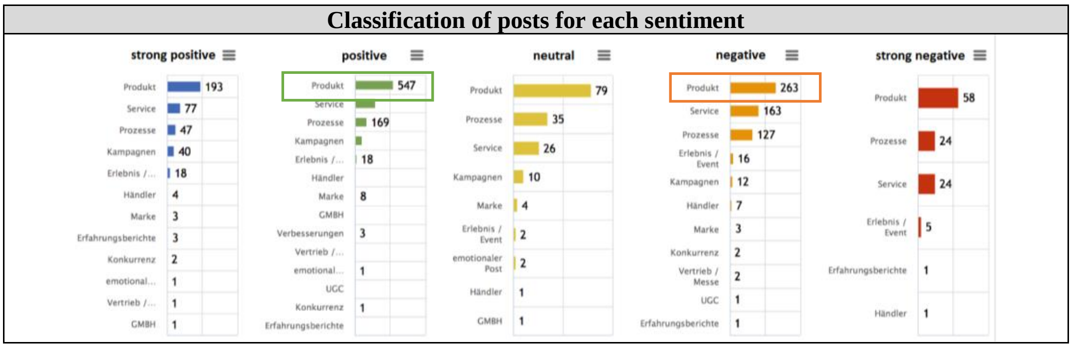

Figure 3. Classification of posts

UR SMART was implemented as a client-server solution. CPU-intensive and time/power consuming operations, which are necessary for realizing the classification of posts, are thus processed by the server (java-based) and can be visualized by web-enabled devices. A major field of application for UR SMART is to identify and visualize trends or to detect weaknesses regarding particular categories (e.g., “product”, “service”, etc.) based on feedback captured in social media posts. The importance of each category for a company was ranked based on a joint decision achieved in workshops with the cooperating partners (see section 4.2).

To evaluate the quality of the classification, a set of approx. 2000 posts from the Facebook sites of our partners was provided considering a time frame of three months. The extracted posts were screened and manually classified by three researchers to come to a manual classification of the posts. The results of the manual classification served as a base for evaluating the accuracy of the automatic classification later on. Posts that were not German or English were not further considered. Accordingly, a data set of 1200 posts was drawn upon for the manual classification. The classification of a post was seen as unambiguous, in case two of three researchers assigned the post to the same category independently from one another at least. This process resulted in a set of 612 posts that were unambiguously classified in a manual way and were drawn upon to evaluate the automatic classification as generated by UR SMART. During evaluation, several challenges came up. A major challenge concerned the appropriate delineation of categories. As an example, the post *“I have a Kite Rebel 2015 12 M. Have to change the hoses. Can’t find spare parts in Brazil. I am waiting for your help. Thanks!”* (company “A”) can be assigned to the categories "product" or "service". At first glance, this post is a clear candidate to be classified as a *"*service*"* post. However, at a second glance, the post is relevant for the category "product" as well. Besides the information about the lack of Brazilian dealers offering spare parts ("service"), the post also captures information that "hoses" are a vulnerable product component *"Rebel 2015 12M"* ("product"). This provides valuable hints to raise customer satisfaction. First, there is the necessity to improve the availability of repair parts in Brazil and second to optimize the quality of the product component "hoses". If the post would be assigned to one category only, crucial information about either the product quality or the service infrastructure would get lost. Thus, an assignment to both categories was done.

To measure the accuracy of our approach, we used the commonly accepted metrics *precision, recall* and *f-measure* (Christen, 2012). To calculate these metrics, the underlying variables are to be defined.

Category (C)	Group	Description
main	true appendant	posts, which are correctly assigned to a category
	false appendant	posts, which are assigned to a category, but are not appendant in real world data

Table 3. Categories and related groups

The metric *precision* focuses on the implemented approach. It calculates the amount of correctly assigned posts in relation to all automatically classified posts for a given category C (see Table 3):

$$\text{precision}(\text{C}) = \frac{|\text{true (C)}|}{|\text{true (C)}| + |\text{false (C)}|}$$

When looking at the category "product" of our cooperating partner company "C" (see Table 4), 90 posts were assigned to the category by the algorithm, but only 67 of them are truly product-related and thus classified correctly. Consequently, the *precision* for the category "product" for company "C" is 67/90 = 0.74 (74%). In comparison, the metric *recall* measures the amount of correctly assigned posts in relation to all posts classified in the real world data for a given category C.

$$\text{recall}(\text{C}) = \frac{|\text{true (C)}|}{\text{all posts classified in the real world data for (C)}}$$

For example, the *recall* for the category "experience/event" for company "A" in our dataset in Table 4 is achieved by dividing 18 classified posts, which matched with the manual classification, by all 21 posts that were unambiguously classified by the researchers by hand (85.71%). To sum up, a high value for *precision* (e.g., close to 1) predicates that a very high number of posts that are assigned to the category C by the algorithm are classified correctly. In contrast, a high value (close to 1) for *recall* for posts of a specific category indicates that most of the truly assigned posts are also classified correctly. Hence, a low value for *recall* indicates that the share of the automatically and correctly classified posts for a category in relation to all posts of this category is low. *Precision* and *recall* aim at different objectives. Therefore, we use a third metric called *f-measure. F-measure* merges *precision* and *recall* to their harmonic mean and gives an overall view of the accuracy of the used approach (Makhoul et al., 1999; Hripcsak and Rothschild, 2005). For example, the *f-measure* for company "B" for the category "processes" is 2*0.89*0.56/0.89+0.56 = 0.69.

$$\text{f} - \text{measure (C)} = \frac{2 * \text{recall (C)} * \text{precision(C)}}{\text{recall(C)} + \text{precision(C)}}$$

Once these metrics are applied to social media posts of our data set, large variations among the different companies can be observed (see Table 4). While the majority of posts regarding company "A" refers to products (103 posts) and experience/events (21 posts), only a minority of posts concerns services (7 posts), processes (2 posts) (delivery, orders, claims) or campaigns (1 post). This can be explained by considering the strategic orientation of company "A", which only operates in a B2B environment. Hence, the bidirectional communication (including campaigns) with end-customers is not desired and should be handled by the resellers instead. The aim of the Facebook presence of company "A" is to merchandise the products and connect them to positive emotions. Thus, product-related and experience-specific/event-specific posts were judged to be relevant. Product-specific posts are classified in an accurate way (recall: 88.35%; precision: 53.22%; f-measure: 66.42%). The high recall value states that a majority of relevant posts was identified. The precision of 53.22% can be explained by fast changing trends within the market segment company "A" operates in. This becomes evident by continuously changing product labels amongst others. To enable the derivation of action recommendations by decision-makers, it was necessary to tolerate an extra classification of extraneous posts. An akin result could be observed for experience-specific/event-specific posts (recall: 85.71%; precision: 58.06%; f-measure: 69.23%). The high value for recall (85.71%) testifies that a majority of relevant posts was correctly detected. The precision value of 58.06% is justified by considering that company "A" operates in a market (fun sports), which is characterized by fast changing trends complicating the definition of seed words. Further, the corresponding posts are imprinted by slang expressions while also photos or videos are posted on the Facebook page of company "A". In contrast, the classification of posts concerning "service" is more inaccurate (recall: 42.86%; precision: 30.00%; f-measure: 35.29%). Posts regarding "processes" and "campaigns" were not considered because of their rare occurrence.

		Manual reference	Algorithm true	Algorithm false	Precision	Recall	F-Measure
company A	product	103	91	80	53.22	88.35	66.42
	service	7	3	7	30.00	42.86	35.29
	experience/event	21	18	13	58.06	85.71	69.23
	processes	2	2	1	66.67	100.00	80.00
	campaigns	1	1	1	50.00	100.00	66.67
company B	product	87	76	151	33.48	87.36	48.41
	service	75	63	100	38.65	84.00	52.94
	UGC/emotional	74	62	60	50.82	83.78	63.27
	processes	61	54	43	55.67	88.52	68.35
	campaigns	40	24	9	72.73	60.00	65.75
company C	product	79	67	23	74.44	84.81	79.29
	service	19	17	17	50.00	89.47	64.15
	UGC/emotional	32	21	27	43.75	65.63	52.50
	processes	4	3	2	60.00	75.00	66.67
	campaigns	7	6	4	60.00	85.71	70.59
total	product	269	234	254	47.95	86.99	61.82
	service	101	83	124	40.10	82.18	53.90
	processes	67	59	46	56.19	88.06	68.60
	campaigns	48	31	14	68.89	64.58	66.67
				Mean values	***53.28***	***80.45***	***62.75***

Legend: the colored lines hint at the categories that were most important for the companies

Table 4. Results of the automatic categorization

The direct distributing company "B" put great emphasis on the bidirectional communication with customers. To increase the level of customer satisfaction, all posts dealing with product orders were to be monitored by the company in particular. To strengthen brand loyalty, company "B" started several campaigns like raffles or surveys. To create a feeling of "togetherness" and to associate the products with positive emotions, company "B" created posts regarding emotional topics (e.g., "merry to Christmas time"). Accordingly, the categories "processes" (61 posts), "campaigns" (40 posts) and "UGC/emotional" (74 posts) were selected to be the most relevant ones. The results of the automatic classification for processes bring about a recall value of 88.52% and a precision value of 55.67% (f-measure: 68.35%). The precision value of 55.67% can be explained by the challenging delineation of the category "processes" to other categories such as "service" or "product" via suitable seed words. "UGC/emotional" posts are categorized with a recall of 83.78% and a precision of 50.82% (f-measure: 63.27%). As "UGC/emotional" content is very difficult to identify, the moderate precision is to be judged in light of the subjective interpretation by humans in this respect. Campaigns are categorized with a recall of 60.00% and a precision of 72.73% (f-measure: 65.75%). The lower recall is justified by the usual lack of context information. A majority of posts regarding "campaigns" is written by directly referencing the context, however, without naming the context like "took part". The high precision of 72.73% states that the automatic approach had a well-adjusted set of training data to identify the most relevant posts regarding campaigns. Company "C" (just as company "A") operates as a B2B distributor. The intention of the social media presence of company "C" is to advertise its products and to strengthen brand loyalty. For that purpose, the bidirectional communication with consumers is crucial. Most posts are product-related (79 posts) and correctly interpreted by the implemented algorithm at large (precision: 74.44%; recall: 84.81%; f-measure: 79.29%). The high number of service posts (19 posts) for a B2B company is striking. In this respect, the slightly lower precision value is owed to the complex delineation of the categories "service", "products" and "processes" for company "C".

Overall, the mean value for *precision* (53.28%) is much lower than the mean value for *recall* (80.45%). The reasons for that are the following: at first, the loss of valuable information by narrowing the range of possible seed word candidates for particular categories was to be avoided. Second, the subjective human interpretation is frequently imprinted by the given context, and thus, relevant information is blinded out. To enhance the precision of the classification, a further refinement of the general categories by the help of subcategories is advisable. For that purpose, we gathered partner-specific lists of the product and service portfolio, which served as a starting point to delineate subcategories regarding the general categories "product" and "service".

Afterwards, the subcategories as defined for "product" and "service" were validated by reflecting them against our abovementioned sample set. In so doing, subcategories could either be merged or further ones could be established. The results were discussed with the partners once again and modifications made until a consensus was reached. Table 5 shows an excerpt of the subcategories for the general category "product" for companies "A", "B" and "C". However, the precise implementation of our approach to enable a classification according to these subcategories is a topic we are currently working on.

Product	Company A	Company B	Company C
Subcategories	board, kite, bar, binding, apparel	games, books, children's room, outdoor, toys, baby care, bags	wood toys, wooden furniture, puppets, dolls

Table 5. Exemplary overview of subcategories for the general category "product"

5 Discussion & Benefits

The dictionary-based approach used for classifying the posts is generally valid, however, the company-specific adaption of the dictionary is crucial for receiving a high level of accuracy in terms of the classification. Further, the delineation of the categories using seed words is challenging and may cause ambiguity during the application. For instance, a post created by a customer who complains about problems during product return, may contain seed words such as "terms of service" and thus address an unsatisfactory customer service (category "service") but also hint at problems of the "product return process" in general (category "processes") by including seed words such as "return process". Nevertheless, even in case of assigning posts to more than just one category, the topics captured by these get evident, while irrelevant categories remain unaffected. As becomes obvious, the classification is especially valuable in combination with the sentiment analysis. That way, negative and positive attitudes towards business relevant topics, such as products or campaigns, are revealed. However, the classification of social media posts and the definition of seed words is far more complex than the sentiment analysis, which may be achieved by the use of freely-available dictionaries, e.g., "SentiwordNet 3.0" (cf. Baccianella et al., 2010), and only analyzes posts in terms of their general tonality.

More, the tool was developed considering the requirements of three partners exclusively, which surely is a restriction considering the generalizability of the solution. However, as a first step to provide means to support SMEs in southern Germany to automatically classify posts, a number of three partners kept the development process manageable as the customer posts had particularities (e.g., regional dialect) that needed to be carefully analyzed and considered for the specification of the dictionary. In general, UR SMART may be applied at other firms without customization as well. Admittedly the lack of adjustment will come at the expense of decreased accuracy levels. However, UR SMART is also adaptable to other company settings. That adaption includes an adjustment of the dictionaries as well as the detection of more company-specific features for instance. With the rising number of adjustments to specific company settings, the generalizability of UR SMART stepwise increases. UR SMART is currently eagerly used to analyze the social media posts of our collaborating partners and several benefits emerge for these companies. Hence, the software is directly integrated in the daily workflows of our partners and supports managerial decision-making for SMEs based on social media data at first. An important intended use of UR SMART thus is to detect weaknesses in current business operations and processes. Principally, the selection of improvement initiatives is a challenging task for many firms (e.g. Thawesaengskulthai and Tannock, 2008) and social media posts provide a valuable reference for decision-makers in this respect. Based on social media posts, critical processes can be identified and business process improvement projects triggered to avoid monetary and also reputational damage (cf. Pande et al., 2000; Snee and Hoerl, 2003). Generally, literature provides further examples on how social media analyses may influence decision-making, e.g., for deriving new service ideas or improving the existing service portfolio (cf. Sigala, 2012a; Sigala, 2012b).

More, the management is made aware of particular critical issues (e.g., problems with product quality), since UR SMART takes into account every single entity of a post during the analysis. This enables to filter exceptionally negative customer posts and to analyze them more closely for example. Subsequently, UR SMART delivers systematic guidance to overcome process weaknesses. Measuring and monitoring the effectiveness of actions taken to optimize process performance is a crucial task. UR SMART allows to analyze social media posts in terms of different timeframes. Based on this functionality, the management of the cooperating companies can determine whether the impact of redesigning a process (e.g., training of employees to increase service satisfaction) is reflected by customer posts in the corresponding social media channels. As an incidence, a decrease of negative posts about the customer service would be an indicator for the success of process improvement initiatives in this respect. Another important factor concerns customers' reaction. Many of our cooperating partners use their social media channels for social media marketing or advertising campaigns. As UR SMART enables a time-dependent analysis, customers' reactions to social media marketing or advertising campaigns become evident (e.g., Castronovo and Huang, 2012). Hence, campaigns favorably received by consumers (e.g., prize competitions or special offers) often entail discussions in the social media channels. With the information and topics captured in these posts, SMEs may purposefully design and plan future campaigns.

As a scientific contribution of our research, we show the applicability of an approach for the automated classification of textual social media content at SMEs from southern Germany. The automated analysis of social media posts is an emerging research field but when it comes to a practical application in a real world scenario we identified various challenges. Especially at niche representatives, like our cooperating partners, the company-specific adaption of the approach is crucial for receiving a high level of accuracy. With UR SMART, we provide a tool that is not only suitable to analyze German and English social media posts but also to specify the analysis towards regional dialect, slang as well as branch-specific language. Our tool supports the sentiment analysis and the classification of posts and allows to get deep insights into customers' current attitudes, needs and expectations.

6 Conclusion

In this research, we described the development of a tool supporting the classification of social media posts. Particular attention was paid to the specific needs of SMEs in southern Germany. For that purpose, we collaborated with three partners from industry by using a dictionary-based approach. The classification of posts provides the SMEs with profound insights into customers' attitudes and thus helps to derive measures for strengthening the customer relationship. As a limitation, the focus on three collaborating partners surely hampers the generalizability of the solution. Nevertheless, a thorough adaption of a dictionary-based classification approach requires to concentrate on few selected partners to receive a high level of accuracy of the classification. Further, the delineation of categories, based on seed words, is challenging as described above and thus a refinement of the dictionary is strived for.

In future, we aim at the creation of a generally valid dictionary applicable for classifying social media posts at SMEs in southern Germany. More, the development of a semi-supervised approach that automatically detects new seed words on base of social media data is a topic for further research as well. Additionally, we plan to automatically derive suggestions for process or product redesign initiatives based on the social media analyses results.

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2.4 Beitrag 4: A hybrid approach combining various Social Media analysis methods

Adressierte Forschungsfrage	**Forschungsfrage 4:** Wie kann eine Kombination aus verschiedenen Social-Media Analyseformen (Sentiment Analyse, Klassifizierung, Clustering und quantitative Analyse) umgesetzt werden und welche Vorteile bietet die Kombination qualitativer Analyseverfahren mit quantitativen Social-Media Daten?
Zielsetzungen	(1) Konzeption und Entwicklung eines hybriden Ansatzes, der verschiedene Analysemethoden von Social-Media Daten (z. B. Stimmungsanalyse, Klassifizierung, Clustering, Social-Media-Insights usw.) kombiniert. (2) Demonstration und Evaluation des entwickelten hybriden Ansatzes auf Basis von Social-Media Inhalten von zwei kooperierenden KMU.
Forschungsmethode	Design Science nach (*Peffers et al., 2007 & March and Smith, 1995)* • Synthese der Aktivitäten „Build / Development“ und „Justify / Evaluate mit dem Ziel, ein Organisationsproblem durch die Entwicklung eines IT-Artefaktes zu lösen.
Kernergebnisse (Überblick)	(1) Hybrider Ansatz welcher die Kombination von Sentiment Analyse, Klassifizierung, Clustering, Social-Media-Insights usw. erlaubt. (2) Vier hybride Analysemethoden: *Sentiment of reactions, Ranking of reactions within a sentiment, Distribution of categories vs. Distribution of reactions, Fan growth per category*. (3) Demonstration und Evaluation des hybriden Ansatzes anhand von Kooperationsunternehmen zur Verfügung gestellter Social-Media Daten.
Publikationsort	Electronic Markets (EM) Journal, (Under Review)
Ranking VHB JQ 3	B
Autor(en) und Anteile	**Schwaiger Josef 100%**

Tabelle 5: Fact Sheet Beitrag 4

A HYBRID APPROACH COMBINING VARIOUS SOCIAL MEDIA ANALYSIS METHODS

Electronic Markets – The International Journal on Networked Business

Abstract:

Social-Media as well as the users within the Social-Media channels are characterized by a steady change and therefore the continuous measurement of Social-Media data is necessary. With the extended use of Social-Media, the amount of data that need to be analyzed and interpreted to monitor Social-Media channels rises quickly. Thus, in recent years, many tools have been dealing with the automated analysis of structured or unstructured Social-Media data, using various approaches to determine insights into the underlying posts and comments. However, existing Social-Media analysis tools often focus on one general approach, prioritizing either the analysis of the posts' semantics or metadata (e.g., sum of likes or shares) as well as connections between them. In this paper, we developed and implemented an approach that supports the hybrid analysis of Social-Media data by combining various Social-Media data analysis methods. The hybrid analysis approach allows to gain even deeper insights into the users' needs and opinions and therefore prepares the ground for the further interpretation of the voice of the customers.

1 Introduction

In recent years, Social-Media have become a key component of today's social life around the globe (Dickey and Lewis, 2010). According to (Chaffey, 2016), the number of people using Social-Media has been increasing tremendously over the last decade. More precisely, globally, 2.62 billion people, 2.23 billion of whom active Facebook users, use some sort of Social-Media (Statista, 2018b, a). Aside from private usage, Social-Media technologies are also increasingly adopted by enterprises integrating them for supporting value-creation (Hanna et al., 2011, McDonald and Aron, 2012). Studies in the field of Social-Media adoption indicate that 72% of all large enterprises have already deployed at least one Social-Media tool (Bughin et al., 2011). For example, 73% of all German companies used Social-Media in 2017 (Statista, 2017).

Consequently, companies are heavily investing in Social-Media, backed by a worldwide marketing spending on social networking sites of about US$ 4.3 Bn (Williamson, 2011). In particular, enterprises strive for improving their bidirectional communication with consumers, brand loyalty as well as establishing a positive online image (Durkin et al., 2013, Lee et al., 2008, Meske and Stieglitz, 2013). The expected benefits from using Social-Media channels are diverse. First, companies try to trigger customer engagement to evolve the connection between customer and business. For example, customers are integrated into so far internal company tasks such as product or service development to increase emotional bonds and improve the overall business performance (Mitic and Kapoulas, 2012, Pagani and Mirabello, 2011, Sashi, 2012). Second, by using Social-Media, companies want to generate "word of mouth", which, according to (Kumar and George, 2007), is one of the most persuasive forms of advertising and thereby increasing the viral dissemination of information (Chan and Ngai, 2011, Jalilvand and Samiei, 2012). At first glance, Social-Media activity seems an easy-to-handle task. However, studies have shown that, especially when targeting digital natives who have grown up knowing Social-Media, several challenges come up as for instance fast changing trends or specific language (Berthon et al., 2012). Even though Social-Media is well known for being the best modern way to communicate and interact with consumers (Hackworth and Kunz, 2011, Selina and Milz, 2009), the understanding of how to use a structured kind of Social-Media and to extract information from Social-Media to gain concrete benefits is fairly low (Dong-Hun, 2010).

As Social-Media as well as the users within the Social-Media channels are characterized by a steady change, the continuous analysis of the gathered Social-Media data is necessary. Additionally, with the extended use of Social-Media, the amount of data that need to be analyzed and interpreted to monitor Social-Media channels, rises quickly. As Social-Media data mostly include huge amounts of unstructured text including ambiguous expressions or grammar and typing errors, the analysis is difficult and, what is more, manually performed analyses cause enormous human efforts (Stieglitz et al., 2014). Thus, in recent years, many tools (e.g., Brandwatch, SocialMediaAnalysisResearchToolkit, etc.) have been dealing with the automated analysis of Social-Media data, using various structured as well as unstructured approaches (Liu, 2012) to determine miscellaneous insights into the underlying posts and comments. However, existing Social-Media analysis tools often focus on one general approach, prioritizing either the analysis of the posts' semantics or structured data (e.g., sum of likes or shares) (Wozniak, 2016). For example, Social-Media data collected by services such as Google Analytics or Facebook Insights mostly refer to the overall activity of users within Social-Media channels but completely lack their opinions or emotions towards the presented content. Approaches prioritizing posts' semantics (e.g., sentiment analysis or classification of user posts), on the other hand, mostly neglect the weighing of the gathered feedback and its influence on other Social-Media users. In contrast, hybrid approaches are multilevel and combine different methods of data evaluation (e.g., structured / unstructured) resulting in a mixed-method approach (Johnson et al. 2007, Johnson and Turner 2003). This allows for more in-depth and novel analysis (e.g., inquisitive or pre-emptive analytics), which promises even greater research value than the isolated application of previously established methods (Kitchens 2018). Therefore, also in the field of Social-Media, a combination of various research methods seems promising and should be able to compensate the underlying drawbacks of each procedure (Greene and Caracelli, 1997, Sidorova et al., 2016, Graffigna et al., 2015).

Hence, the goal of this paper is the design and development of a hybrid approach that combines various analysis methods of Social-Media data (e.g., sentiment analysis, classification, clustering, Social-Media insights, etc.) and consequently offers even deeper insights into Social-Media posts and comments. The hybrid approach is prototypically implemented and integrated into an existing Social-Media analysis software tool. Thus, specific benefits coming from a combined analysis of Social-Media data should be identified by applying an approach that targets real world data.

The structure of this paper is as follows: in section two, related work on Social-Media, (the corresponding) analysis techniques as well as existing tools are presented. Next, the procedure of the research following the Design Science (DS) approach (Hevner et al., 2004, Peffers et al., 2007) is described in section three. Section four deals with the design and development of an approach for a hybrid analysis of Social-Media data. Section five shows the application of the demonstrated approach on our cooperating partners' Social-Media data and the resulting outcomes, which are additionally evaluated and interpreted. Afterwards, the benefits of the research for both science and practice are emphasized. The paper ends with a conclusion and an outlook on further research.

2 Conceptional Background

2.1 Social-Media analysis

Customer reactions in Social-Media platforms (e.g., a company's Facebook or Twitter page) contain a lot of information about the users' current expectations towards products, services or a company in general (Hienerth et al., 2011, Sigala, 2012a, Sigala, 2012b). These so called "voices of the customer" (VOCs) (Lunau et al., 2008), aside from pure transaction profit, are part of the value that customers provide for a company and point out "what's important to customers" (Pande et al., 2000, p. 190), although, with the extended usage of Social-Media channels, the number of fans and their reactions are also rising quickly. Therefore, the amount of Social-Media data that needs to be analyzed and interpreted to fully utilize the included information rapidly leads to enormous efforts (Kumar and George, 2007, Womack and Jones, 1996).

As a consequence, the automated analysis of Social-Media data is a crucial task, which many companies are not familiar with (Dai et al., 2011). In research, Social-Media analysis can be divided into two research fields (Lee and Hubona, 2009, Myers and Avison, 2002). First, the analysis of structured Social-Media data (e.g., timestamps, like-counts, share-counts) found within the extracted Social-Media data, featuring methods such as empirical statistical tests (Wilde and Hess, 2007, Castan 2011). The main goal of this analysis approach is to identify and measure casual relationships between existing values by using techniques as for instance randomization, blinding and highly structured protocols (Lincoln and Denzin, 1994). Additionally, sample sizes used in structured Social-Media data analysis are much larger in comparison to those used in semantic research to ensure a representative status of the analyzed data (Carey, 1993). The analysis of structured Social-Media data is a widespread form of analysis, as many Social-Media platforms such as Facebook and Twitter offer freely available services (e.g., Facebook Insights, Twitter analytics) on their websites. Therefore, rudimental analysis methods such as like counts, share counts or user numbers over specific time frames are accessible. Although this analysis method can clearly prove coherences in the given metadata of Social-Media content based on calculations, semantic factors as for instance sentiments, opinions and topic references (e.g., a post's affiliation towards a specific topic), which are key components of the earlier mentioned VOCs, are completely missing.

Second, in contrast to the analysis of structured Social-Media data, the content-related analysis of unstructured Social-Media data (e.g., text) focuses on the substance by identifying the textual data themselves (Mayring and Fenzl, 2014). Therefore, the aim of the analysis and the context of the situation are interactively linked (Guba and Lincoln, 1994, Lincoln and Denzin, 1994). In this context, the computer-assisted analysis of textual data to identify specific patterns within large text collections is described as text-mining (Feldman and Sanger, 2007, Heyer et al., 2006). The most important examples of usage in this field are sentiment analysis and clustering as well as classification.

Sentiment analysis, meaning the field of study that analyzes "people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions" (Liu, 2012, p. 415), consists of different subareas: (1) document-based approaches aiming towards the classification of the sentiment of a whole text corpus (e.g., newspaper articles), (2) sentence-based approaches analyzing single sentences and classifying if they have a positive, negative or neutral sentiment. Additionally, there are also (3) aspect-based approaches, which focus on entities and their aspects. For example, in product reviews, the attributes (aspects) of the reviewed products (entities) could have different characteristics (Feldman, 2013, Liu, 2012, Vohra and Teraiya, 2013). As (Zhao and Rosson, 2009) state, the specific peculiarity of Social-Media data lies in the shortness of the posts (e.g., 140-character limit on Twitter). Therefore, sentence-based approaches are preferentially used when it comes to the sentiment analysis of Social-Media.

Other examples of the analysis of unstructured Social-Media data are clustering and classification. First, clustering approaches as for instance k-means (MacQueen, 1967), expectation maximization (Dempster et al., 1977) or agglomerative hierarchical clustering (Tan et al., 2005) renounce a reduction of dimensionality and try to assemble elements of the dataset towards automatically defined homogenous groups based on their statistical structures and patterns (Dayan, 1999, Feldman and Sanger, 2007, Heyer et al., 2006). In contrast to clustering, classification describes a supervised ML technique providing the automated mapping of data and using labeled training data to determine the affiliation towards previously defined categories (Feldman and Sanger, 2007, Heyer et al., 2006). Typical approaches in the research field of classification are k-nearest-neighbor (Cover and Hart, 1967), naïve bayes (NB), multinomial naïve bayes (MNB) (McCallum and Nigam, 1998, Tuarob et al., 2014) or support vector machines (SVM) (Gunn, 1998). Focusing on the analysis of large data sets with specialized event models such as Social-Media posts, SVM and NB/MNB deliver convincing results (Jin et al., 2013, Kibriya et al., 2004, McCallum and Nigam, 1998, Tuarob et al., 2014). Therefore, the users' sentiments and opinions on several topics become evident, leading to a better understanding of the needs of customers.

2.2 State of the art of commercial Social-Media analysis

As mentioned above, various commercial software tools for analysing Social-Media content already exists. To deliver an overview of existing functionalities, we conducted interviews with several companies operating in both B2C and B2B sectors to explore the actual needs of companies as well as the current state of the art of Social-Media analysis. Thereby, 13 different software tools were analyzed. To ensure the applicability on Social-Media content, tools such as "reviewpro" and "reinvate", which operate in different areas than Social-Media (e.g.,travel industry), were eliminated in a first step. Second, there are various statistical software tools as for instance "R", "SAS" or "MAXQDA", which offer the ability to implement Social-Media analysis, but heavily rely on specific abilities in statistics as well as programming and do not offer Social-Media analysis in an easy-to-use way. Additionally, some tools were already sold or discontinued ("radian6", "klout" as well as "scoutlabs") and therefore eliminated.

Table 1. Social-Media analysis tools

		Brandwatch	Sysomos	Netbase	Social Mention	Sproudsocial
Sentiment-analysis	*functionality*	●	○	●	●	○
	customizable	●	○	●	●	○
	multi-language	●	○	●	○	○
Classifi-cation	*functionality*	●	○	●	○	○
	customizable	○	○	○	○	○
Social-Media Data analysis	*functionality*	●	●	●	●	●
	customizable	○	●	●	○	○
Hybrid analysis	*functionality*	●	○	○	○	○
	customizable	○	○	○	○	○

Legend: ○ = function not available ● function available

Finally, the five remaining tools were analyzed as to their abilities in view of sentiment analysis, classification, Social-Media data analysis as well as possibilities to customize and adapt the analyses in regard to company- and region-specific characteristics based on the information provided by the tool's manufacturer (website as well as inquiries). Looking at the results (see table 1), it becomes obvious that even though many of the existing tools can handle individual tasks as for instance sentiment analysis or classification well (e.g.,Brandwatch, Netbase), each tool focuses on specific analysis methods and therefore neglects the benefits of combining several analysis steps towards a hybrid analysis, including structured data. Therefore, the design, development and prototypical implementation of a highly customizable hybrid approach for combining various Social-Media analysis methods seems promising.

3 Procedure of the research

In recent years, Design Science (DS) by (Hevner et al., 2004) as well as (Peffers et al., 2007) has gained high popularity and has become a legitimate IS research method (Alturki et al., 2011, Gregor and Hevner, 2013). A widely recognized suggestion on how to conduct DS projects was introduced by (March and Smith, 1995) and (Peffers et al., 2007), representing a synthesis of the activities "build/development" and "justify/evaluate" with the aim of addressing an organizational problem by developing an IT-artifact (Cleven et al., 2009, Hevner et al., 2004). Therefore, this paper's research follows DS to design and develop an approach for a hybrid analysis of Social-Media data.

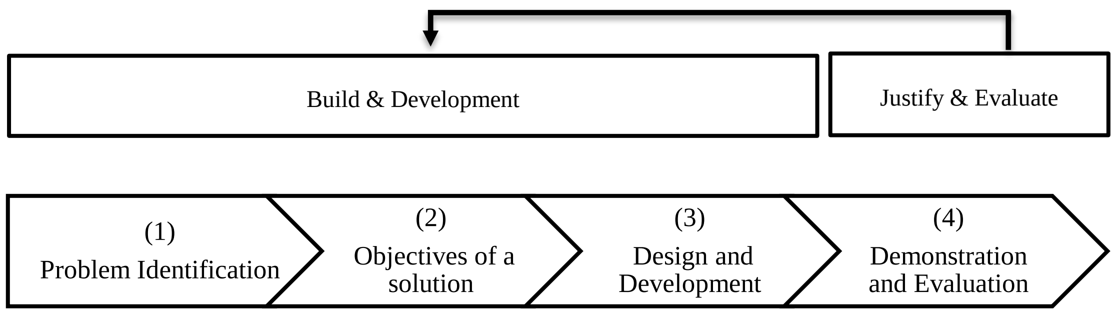

Figure 1. Procedure of the research

As a first step (1), **corresponding problems** and drawbacks of individual relevant Social-Media data analysis methods were identified (see section "Introduction"). Based on their application on Social-Media data, various gaps that cannot be bridged by any of the independent analysis approaches alone were perceived. Consequently, various benefits, arising from the combined usage of various analysis approaches such as the sentiment analysis or classification as well as the data analysis such as like counts or share distributions of Social-Media data were collected and described in the second phase (2) **define objectives of a solution** (see section "Conceptional basics"). The next step (3) was the **design and development** of a solution (see section "Design and development of a hybrid approach"). The technical realization and evaluation of the sentiment analysis as well as the classification towards company-specific classes were done in previous research (author-self citation 2016, author-self citation 2017). Additionally, the metadata (e.g., likes, shares and comments) of our two cooperating partners' Social-Media data was extracted to obtain an overall view of the existing data pool. In this regards, the data pool resulting from our Social-Media analysis tool was gathered. To fill the gaps identified within phase (1), algorithms capable of combining semantic as well as statistic data results were developed. Subsequently, our Social-Media analysis tool was enhanced to support new analysis methods and to eliminate the existing disadvantages that each unilateral analysis method brings along. For the **demonstration and evaluation** (4) of the solution (see section "Demonstration and evaluation of the results"), the developed approach was applied on our two cooperating partners' Social-Media posts. The overall results of the application of the analysis are shown in a table view as well as in analysis-specific graphics. To evaluate the gathered results, we conducted several interviews as well as a conjoint workshop with Social-Media-responsive staff of our cooperating companies. An evaluation of the quantifiable outcomes of the developed hybrid approach is planned for future research by applying our software in various companies from different industries.

4 Design and development of a hybrid analysis approach

While analysis techniques for unstructured Social-Media data (e.g., text) offer important insights into the Social-Media data's semantic content, they outline only one side of the medal and completely neglect the associated metadata (e.g., like counts or share counts). In contrast, the analysis of structured Social-Media data mostly provides generic results that do not take into account the specific characteristics of a company and its followers and therefore a quantifier for measuring the impact of specific opinions and topics as well as an indicator as to how the users incorporate topics are clearly missing. (Esch und Eichenauer 2016).

Additionally, by only considering each approach individually, some plausible alternative explanations for conclusions drawn from the data might be neglected (Johnson and Turner 2003). To eliminate those alternatives, a combination of various Social-Media analysis approaches seems promising and results in the most accurate and complete depiction of the phenomenon under investigation (Patton 1990, Johnson 1995, Tashakkori and Teddlie 1998, Johnson and Christensen 2000, Kim et al., 2017, Shah and Jivani 2018).

Despite the accompanying extra effort of multiple analysis methods, many research areas (e.g., public health or bioscience) state that there are several benefits resulting from combining various analysis methods (Creswell and Clark, 2007, Johnson and Onwuegbuzie, 2004, Tashakkori and Creswell, 2007).

- First, the two approaches share the goal of understanding real-world problems and have the same unified logic and rules of inference (Haase and Myers, 1988, King et al., 1994).
- Second, hybrid methods combine confirmatory and exploratory research questions at the same time, allowing to back interpretations of the results up with concrete quantitative data (Tashakkori and Teddlie, 2010, Teddlie and Tashakkori, 2009).
- Third, hybrid approaches usually feature multiliteral and more clear-sighted conclusions on the real-world context than one-sided research (Teddlie and Tashakkori, 2003). Finally, hybrid research approaches can support the declaration of contradictory or complementary results. With divergent results often occurring during research, hybrid approaches can enrich the acquired insights and assess the limits of the current research as well as initiate future research questions (Teddlie and Tashakkori, 2003, Teddlie and Tashakkori, 2009, Yavas et al., 2004).

Hence, hybrid approaches can be defined as a fundamental attempt to combine various analysis methods in such a way that has complementary strengths and non-overlapping weaknesses by recognizing their individual advantages as well as limitations (Brewer and Hunter 1989, Tashakkori and Teddlie 1998, Johnson and Turner 2003).

4.1 Functions and classmodel of the hybrid approach

The process of designing and developing an approach for the hybrid analysis of Social-Media data is based on a Social-Media analysis tool resulting from previous research (author-self citation 2016, author-self citation 2017). First of all, the existing four functions of the Social-Media analysis tool shall be described (see figure 2).

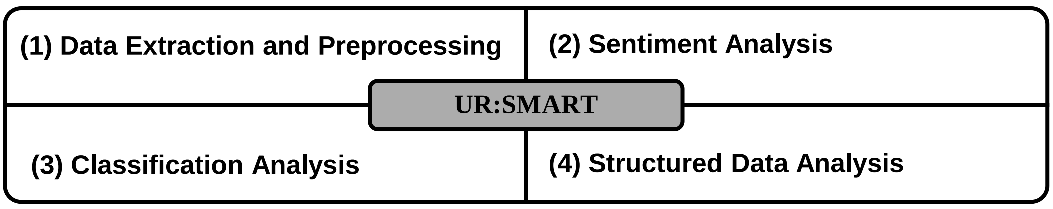

Figure 2. Functions of the Social-Media analysis tool

The ability to extract Social-Media data directly by connecting to the channels' Application-Programming-Interfaces (API) (e.g., Facebook API, Twitter API) as well as preprocessing the extracted data using various techniques as for instance tokenization, stop word reduction, stemming and normalization is the **first (1)** key function (Aggarwal and Zhai, 2012). As Social-Media data often includes unstructured text, which is a huge disadvantage in subsequent analyses, preprocessing the gathered data is a crucial task. First, tokenization decomposes posts or comments into individual parts (e.g., single words) and eliminates symbols, punctuation as well as special characters (Carstensen et al., 2009). Second, during the process of stop word reduction, words that do not carry opinions are removed, based on openly available stop word lists (Angulakshmi and ManickaChezian, 2014). Additionally, company specific stop words were added to these lists. Third, words are "stemmed" to their basic form to support further analysis. In particular, the verb "talking" is reduced to its base form "talk" to eliminate grammatical characteristics as for instance tenses (Akaichi et al., 2013). Finally, during normalization, all remaining text fragments are transformed to lower case characters (Angulakshmi and ManickaChezian, 2014). Based on the resulting preprocessed data, function **two (2)** allows the determination of the sentiment of each customer post. To do so, the Social-Media analysis tool uses the widely accepted dictionary-based approach SentiWordNet 3.0, which represents a generally accepted approach for the automated sentiment analysis of English textual content (Baccianella et al., 2010). To support a multilingual analysis, combining German and English Social-Media posts, SentiWordNet 3.0 was merged with SentiWS, a German language resource for analyzing the sentiment of German texts (Remus et al., 2010). Therefore, the structure of SentiWS was converted to be integrated into the present architecture of SentiWordNet 3.0, leading to a lexical resource with over 45k annotated words for each sentiment (positive, negative or neutral) (Feldman, 2013, Remus et al., 2010). Additionally, to take into account often used structures in Social-Media data such as smilies, emojis as well as slang, we also implemented a dictionary for identifying these specialized text components. For the consideration of negations, a multilanguage negation detection was implemented to detect reversive words and take them into account properly. The sentiment of each word (as well as each special text component) is expressed by the variable "*sentiScore*", a number within a predefined range of [-2;+2], with a high number near +2 representing a very positive and a low number towards -2 a rather negative sentiment (Feldman, 2013). In consequence, the overall sentiment of a post or comment is evident and ascribed to the categories strong positive, positive, neutral, negative and strong negative. The gathered data is stored within a database and can be graphically displayed in pie charts and an ECG-like representation featuring a temporal scale of sentiment progression.

After performing the sentiment analysis, the **third (3)** feature, a classification of the posts, is conducted. In a first step, to provide the ability of adapting the classification to individual or fast changing contexts (e.g., upcoming campaigns or fast changing trends), the software tool focuses on the assembly of data towards predefined classes (Feldman and Sanger, 2007, Heyer et al., 2006, Read et al., 2012). Therefore, a set of generally valid main categories (e.g., service, product or campaigns), independent from company or branch specifics worked out in cooperation with practice partners. Additionally, to handle the individual topics and needs of each company, (corresponding) subcategories for each main category can be determined. These subcategories are highly specialized and tailored towards the companies' specifics as well as to the aims of their Social-Media channels. The main category "product", for example, is extended by the integration of several subcategories, including company-specific product lists, parts lists as well as product accessories. For the identification of the category of a post or comment, the Social-Media analysis tool combines multinomial naïve bayes (MNB) with a dictionary-based seed word library. This library includes specific seed words for all acquired main and subcategories and therefore allows an assignment of posts and comments to predefined classes (Zagibalov and Carroll, 2008). Starting from the preprocessed data, all words of a post or comment are analyzed regarding these seed words, enabling a strong customization of the classification. Additionally, by identifying similar words surrounding existing seed words, the seed word library is constantly enhanced by company-specific expressions (Liu, 2012). As a result, topics that are currently popular amongst Social-Media users within a Social-Media channel, can be identified and graphically displayed. The results of the sentiment analysis and the classification to the defined classes are then brought together by an overall view, featuring the most represented categories and subcategories within each sentiment section. Additionally, all underlying posts are obtained with the help of various sort and filter algorithms. In addition to the semantic data gathered by the analysis of the Social-Media posts, the extracted posts also include structured metadata (e.g., likes, shares, number of comments, timestamps, etc.). Thus, the **fourth (4)** function of our software tool aggregates this data and uses it to calculate elementary metrics, for example the total number of posts, comments, likes or shares within the entire Social-Media channel or a selected time period. Additionally, like and share distributions can be viewed to identify the reactivity of each company post over time.

In this research, we enhanced an existing Social-Media analysis tool to support the combination of various text mining methods. At the outset, all available data was brought together and consolidated within **a class model** to design the underlying database (see figure 3). For this purpose, a company post itself was considered as an entire unit (object), including various attributes (e.g., ids, timestamps, message, sentiment, category, reactions, etc.) and connections towards other corresponding objects such as the Social-Media account in general, the associated main-/sub categories as well as all associated comments with their reactions included.

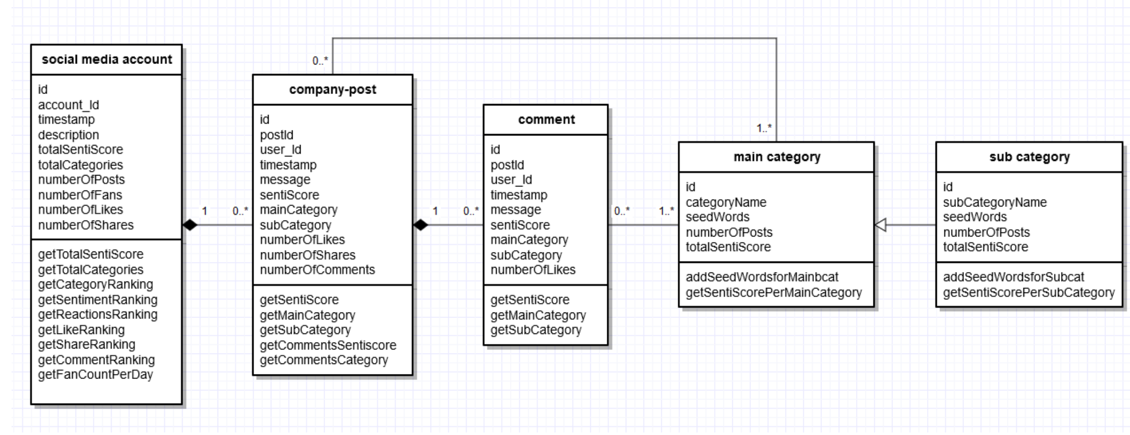

Figure 3. **Class model of the approach**

As figure 3 shows, the class Social-Media account may consist of one or many company post classes, and each company post again can have various comment classes. These connections are characterized by compositions, meaning that the deletion of the superior Social-Media account results in an elimination of all corresponding posts and comments as well (Dumas and Ter Hofstede, 2001). Amongst general attributes as for instance id, timestamp or message, every company-post includes its own semantic attributes, namely "*sentiScore*" for the underlying sentiment, "main- and subcategory" for the associated category (e.g., product or service) as well as the number of likes, the number of shares and the number of comments (reactions of customers). A comment includes these attributes, too, with the exception of "shares" and "comments", which are not available for comments. In terms of classification, the class model offers the classes "*mainCategories*", which are connected to a company post or comment, and also "*subCategories*", an extension to specify categories in a more exact way.

4.2 Hybrid analysis methods

Additionally, the approach includes methods to combine several attributes to gather subsequent analysis forms. These methods are located at the lower end of the classes and trigger the following approaches to edit and process data for the hybrid analysis.

Sentiment of reactions:

The first analysis approach takes aim at the problem that pure reaction data (e.g., like-counts or share-counts) does not carry specific tonalities or meanings. To solve this issue, the approach combines the methods *getSentimentRanking, getCategoryRanking and getTotalSentiScore.* As the first two methods only deliver the pure distribution of sentiment and categories amongst all posts, the combination with reaction data as well as an overall sentiment score ("*totalSentiScore*") allow to determine the number of positive, negative or neutral reactions within a specific main- or subcategory. Therefore, all posts and comments of a category are collected. Up next, the overall *totalSentiScore* for each company post and all of its included comments is calculated. With the help of this score, "likes" and "shares", which previously only emphasized that a user approves the underlying post, can now be allocated to the underlying tonality. For instance, a positive *totalSentiScore* indicates that the general sentiment of all comments in relation to a company post is positive and therefore all reactions towards the post can be seen as positive as well. Nevertheless, partially occurring negative comments are still recorded for further improvement. The *totalSentiScore (tS)* is calculated as follows: First, the sentiment of the company post itself is aggregated with the sum of all the sentiment scores of the comments. The result is then divided by the number of comments + 1.

$$totalSentiScore\ (tS) = \frac{sentiment\ (s)\ of\ post\ (p) +\ \sum_{c=1}^{n} sentiment\ (s)\ of\ comment\ (c)}{1 +\ number\ of\ comments}$$

Ranking of reactions within a sentiment:

Based on the totalSentiScore, the next hybrid analysis variant addresses the problem that most companies struggle with, namely the right adaption of their Social-Media channels. To develop a solution, all posts of a Social-Media account are displayed within an overall ranking of "like", "share" and "comment" progressions. This method is described as getReactionsRanking (getLikeRanking, getShareRanking, getCommentRanking) and gathers all reaction data from each and every post and comment within the Social-Media account. The corresponding reactions of all posts are aggregated and sorted by the highest "like" and "share" count. Additionally, the number of comments shows the amount of active answers to each post. By further combining this information with the semantic analysis results of the sentiment analysis (getSentimentRanking) and classification (getCategoryRanking), it is now possible to gain insight into what categories are the most popular amongst all users indicated by the highest reaction-count. Additionally, categories, which generate much positive or negative feedback and therefore should be expanded or reduced in future postings, can be identified. As a consequence, the method getReactionsRanking delivers an overview of the most reactive categories within the Social-Media channel and therefore allows the alignment of the underlying Social-Media strategy.

Distribution of categories vs. Distribution of reactions:

The next promising hybrid approach for verifying the alignment of a company's Social-Media activities is the comparison between the distribution of categories (doc) and the distribution of reactions (dor), making it possible to determine distinctions between the published topics and the obtained reactions. In contrast to the classification (getCategoryRanking), which only gives an overview of the most posted and mentioned categories on a Social-Media channel, the distribution of reactions (getReactionRanking) can add a quantifier to specific posts and comments. By a comparison of the two analysis forms, deviations between categories and reaction distributions can be identified. For example, if a company publishes 75% of its posts about its products and 25% of its posts about campaigns such as contests or raffles, with a high amount of reactions assigned to the second category, the company should counteract this inadequate quantifier.

$$doc\ (c) = \frac{\sum posts\ for\ category\ (c)}{\sum total\ posts} \leftrightarrow\ dor(rc) = \frac{\sum reactions\ (likes, shares, comments) for\ category\ (c)}{\sum total\ reactions}$$

Fan growth per category:

One of the main goals of companies is to gather new fans to extend the target audience for their Social-Media channels (Williams and Chinn, 2010). Hence, knowing what posts prompt Social-Media users to hit the follow-button is a crucial task. The combination of the methods *getFanCountPerDay, getSentimentRanking and getCategoryRanking* offers a solution to gain insights into the concrete fan growth or decline. Usually, Social-Media platforms as for instance Facebook offer detailed information on fan counts. As a consequence, fan growth can be measured on a daily basis. With the help of the included timestamps in posts and comments, an allocation to specific days is equally possible. Combining this data with the results of sentiment analysis and classification offers a deeper understanding of posts responsible for either fan growth or fan decrease. Therefore, posts with certain topics and sentiments obviously encouraging users to follow or unfollow a Social-Media channel can be identified. For example, initially, contests can attract the attention of users and lead to a fan increase but can also become boring over time and result in user migration. Thus, a continuous measurement is necessary to conceive the actual interests of Social-Media users on a company's Social-Media channel.

$$fanGrowthPerDay\ (fG) = fanCount(day\ x) - fanCount(day\ x - 1)$$

5 Demonstration and evaluation of the results

5.1 Construction of the scenario

To gain valuable insights into the possibilities of an approach for a hybrid analysis of Social-Media data, we started by selecting two adequate collaborating partners. For the selection of suitable partners, the criteria for our company search were threefold. First, the companies needed to be openly committing to Social-Media usage, e.g., by actively operating several Social-Media channels and heavily embedding Social-Media into their company strategies as well as by updating their channels on a regular basis, thus generating current and vivid content. Second, the number of active users and fans on the companies' Social-Media channels needed to be used for judging their online visibility. Third, to examine the wide applicability of the hybrid analysis, the branches in which the companies operated also needed to be strongly different. Indeed, the overall company size was not considered, as, in our investigations, Social-Media activities are not linked to the total size of the company. To gain an overall perspective, we selected candidates from different branches and invited them to join our study.

Eventually we succeeded in recruiting two companies, the first one a market leader in fun sport equipment for water sports (company A) and the second one a German local bank with a focus on private savings, building society savings and credit business (company B). To gather detailed information on our partners' Social-Media appearances, we extracted 635 datasets from their Facebook accounts, as Facebook is their prioritized Social-Media account, including the numbers of fans, posts, comments as well as the corresponding metadata (e.g., number of likes, number of shares and number of comments) for each entry from January 2017 until September 2017. The extraction was performed by our social analysis tool, which includes the functionality to directly connect towards the APIs of Social-Media platforms such as Facebook or Twitter to collect all valuable data within a Social-Media channel. The results are shown in table 1.

Table 2. Collaborating partners

Company	Industry/Description	# of Facebook fans (approx.)	# of posts	# of likes	# of shares	# of comments
Company "A"	Market leader in fun sport equipment for watersports	89.000	304	3.4791	11.178	1.746
Company "B"	German local bank with a focus on private savings, building society savings and credit business	7.447	331	13.004	4.111	10.477

Previous research has shown that, when it comes to the analysis of Social-Media data, a customized adaption of the analysis algorithm to individual characteristics in terms of company culture, the aim of the Social-Media channel as well as the target audience is a crucial task. As Social-Media plays a significant role in the two collaborating companies, we interviewed the responsible Social-Media staff to gain a deeper understanding of their Social-Media strategy and the objectives and goals of their Social-Media presences. Additionally, we examined several specifics in regards to the language used on our companies' Social-Media channels to align our analysis even further. Thus, especially peculiarities in terms of branch-specific language, non-standard language elements as for instance emoticons, internet slang (e.g., the expression "4u"), multiple languages (namely

German and English) within a post or spelling errors were considered (Laboreiro et al., 2010, Petz et al., 2013).

Company “A”, a manufacturer of water sports equipment (e.g., surfing, kiteboarding, etc.), targets a very active, sportive and adolescent audience. Social-Media users on their Social-Media channels are very heterogeneous and highly associated with the company’s brands. Thus, company “A” mainly focuses on publishing many positive posts including photos or event reports from various event locations around the world, relating its brand name and products to joyful emotions. Therefore, for the classification of company “A’s” posts, the categories *product*, *user-generated content (UGC)* (e.g., images or product reviews from customers), *brand* and *event* were defined amongst others. In contrast, company “B” operates in a very different business area, as customers of German local banks are considered rather conservative and businesslike (Yavas et al., 2004). As the company’s Social-Media channel had been in the setup period for over a year, the German local bank was, at the time, aiming at familiarizing their customers with this new form of interaction and focused on the growth of user numbers and user activity and on encouraging both existing customers and interested new user groups to join the channel by posting branch-specific news and current campaigns in terms of charity and social commitment.. Consequently, the categories *campaigns*, *product*, *service* as well as *brand* are predominant examples for company “B”.

5.2 Results and interpretation of the hybrid analysis approach

For the presentation of the results, we applied the demonstrated approach on the extracted Facebook data of the cooperating partners. An overview of the results is shown in table 2, which is structured as follows: First, the various, previously defined categories are presented for both companies. The first column (“# of posts”) indicates the number of posts within each category, sorted by height. Next, the numbers of the corresponding “# of likes”, “# of shares” and “# of comments”, separated into the sentiments positive (+), neutral (O) and negative (-) are presented. As the performed analysis determines a sentiment score for every post including all comments, the columns “+ totalSentiScore” and “- totalSentiScore” show the average tonality of all posts (“# of posts”), assigned to the respective sentiment. Additionally, in the last column (“O - # of posts), the number of neutral posts still missing, which do not include opinion-carrying words, is shown.

Table 3. Results

	category	# of posts	# of Likes (per sentiment)			# of Shares (per sentiment)			# of Comments (per sentiment)			+ totalSenti-Score	- totalSenti-Score	O
			+	O	-	+	O	-	+	O	-	(# of posts)	(# of posts)	(# of posts)
company A	Product	123	7749	3365	2664	1470	1488	950	166	249	166	0,72 (81)	-0,37 (27)	19
	UGC	76	4104	3913	2477	1287	1891	824	156	290	150	0,66 (37)	-0,48 (22)	17
	Brand	44	2328	427	2031	955	218	766	60	25	140	0,53 (25)	-0,50 (17)	2
	Event	24	809	256	366	80	21	23	22	28	7	0,68 (13)	-0,47 (9)	2
	Service	22	908	0	**1894**	209	0	**770**	22	0	**141**	**0,92 (10)**	**-0,45 (12)**	0
	Competitors	8	187	0	322	20	0	54	1	0	1	0,85 (2)	-0,57 (6)	0
	Emotional	8	**991**	0	0	**197**	0	0	27	0	0	0,78 (8)	-	0
	total	305	17076	7961	9754	4218	3618	3387	454	592	605	Ø 0,73 (176)	Ø -0,47 (93)	40
company B	Campaigns	89	4882	123	487	2716	20	46	**10103**	2	36	1,16 (80)	-0,43 (6)	3
	Product	46	1337	0	63	221	0	0	49	0	7	1,22 (40)	-0,43 (6)	0
	Service	44	1180	0	22	251	0	67	56	0	9	1,06 (41)	-0,47 (3)	0
	Brand	43	1352	29	83	245	9	67	51	0	8	1,27 (36)	-0,37 (4)	3
	UGC	32	593	44	101	71	14	18	17	0	3	1,13 (27)	-0,90 (2)	3
	Technology	23	**739**	35	**2**	116	12	**0**	32	0	**2**	**1,23 (20)**	**-1,15 (2)**	1
	Event	19	253	9	61	43	2	0	4	0	1	1,06 (15)	-0,18 (2)	2
	Staff	14	708	115	0	87	18	0	33	2	0	1,22 (12)	-	2
	Emotional	12	318	0	2	47	0	0	14	0	2	1,39 (10)	-1,15 (2)	0
	Thanks	9	444	0	0	40	0	0	45	0	0	1,68 (9)	-	0
	total	331	11806	355	821	3837	75	198	10404	4	68	Ø 1,24 (290)	Ø -0,64 (27)	14

Legend: + = positive / - = negative / O = neutral; bold cells reference important findings

Overall, the hybrid analysis of the Facebook channels of the two companies identifies important differences between them, which can be explained by considering the strategic orientations of the cooperating companies. As company “A”, a market leader in the area of fun and water sports, operates in a B2B environment only, its Social-Media channel is not for bidirectional communication (e.g., service or complaint handling) with end-customers, such communication is supposed to be processed directly by retailers. Nevertheless, the category “service” exists (22 posts) on their Social-Media channel providing interesting insights. At first glance, the high value of reactions hints at a strong user interest in this category and seems to be a positive sign.

However, the application of the hybrid approach “***sentiment of reactions***” shows that it is not possible to infer from the mere number of reactions as for instance 2802 likes, 979 shares and 263 comments on the positive or negative opinions of the users. By analyzing the *totalSentiScore* for each post (average of +0,92 for positive and -0,45 for negative posts), the reaction numbers can be assigned to tonalities. The results for the category “service” can be seen differently (see figure 4). The hybrid analysis shows, for example, that only 21% (209) of all shares in this category evidence a positive tonality, but 79% (770) a negative sentiment. The same trend is recognizable for likes and comments as well. Neutral reactions as for instance name sharing did not appear in this category in particular. These results suggest that company “A” should reconsider their activities and either put more effort into service and complaint handling to receive more positive feedback on their Social-Media channel or observe their strategy and avoid service-related posts completely, since most reactions in this category are in fact negative.

Share distribution of category "service" (company A)

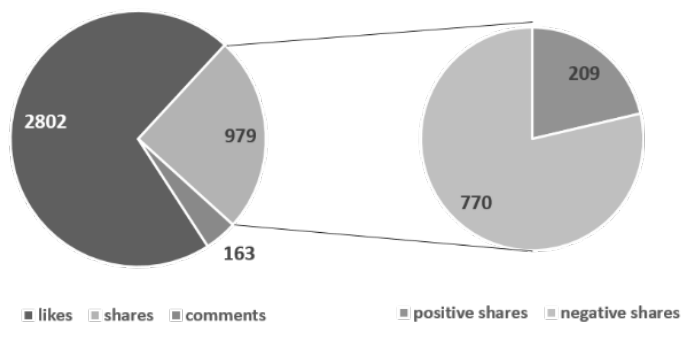

Figure 4. Sentiment of reactions (company A)

Company "B", a German local bank, operates in a very different business area. Many of the rather conservative customers were only just starting to use Social-Media at the time. The analysis of company "B's" Facebook channel showed that besides categories such as campaigns, service or products, technology is a trending topic. As customers expect new technologies as for instance online banking or banking apps to be available, these sections are in the focus of Social-Media analysis. In contrast to company "A", the application of the hybrid approach ***"sentiment of reactions"*** shows that, in the field of technology (23 posts) including 776 likes, 228 shares and 34 comments, the fairly high reactivity hints at the positive intentions of the Social-Media users. With 20 posts having a very positive average *totalSentiScore* of +1,23 and only 2 posts including negative sentiments (-1,15), 739 (95%) of all likes can be assigned to a positive tonality. In contrast, only two likes are considered negative (see figure 5).

Distribution of "Likes" for category "technology" (company B)

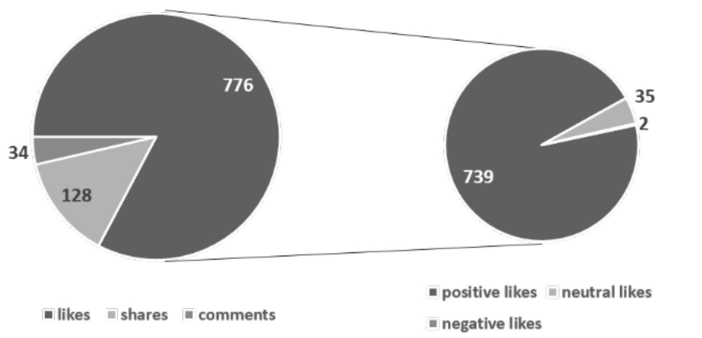

Figure 5. Sentiment of reactions (company B)

In general, these results indicate that most of the bank's customers are very satisfied with the technical services as well as the development of company "B"'s applications. Especially regarding the fast technical progress and increasing interest of customers when it comes to online and mobile banking, the announcement of further technical enhancements and new features for example in the field of apps and security seems promising.

This statement is especially true when considering another hybrid approach, the ***"ranking of reactions within a sentiment"***. As figure 6 indicates, particularly the categories technology, emotional (indicating very emotional posts), thanks and staff include very few to no negative reactions (4 likes, 0 shares, 5 comments) and therefore can be seen as potential topics for future publishing.

Ranking of negative reactions (company B)

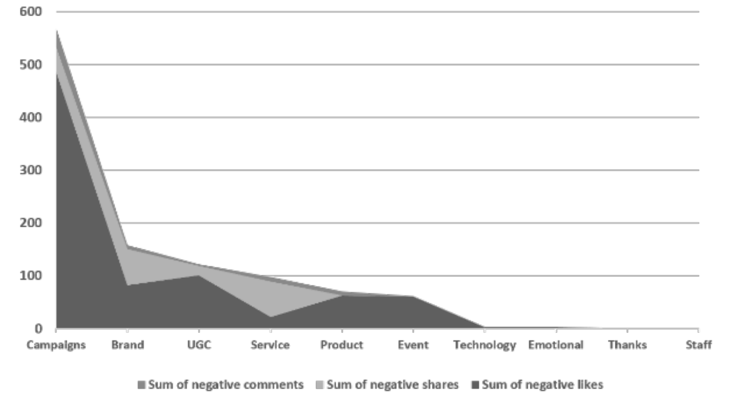

Figure 6. Ranking of reactions (company B)

Other categories such as campaigns or brand need to be compared to the positive ranking. For instance, in summary, campaign-related posts can also lead to overall beneficial effects, as the positive reactions (e.g., positive likes 4882) surpass the negative ones (487) by far and can therefore also produce overall positive WOM for company “B”.

For company “A”, the basic distribution of categories, delivered by the processed classification, states that the category “emotional” is the least popular one with only eight posts. However, when looking at the ranking of the reactions within the positive sentiment for company “A”, more information becomes evident (see figure 7). In terms of reactions, the category “emotional” performs far better than initially expected, with a *totalSentiScore* of +0,78 and a corresponding count of 1215 (991 likes + 197 shares + 27 comments) positive reactions. In addition, negative posts and reactions are completely missing in this category. This is especially plausible, as the aim of the Social-Media presence of company “A” is to merchandise the brand and products and connect them to positive emotions. Therefore, the pursued Social-Media strategy of company “A” seems promising and should be continued.

Ranking of positive reactions (company A)

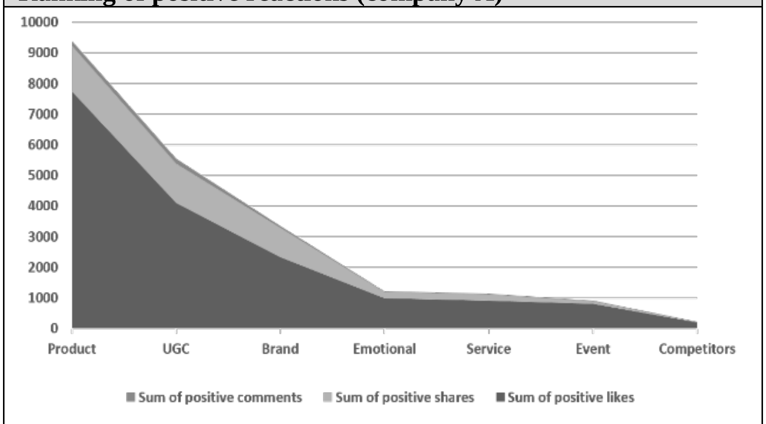

Figure 7. Ranking of reactions (company A)

As mentioned earlier, the strategic planning of a company's Social-Media activities is crucial for receiving high traffic and positive reactions. Therefore, the continuous adaption of this strategy towards the users' preferences is important. The hybrid analysis approach ***"Distribution of categories vs. Distribution of reactions"*** addresses this issue. When comparing the overall distribution of the company posts' categories of company "A" to the distribution of the overall reactions (likes + shares + comments), mostly a consistency is noticeable, as the percentages of the categories product (40% vs. 38%) and brand (14% vs. 15%) are nearly identical (see figure 8).

Distribution of categories vs. reactions (company A)

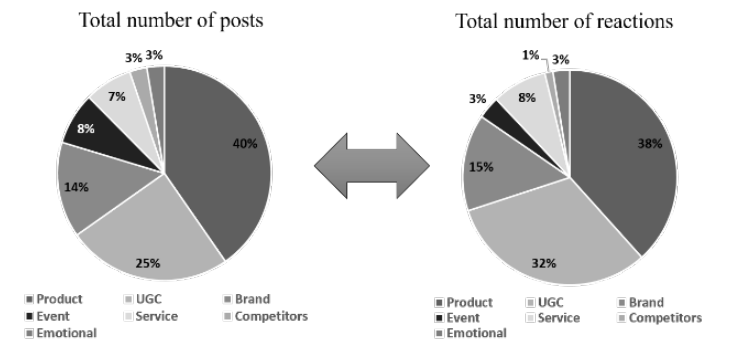

Figure 8. Distribution of categories vs distribution of reactions (company A)

Although there are some minor differences in the categories UGC (25% vs. 32%) and event (8% vs. 3%), it is clearly visible that the postings on company "A's" Social-Media channel reflect the users' interests and reactions in general. Therefore, the basic alignment of their Social-Media activities is correct and company "A" should focus on topics that generate positive reactions as shown by previous analyses.

Distribution of categories vs. reactions (company B)

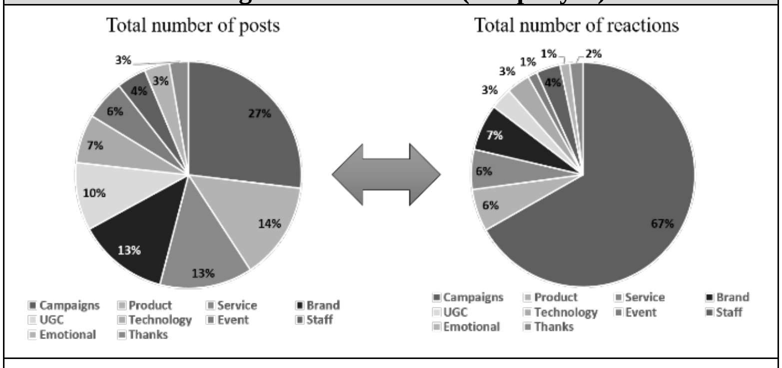

Figure 9. Distribution of categories vs distribution of reactions (company B)

Looking at the same analysis for company "B" shows results different in certain respects. As figure 9 indicates, for various categories, the distribution of reactions differs from the actual dispersion of the posts. Especially the category "campaigns" obtains 67% of all reactions, despite representing only 27% of all company posts on the Social-Media channel. Therefore, an expansion of those categories seems promising for all further content planning of company "B".

In contrast, other categories are clearly underrepresented (e.g., "product" (14% vs. 6%), "brand" (13% vs. 7%) and "service" (13% vs. 6%). Thus, it is discernible that the customers of company “B” heavily respond to campaign-related posts, which is why, in addition to other categories that trigger very positive feedback as for instance “technology” or “staff”, Social-Media campaigns should be expanded.

Unfortunately, the necessary fan data for the last hybrid approach ***“fan growth per category”*** is not publicly available. To be able to gather this data, an access token for accessing a Social-Media page’s private data is mandatory. Due to the privacy guidelines of the cooperating companies, this information is classified. Nevertheless, we discussed this analysis variant with the cooperating companies and they think it a very interesting metric to support the general goal of evolving and increasing their Social-Media channels and fan numbers as well as planning future editors programs.

The demonstration and initial evaluation of the hybrid approach is twofold. First, the text analysis methods used for the sentiment analysis and the classification of posts are generally known and accepted approaches (Baccianella et al., 2010, Feldman, 2013, Kibriya et al., 2004, McCallum and Nigam, 1998, Tuarob et al., 2014). Both approaches were also separately evaluated in previous research, reaching high accuracy levels when being applied on Social-Media data. Second, we demonstrated its application on data sets from two cooperating partners and conducted interviews and held workshops with Social-Media responsive staff to ensure the related benefits. Both companies state that they consider all of the hybrid analysis approaches as well as the resulting outcomes very interesting and highly beneficial for the enhanced analysis of Social-Media data. For instance, company “A”, whose customers generally are very emotional, acknowledged that the approach ***sentiment of reactions*** delivers important information about their customers’ true opinions. Company “B” underlined that the approaches ***ranking of reactions within a sentiment*** as well as ***Distribution of categories vs. Distribution of reactions*** were highly beneficial to them, as they had just started to expand their Social-Media activities and required comprehensive knowledge about their customers’ needs and interests.

6 Discussion and Contribution of the hybrid approach

As shown, a combination of relevant analysis approaches brings various benefits for the interpretation of Social-Media data, starting with “likes” and “shares”, which are the predominant reaction forms on Facebook (Castillo et al., 2014, Naylor et al., 2012). Contrary to its detonation, a “like” is not exclusively positive. In fact, hitting the “like”-button only emphasizes that a user approves the underlying post. For example, if company “A” has technical issues concerning one of their products and publishes a statement within their Facebook channel, “liking” it does most certainly not indicate a positive statement. Similarly, sharing a post (e.g., a post including a product review or information about a product recall) admittedly distributes the included information but also neglects the underlying sentiment or category of the post and therefore cannot be considered as a positive or negative reaction in the first instance. By enriching this structured metadata with the sentiment analysis offered by our Social-Media analysis tool, it is now possible to link specific reactions including “shares” and “likes” with corresponding sentiments and, in so doing, associate the reactions with concrete opinions. Hence, the determined sentiment of each Social-Media post and comment can even be strengthened depending on the number of “likes” and “shares” thus enabling a more distinct interpretation. Additionally, the sentiment of a company post itself can be identified in a comprehensive way. In particular, not only the sentiment of the company post itself, which often is positive due to the aim of distributing positive "word of mouth", but also the sentiment of all corresponding comments can be identified. As a consequence, an overall view of the popularity of specific posts amongst the users is possible. Furthermore, the combined sentiment and quantitative data can additionally be expanded by a topic-based classification. By that, it is not only possible to determine the sentiment of posts, comments and the included reaction data, but also the various categories they are related to. Consequently, if the relation between the distribution of categories and the distribution of reactions towards these categories strongly differ, a hybrid analysis approach offers the opportunity to identify differences and supports the application of countermeasures in further publishing.

In summary, the contributions for practitioners are twofold. First, this research offers a software tool that supports the extraction, preprocessing as well as the hybrid analysis of Social-Media data from various sources by combining various analysis methods. Second, the hybrid analysis allows to gain even deeper insights into the users' needs and opinions and therefore prepares the ground for the further interpretation of the VOCs.

As a scientific contribution of this research, it was shown that the combination of primarily independent methods in the field of Social-Media analysis is applicable and highly beneficial. Therefore, several hybrid analysis methods were presented, allowing to gain deep insights into customers' current opinions, needs and interests. With our approach, we provide a solution that is not only suitable for extracting all underlying Social-Media data (including metadata) and processing sentiment analysis as well as classification, but also for combining the gathered results to enhance the accompanying information gained even further.

Aside from these benefits, there are also some general challenges conceivable. First, as Social-Media is generally known as a fast-changing field, the analysis always only describes a momentary state. In terms of classification, this means that the previously defined classes reflect the current state, but neglect potential future topics. Therefore, a combination of classification and clustering to identify newly emerging topics seems promising. Second, the delineation of the categories during the classification is challenging and may cause ambiguity. For example, if company "B" publishes a post dealing with a new chat service for app customers, the post can be classified into either the categories service or technology. In this case, the corresponding allocation of reactions is necessarily imprecise.

Third, although the accuracy of the used approach for the sentiment analysis is fairly high with an average value of up to 94%, a completely flawless analysis is not attainable, due to fast changing specifics in regards to the language used (e.g., slang or irony) and non-standard language elements as for instance emojis and abbreviations (Laboreiro et al., 2010, Petz et al., 2013). Therefore, false positive and false negative posts occasionally occur. When combining the latter with quantitative metadata, the inaccurate results are carried forward, possibly influencing management decisions due to misinterpretations.

7 Conclusion and outlook

In this research, the design and development of a hybrid analysis approach combining various Social-Media analysis methods were shown. For that purpose, we collaborated with two partners from different industries. Therefore, all posts, comments and metadata from the companies' Facebook sites were extracted and analyzed regarding their sentiment and category with the help of our Social-Media analysis tool. The results were combined with quantitative data (e.g., like-, share or comment-counts) by several hybrid analysis approaches. The resulting software tool was applied to a real-world use case at our cooperating partners, demonstrating not only the applicability, but also the benefits of our solution in a practical environment.

Future research, on the one hand, aims at the evaluation of the quantifiable benefit of the hybrid analysis approach by its application in several additional companies from different industries. On the other hand, additional hybrid analysis approaches should be developed. For instance, the approach "***fan growth per category***", the application of which is missing in this research due to the privacy guidelines of our cooperating partners, will be implemented in the future, amongst others by setting up company-specific privacy contracts. Further, the amount of quantitative Social-Media data will be increased, for instance by adding different types of interactions besides the "like" button, such as "sad" or "angry" to describe the emotions related to reactions even better.

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2.5 Beitrag 5: Analyzing social media content from a qualitative and quantitative perspective - design and development of a hybrid approach

Adressierte Forschungsfrage	**Forschungsfrage 4:** Wie kann eine Kombination aus verschiedenen Social-Media Analyseformen (Sentiment Analyse, Klassifizierung, Clustering und quantitative Analyse) umgesetzt werden und welche Vorteile bietet die Kombination qualitativer Analyseverfahren mit quantitativen Social-Media Daten? **Forschungsfrage 6:** Welchen Nutzen und welche und Usabilty bietet die entwickelte Softwarelösung für KMU im süddeutschen Raum?
Zielsetzungen	(1) Identifikation von Anwendungsszenarien für die hybride Analyse von Social-Media Inhalten. (2) Evaluation des Artefaktes UR:SMART im Unternehmenseinsatz bei KMU im süddeutschen Raum. (3) SUMI Usability Studie des Artefaktes UR:SMART.
Forschungsmethode	Design Science Research nach (*Sonnenberg and vom Brocke 2012)* • Unterscheidung zwischen Ex-ante- und Ex-post-Evaluation • Evaluationsprozess aufgeteilt; separate Evaluation der Problemstellung (1), des Artefaktdesigns (2) und des konstruierten Artefakts (3).
Kernergebnisse (Überblick)	(1) Zwei konkrete Anwendungsszenarios „*Product Commendation/Criticism*“ und „*Topic Identification*“. (2) Anwendung und Evaluation des Artefaktes UR:SMART auf Basis von 635 Datensätzen eines Partnerunternehmens. (3) SUMI Score von 60.31% (“efficiency”, 58.83%; “graphical user interface”, 60.46%; etc.).
Publikationsort	Business & Information Systems Engineering (BISE) Journal (Under Review)
Ranking VHB JQ 3	B
Autor(en) und Anteile	**Schwaiger Josef** **40%** Johannsen Florian 20% Susanne Leist 15% Thomas Falk 15% Timo Hammerl 10%

Tabelle 6: Fact Sheet Beitrag 5

Analyzing social media content from a qualitative and quantitative perspective - design and development of a hybrid approach

Abstract: The digital transformation, with its ongoing trend towards electronic business confronts companies with increasingly growing amounts of data which have to be processed, stored and analyzed. The instant access to the “right” information at the time they are needed is crucial and thus, the use of techniques for the handling of big amounts of unstructured data, in special, becomes a competitive advantage. In this context, one important field of application is the customer relationship management (CRM) because sophisticated data analysis allows companies to gain deeper insights into customer needs and behavior based on their reviews, complaints as well as posts in online forums or social networks. However, existing tools for the automated analysis of social content often focus on one general approach by either prioritizing the analysis of the posts’ semantics or the analysis of pure numbers (e.g., sum of likes or shares). Thus, this research developed the software tool UR:SMART, which supports the hybrid analysis of Social-Media data by combining various qualitative and quantitative analysis methods. The hybrid analysis approach allows to gain even deeper insights into the users’ needs and opinions and therefore prepares the ground for the further interpretation of the voices of the customers.

1 Introduction and Motivation

The digital transformation, with the rise of new technologies such as “Cyber-Physical-Systems (CPS)”, “Virtual Reality”, “3-D Printing” or “Auto-ID-Techniques” (Hänisch 2017) and the ongoing trend towards electronic business confront companies with increasingly growing amounts of data that have to be processed, stored and analyzed (CapGemini 2019; Fill and Johannsen 2016). The instant access to the “right” information at the time they are needed is crucial and thus the use of techniques for the handling of big amounts of unstructured data, in special, becomes a competitive advantage (Grover et al. 2018; Fill and Johannsen 2016). This is particularly true for so called knowledge-intensive business areas where the processing and the analysis of big data become highly relevant.

In this context, one important field of application is customer relationship management (CRM) because sophisticated data analysis allows companies to gain deeper insights into customer needs and behavior (Kitchens et al. 2018; Schwaiger et al. 2017). For this purpose, it is necessary to get to know customers’ opinions and preferences in the most direct and genuine way possible. In a digitalized world, user generated content, such as guest reviews, complaints, posts in online forums or social networks, etc., is particularly suitable for this task (cf. (Sigala 2012; Pinto and Mansfield 2012)). Above all, data from Social-Media provide a valuable source, since more and more customers preferably contact a company via Social-Media to utter service requests and complaints or to settle transactions (Hanna et al. 2011). Furthermore, Social-Media have advanced to a key component in today’s social life, counting 2.62 billion people, thereof 2.23 billion active Facebook users, using some sort of Social-Media (Statista 2018b, a). Those platforms are often used to honestly express someone’s opinions and they also cover a wide range of both customers and non-customers at a time. Therefore, Social-Media data contain considerable potentials for CRM efforts that can be exploited by IT-based data analytics (cf. (Malthouse et al. 2013; Trainor et al. 2014)).

However, because of the particular characteristics of the underlying data basis as well as the intended analytical methods, this type of data analysis carries certain challenges (cf. Sivarajah et al. 2017b). With regard to the data basis, it requires the gathering, processing and analysis of extremely big and complex amounts of data, which emerge and change with high velocity in addition (Fill and Johannsen 2016). One crucial aspect in this context is the handling of data containing errors (e.g., misspelling) or ambiguous data (e.g., irony, slang etc.) and their correct interpretation concerning the content (cf. (Laboreiro et al. 2010; Naaman et al. 2010; Petz et al. 2013)). With regard to analytical methods, there is a noticeable trend towards more complex forms of analyses. These include, among others, making forecasts, revealing cause and effect relationships, and providing guidance on how to act in specific situations (Sivarajah et al. 2017b; Hübschle 2017). In order to properly address those issues, a sophisticated hybrid analysis approach is required that allows the combination and integration of various data sources, formats and analysis techniques.

In the domain of CRM and Social-Media, many analysis and monitoring tools for collecting and processing user data directly from platforms like Facebook or Twitter have emerged in recent years. Tools such as Brandwatch[7], Social Bench[8], etc. *"offer access to real customers' opinions, complaints and questions, at real time, in a highly scalable way"* (Stavrakantonakis et al. 2012) and thus have helped to reduce the manual analysis efforts. However, existing tools cannot completely meet the aforementioned challenges as they, for example, do not include data extraction from multiple Social-Media platforms or are restricted regarding the availability of certain methods (e.g., sentiment analysis) for languages other than English (Stavrakantonakis et al. 2012). Moreover, most Social-Media analysis tools only focus on one analysis approach using either quantitative methods, e.g., the number of fans, likes and shares, or qualitative methods, e.g., the analysis of the posts' semantics. Such an isolated view entails significant drawbacks since the capabilities for conducting sophisticated analyses are restricted.

For that reason, we propose a hybrid analysis approach in the form of a multi-stage procedure that combines different analysis techniques (e.g., qualitative, quantitative) and various data formats (e.g., structured, unstructured). The hybrid analysis approach facilitates a more thorough investigation of a given data basis, including Social-Media posts or comments on a company's fan page or website. Hence, it is capable of addressing a wider range of, even more complex, issues by allowing the combination of various analysis forms and new types of analysis, such as inquisitive or pre-emptive analytics (cf. (Sivarajah et al. 2017a)). In this way, a company using the hybrid analysis may directly learn, as for instance, about the reasons that lead to positive or negative customer experience (e.g., customer service, product quality, etc.). Pieces of information like that constitute a substantial gain of knowledge and can be utilized in many reasonable ways, for example as a reliable basis for decision making while planning future CRM campaigns.

The paper is structured as follows: After the introduction, section 2 covers the conceptual basics and related work regarding Social-Media analytics. In section 3, the procedure of

[7] https://www.brandwatch.com/brandwatch-analytics/

[8] http://www.socialbench.com/social-media-analytics/

research, which corresponds to design science research in general and an iterative evaluation according to (Sonnenberg and vom Brocke 2012) in particular, is outlined. Section 4 analyses the underlying problem and evaluates it based on several interviews with practitioners. Afterwards, section 5 shows the design of the software tool UR:SMART and its functionality as well as typical usage scenarios. Finally, in section 6, the construction of UR:SMART is described as well as an in-depth case study for one specific case. More, a usability study by means of the SUMI (Software Usability Measurement Inventory) approach (cf. (Kirakowski and Corbett 1993)) was performed as a first step to assess the wide-ranging applicability of UR:SMART. The results and implications for the field of research are discussed in section 6. The paper ends with a conclusion and an outlook on future research.

2 Conceptual Basics and Related Work

2.1 Automated Data Analysis

The automated analysis of customer data such as product reviews or customer opinions on Social-Media is a crucial task, which many companies are struggling with (Dai et al. 2011; Johannsen et al. 2016). In research, the analysis of customer data can be divided into two main research fields (Lee and Hubona 2009; Myers and Avison 2002). First, quantitative analyses, e.g., the analysis of metadata (e.g., timestamps, activity, like-counts, share-counts) found within the data use quantitative analysis methods such as empirical statistical tests (Wilde and Hess 2007). Second, qualitative analyses deal with the contextual information within a text by considering its specific assertion (Mayring and Fenzl 2014).

2.1.1 Quantitative Analysis

Quantitative analysis approaches are used to identify and measure casual relationships between existing values by using techniques as for instance randomization, blinding and highly structured protocols (Lincoln and Denzin 1994). Sample sizes used in quantitative analysis are much larger in comparison to qualitative research to ensure a representative status of the analyzed data (Carey 1993). Although these analysis methods can clearly prove coherences within the given metadata of customer data based on calculations, semantic factors as for instance sentiments, opinions and topic references (e.g., a post’s affiliation towards a specific topic), which are key components of the earlier mentioned voice of the customer statements, are completely missing. Hence, research outcomes are often quite general and do not consider the specific characteristics of companies and their Social-Media users and are therefore not directly differentiable and exploitable in practice.

2.1.2 Qualitative Analysis

In contrast to the quantitative analysis, the content-related qualitative analysis of customer data focuses on the substance by identifying specific information within the textual data themselves (Mayring and Fenzl 2014). Therefore, the aim of the analysis and the context of the situation are interactively linked (Guba and Lincoln 1994; Lincoln and Denzin 1994). The computer-assisted analysis of textual data to identify specific patterns within large text collections to predict future data is described as text-mining (Feldman and

Sanger 2007; Heyer et al. 2006; Murphy 2012). The most important examples of usage in this field are sentiment analysis and classification as well as clustering the three of which are explained in section 2.2.

2.1.3 Hybrid Analysis

The combination of qualitative and quantitative analysis methods is widely used in research due to the fact that mixing these methods results in a more accurate and complete depiction of the phenomenon under investigation (Tashakkori and Teddlie 1998; Patton 1990; Johnson and Christensen 2000; Johnson 1995). Correspondingly, in different research fields, combinations of qualitative and quantitative analysis methods were successfully applied.

- The term triangulation refers to a combination of multiple methods in the study of the same object (Webb et al. 1966; Denzin 1978; Campbell and Fiske 1959). The argument was to use more than one method in the validation process to reduce variances due to the method (Campbell and Fiske 1959; Jick 1979). Accordingly, triangulation was often used as an instrument for validating and cross-checking results especially by combining multiple techniques within a given method (e.g., multiple scales or indices in survey research) (Jick 1979). However, triangulation could also enrich the understanding by allowing for new or deeper dimensions of the phenomenon to emerge (Jick 1979). This kind of triangulation mixes different types of methods for cross-validation when the methods found are congruent and yield comparable data (e.g., the effectiveness of a leader can be studied by interviews, observations and performance records). It forces the researcher to question the mixed method results and to find a logical pattern. Therefore, the "between-method" triangulation aims to test the degree of external validity, while triangulation "within-methods" essentially support-cross checking for internal consistency or reliability (Jick 1979).
- (Johnson and Turner 2003) refer to them as intermethod mixing or mixed method research (Johnson et al. 2007), meaning that quantitative and qualitative methods (e.g., interviews, tests, observations) are employed for a single study to address one's research question(s) (Johnson et al. 2007). According to Jonson/Turner, the fundamental principle is to mix methods in such a way that has multiple (divergent and convergent) complementary strengths and non-overlapping weaknesses (Johnson and Turner 2003), which means in simple terms the aim for mixing the methods is to compensate the weaknesses of one method with the strengths of another one.

In scientific literature, not only the combination of data analysis methods to improve the validity and reliability of the data were discussed but also the value of multi-method approaches for other fields received significant attention.

- (Gable 1994) demonstrated the usefulness of combining research methods in IS research based on a reference study. In doing so, he integrated a case study with a survey into a larger, more complex research design and identified benefits of case study findings from the reference study for subsequent model building and triangulation of results (Gable 1994). He supports the argument of (Kraemer

1991) that survey research is greatly improved when used with other qualitative research methods.

- In process-oriented quality management (cf. (Stracke 2006)), companies have combined established quality management methods, such as Lean Management or Total Quality Management (TQM) (cf. (Womack and Jones 2005; Karuppusami and Gandhinathan 2006)), with upcoming approaches like Six Sigma (cf. (Pande et al. 2014; Snee and Hoerl 2003)) in the recent past. Hence, the strengths of the newly risen quality methods could be exploited without having to abrogate those approaches (e.g., TQM) that are already widely-used within companies (cf. (Pfeifer et al. 2004; Bendell 2006; Black and Revere 2006)). Considering the interplay between quality management methods, different approaches may either presuppose their mutual application (conditional interdependency), complement each other during application (complementary interdependency), substitute each other (substituting interdependencies) or produce contradictory solutions (rivalling interdependencies) (cf. (Bruhn 2013; Johannsen 2017)).
- Likewise, in Method Engineering, researchers substantiate the value combining different information systems development methods to construct a so-called situational method (cf. (Brinkkemper 1996; Tolvanen et al. 1996; Ralyté et al. 2003). Since it has so far been preferred to develop a new method for each occurring problem, the potential of already existing methods was not exploited, and by putting up with unnecessary double applications, the (already) high number of methods was constantly growing. To counteract this tendency, approaches were developed in Method Engineering that support the construction of new methods based on already existing ones. The main arguments are the achievement of a higher flexibility due to multiple combinations and a higher quality since relevant results and experiences from completed projects find their way into the new ones. In view of the aim to construct situational methods, researchers separated different influencing factors, which are caused by the project type (specific characteristics of software development project, e.g., initial development) and the context (e.g., environmental contingency factors) and which have to be considered during the construction. More, they differentiate certain patterns to construct a method (e.g., situational selection and orchestration of method(s) (fragments) vs. configuring one single base method).

The use of complementary methods is generally thought – as confirmed by all above-mentioned examples – to lead the investigation to more valid results either by extending the investigation’s perspectives or by uncovering new or deeper dimensions. This rests on the premise that the weaknesses in each single method will be compensated by the counter-balancing strength of another one (Jick 1979). Additionally, positive effects can be achieved by reusing approved methods and considering past experiences in a systematic way. Since combining methods is time-consuming and compensation relations between methods are not always obvious, a multi-method approach is not without some shortcomings and may not be suitable for all research purposes (Jick 1979). The selection of the appropriate methods in combination needs to be carefully justified and made explicit with regard to the definite research aim. Based on the findings in Method Engineering, additional influencing factors such as context and project type should also be considered.

2.2 Techniques of automated Data Analysis

2.2.1 Sentiment Analysis

Sentiment analysis deals with the analysis of *"people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions"* ((Liu 2012), p. 415). Consequently, automated sentiment analysis works on specific texts and is an interdisciplinary research field, in which a variety of publications in the areas of Natural Language Processing, Text Mining, Web Mining and Information retrieval exist (Liu 2012). Approaches with reference to sentiment analysis can be categorized into three different classes. At first, document-based approaches aim towards the classification of the sentiment of a whole text corpus, for example newspaper articles. The second category focuses on sentence-based approaches, which analyze whether a single sentence can be classified as having a positive, negative or neutral sentiment. The third category considers aspect-based approaches, focusing on entities and their aspects (Vohra and Teraiya 2013; Feldman 2013; Liu 2012). As (Zhao and Rosson 2009) state that the specific peculiarity of Social-Media data lies in the shortness of the posts (e.g., 140-character limit on Twitter). Therefore, sentence-based approaches are preferentially used when it comes to the sentiment analysis of Social-Media.

In literature, five different procedures for sentence-based approaches are discussed: namely dictionaries, corpus-based approaches, syntactic patterns, artificial neural networks and treebanks (Medhat et al. 2014). When using dictionaries, the sentiment of each entity (e.g., each word) from a text is classified into a positive or negative class using dictionaries. The dictionaries annotate opinion-carrying words. The sentiment of the whole text is determined by considering the sum of the combined scores of all its entities (Turney 2002; Kundi et al. 2014). Corpus-based approaches determine the sentiment based on a domain specific text corpus regarding the context of the sentence, which can be recognized by particular adverbs (Liu 2012). Treebanks disassemble the sentence into a hierarchical grammatical structure (Turney 2002; Sadegh et al. 2012). Artificial neural networks consist of parallelly operating units (neurons) to classify the sentiment of a sentence. The words that need to be classified traverse the network through weighted branches. The network can be trained by adjusting the weights of the branches (Sebastiani 2002).

2.2.2 Classification

Classification describes supervised analysis techniques, which provide the automated mapping of data and use labeled training data to determine the affiliation towards previously defined categories (Feldman and Sanger 2007; Heyer et al. 2006). Typical approaches in the research field of classification are k-nearest-neighbor (Cover and Hart 1967), naïve bayes (NB) respectively multinomial naïve bayes (MNB) (McCallum and Nigam 1998; Tuarob et al. 2014) or support vector machines (SVM) (Gunn 1998)). Focusing on the analysis of large data sets with specialized event models such as Social-Media posts, SVM and NB/MNB deliver convincing results (Jin et al. 2013; Kibriya et al. 2004; McCallum and Nigam 1998; Tuarob et al. 2014). The classifier implements the NB algorithm for multinomially distributed data. This NB variant is often used within the classification of textual data. Especially when handling a large amount of data, according to (McCallum and Nigam 1998), MNB achieves better results than NB (Tuarob et al. 2014).

2.2.3 Clustering

In contrast to classification, clustering describes unsupervised analysis approaches, which focus on the assembly process of data to achieve automatically defined homogenous groups by identifying statistical structures and patterns (Dayan 1999). Clustering approaches like k-means (MacQueen 1967), expectation maximization (Dempster et al. 1977) or agglomerative hierarchical clustering (Tan et al. 2005) renounce a reduction of dimensionality and try to group matching elements of the dataset based on their structure (Feldman and Sanger 2007; Heyer et al. 2006). The resulting clusters are derived directly from the structure of the data themselves (Feldman and Sanger 2007; Heyer et al. 2006). A common distinction between different types of clustering is whether the set of clusters is nested or not. The former is called hierarchical clustering, in the latter case partitioning clustering. Hierarchical clustering means clusters can also have subclusters, whereas partitioning clustering does not (Tan et al. 2005).

3 Procedure of the Research

The aim of our research is to create new artifacts (a hybrid analysis approach and a corresponding software tool) based on the guidelines of Design Science Research (DSR) because DSR provides clear procedures to tackle identified problems by designing and constructing an appropriate solution for them (Hevner et al. 2004). In this respect, we followed (Sonnenberg and vom Brocke 2012) and distinguished between an ex ante and ex post evaluation to cope with the great importance of evaluating new artefacts in DSR. Hence, we split the process of evaluation and separately performed an evaluation (1) of the problem, (2) of the artefact design (concept for the hybrid analysis approach) and (3) the constructed artefact (software tool). (cf. (Sonnenberg and vom Brocke 2012)). The mentioned research process is shown in Figure 1.

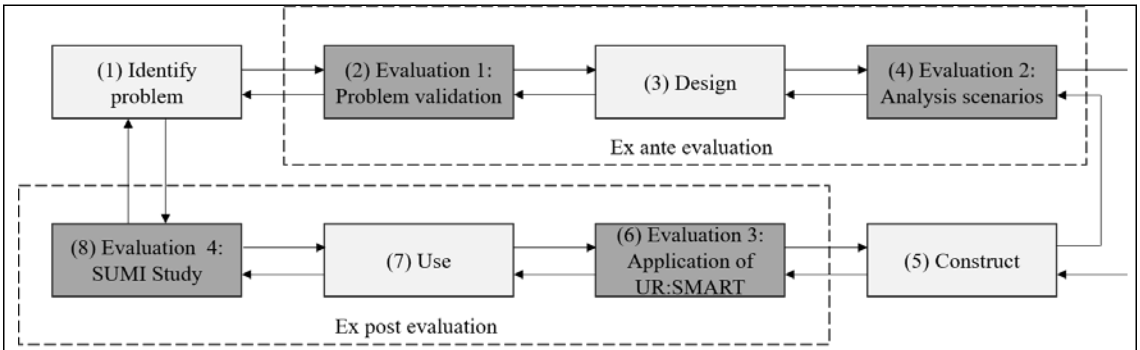


Figure 1: Procedure of the research (Sonnenberg and vom Brocke 2012)

To identify the problem in step **(1)**, we drew upon the fact that efficient tools and methods need to be provided in order to tackle the rising amount of digital data for gaining deeper insights into the customers' needs (for details see section **Fehler! Verweisquelle konnte nicht gefunden werden.**). Thus, we conducted several interviews with cooperating partners to gather requirements on corresponding tools as well as current limitations of their analysis efforts in step **(2)**. By consolidating the conducted interviews, we identified the core analysis functionalities to be implemented in the tool, which was the starting point for the design of the artefact in step **(3)**. The artefact design comprised several functions (e.g., classification of data, sentiment analysis) and a concept to combine these functions (hybrid approach). To prove the artefact design, we developed different scenarios based on the conducted interviews in step (2) as "evaluation 2" in step **(4)**. In step **(5)**, the software tool (UR:SMART) was constructed and evaluated in step **(6)**. For the "evaluation 3", we applied our software solution in a real case with a financial institute and demonstrated its applicability and usefulness. UR:SMART is still used by this financial institute and also by further cooperation partners (step **(7)**). Considering the final evaluation 4 (step **8**), a SUMI usability study was performed as a first step to prove the tool's broad applicability.

4 Problem Identification and Evaluation 1 (step 1 & 2)

To evaluate the problem statement as described in the introduction (step 1), we conducted interviews with eleven companies operating in both B2C and B2B sectors to explore the current state of the art of Social-Media analysis as well to uncover specific problems occurring in practice. First, we asked whether the companies were using automated tools to analyze their Social-Media data. Second, the specific aim and field of use of each analysis was studied (e.g., on products, brand building, reputation or recruiting). Another object of investigation was the analysis method, describing the way in which Social-Media content was being analyzed (either manually or in an automated way). Furthermore, limitations of the tools and desired enhancements of their analysis functionality were also considered.

By doing so, we were able to discover several problems as well as limitations faced by these companies concerning Social-Media analysis. Overall, it became evident that the efforts required for a manual data analysis are still a big challenge throughout all sectors independent of the company size. Most companies rely on manual efforts for data analyses, as only 36% of the companies interviewed use a Social-Media analysis tool (e.g., Brandwatch, Iconsquare, SentiOne, etc.) whereas the rest purely relies on the integrated analytics functionalities of the single Social-Media platforms (e.g., Facebook Analytics), which are very generic and limited.

Regarding the field of use of the Social-Media activities, most companies put an emphasis on brand and reputation building as well as improving their products based on the "voice of the customer" (Pande et al. 2014). In this regard, the desire of gaining more detailed insights into the customers' opinions extending the capabilities of a manual analysis became evident during the interviews. Several questions such as, *"how can product criticism be automatically detected for specific product improvements?"* or *"how can a shitstorm be detected, so that it does not result in a loss of reputation?"* arose, which only can be answered with the help of an automated analysis approach.

5 Design of UR:SMART and Evaluation 2 (step 3 & 4)

Prior to the design of our tool, we conducted multiple interviews with eleven companies ("step 2" – "evaluation 1" in Figure 1), operating in both B2C and B2B sectors to identify their needs as well as limitations regarding Social-Media analysis (see section 4). We ended up with several functionalities as shown in Figure 2, which guided the upcoming design phase of our research.

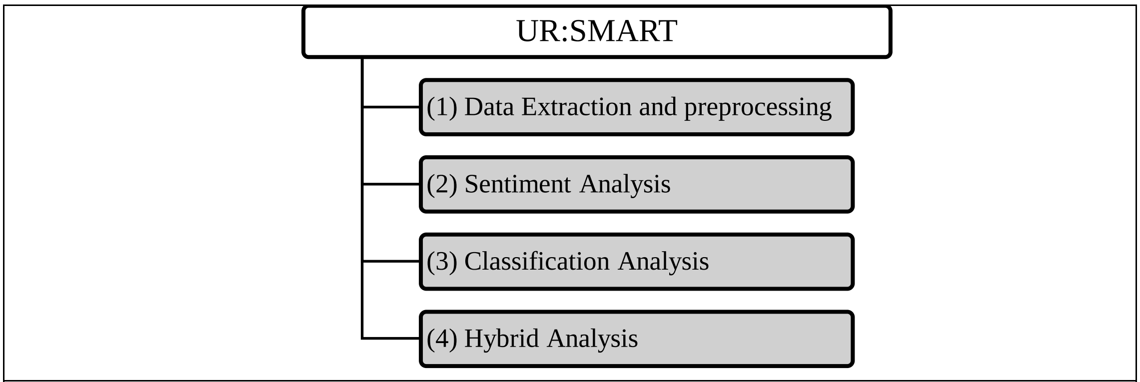


Figure 2: Functionalities of UR:SMART

5.1 Design of UR:SMART (step 3)

In the first step of the design of UR:SMART, it was necessary to conceive an overall data model for the underlying database (see Figure 3) to ensure consistent data formats, the free combination of various analysis methods as well as suitable data treatment for every analysis combination.

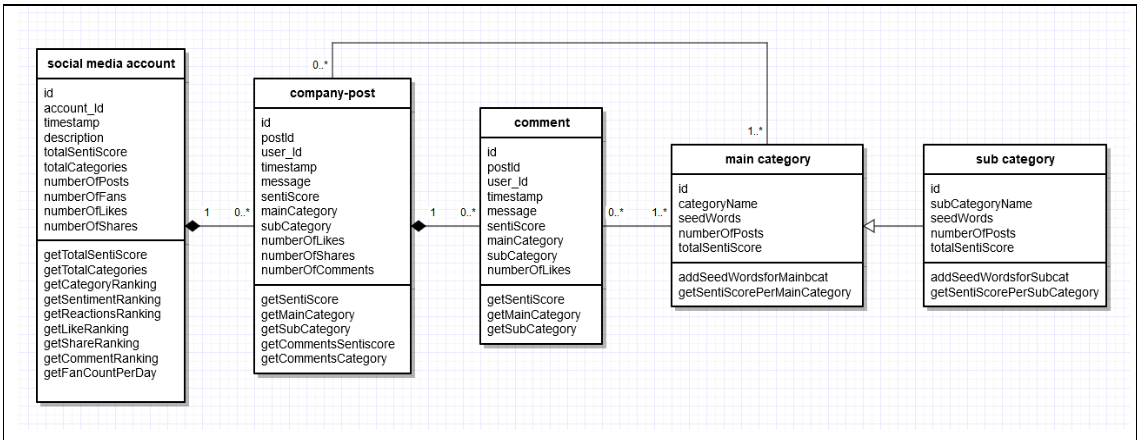


Figure 3: Class model

Before considering various analysis methods, Data Extraction and Preprocessing (1) was the initial step, as these techniques are the basis of all further analyses. Text data needed to be extracted from various sources e.g., Social-Media channels such as Facebook and Twitter and converted into a consistent data format for an effective further processing (Akaichi et al. 2013; Feldman 2013). Simultaneously, Data Preprocessing, including various techniques such as tokenization, stop word reduction, stemming and normalization, was being performed to prepare the data for further analysis (Aggarwal and Zhai 2012). Afterwards, the extracted textual data needed to be further analyzed.

During the design phase, a literature review regarding sentiment analysis (2) was conducted to identify relevant approaches and algorithms suitable to analyze the sentiment of customer posts (cf. (Vom Brocke et al. 2009)). An investigation of 196 relevant publications led to total of 17 potentially suitable approaches. Due to the characteristics of Social-Media posts (e.g., shortness, emojis, company specific language), dictionary-based approaches represent a generally accepted approach for the automated sentiment analysis of such textual content (Feldman 2013). The sentiment of every text element is determined. Depending on the sentiment of each single token (e.g., word, emoticon), an aggregated sentiment-value is calculated with the value indicating a positive (> 0), neutral (0) or negative (<0) post (Feldman 2013).

During the design phase for the function classification analysis (3), 130 relevant publications were examined during a second literature review, leading to nine potentially suitable approaches for data classification. To provide the capability of adapting the classification to individual or fast changing contexts (e.g., upcoming campaigns or fast changing trends), UR:SMART focuses on the assembly of data towards predefined classes (Feldman and Sanger 2007; Heyer et al. 2006; Read et al. 2012). Therefore, a set of generally valid main categories (e.g., service, product or campaigns), independent of company or branch specifics, were worked out in cooperation with our practice partners. Additionally, to handle the individual topics and needs of each company, (corresponding) subcategories for each main category can be acquired. These subcategories are highly specialized and tailored towards the companies' specifics as well as to the aims of their Social-Media channels.

Additionally, UR:SMART includes a hybrid analysis approach (3) to combine the presented analysis methods with quantitative data (e.g., likes, shares, comments etc.) from Social-Media channels, to enhance the analyses even further. A company post itself was considered as an object, including various attributes (e.g., ids, timestamps, message, sentiment, category, reactions etc.) and connections towards other corresponding classes (see Figure 3). Amongst general attributes as for instance "id", "timestamp" or "message", every company-post includes its own qualitative and quantitative attributes, namely "*sentiScore*" for the underlying sentiment, "main- and subcategory" for the associated category (e.g., product or service) as well as the number of likes, the number of shares and the number of comments (reactions of customers). A comment includes these attributes, too, with the exception of "shares" and "comments", which are not available for comments. In terms of classification, the class model offers the classes "*mainCategories*", which are connected to a company post or comment, and also "*subCategories*", an extension to specify categories in a more exact way.

A further important step of the design phase focused the design of the GUI of UR:SMART (see Figure 4). For that purpose, we used wireframes to come to a first shot of the GUI. The intention was to provide an intuitive navigation with a limited set of buttons and elements only. Hence, in the upper area of the screen (see Figure 4), the selection of the Social-Media channels to be analyzed was supposed to be made along with an indication of the aspired timeframe of the analysis. Then, the results were to be shown immediately with separate graphics being used for the sentiment analysis as well as the classification of posts (see lower screen of Figure 4).

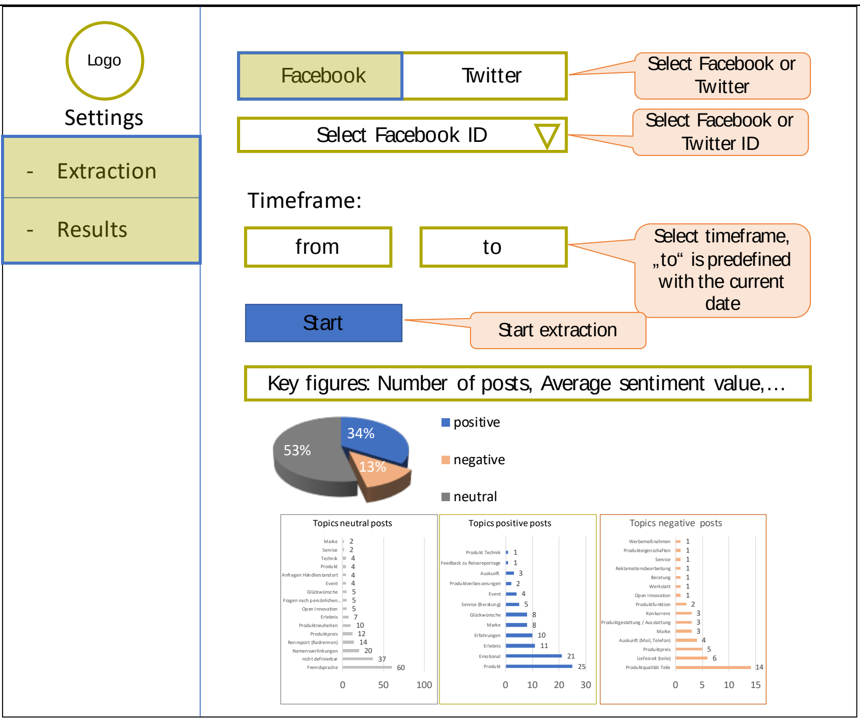


Figure 4: Wireframe for the design of the GUI

5.2 Evaluation 2: Analysis Scenario (step 4)

For the evaluation of our design, we cooperated with a total of five companies from various industries having different target audiences. Following the principles of agile software development (e.g., SCRUM), the purpose of the collaboration at this stage was to receive immediate feedback on each increment of the software tool (cf. (Schwaber and Beedle 2002)). The feedback was used to revise and enhance the corresponding increment in a subsequent design cycle to finally come to a first shot of UR:SMART.

Based on the questions emerging from the interviews that had been conducted as described in section 4 as well as on the design of our solution UR:SMART, we derived two specific scenarios for the application of Social-Media content analysis to answer the emerged questions by using hybrid analysis methods: “Product Commendation/Criticism” as well as “Topic Identification”. The scenarios were developed, considering those topics and requirements mentioned most often by the interviewees so that they could be taken to represent common expectations on Social-Media analysis and typical use cases that are relevant in practice, as well as to tackle the aforementioned questions. Further, only those scenarios that necessarily involved a hybrid analysis were chosen, i.e., the application of two or more different analysis steps in combination. The resulting scenarios together with their corresponding analysis steps within the scope of a hybrid analysis are described in the following. The design of our solution needed to address these scenarios accordingly to justify our design specification (see section 4).

5.2.1 Product Commendation/Criticism

In the first scenario – "Product Commendation/Criticism" – a company seeks to learn whether its products and services are appreciated by (potential) customers or not. One advantage of using Social-Media analysis for this purpose is that information gathered from Social-Media platforms usually does not only reflect the opinion of existing customers but also of other interested parties or the general public. The initial step of an analysis to answer questions such as *"which products are praised/criticized most and why?"* is to perform a sentiment analysis on all available Social-Media posts to identify and extract those posts that entail a positive or negative sentiment. Depending on whether product commendation or product criticism is of interest, either only positive or only negative posts are referenced in a further analysis, decreasing efforts for extracting insights from the data. To identify specific products affected by commendations or criticism, the second step in this scenario is a classification of the remaining posts according to product categories. In this context, the categories have to be determined by each company individually. To properly address complex product families and to answer more precise questions as for instance *"which feature of product X gets a negative feedback?"*, this step can be extended by using one or more subcategories (e.g., different versions of a product or specific product features). That way, it is also possible to get valuable information on a company's product offerings and to address content-specific aspects. Posts that cannot be assigned to any given (sub)category unambiguously are allocated to the category "miscellaneous". When reaching a significant scope of posts assigned to this category, the data may be investigated more closely to define new categories. The final step in this scenario is a quantitative analysis of the classified posts to answer additional questions such as *"how severe is the criticism and how should the countermeasures be prioritized?"*. This step assesses, amongst others, data such as "Likes" and "Shares" that are related to the considered posts. That way, a better understanding of a particular commendation or criticism is enabled; especially it allows to estimate the severity of the criticism and to trigger possible countermeasures. For example, a negative post on a product that receives a high number of "Likes" or "Shares" indicates that many people share the negative opinion, an indicator that a quick response to fix the problem is required by the company. On the other hand, comments that do not get this much attention in terms of "Likes" and "Shares" can be considered as individual opinions and may be judged to be of lower priority. The described steps of the analysis as well as optional paths of this scenario are depicted in Figure 5.

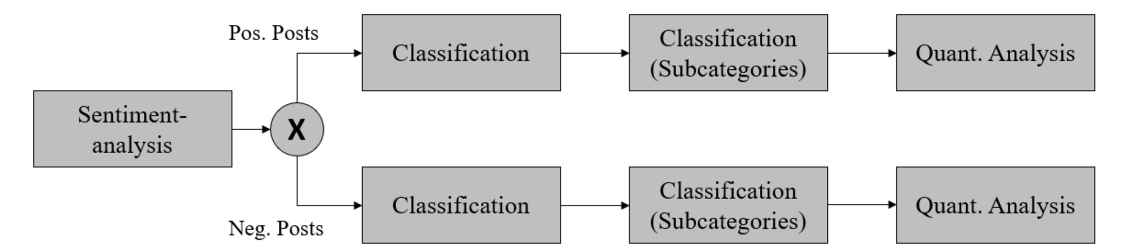


Figure 5. Scenario: Product Commendation/Criticism

5.2.2 Topic Identification

The purpose of the scenario "Topic Identification" is to detect those topics that are primarily discussed on a company's social networking website. Considering an organization's image, it is of special interest as to how a company, its products and services, managers or employees are mentioned in such discussions. This issue may bring up a vast range of potential topics and, hence, an exhaustive list of predefined categories cannot be provided in advance. For this reason, the first analysis step in this case is a clustering, which does not require any predefined categories but analyzes the Social-Media posts with the purpose to group them to clusters on the basis of content similarity (cf. (Bär et al. 2012; Mayring 2000)). Thus, all relevant topic areas can be detected, even if they may have been unknown up to this point. Topics of interest may be diverse ranging from a company's pricing model to employee friendliness or a company's ecological policy, to name but a few examples. After identifying the topics, a sentiment analysis of each cluster is performed to determine as to what extent the singular topics have a positive or negative connotation. In this regard, especially the ratio of positive to negative posts is an important indicator. The final step, similar to our first scenario, is the quantitative analysis of "Likes" and "Shares" associated with the posts in each cluster, to better assess the importance of the respective topic (see Figure 6).

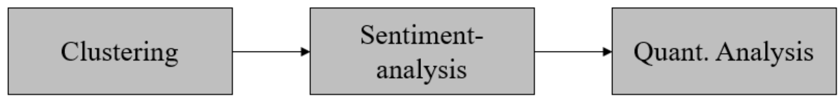


Figure 6. Scenario: Topic Identification

The second evaluation (evaluation 2) served the validation of our tool design that was described in section 5.1. Hence, two scenarios addressing practitioners' current needs for Social-Media analysis were derived. These scenarios were explicitly covered by the designed functionalities of UR:SMART, thus preparing the ground for the construction of the tool. With this in mind, our design could be assumed to be complete and correct (cf. (Sonnenberg and Brocke 2012)) regarding the intended fields of application.

6 Construction of UR:SMART and Evaluation 3 (step 5 & 6)

For the construction of the Social-Media analysis tool UR:SMART, we used the widespread programming language JAVA, to ensure high performance and provide standardized libraries and interfaces. The graphical representation of the results was implemented as a platform-indented web application.

6.1 Construction of UR:SMART (step 5)

The initial step for the construction of UR:SMART was to realize the Data Extraction and Preprocessing functionality, as these techniques are the basis of all further analyses. As a first step, tokenization decomposes all textual data into smaller parts, for example single words, and removes unneeded symbols and special characters (Carstensen et al. 2009). Additionally, stop word reduction eliminates words that do not carry opinions by using publicly available stop word lists (Angulakshmi and ManickaChezian 2014). Subsequently, a stemming process eliminates prefixes and suffixes, reducing all words to their stem or basic form (Akaichi et al. 2013). Finally, a normalization algorithm completes the step of *Data Preprocessing* and transforms all remaining text into lower case characters (Angulakshmi and ManickaChezian 2014).

For the construction of the sentiment analysis, we used the widely accepted implementation of a dictionary-based approach SentiWordNet 3.0. SentiWordNet 3.0 represents a lexical resource for an automated sentiment classification (Baccianella et al. 2010). However, SentiWordNet 3.0 only provides a lexical resource for English. To support German Social-Media posts as well, we used SentiWS, a German language resource for analyzing the sentiment of German texts (Remus et al. 2010). As SentiWS did not match the structural requirements of the SenitwordNet 3.0 approach, we adapted SentiWS by converting the structure of the German dictionary to fit the one of SentiWordNet 3.0 (Remus et al. 2010). Both resources contain lists of words carrying a positive or negative opinion, respectively. Despite the mentioned techniques, most approaches for sentiment analysis cannot handle some special content immediately (e.g., emoticons). Therefore, a feature extraction functionality considering the definition of feature types and the selection of specific features (e.g., emoticons, part of speech, sentiment-carrying expressions) is necessary (Selvam and Abirami 2013). Due to the frequent occurrence of these features in our datasets, we integrated specific dictionaries to meet certain characteristics (e.g., dialect or emojjs) of textual data. To establish a proper feature resource, we examined our dataset and extracted the most common features.

For identifying irony and slang, the dictionary was extended with expressions pointing to special events (e.g., product launch) of the branches considered. Further, we classified the occurring emoticons into positive and negative ones to identify the expressed emotions within the posts. The sentiment of each word (as well as each special text component) is expressed by the variable “*sentiScore*”, a number within a predefined range of [-2;+2], with a high number (near +2) representing a very positive and a low number (towards -2) a rather negative sentiment (Feldman 2013). Consequently, the overall sentiment of textual data is reportable and ascribed to the categories “strong positive”, “positive”, “neutral”, “negative” and “strong negative”. The gathered data is stored in a database and can be graphically displayed in pie charts and an ECG-like representation featuring a temporal scale of sentiment progression.

For the construction of the classification analysis in UR:SMART, we combined multinomial naïve bayes (MNB) with a dictionary-based seed word library to identify the category of textual data. This library includes specific seed words for all acquired main and subcategories and therefore allows an assignment of posts and comments to predefined (Zagibalov and Carroll 2008). The main category “product”, for example, is extended by the integration of several subcategories, including company-specific product lists, parts lists as well as product accessories. Starting from the preprocessed data, all words are analyzed regarding these seed words, enabling a strong customization of the classification. Additionally, by identifying similar words surrounding existing seed words, the seed word library is constantly enhanced by company-specific expressions (Liu 2012). As a result, topics that are currently popular amongst customers, e.g., within a Social-Media channel can be identified and graphically displayed. The results of the sentiment analysis and the assignment to the defined classes are then brought together by an overall view, featuring the most represented categories and subcategories within each sentiment section. Additionally, all underlying textual data are obtainable with the help of various sort and filter algorithms.

For the construction of the hybrid analysis, we implemented the consistent data model using an H2-mysql-database and ensured the data compatibility of the various analysis approaches by using predefined and documented data interfaces. Therefore, it is ensured that the input as well as output of every analysis method is standardized and that an individual combination of various analysis approaches is practicable. Additionally, it is possible to reduce the data size purposefully after every step, leading to a significantly faster analysis time. This deep integration of all supported analysis approaches allows a purposeful multidimensional analysis, which combines the described techniques in various ways to obtain more profound results and a deeper understanding of the underlying data. To identify several combinations and to evaluate their effectiveness within the analysis, we proceeded with an evaluation in the next section. Screenshots of UR:SMART are shown in Figure 7. The screenshots on the right show the results from a sentiment analysis as well as a classification of posts. On the left side, the mask to determine the posts to be extracted from Social-Media channels as well as a short excerpt of the post database, after the extraction has been completed, is shown.

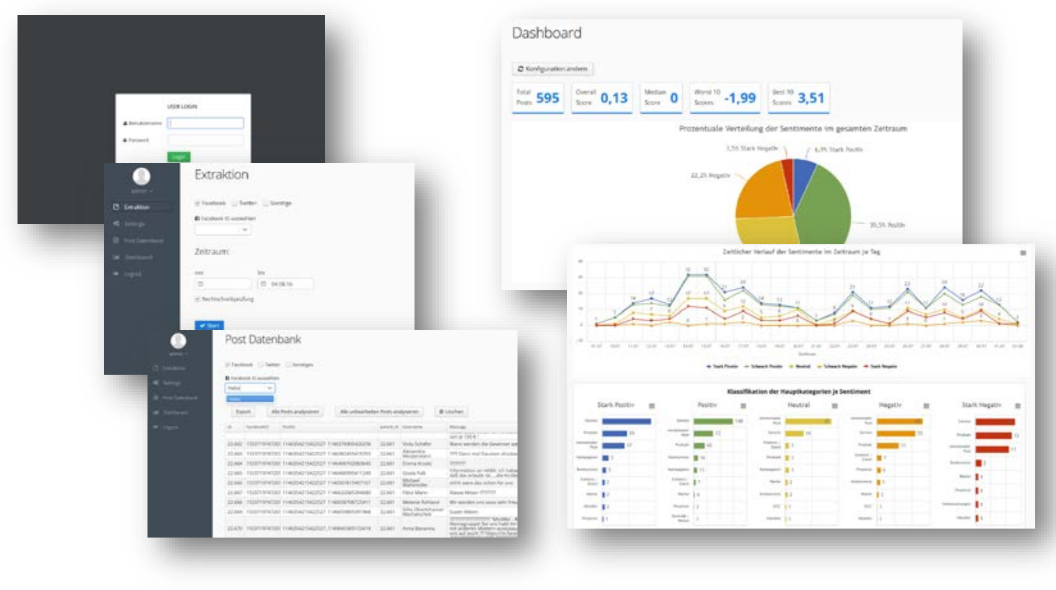


Figure 7: Screenshots of UR:SMART

6.2 Evluation 3: Application of UR:SMART at a cooperating Partner (step 6)

To gain valuable insights into the practical applicability (cf. (Sonnenberg and Brocke 2012)) of UR:SMART, we cooperated with a German local bank that has a focus on private savings, building society savings and credit business. As local banks in Germany are struggling with the market pressure exerted by online banks and the start-up driven fintech industry, they see a huge potential in assessing users' data to derive new insights by means of various analysis methods.

As a modern way to communicate with customers, the German local bank built up a Social-Media channel to familiarize their customers with this new form of interaction. More, the bank has continuously been striving to increase the user numbers and to foster users' Social-Media activity. To gather detailed insights into the partners' customer data, we extracted 635 datasets from their Facebook account, as Facebook is their prioritized Social-Media account, including the numbers of fans, posts, comments as well as the corresponding metadata (e.g., number of likes, number of shares and number of comments) for each entry from January 2017 until January 2018.

To validate UR:SMART (evaluation 3) and to present the results in a structured manner, we applied UR:SMART on this data set. Therefore, qualitative analysis methods (sentiment analysis and classification) was employed and a quantitative analysis was conducted. An overview of the results is shown in Table 1, which is structured as follows: First, the various categories, which were previously defined, are presented. The first column (“# of posts”) indicates the number of posts within each category, sorted by height. Next, the numbers of the corresponding “# of likes”, “# of shares” and “# of comments”, separated into the sentiments positive (+), neutral (O) and negative (-) are presented. As the performed analysis determines a sentiment score for every post including all comments, the columns “+ totalSentiScore” and “- totalSentiScore” show the average tonality of all posts (“# of posts”) assigned to the respective sentiment. Additionally, in the last column (“O - # of posts), the yet missing number of neutral posts, which do not include opinion-carrying words, is shown.

category	**# of posts**	**# of Likes (per sentiment)**			**# of Shares (per sentiment)**			**# of Comments (per sentiment)**			**+ totalSenti-Score**	**- totalSenti-Score**	**O**
		+	**O**	**-**	**+**	**O**	**-**	**+**	**O**	**-**	**(# of posts)**	**(# of posts)**	**(# of posts)**
Campaigns	89	4882	123	487	2716	20	46	10103	2	36	1,16 (80)	-0,43 (6)	3
Product	**46**	**1337**	**0**	**63**	**221**	**0**	**0**	**49**	**0**	**7**	**1,22 (40)**	**-0,43 (6)**	**0**
Service	44	1180	0	22	251	0	67	56	0	9	1,06 (41)	-0,47 (3)	0
Brand	43	1352	29	83	245	9	67	51	0	8	1,27 (36)	-0,37 (4)	3
UGC	32	593	44	101	71	14	18	17	0	3	1,13 (27)	-0,90 (2)	3
Technology	23	739	35	2	116	12	0	32	0	2	1,23 (20)	-1,15 (2)	1
Event	19	253	9	61	43	2	0	4	0	1	1,06 (15)	-0,18 (2)	2
Staff	14	708	115	0	87	18	0	33	2	0	1,22 (12)	-	2
Emotional	12	318	0	2	47	0	0	14	0	2	1,39 (10)	-1,15 (2)	0
Thanks	9	444	0	0	40	0	0	45	0	0	1,68 (9)	-	0
total	331	11806	355	821	3837	75	198	10404	4	68	Ø 1,24 (290)	Ø -0,64 (27)	14

Legend: + = positive / - = negative / O = neutral; bold cells hint at important findings

Table 1: Overall results

To identify commendation or criticism towards specific products, first (1) a sentiment analysis was performed, which resulted in a total of 176 positive posts (avg. score of +0.73) as well as 93 negative posts (avg. score of -0.43), indicating a huge amount of positive posts on our cooperating partners Facebook site (see table 2). The variables “+ totalSentiScore” and “- totalSentiScore” have values within the predefined range of [-2;+2]. Although this information is useful to measure customers’ overall mood, a clear hint at specific commendations or criticism concerning products was still missing. Therefore, in a second step (2), a classification was performed to identify all posts that can be assigned to the category “products”. This category was previously defined by analyzing the product portfolio of our cooperating partner. As a result of this combined analysis, we could identify 40 positive posts (avg. score +1.22) as well as six negative posts (avg. score -0.43) directly related towards the category “product”, indicating that most customers are very satisfied with the products, although there is occasional criticism. Even though this information is interesting, a clear hint at specific products was still missing. Therefore, as a third step (3), an additional classification into subcategories was performed, resulting in a fine-grained overview (see Table 2).

subcategory (of product)	**# of posts**	**# of Likes (per sentiment)**			**# of Shares (per sentiment)**			**# of Comments (per sentiment)**			**+ totalSenti-Score**	**- totalSenti-Score**
		+	**O**	-	+	**O**	-	+	**O**	-	**# of posts**	**# of posts**
checking account	25	685	0	10	14	0	0	6	0	0	1,09 (23)	-0,31 (2)
wealth creation	9	537	0	8	16	0	0	8	0	6	0,51 (8)	-0,01 (1)
creditcard	7	58	0	36	6	0	0	2	0	0	0,90 (4)	-0,57 (3)
loan	3	27	0	0	180	0	0	31	0	0	1,21 (3)	-
insurance	2	10	0	9	5	0	0	2	0	1	0,71 (1)	-1,58 (1)
total	46	1337	0	63	221	0	0	49	0	7	1,22 (40)	-0,43 (6)

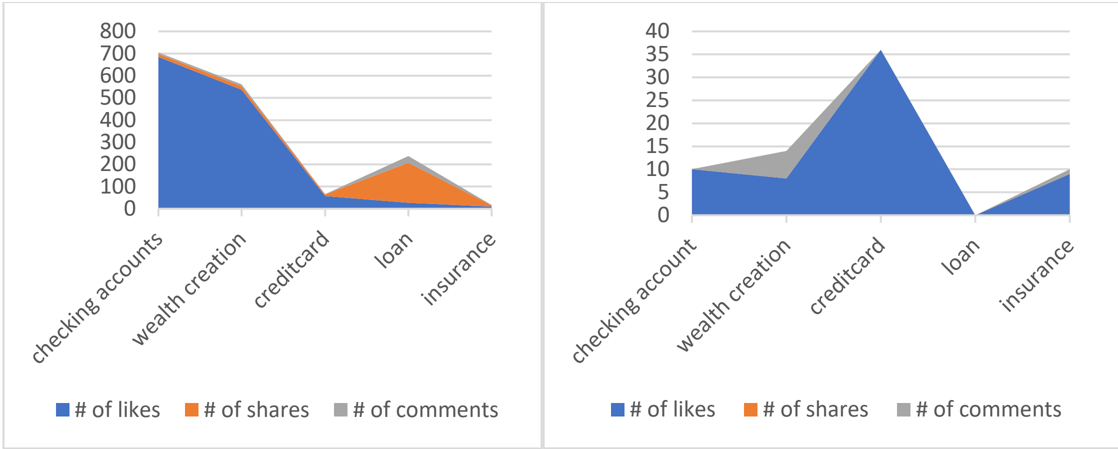
Legend: + = positive / **-** = negative / O = neutral; bold cells hint at important findings

Table 2: Detailed results subcategories "product"

After the classification into subcategories was done, it became obvious that customers were rating products such as checking accounts, wealth creation as well as loans as positive (see Table 2). For instance, "checking" accounts is one of the main products of our cooperating partner, offered for free in contrast to competitors, resulting in a high avg. positive score of +1.09. Additionally, wealth creation and loans are important business fields. As the local bank offers various saving plans as well as financing plans for both private and business constructions, the affiliated scores were positive as well (+0.51; +1,21).

In contrast, it also became evident that products such as credit cards (-0.57) or insurances (-1.58) are discussed in a more critical way. On the one hand, customers complain about credit card fees and missing functionalities (e.g., wireless payment as well as mobile payment) and on the other hand also doubt the necessity of specific insurances.

At first glance, this criticism seems negligible based on the rather low numbers of negative posts. Indeed, also single posts can cause tremendous impact by generating word of mouth within Social-Media. To ensure the results and gain an even better understanding of the findings, a quantitative analysis was performed as a last step (4). As part of this analysis, not only the number of posts with the corresponding sentiment and assigned categories were considered, but also the customers' reactions (likes, shares as well as comments) towards all posts. Therefore, it was now possible to determine the specific influence of posts within the Social-Media channel or the community in general. Figure 8 shows the number of positive/negative reactions belonging to various subcategories of the general category "products".



Positive reaction (subcategories “product) *Negative reaction (subcategories “product”)*

Figure 8: Positive/Negative reactions subcategories “products”

When comparing this extended hybrid data analysis with the previous results from step three, it now became apparent that the topic “wealth creation” had received a high proportion of positive reactions (537 likes, 16 shares, 8 comments) for example, even though this topic was accountable for only 20% (8 out of 23) of all posts in this category. The same held true when looking at “loans”. Although only being accountable for less than 1% of all positive posts, 180 shares (more than 80% of all positive shares) were attributable. In contrast to this positive customer feedback, it was also possible to enrich the negative criticism by using the extended hybrid data analysis. At first glance, criticism concerning “credit card” seemed balanced with three negative posts (avg. score -0.57) compared to four positive posts (avg. score 0.90). But when taking a closer look at negative reactions towards the subcategories for “products”, it was striking that one of the key sources of criticism occurred in the subcategory “credit card” (about 57%), mainly because of high fees and missing mobile payment solutions.

Summarizing, based on the applied hybrid approach, our cooperation partner identified various positive rated product categories, which are potential candidates for future marketing as well as Social-Media campaigns based on their popularity in this research. Additionally, also negative rated categories such as “credit card” or “insurance” were identified and are being reworked to better match the customer needs.

Overall, the application of UR:SMART on our cooperating partner’s data shows that the combination of various analysis methods not only enhances the richness of the findings, but also allows to identify new potential sources of commendation and criticism.

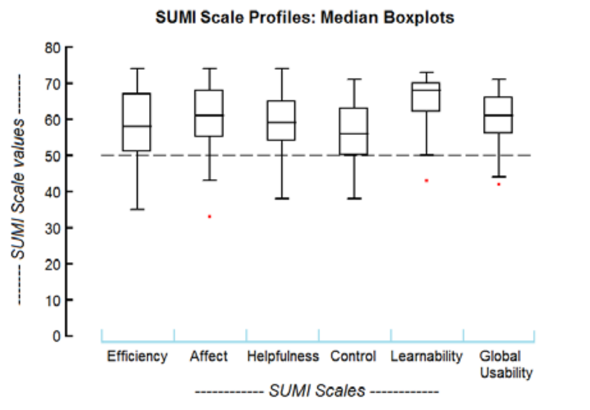
7 Use and Evaluation 4: SUMI Usability Study (step 7 & 8)

The fourth evaluation step according to (Sonnenberg and Brocke 2012) concerns the far-reaching applicability and usefulness of an artifact in practice. Currently, the tool UR:SMART is in use at the five collaboration partners that accompanied the design and construction steps. The long-term results of this practical application will be acquired in the months to come and present an important component of “evaluation 4”.

However, as a further step of such a comprising evaluation, we strived for extending the user base to see whether a larger user set would confirm the positive feedback gained from evaluation 3 (see section 6.2) or not. For that purpose, we assessed the tool's usability in a larger laboratory experiment by means of a SUMI study (cf. (Wohlin et al. 2012); (Kirakowski and Corbett 1993)). The SUMI questionnaire – as designed by the Human Factors Research Group (HFRG)[9] at the University College Cork – comprises 50 different items (e.g., "I feel in command of this software when I am using it") to assess users' satisfaction with a software according to the dimensions "efficiency", "affect", "helpfulness", "control", and "learnability" (Kirakowski and Corbett 1993).

72 Master degree students in business administration and business information from a German University participated in our usability study of UR:SMART. The students were supposed to analyse the comments on the Facebook site of one of our cooperation partners over a freely selectable period of time of three months. The students could earn extra credits for the course, which was an incentive to take the experiment seriously (cf. (Wohlin et al. 2012)).

The students attending the experiment were made familiar with UR:SMART and were handed out accompanying training material. The data from the questionnaires was entered into the SUMI online form and the results of the study were made available by the HFRG (see Figure 9).



	Mean	St Dev	Median
Global	60.31	6.65	61.0
Efficiency	58.83	9.81	58.5
Affect	60.46	8.43	61.0
Helpfulness	58.60	7.71	59.0
Control	56.33	7.69	56.5
Learnability	65.40	6.44	68.0

Dimensions of the SUMI questionnaire (cf. 'http://sumi.uxp.ie/' or '(Sauro and Lewis 2012)'):

Efficiency: This dimension deals with the degree as to which the software supports the user in conducting tasks.

Affect: The user's emotional attitude towards the software is captured.

Helpfulness: This dimension rates the degree as to which the software is self-explanatory.

Control: The circumstance as to whether users are able to handle the software or not is judged.

Learnability: Users assess the efforts required for learning to handle the software.

Figure 9: Results of the usability study according to the SUMI dimensions (graphics provided by the HFRG)

[9] http://sumi.uxp.ie/ (last access: 2019-04-28).

The global scale of our tool (60.31) was clearly above the value of “50”, which is considered to be the average value according to the SUMI reference database (cf. (Kirakowski and Corbett 1993; Arh and Blažič 2008; van Veenendaal 1998)). More, UR:SMART was judged to purposefully support the analysis of Social-Media data (dimension “efficiency” – median “58.83”) and its graphical user interface was considered attractive by users (dimension “affect” – median “60.46”). More, the tool was seen as rather self-explanatory (dimension “helpfulness”), easy to control (dimension “control”) and only little effort was required to get acquainted with the tool’s functionalities (dimension “learnability) (see Figure 9).

To sum up, the usability study led to encouraging results and the tool was clearly judged to purposefully support Social-Media analyses.

8 Discussion and Contribution

Starting with the drawbacks of current Social-Media analysis efforts, either taking a qualitative or quantitative perspective, this paper introduces a hybrid analysis approach integrating both these aspects. Based on real-world problems as well as characteristics concerning the analysis of Social-Media data, which we identified by interviewing practitioners, beneficial application scenarios, in which the hybrid approach outperforms individual qualitative and quantitative analysis, were introduced. In doing so, it became evident that the development of a universal analysis approach suitable for all use cases is not effective, as every company pursues individual aims of investigation (e.g., measuring the success of a Social-Media marketing campaign or identifying specific user groups such as influencers or key users). To ensure the general applicability as well as the individual customization of our solution, we developed a software solution that allows the individual and purposeful combination of standardized analysis methods (e.g., sentiment analysis, classification etc.) and reduces the tradeoff between generalization and individualization. In section 5.2, two specific combination scenarios are highlighted, though the extension of various new analysis methods as well as analysis scenarios is fairly easy by the usage of standardized interfaces.

Artificial Intelligence (AI), which describes scalable machine learning techniques, such as recent unsupervised learning techniques for analyzing unstructured data, is a trending topic in recent research and receives more and more attention in digital transformation initiatives (cf. (Henning 2018)). Though the promising unsupervised learning methods are currently working as a so-called "black box", as the analysis itself as well as decision-making channels are hidden from the user and cannot be actively influenced. Because of the compliance required for business decisions, however, it is necessary that these remain transparent and comprehensible, especially when handling special context as for instance slang, emojis or branch-specific language. In addition, AI systems are extremely complex in terms of development, training and deployment, and therefore less suitable for SME target audiences. For these reasons, our solution favors the integration of lexicon-based approaches to ensure extensive and flexible adaption of the analysis approaches towards company-specific as well as language-specific characteristics.

Although, processing speed as well as memory performance and sizes have grown steadily over the past few years, the reduction of processing expenditure is still a major target when it comes to data analysis, particularly when using scalable processing as a service. Therefore, defining a specific scope of the analysis is a significant step. With our hybrid solution, it is possible to purposefully filter the amount of data after every analysis step and thus reduce the amount of data to the necessary minimum.

8.1 Contribution for Practice

The research brings up several contributions for practice. First, the efforts and resources required for performing Social-Media analysis that is introduced by more and more companies in the course of their digitalization efforts can be significantly reduced by our solution through an automated and target-oriented analysis. Practitioners may stick to the identified scenarios (see section 5.2) to conduct analyses that truly lead to beneficial insights while reducing the amount of data after every analysis step. Hence, our solution strongly contributes to a better understanding of the Social-Media data, with the generation of insights from large data sets being an issue many companies are still struggling with these days (cf. (Ried 2019)). Based on the findings from an automated Social-Media data analysis, process improvement efforts may be triggered or countermeasures taken to avoid customer dissatisfaction amongst others.

Second, the application of a hybrid Social-Media analysis approach generates beneficial insights that are superior to those findings that will be received from either performing a qualitative or a quantitative analysis. For instance, by the target-oriented combination of analysis approaches, it is not only possible to cluster user suggestions on how to improve the product or service portfolio by topics and sentiment (qualitative analysis), but also to easily deduce a prioritization of these propositions, e.g., based on “Likes” and “Shares” (quantitative analysis). That way, employees receive a more profound and individual foundation for decision-making based on the information captured in Social-Media posts.

Third, the software tool facilitates the formulation of entrepreneurial initiatives triggered by Social-Media data. These may be process improvement initiatives that are defined against voice of the customer statements extracted from Social-Media channels for instance. As mentioned above, Social-Media data provides fast access to customers’ current moods and expectations. In addition, reactions to Social-Media marketing or advertising campaigns become evident (cf. (Castronovo and Huang 2012)). Hence, campaigns favorably received by consumers (e.g., prize competitions or special offers) often entail discussions in the Social-Media channels. Based on the topics captured in these posts, which are recognized by our tool, practitioners may purposefully design and trigger future campaigns to strengthen customer loyalty.

Fourth, the SUMI usability study brought up encouraging results concerning the design of our tool (see section 7). The proposed design may thus serve as a reference for constructing Social-Media analysis tools. Hence, the arrangement of the elements and menu fields of the GUI, enabling an easy extraction of Social-Media posts as well as the graphical presentation of the results in the form of pie charts, histograms and control charts put users in the position to easily navigate through the tool and derive insights from the data analysis (see section 7). Additional findings are indicated by the key figures as provided by the quantitative analysis. More, the functionality captured by the design along with the data model provided those features by which users felt ideally supported when working on a Social-Media analysis case study in our experiment.

8.2 Contribution for Research

In addition to practice, our approach also proposes several benefits for academia. First, as shown in section 2.2, the combination of data analysis approaches as well as the integration of methods in general has proven useful for various research disciplines. This concerns the development of scientific procedures such as triangulation or inter-method mixing (cf. (Johnson and Turner 2003; Jick 1979)) but also topics as for instance Method Engineering or process-oriented quality management amongst others (cf. (Brinkkemper 1996; Tolvanen et al. 1996; Ralyté et al. 2003; Johannsen 2011)). In this paper, we transfer the idea of combining different data analysis methods to the field of Social-Media. It becomes evident that the concept of “value-adding functional interdependencies” from the field of process-oriented quality management (PQM) – with the functional interdependencies describing beneficial synergies between methods, which may be purposefully combined in projects (cf. (Bruhn 2013; Johannsen 2017)) – can be transferred to the field of Social-Media analysis. Concretely, we propose to integrate a qualitative with a quantitative perspective on the Social-Media data. We could show that this allows to retrieve additional information from the data (e.g., the reasons for customers’ negative attitude towards certain offerings) complementing findings (complementary interdependency) gained by a solely qualitative or a solely quantitative analysis in isolation. This fosters a company’s “understanding” of the massive amount of data extracted from Social-Media channels, which is a topic firms do have to approach actively according to a current IT-trend study of CapGemini (cf. (CapGemini 2019)). Considering this, the concept of “value-adding interdependencies” in PQM may thus help to better understand the benefits arising from a combined use of qualitative and quantitative analyses in the field of Social-Media as well.

Second, the automated analysis of Social-Media posts still holds various challenges when it comes to its practical application. In our research, we built on a dictionary-based approach for the sentiment analysis. While freely available lexical resources exist for that purpose (e.g., SentiWordNet), these are not customized for particular industries or company types. Hence, for raising the accuracy level of our approach, the lexical resource (SentiWordNet 3.0) had to be adapted to match the particular needs of our collaborating partners that mainly came from southern Germany. The aforementioned modifications referred to the handling of regional slang, special events and irony amongst others. Hence, a dictionary emerged that helps to significantly increase the accuracy of the sentiment analysis for companies in southern Germany. This dictionary may be the basis for further refinement of dictionary-based approaches targeting the Social-Media analysis at companies in that region. So, researchers are called to enhance freely available dictionaries by branch-, regional- and company-specific language peculiarities to help raise the accuracy levels of such resources that can be used by researchers straight away.

Third, while most companies are nowadays able to process and store large amount of data (e.g., by help of Apache Hadoop), they still do not know how to extract valuable insights from the data sets (cf. (CapGemini 2019; Ried 2019)). This can also be seen as one reason for the lack of success of digital transformation initiatives (cf. (CapGemini 2019)). Based on a series of interviews with eleven cooperation partners, we deduced highly relevant application scenarios for analysing Social-Media content that help companies to purposefully trigger improvement efforts based on the analyses for instance (see section 5.2). While the technical side of Social-Media analysis is a lively discussed topic (cf. (Feldman and Sanger 2007; Liu 2012; Medhat et al. 2014)), the question of how to use and combine the existing analysis approaches – to truly derive beneficial insights for firms

– has somehow been neglected recently (cf. (Ried 2019)). Hence, the research brings up valuable indications for promising application scenarios for Social-Media analysis.

Fourth, this research largely contributes to current investigations in business process improvement (BPI). It focuses on the questions of how to utilize employees' process knowledge to eliminate process weaknesses (cf. (Seethamraju and Marjanovic 2009)) by means of systematic procedure models (cf. (Adesola and Baines 2005; Coskun et al. 2008; Harrington 1991; Povey 1998; Zellner 2011)), of how to use und develop "patterns" to support the "act of improvement" (Forster 2006) (cf. (Bergener et al. 2015; Höhenberger and Delfmann 2015; Lang et al. 2015)) and of how to apply process mining techniques for acknowledging deviations between an as-is and a should-be process (cf. (Van Der Aalst 2012)). In this respect, a major question for all these research streams concerns the proper identification of the voice of the customer and, hence, consumers' expectations (cf. (Pande et al. 2014)). At this point, our concept of a hybrid Social-Media analysis approach represents a helpful instrument to identify the voice of the customer based on freely available Social-Media data. Thus, research may focus on the integration of BPI approaches and Social-Media analysis in more depth.

9 Conclusion and Outlook

In the paper at hand, a concept for a hybrid analysis approach, its implementation as a software tool and its evaluation based on different evaluation steps of the DSR approach were described. We started with an explication of the problem statement (see Figure 1). We observed that the currently available Social-Media tools either support a quantitative or qualitative data analysis but neglect the combination of these two perspectives. In a first evaluation (evaluation 1), this gap was confirmed by eleven companies, which were interviewed with the purpose of identifying current challenges of Social-Media analysis efforts (see Figure 1 – step 2). Based on their statements, the concept of a hybrid approach along with an accompanying software tool was designed (see Figure 1 – step 3). Then, in a subsequent evaluation of the design (see Figure 1 – step 4), we showed that our solution helps to solve current challenges of Social-Media analyses (cf. (Sonnenberg and Brocke 2012)) by describing its potentials for two major application scenarios. Afterwards, the software tool was constructed (see Figure 1 – step 5). The practical applicability of our solution was demonstrated by referring to the example of a German bank (see Figure 1 – step 6). The tool is currently in use at several cooperation partners (see Figure 1 – step 7). As one important aspect of a more compressive evaluation of the tool's far-reaching applicability (evaluation 4), we assessed the usability of our solution by means of a SUMI study with 72 students of a German university (see Figure 1 – step 8).

However, there are also some limitations to this research: so far, we have so far carried out in in-depth evaluation of our hybrid approach along with the tool at one company only. Further evaluations with firms from various branches are currently performed as the software is in use at several of our cooperating partners. Our solution is not subject to a branch-specific imprint and its underlying mechanisms are suitable for both service and production settings, assuring its inter-sectoral usability. The application scenarios and challenges of Social-Media analyses were derived from interviews conducted with eleven companies. Although this is a sample set of considerable size, completeness of the challenges and scenarios cannot be guaranteed. The SUMI usability study was performed with Master degree students, which also is a limitation. Therefore, a corresponding SUMI study with practitioners is an open issue still to be completed.

Several topics for future work have emerged: first, we will further evaluate our hybrid approach in usability studies including practitioners but also in real-life Social-Media projects with companies of different sizes and across branches (see “evaluation 4” – Figure 1). The prototype’s contribution to supporting the elicitation of business-relevant information is to be precisely assessed for different cases, in addition to the previously described scenarios (see section 5.2). Project participants will be asked to complete the SUMI questionnaire to rate the software on the base of the five dimensions as introduced in section 7. By that, opportunities for the advancement of the prototype will emerge, possibly concerning the incorporation of more explanatory information supporting the user during the interaction with the tool or its visual redesign.

Second, we will investigate more closely how companies may use the information received from Social-Media analysis for entrepreneurial decision-making. In this respect, we will investigate as to what degree it is possible to automatically derive action recommendations from the analysis results, e.g., the launch of process improvement initiatives or marketing campaigns, to address the voice of the customer. More, the integration of Social-Media data analyses into strategical decision-making will be in the focus.

Third, we strive for the definition of further beneficial application scenarios for hybrid Social-Media analyses. In this respect, helpful feedback will emerge from the practical use of the tool at our cooperation partners.

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2.6 Beitrag 6: Measuring the Success of Social Media: Matching Identified Success Factors to Social Media KPIs

Adressierte Forschungsfrage	**Forschungsfrage 7**: Welche Critical Success Factors (CSFs) von Social-Media für Unternehmen (B2C) können aus der Literatur identifiziert werden und wie können sie klassifiziert werden? **Forschungsfrage 8:** Welche Social-Media Key Performance Indicators (KPIs) können mit den identifizierten CSFs abgeglichen werden?
Zielsetzungen	(1) Entwicklung eines Ansatzes zur Kategorisierung von CSFs von Social-Media Anwendungen (2) Matching von CSFs mit entsprechenden KPIs zur Erfolgsmessung von Social-Media
Forschungsmethode	Design Science Research Methodology *(Peffers et al. 2007)* • 2 Literaturanalysen zum Thema CSFs & KPIs von Social-Media nach *(Vom Brocke et al. 2009)* • Klassifikation der CSFs • Matching der identifizierten KPI zu den klassifizierten CSFs
Kernergebnisse (Überblick)	(1) Identifikation von 42 CSFs für Social-Media. (2) Klassifikation der 42 CSFs in fünf Cluster *User, Content, Management (Mgmt), Determining Factors (DF) und Team.* (3) Identifikation von 99 KPIs zur Erfolgsmessung von Social-Media. (4) Zuordnung von 55 KPIs zu konkreten CSFs.
Publikationsort	Proceedings of the 52nd Hawaii International Conference on System Sciences (HICSS) 2019
Ranking VHB JQ 3	C
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Tabelle 7: Fact Sheet Beitrag 6

Measuring the Success of Social Media: Matching Identified Success Factors to Social Media KPIs

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Abstract

With the rise of social platforms such as Facebook, Twitter, Instagram etc., recently, a lot of excitement and optimism around the potential of corporate social media usage have emerged. Social media activities allow companies to reach an attractive mass audience segment, but just as for any other marketing medium, measurement is a critical component of success. Hence, many critical success factors (CSFs) necessary for successful B2C social media efforts have been compiled in literature over the last years. Although these CSFs are numerous, a classification for a purposeful application as well as corresponding key performance indicators (KPIs) for the concrete measurement of CSFs are missing. Therefore, first (1), this research aims at the identification of existing CSFs for social media in enterprises in literature and classifying them by their specific application. Second (2), to allow the definite measurement of CSFs, corresponding KPIs are identified and matched towards them.

1. Introduction

Over the last decade, social media has become a key component of people's social life as well as the primary communication method worldwide [1, 2]. The number of people using social media has been increasing tremendously over the last years [3]. However, the use of social media has not only affected the way private persons communicate with one another, but has also led to a shift of customer expectations concerning the communication channels offered by companies [4]. According to [5], by 2011 72% of large enterprises had already deployed at least one social media tool. Additionally, already in 2010, 40% of large enterprises also stated that social networking tools as well as blogs were in use for example to efficiently handle customer inquiries (e.g., [6]), widely share marketing material (e.g., [7]) or solve customer complaints quickly (e.g., [8]).

Driven by this dramatic change, companies are heavily engaged these days in integrating upcoming social technologies with their offerings [9].

Using social media channels can result in various benefits for enterprises. Since the focus of this paper lies on B2C applications, the most prominent benefits are twofold. First, social media triggers customer engagement to increase emotional bonds, brand loyalty and to improve the overall business performance. For example, customers may be integrated into so far internal company tasks such as product or service development [10-12]. Second, social media generates "*word of mouth*", the most persuasive form of advertising and increasing the viral dissemination of information [13, 14].

Even though social media is being used by most enterprises and also well known for being the best modern way of interacting with consumers via the internet [15, 16], the know-how of how to use social media as well as of how to extract information from social media to gain concrete benefits in a structured way is fairly low [17].

As user-networks, communities as well as topics and interests within the social media channels are characterized by a steady change, the continuous measurement of proposed social media efforts is absolutely essential. To do so, many researchers as for example [18] provide various critical success factors (CSFs) to determine the success of corporate social media activities. However, diverse CSFs in the literature are often presented in an isolated manner and a consistent classification is missing (e.g., [19, 20]).

Thus, the present research first (1) deals with the identification of CSFs for social media in enterprises and their categorization towards predefined classes resulting in the following research question (RQ):

(1) *RQ1: Which CSFs of social media for enterprises (B2C) can be identified in literature and how can they be classified?*

URI: https://hdl.handle.net/10125/59681
ISBN: 978-0-9981331-2-6

Although, these success factors permit to take aim at specific features of a successful social media offering, the corresponding key performance indicators (KPIs) that measure the performance of a company's social media efforts are mostly missing. Therefore, a combination of CSFs and matching KPIs to measure the performance of social media activities seems promising, leading to the second (2) addressed gap of this research:

(2) RQ2: Which social media KPIs can be matched towards the identified CSFs?

Summing up, the aim of this research is to develop an approach that categorizes existing CSFs for social media at enterprises in the literature by their specific application and combines them with corresponding KPIs. Thus, the approach allows the measurement of the performance of corporate social media usage.

This paper unfolds as follows: in section 2, conceptual basics on social media, CSFs and corresponding KPIs are introduced. Afterwards, the procedure of our research is presented (section 3). Section 4 presents and discusses the results of the investigation. The results are then applied on a specific use case and interpreted in section 5. The paper is rounded off with a conclusion, limitations and an outlook on future research.

2. Conceptual basics

In literature, the term "social media" is often described 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 (UGC)"* [21]. The field of social media contains various technologies for supporting user or customer engagement respectively, such as online social networks (OSN) (e.g., Facebook), or Wikis amongst others [22].

With their increased adoption by enterprises, the question arises of how to make social media success measurable? Therefore, approaches for the measurement as well as the support of value-creation become more and more significant.

In economic research, an objective approach that is widely used to define success is the degree of the achievement of objectives [23]. This definition appears also in the IS success model of DeLone & McLean and is described with the indicator "net benefit" [24]. Since social media by definition is not an end in itself but an instrument to achieve certain goals (e.g., [25]), we will use the degree of achievement of these goals as an indicator for its success. Therefore, we draw upon a second well known concept in economic research from Rockart, who suggests to define CSFs and measure them to reach the defined goals [26].

According to [26], there are three essential components to measure the degree of achievement of goals as shown in figure 1.

Figure 1. Measurement approach [26]

In order to identify relevant CSFs for the success of social media or the companies' social media efforts, goals need to be defined. According to [27], goals represent the end points that an organization intends to reach at a given point in time. Due to the very individual characteristics of specific company goals, it is necessary to identify CSFs, to facilitate the measurement of relevant metrics and to support the systematization of goals. CSFs are the areas in which good performance is necessary to ensure the achievement of those goals [27].

The respective measurement instruments are KPIs. In the literature, different perceptions regarding KPIs and measures can be found. According to several authors, KPIs are quantifiable measurements and concise indicators designed to measure the achievement of strategic objectives by combining a lot of information [28-30]. Further [31] state that KPIs are often used by an organization to analyze the CSFs of a particular activity in which it is engaged.

3. Methodology

To develop an approach, we followed the Design Science (DS) approach [32, 33].

In phase one, **problems were identified** by unveiling the missing connections between CSFs and corresponding KPIs. Phase two defined the **objective of our solution** (measurement of social media success based on CSFs and KPIs). To **design and develop** this solution, we conducted a literature review to identify CSFs as well as KPIs regarding corporate social media usage following the methodology provided by [34]. Afterwards, we manually categorized existing CSFs for social media in enterprises and matched them to corresponding KPIs (phase three). For the **demonstration and evaluation** (phase four and five) of the developed approach, we applied our solution to a German university and discussed our results in several interviews as well as workshops with the university's responsible social media staff. The publication of the results (phase six: communication) is also part of this article.

To proceed with phase three of the DS approach, we conducted a literature review to identify existing CSFs as well as KPIs to fit the proposed model. However, while searching for CSFs, we learned that, to the best of our knowledge, there is no connection between existing CSFs and corresponding KPIs, which is why we conducted a second literature review to identify social media KPIs and matching them afterwards (see section 4.3).

The **first literature review** regarding CSFs followed the proposed procedure of [35].

First, the **review scope** was defined in accordance with the research questions (cf. [36], see section 1). As suggested by [35], we drew on an established taxonomy presented by [37].

Second, for the **conceptualization of the topic,** seminal works that deal with social media (e.g., [38-40]) were drawn on to define key terms and to extract key concepts that were later used to define the search terms, databases and the time period for the literature search (see table 1). It turned out to be most promising to search for relevant literature beginning in the year 2003, when social media started to become a global phenomenon and, indeed, first works were found for that year [41] [42]. Since the area of success factors of social media is an interdisciplinary research field, not only IS works were considered, but also works in the fields of finance, marketing, PR, and others.

Third, the initial **literature search** resulted in a total of 5,049 publications. As described in table 1, this initial search number also resulted from the generic search terms such as “success” and “social media”, but in most of them the focus on CSFs was missing. Further, we discovered that older publications did not have any relevance to our approach, even though search terms such as “success factors” were used. This may be attributable to the fact that, in the beginnings, the focus lay more on understanding the functionalities and not on assessing the success of these applications. As a next step, duplicates found in the databases were eliminated. Irrelevant works regarding ERP systems, knowledge systems, maturity models or e-government could also be eliminated. Further, our focus did not lie on the evaluation of Web 2.0 applications (e.g., forums) or virtual worlds, which led to a further reduction of the literature, too. Also, as social media in B2C was in our scope, publications focusing on e.g., enterprise social networks (ESN) or supplier networks were not included. In addition, only peer-reviewed literature was considered, leading to 15 relevant works. On these papers, a backwards and forwards search was conducted that led to an increase to a total number of 17 publications dealing with CSFs in connection with social media. As mentioned, the literature search covered a wide area of research fields resulting in a very diverse set of publications.

The **literature analysis** as step four is based on the qualitative content analysis according to [43] to answer *RQ1*. As a first step, the literature was manually searched to identify potential categories (e.g., [18]) (deductive category application).

However, not all identified CSFs could be assigned to the categories as described in [18], hence, self-defined categories were developed by grouping similar CSFs and analyzing what component of social media, in the eyes of the researchers, had the most influence on the success of social media (inductive category development).

Table 1. Overview of search parameters

Time period	2003 -2017
Databases	Google Scholar; EBSCOhost; AISeL; ScienceDirect
Search Fields	Full-text, (except AISeL: Title, Abstract, Keywords)
Search Terms (all combinations)	Success factors; success; benefits; enablers AND Social Media; social networks; OSN; SM

To reduce the subjectivity of the categorization approach [43], all steps (identification of potential categories, assigning CSFs to the categories and self-definition of categories) were performed by two researchers individually to reduce subjectivity. In case of disagreement, the article in question was analyzed by a third researcher followed by a discussion until a consensus was reached. This resulted in a total of five categories, three of which were extracted form literature and two self-defined (see section 4.1).

Fifth, a **research agenda** was compiled by giving an outlook as well as identifying new areas of research in terms of CSFs and KPIs**.**

As **for the second literature review** to identify KPIs, Peters et al. [44] could be drawn upon who performed an exhaustive literature review regarding the identification of social media metrics (further called KPIs). Therefore, we chose a representative coverage since [44] already provided the foundations.

Besides [44], we conducted a forward search with the emphasis on the years 2013 to 2017 and found additional publications to characterize social media metrics further in order to answer *RQ2*. This literature review led to an analysis of 21 publications.

The matching process of the CSFs to the KPIs was performed by two researchers individually. In case of a disagreement between them, a third researcher would be invited to mediate the discussion until a consensus was reached.

4. Results and interpretation

4.1 Results literature review (CSFs)

To categorize the CSFs, we identified five clusters in accordance with the approach by [43] as described in section 3 to answer *RQ1*. These clusters (a combination of already existing classes in the literature (e.g., [18]) and self-defined classes) are *User, Content, Management (Mgmt), Determining Factors (DF)* and *Team*, with the latter two resulting from the self-defined classes. Figure 2 illustrates the five identified clusters with the number of identified CSFs.

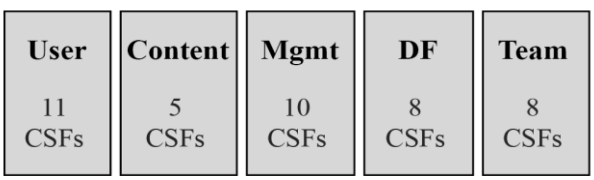

Figure 2. Clusters with number of CSFs.

One finding of the LR is the fact that some authors only define their identified success factors without evidence. Therefore, we divided the identified CSFs into unverified CSFs (marked with an * in table 2) and verified ones. Altogether, 42 CSFs could be identified 12 of which were classified as unverified-CSFs and 30 as verified-CSFs. In the following, an example for each cluster is given.

The cluster *User* summarizes all CSFs that have a direct impact on the user (e.g., customer, prospect, etc.) of a specific social media network. For this reason, [18] define the interactivity as being an essential CSF. This can be justified with the general characteristic of social media [21] because, without interactivity, there would be no added value to such an application. This CSF also works in favor of engaging with a target group easily, e.g., via responding to users' needs or finding creative ways to address users. In doing so, it is possible to obtain insights into users' preferences enabling to identify more easily users' needs, which eventually leads to a boost in user engagement.

To attract users to certain posts, understanding the specific characteristics of a social media post is an essential part of accomplishing the successful engagement with the users. CSFs concerning these characteristics are summarized in the *Content* cluster. Providing qualitative content as defined by [40, 45, 46] can support the goal of engaging and attracting users. The adage 'quality over quantity' is applicable here, since providing real value to the users is far more important than posting as much as possible.

Involving the management in the decision process to receive their full support is seen as critical to success [18, 45, 46]. Additionally, having the management's support also makes taking action easier. Due to this reason, CSFs dealing with decision makers are summarized in the cluster *Management*.

CSFs in the cluster *Determining Factors* are to be considered by the social media team before implementing a social media strategy in their organization. By acting according to those defined CSFs, the rectification of faults resulting in monetary or human resource costs should be minimized afterwards. [46] state that it is essential to define responsibilities in order to make the whole social media effort and process efficient and to optimize response times for instance. If responsibilities are clear, a social media team knows when and how to take appropriate action.

CSFs adhered to by the social media team are consolidated in the cluster *Team*. A committed team, as defined by [18], can be relied on, resulting in better posts and more qualitative content, since more efforts are made to bring out the best of social media. The difference between the two clusters *Determining Factors* and *Team* is the fact that CSFs in the cluster *Team* are also applicable, when the implementation of the social media presence is already accomplished.

4.2 Results literature review (KPIs)

As described in section 1, we figured out that the CSFs identified by the literature review had not so far been matched to KPIs to make social media success measurable. To close this gap, we elicited widely used KPIs from the literature as a first step to answer *RQ2*.

As a result of the conducted LR regarding the KPIs, a list containing 99 potential social media KPIs was compiled (e.g., centrality measures, social media key figures, etc.). [44] identified four different domains to which the KPIs were mapped. These domains support the understanding of the specific focus of a single KPI and were used to help matching the KPIs to the CSFs as described in section 4.3.

However, the list of 99 KPIs still contained duplicates as well as similar KPIs that could be summerized. For example, the KPIs ‘average rating over time’ [47], ‘average rating’ [48], ‘rating’ [49, 50] and ‘difference in ratings’ [51] could be summerized to the KPI ‘average rating’, since these KPI all express fairly the same. After consolidating the KPI list a total of 70 social media metrics remain [50, 52-65].

Due to space restrictions, this full list can not be described here, but is accessable via this web appendix: *https://bit.ly/2sYb9Xs*.

4.3 Matching and discussion

After identifiying the two isolated components, the matching of KPIs to CSFs was conducted manually in accordance with the specific features of those KPIs that allow a potential measurement of success.

The results of the complete matching process are presented in table 2. The first CSF is assigned to the category user and postulates to *be unique*. Uniqueness in social media requires authenticity and engagement in the way participants of the network share the same values and relate themselves to or identify themselves with the network community, respectively. Because of the qualitative nature of this CSF, a matching KPI should rather capture the effects of authenticity and engagement to the community than authenticity and engagement in itself. Consequently, as corresponding KPIs, *vividness*, meaning to measure both the number of comments/shares/likes and the response times as well as *entertaining content*, aiming to capture the share of content that initiates user engagement, are proposed. For the CSF *interactivity* the *interaction rate* (e.g., number of comments, shares, likes, …), the *number of postings* or *ratings* as well as the *recurring rate* (e.g., share of recurring users) are suggested as KPIs to indicate success. Even though a large number of KPIs could be matched, a few CSFs remain for which a useful allocation was not possible, e.g., the qualitative CSF ‘cultural consideration’ [40] or the CSF ‘establishing a project management’ [45], the description of which is too vague.

Other CSFs give quite good options to match multiple KPIs. For instance, the CSF ‘provide up-to-date content’ [19, 20, 40, 46] can be measured with KPIs as for example the ‘interaction rate [50]’, which includes all metrics such as number of likes, number of shares, etc. With up-to-date content it is most likely that such content receives a lot of attention and strikes a chord with the users, which normally results in a high amount of virality. This can lead to an increase of the net-reach meaning that a particular social media site is seen by a lot of users.

The smallest number of KPIs was allocated to the cluster *Management* due to the fact that only social media KPIs were considered, even though the cluster *Management* contains CSFs that need a higher number of generic KPIs to successfully measure them - as for example CSFs such as ‘human resources for planning and implementation’ [18, 19, 66] or a ‘strategy implementation’ [45]. These CSFs are applicable to any new project and therefore do not need specific social media KPIs. Hence, in order to achieve better results, it is desirable to also investigate general KPIs in terms of their applicability to the *Management* CSFs.

However, additional KPIs could easily be developed and allocated to CSFs, such as the cost of warnings (to be allocated to the CSF *comply copyright* [67]) or the number of slang words (to be allocated to the CSF *unprofessionalism* [18, 21]), and can be used for further research to extend table 2.

Multiple allocations of one and the same KPI are presented in table 2. This is due to the fact that the literature describes some generic KPIs, as for example the *social media interaction rate,* which is applicable to a total of 7 CSFs. This example also suggests that there is not exactly one KPI for each identified CSF.

From the pool of 70 metrics, the interviewed social media experts could match 55 KPIs to corresponding CSFs and answer *RQ2*. This leads to the assumption that only these 55 KPIs are critical to measuring success, whereas the remaining 15 KPIs need to be reviewed. By glancing at the characteristics of some KPIs, this non-allocation can be explained. For instance, the KPI *homophily* [53] expresses the positive relationship between the similarity of two nodes in a network and the probability of a tie between them [68]. This coherence between two nodes can be interpreted in many different ways, which is why it was not possible to clearly allocate this KPI to a specific CSF. However, we cannot exclude the fact that, in some other context, this KPI could be useful. Homophily is part of the *network structure domain* as defined by [53]. Interestingly, this domain also contains most of the afore-mentioned 15 KPIs that could not be matched to CSFs resulting in the assumption that the network structure domain may as well be too generic, which makes a clear allocation of KPIs a challenging task.

Table 2. CSF and KPI matching

	CSFs	*KPIs*
User	Be unique [69]	Vividness [57]; entertaining content [57];
	Identify shared interested [67]*	Informational content [57]; net-reach [50]
	Interactivity [18, 70]	Interaction rate [50]; # of postings [55]; # of ratings [62]; recurring rate [50]
	Be interesting [21]*	# of site visits [50]; recurring rate [50]; # of subscribers [50]; length of stay [50]
	Increase customer happiness [67]*	# of positive mentions [50]; customer satisfaction [50]; Net Promoter Score [50]; Sentiment Index [50]; Δ of pos. and neg. chatter [51];
	Benefit for the individual [71]*	# of pos. product rating [50] ; informational content [57], entertaining content [57]; vividness [57]; Valence [56]
	Understanding user needs [19]	# of product improvements [50]; # of product ideas [50]; Δ of pos. and neg. chatter [51]
	Creative ways to address users [19]	Aided/unaided recall [50]; # of attended events [50]; interaction rate [50]; entertaining content [57]
	Building trust [72]*	Recommendations [50]; service satisfaction [50]; avg. ratings [47-50] ;
	Address target group consistent [40]	Reach within target group [50]; net-reach [50];
	Social connection [70, 73]	Interaction rate [50]; # of subscribers [50];
DF	(Web) Application knowledge [18, 21, 69, 74]	Reduction of workshop costs [50]; degree of knowledgeability [50]
	User-friendliness [40, 70, 71]	Time saving in regards of communication [50]
	Comply copyright [67]*	-
	Personalization [40]	recurring rate [50]; # of visits [50]
	Set up Guidelines / Netiquette [40, 45]	Sentiment Index [50]; valance of information [56]
	Privacy protection [40, 67]	-
	Social media is personal [20]	Interaction rate [50]; response rate [50]
	Define responsibilities [46]	Reaction speed [50]; time and staff expenses per service request [50]
Team	Be active [21]*	Interaction rate [50]; frequency of contacts [50]; reaction speed [50]; net-reach [50]; # of postings [55];
	Collaboration [70, 74]	# of product improvements [50]; # of product ideas [50]; # of requests answered by the community [50], bidirectional link intensity [53]
	Engage in conversations [67, 74]*	Interaction rate [50], reaction speed [50]
	Committed team [18, 70]	Churn rate [50]; employee satisfaction [50]
	Identify and determine KPIs [69]	-
	Cultural consideration [40]	-
	Reaction speed [66, 67]*	Reduction of response time [50]
	Conduct workshops [45, 46, 70]	Employee satisfaction [50]; # of operating errors [50]; churn rate [50]; service satisfaction [50]
Content	Be honest [18, 21]	# of recommendations [50], avg. ratings [47-50]
	Provide qualitative content [40, 45, 46, 70]	rate of growth [50]; retention period [50], conversion intensity [50]; vividness [57]; informational/entertaining content [57]
	Constant posts [18]	avg. net-reach [50]; # of postings [55]
	Unprofessionalism [18, 21]	-
	Provide up-to-date content [19, 20, 40, 46, 70]	avg. net-reach [50], interaction rate [50], rate of growth [50]; retention period [50], conversion intensity [50], share of buzz [50]; interactivity [57]; informational/entertaining content [57]
Management	Building a Reputation [40]	# positive mentions [50]; brand awareness/popularity [50]; recommendations [50]; sentiment index [50]; contentment [50]; # of job applications [50]; net promoter Score [50];
	High level of social presence [67]*	Interaction rate [50]; interactivity [57]
	Providing no alternatives [70, 71]	-
	Cheap advertisement [20]	costs for social media ads vs. costs for traditional ads [50]; net-reach [50]
	Management Support [18, 45, 46]	employee satisfaction [50], spending for further trainings [50]; labor turnover-rate [50]; employee-rating [50]
	Annoying but necessary advertisement [20]	# ad conversions [50]; avg. ratings [47-50]
	Human Resources for planning and implementation [18, 19, 66]	-
	Establish project management [45]*	-
	Social responsibility [20]	-
	Strategy implementation [45]*	-

Hence, as our research agenda, it needs to be investigated more precisely what KPIs of the network structure domain contribute for the success of social media. Also, the network structure domain in general seems promising for further research regarding social media success. This domain contains a lot of KPIs that describe features of social media as defined by [21]. As for example, centrality measures give an insight into how influential persons are in a network [53] therefore contributing to the exchange of UGC. Furthermore, it needs to be investigated how social media success can be defined in greater detail, since the identified 42 CSFs and 70 KPIs provide a capital basis for explaining social media success. Additionally, more generic KPIs (e.g., for the cluster *Management*) need to be taken into consideration for further research.

5. Demonstration

The demonstration of our approach takes place in a German university having just recently started their social media activities. We aimed at demonstrating the usefulness of our approach for both novices as well as experts in the field of social media. Since the university's social media team consists of these two groups, this use case was suitable. Also, the target group of the university is fairly young (prospect students), which makes it even more promising, since young users are believed to be more affine to social media and therefore more active. Furthermore, as [75] compares universities with service companies, we were able to further prove the applicability of our approach in the B2C area. We accompanied this social media project and observed the application of our approach from March to May 2018.

As a first step, the university's social media team defined the specific social media goals that were seen as indicators for the success of the project. In so doing, the team specified the purpose of the social media presence (attraction of students) in compliance with the main goals of the university and derived the following three social media goals: building a reputation (1), developing a community for better (knowledge) exchange (2) as well as developing a social media governance (3).

The second step involved the selection of relevant CSFs and KPIs. In accordance with Rockart [27], not all possible CSFs were selected, but only the most promising indicators of the degree of achievement of the goals and correspondingly of the success. In three discussion rounds with the university's social media staff, a consensus on the most relevant CSFs was reached, which are 'provide up-to-date content' [19, 20, 40, 46], 'reaction speed' [66, 67] and 'interactivity' [18]. Thus, afterwards, the relevant KPIs to measure the achievement of these CSFs could easily be identified with the help of table 2.

Providing up-to-date content [19, 20, 40, 46] helps to attract more persons who use the social media site as an information source, possibly triggering discussions on a specific topic, resulting in a higher interaction rate [50]. By engaging in these discussions, the university's social media staff can support the users by answering their requests, which can eventually lead to improving the university's reputation (1) by publicly addressing the concerns of its fans (e.g., students). The university's reaction speed to requests is also critical to success [66, 67]. As German universities, in general, have the reputation of taking their time to provide the desired information, a reduced response time [50] can help to reach the defined goals. Interactivity, for instance, can be measured by the recurring rate [50], the number of postings [55] as well as by the number of ratings [62] and the social media interaction rate [50]. Since interactivity [18] is an essential part of the definition of social media [21] (see section 2), it should also be a mandatory CSF.

To investigate the usefulness of our approach, we set up a workshop to discuss its application with the social media team. Particular emphasis was laid on both the relevance and the comprehensibility of the approach: The social media team considered the approach as appropriate for being used in social media projects, especially emphasizing its effective support in selecting relevant CSFs and KPIs with the help of table 2. The team substantiated their approval by reporting an impressive experience they had made: to raise interaction via comments (e.g., trading requests), likes and shares, a post dealing with the then upcoming soccer world cup was created offering the users to collect and exchange popular soccer player cards. Much to the team's surprise, barely any interaction was achieved. Another post that was only considered as an informational post without the intention of creating or even raising interaction achieved a huge number of likes and comments, underlining its popularity. This post was used for the creation of a campaign called 'university faces', where students, employees and professors were interviewed to convey a more "private" picture of themselves to the social media users.

It turned out, however, that identifying relevant CSFs is challenging so that extending the list with corresponding social media goals would be of great help. Specifically, the way of describing the goals is crucial as this description determines their applicability in this context. The achievement of success regarding abstract or generic goals can be measured by too many CSFs. A thorough trade-off between goals, as abstract as possible and as specific as necessary, will be of great importance for the further development of our approach. Although the university's social media project is still in an early phase, the social media team has already been able to identify and stress the necessity of continuously using the approach and evolving and adapting CSFs as well as KPIs, since success in social media depends on different factors such as the changing background of user preferences or new technical solutions.

A tool to automatically analyze the degree of goal achievement by measuring the degree of fulfilling defined CSFs would be helpful. To integrate social media analytics into such a tool in order to access social media data, recommendations regarding alternative CSFs can be given in case of being behind schedule with the achievement of goals.

6. Conclusion

This research paper addresses the identified gap of a nonexistent allocation of KPIs to corresponding CSFs to make the success of social media measurable by using the basic idea of [26]. To close this gap, we developed an approach by applying design science according to [32, 33]. First, we conducted two literature reviews in order to identify relevant social media CSFs as well as KPIs and matched them.

To demonstrate its applicability, the approach was applied to a social media project at a university in Germany, followed by a discussion of its usability with the responsible social media team.

Our research contributes to both theory and practice. As a contribution to theory, we developed a comprehensive overview of all CSFs and KPIs regarding the use of social media and organized them in five clusters. The resulting list can be seen as an important step for measuring social media success. By applying our approach to a social media project at a German university, we could prove its appropriateness in practical settings. The results of the application were discussed in a workshop with the social media team, as a first step towards the evaluation of our approach, which was considered meaningful as were the selected CSFs and their corresponding KPIs.

However, our research is not without limitations. Although we conducted a comprehensive literature review, some CSFs or KPIs still might have been left out in the search process. Also, an empirical study to evaluate the CSFs needs to be conducted. In addition to the pilot project, further validations of the approach would provide deeper insight into the general applicability of our approach for further refinements.

The findings presented in our paper also point to areas of further research, such as the extension of the table with social media goals and the need for a success measurement tool that enables the monitoring of social media success regarding CSFs and KPIs. Furthermore, an investigation of the network structure domain [53] together with its contribution to success seems promising. Additionally, extending this study by introducing data mining analysis tools to obtain deeper insights into the frequency of the used KPIs and CSFs as well as their characteristics in the papers.

7. References

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3 Artefakt der Dissertation: Universität Regensburg Social-Media Analysis Research Toolkit (UR:SMART)

Nach der Vorstellung der wissenschaftlichen Beiträge (Kapitel 2.1 bis 2.6) wird in diesem Abschnitt nochmals auf das im Rahmen der Dissertation entwickelte Softwareartefakt UR:SMART eingegangen. Dabei steht ein Überblick über den Aufbau und die Funktionalitäten, die Design- und Entwicklungsphasen sowie der aktuelle Stand der Social-Media Analyse Software UR:SMART im Vordergrund. Abschließend erfolgt ein Ausblick auf Weiterentwicklungen und Potentiale von UR:SMART.

3.1 Designphase: Aufbau und Funktionalitäten von UR:SMART

Bevor mit der Designphase des Social-Media Analyse Tools UR:SMART begonnen werden konnte, wurden mehrere Interviews mit elf Unternehmen, die sowohl im Business-to-Consumer (B2C) als auch im Business-to-Business (B2B) Bereich tätig sind, durchgeführt, um deren Bedürfnisse sowie Einschränkungen in Bezug auf die Analyse von Social-Media Inhalten zu ermitteln. Auf Basis dieser Interviews, wurden die grundlegenden Funktionen von UR:SMART definiert, welche in Abbildung 4 dargestellt sind.

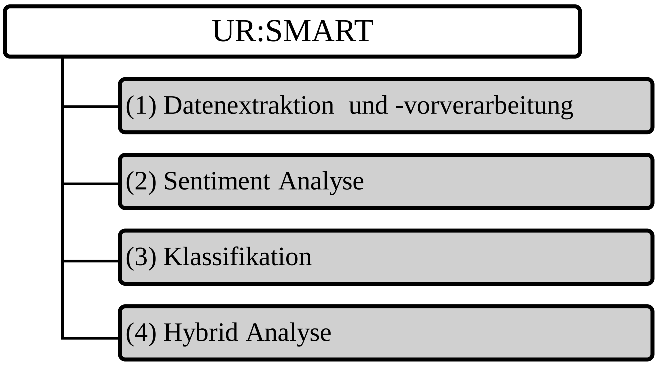

Abbildung 4: Funktionaltäten von UR:SMART

Bevor verschiedene Analysemethoden in Betracht gezogen wurden, war die **Datenextraktion und -vorverarbeitung (1)** der erste Schritt, da diese Techniken die Grundlage für alle weiteren Analysen bilden. Hierbei müssen textuelle Social-Media Daten aus verschiedenen Quellen extrahiert werden, beispielsweise aus Social-Media Kanälen wie Facebook und Twitter und für eine effektive Weiterverarbeitung in ein konsistentes Datenformat konvertiert werden (Akaichi et al., 2013, Feldman, 2013). Gleichzeitig wird eine Datenvorverarbeitung durchgeführt, die verschiedene Techniken wie Tokenisierung, Stoppwortreduktion, Stemming und Normalisierung umfasst, um die

Daten für die weitere Analyse vorzubereiten (Aggarwal and Zhai, 2012a). Anschließend können die extrahierten und vorverarbeiteten Textdaten mit Hilfe der Analyseformen Sentiment Analyse, Klassifikation, Clustering oder einer hybriden Kombination der Verfahren weiter analysiert bzw. mit quantitativen Social-Media Daten angereichert werden.

Als erste Social-Media Analyseform unterstützt UR:SMART die **Sentiment Analyse (2),** zur Analyse der Stimmung von Kundenbeiträgen. Aufgrund der Besonderheiten bei Social-Media Posts (z. B. Kürze der Beiträge, Emojis, unternehmensspezifische Sprache) stellen wörterbuchbasierte Ansätze einen allgemein akzeptierten Ansatz für die automatisierte Stimmungsanalyse solcher Textinhalte dar (Feldman, 2013). Dabei wird die Tonalität jedes Textelements (Tokens) bestimmt. Abhängig von der Stimmung jedes einzelnen Tokens (z. B. einzelnes Wort oder Emoji) wird ein aggregierter Stimmungswert berechnet, wobei der Wert einen positiven (> 0), neutralen (0) oder negativen (< 0) Wert annehmen kann (Feldman, 2013).

Des Weiteren wird die **Klassifikation (3)** der Social-Media Inhalte nach vordefinierten Klassen unterstützt. Um die Klassifizierung an individuelle oder sich schnell ändernde Kontexte (z. B. anstehende Kampagnen oder sich schnell ändernde Trends) anpassen zu können, konzentriert sich UR:SMART auf die Klassifikation von Daten zu vordefinierten Klassen (Feldman and Sanger, 2007, Heyer et al., 2006, Read et al., 2012). Daher wurde in Zusammenarbeit mit unseren Praxispartnern eine Reihe allgemein gültiger Hauptkategorien (z. B. Service, Produkt oder Kampagnen) ausgearbeitet, die unabhängig von Unternehmens- oder Branchenspezifikationen sind. Zusätzlich können (entsprechende) Unterkategorien für jede Hauptkategorie ergänzt werden, um die individuellen Themen und Bedürfnisse jedes Unternehmens zu behandeln. Diese Unterkategorien sind hochspezialisiert und sowohl auf die Unternehmensspezifikationen als auch auf die Ziele ihrer Social-Media Kanäle zugeschnitten.

Zusätzlich enthält UR:SMART einen **hybriden Analyseansatz (4)**, um die vorgestellten Analysemethoden frei zu kombinieren sowie mit quantitativen Social-Media Daten (z. B. Likes, Shares, Kommentare usw.) aus den Social-Media Kanälen anzureichern und so die Analysen noch weiter zu verbessern. Um einheitliche Datenformate sowie die freie Kombination der verschiedenen Analysemethoden sicherzustellen, wurde ein Datenmodell für die zugrunde liegende Datenbank erstellt (siehe Abbildung 5).

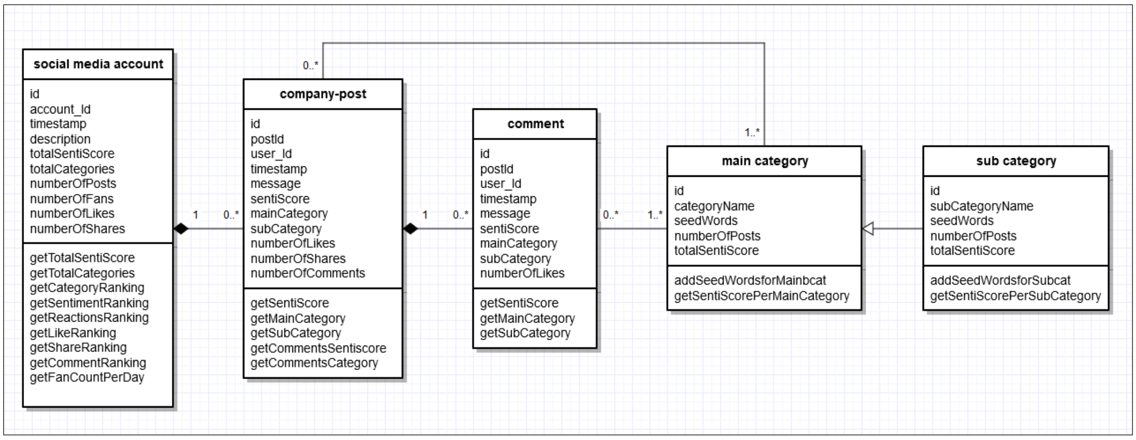

Abbildung 5: Datenmodell von UR:SMART

Dabei wird jeder Social-Media Post eines Unternehmens als Objekt betrachtet, einschließlich verschiedener inkludierter Attribute (z. B. IDs, Zeitstempel, Nachricht, Sentiment, Kategorie, Reaktionen usw.) und Verbindungen zu anderen entsprechenden Klassen. Neben allgemeinen Attributen wie *id*, *timestamp* oder *message* enthält jeder Post seine eigenen qualitativen und quantitativen Attribute, nämlich *sentiScore* für das zugrunde liegende Sentiment, *main*- und *subCategory* für die assoziierte Kategorie (z. B. Produkt oder Dienstleistung) sowie die Anzahl der Likes (*numberOfLikes*), die Anzahl der Shares (*numberOfShares)* und die Anzahl der Kommentare (*numberOfComments*). Ein Kommentar enthält diese Attribute ebenfalls, mit Ausnahme von *numberOfShares* und *numberOfComments*, da diese für Kommentare nicht zur Verfügung stehen. In Bezug auf die Klassifizierung bietet das Klassenmodell die Klassen *main Category*, die mit einem Unternehmenspost oder -kommentar verbunden sind, sowie *sub Category*, eine Erweiterung, um Kategorien genauer zu spezifizieren. Dieser generische Aufbau ermöglicht sowohl die freie Kombination der verschiedenen Analyseverfahren, als auch die Entwicklung und Integration neuer Social-Media Analyseverfahren und stellt somit die Basis für die hybride Social-Media Analyse dar.

Ein weiterer wichtiger Schritt in der Designphase war das Design der GUI von UR:SMART. Zu diesem Zweck wurden Wireframes verwendeten, um eine erste Ansicht der GUI zu erhalten. Ziel war es, eine intuitive Navigation mit einer begrenzten Anzahl von Schaltflächen und Elementen zu ermöglichen. Daher soll im oberen Bereich des Bildschirms (siehe Abbildung 6) die Auswahl der zu analysierenden Social-Media Kanäle zusammen mit einer Angabe des angestrebten Zeitrahmens der Analyse erfolgen. Anschließend sollen die Ergebnisse sofort angezeigt werden, wobei separate Grafiken für die Sentiment Analyse sowie die Klassifizierung der Beiträge verwendet werden.

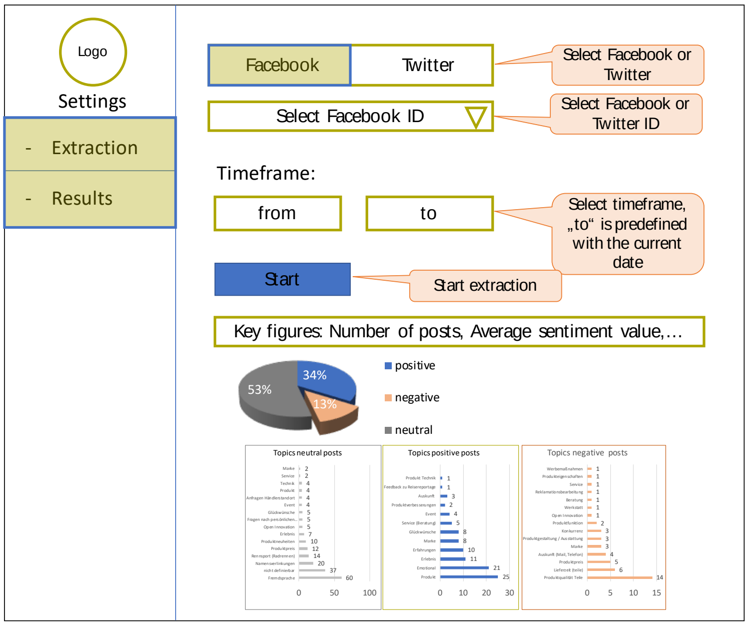

Abbildung 6: Wireframes der GUI von UR:SMART

3.2 Developmentphase: Technische Umsetzung von UR:SMART

Für die Implementierung des Softwaretools UR:SMART wird die Programmiersprache JAVA, sowie das Vaadin-Framework zur grafischen Darstellung verwendet. Die Applikation (Backend) läuft dabei auf einem Webserver (z. B. Tomcat). Die grafische Oberfläche (Frontend) wird webbasiert über den Browser im HTML5/CSS Standard ausgeliefert und ist somit plattformunabhängig sowohl von Desktop- als auch von Mobilgeräten erreichbar. Die Kommunikation zwischen Frontend und Backend wird mit der JavaScript Object Notation (JSON) realisiert. Abbildung 7 zeigt die technische Architektur von UR:SMART.

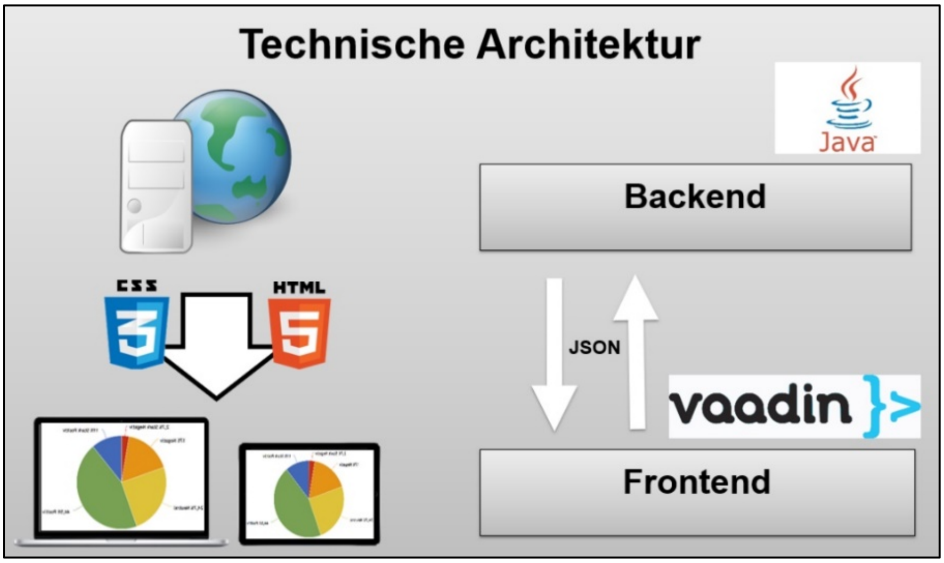

Abbildung 7: Technische Architektur von UR:SMART

Der erste Schritt für die Entwicklung von UR:SMART bestand in der Realisierung der Datenextraktions- und Vorverarbeitungsfunktionen, da diese Techniken, wie bereits beschrieben die Grundlage für alle weiteren Analysen bilden.

Zunächst zerlegt die Tokenisierung alle Textdaten in kleinere Bestandteile, beispielsweise einzelne Wörter und entfernt nicht benötigte Symbole und Sonderzeichen (Carstensen et al., 2009). Darüber hinaus werden durch die Stoppwortreduzierung Wörter entfernt, die keine Tonalität beinhalten. Hierfür werden öffentlich zugängliche Stoppwortlisten verwendet (Angulakshmi and ManickaChezian, 2014). Anschließend werden bei einem Stemming-Prozess Präfixe und Suffixe entfernt und alle Wörter auf ihren Stamm oder ihre Grundform reduziert (Akaichi et al., 2013). Zuletzt schließt ein Normalisierungsalgorithmus den Schritt der Datenvorverarbeitung ab und transformiert den gesamten verbleibenden Text in Kleinbuchstaben (Angulakshmi and ManickaChezian, 2014).

Für die Umsetzung der Sentiment Analyse wird die allgemein akzeptierte Implementierung des wörterbuchbasierten Ansatzes „SentiWordNet 3.0“ verwendet. „SentiWordNet 3.0“ stellt eine lexikalische Ressource für eine automatisierte Sentiment Analyse dar (Baccianella et al., 2010). Um neben englischsprachigen Social-Media Inhalten auch deutsche Social-Media Beiträge zu unterstützen, wurde zusätzlich der Ansatz „SentiWS“ verwendet, welcher eine deutschsprachige Ressource zur Analyse der Stimmung deutscher Texte zur Verfügung stellt (Remus et al., 2010). Auf Basis der in Kapitel 2.1 und 2.2 identifizierten sprachlichen Besonderheiten von Social-Media Inhalten wurden zudem spezielle Wörterbücher integriert, um bestimmte Merkmale (z. B. Dialekte oder Emojis) zu identifizieren (Selvam and Abirami, 2013). Zur Erkennung von Ironie und Umgangssprache wurde das Wörterbuch zusätzlich um Ausdrücke erweitert, die auf besondere Ereignisse (z. B. Produkteinführung) der betrachteten Branchen hinweisen.

Das Sentiment jedes Wortes (sowie jeder speziellen Textkomponente) wird durch die Variable *sentiScore* ausgedrückt, eine Zahl innerhalb eines vordefinierten Bereichs von [-2; +2], wobei eine hohe Zahl (nahe +2) eine sehr positive Stimmung darstellt und niedrige Zahlen (gegen -2) eher negative Stimmungen repräsentieren (Feldman, 2013). Die Gesamtstimmung der Social-Media Daten wird somit ersichtlich und kann den Kategorien „stark positiv“, „positiv“, „neutral“, „negativ“ und „stark negativ“ zugeordnet werden. Die gesammelten Daten werden in einer Datenbank gespeichert und können grafisch in Kreisdiagrammen und einer EKG-ähnlichen Darstellung mit einer zeitlichen Skala des Stimmungsverlaufs angezeigt werden (siehe Abbildung 8).

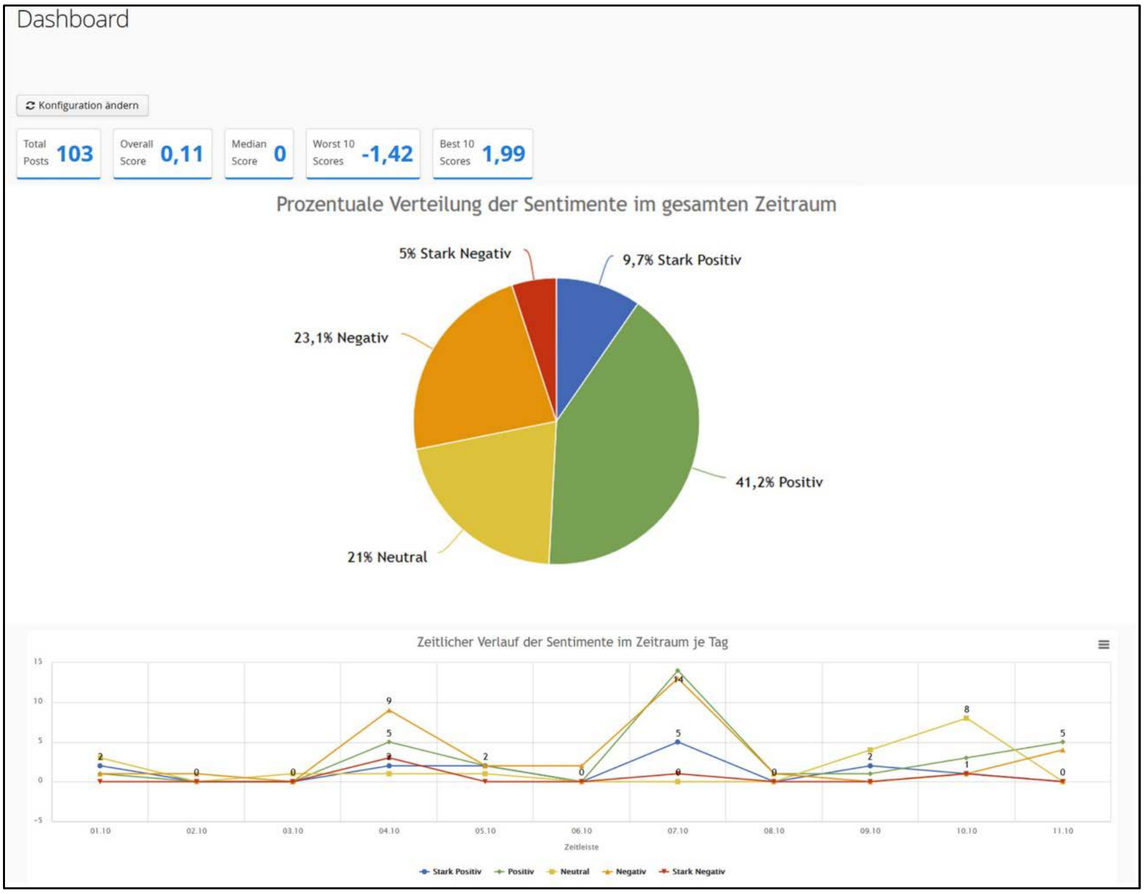

Abbildung 8: GUI der Sentiment Analyse in UR:SMART

Für die Implementierung der Klassifikation in UR:SMART wurde ein Multi-Nominal Naive Bayes (MNB) mit einem wörterbuchbasierten Klassifikationsansatz kombiniert, um die Kategorie der Social-Media Daten zu identifizieren (Giannakopoulos et al., 2012). Diese Klassifikationsbibliothek enthält dabei spezifische Trigger-Wörter für alle erhobenen Haupt- und Unterkategorien und ermöglicht daher die Zuordnung von Posts und Kommentaren zu vordefinierten Kategorien (Zagibalov and Carroll, 2008). Die Hauptkategorie „Produkt“ wird beispielsweise durch die Integration mehrerer Unterkategorien erweitert, darunter firmenspezifische Produktlisten, Teilelisten sowie Produktzubehör. Ausgehend von den vorverarbeiteten Daten werden alle Wörter hinsichtlich dieser Trigger-Wörter analysiert, was eine starke Anpassung der Klassifizierung ermöglicht. Durch die Identifizierung ähnlicher Wörter, die vorhandene Trigger-Wörter umgeben, wird die Klassifikationsbibliothek außerdem ständig durch unternehmensspezifische Ausdrücke erweitert (Liu, 2012). Infolgedessen können

Themen, die gegenwärtig bei Kunden beliebt sind (z. B. innerhalb eines Social-Media Kanals) identifiziert und grafisch angezeigt werden. Die Ergebnisse der Sentiment Analyse und die Zuordnung zu den definierten Klassen werden in einer Gesamtübersicht zusammengefasst, in der die am häufigsten vertretenen Kategorien und Unterkategorien in den einzelnen Sentiment-Bereichen aufgeführt sind. Zusätzlich sind alle zugrunde liegenden Social-Media Daten mit Hilfe verschiedener Sortier- und Filteralgorithmen abrufbar (siehe Abbildung 9).

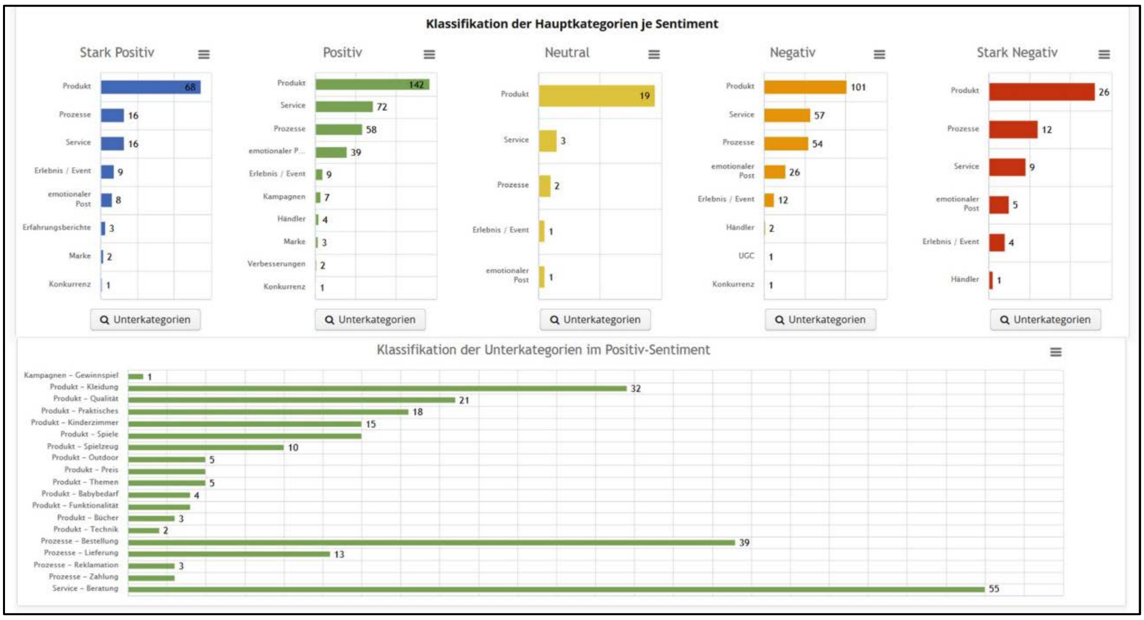

Abbildung 9: GUI der Klassifikation in UR:SMART

Für die Implementierung der hybriden Analyse wurde zunächst das in Kapitel 3.1 beschriebene konsistente Datenmodell mit Hilfe einer H2-MySQL-Datenbank umgesetzt. Zusätzlich wurden vordefinierte und dokumentierte Datenschnittstellen ergänzt, um Input bzw. Output jeder Analysemethode zu standardisieren und eine individuelle Kombination verschiedener Analyseansätze zu ermöglichen. Des Weiteren ist es möglich, die Datengröße nach jedem Schritt gezielt zu reduzieren, was zu einer deutlich kürzeren Analysezeit führt. Diese tiefe Integration aller unterstützten Analyseansätze ermöglicht eine gezielte, mehrdimensionale Analyse, bei der die beschriebenen Techniken auf verschiedene Weise kombiniert werden. Dadurch ist es möglich, tiefgreifendere Ergebnisse und ein tieferes Verständnis der zugrunde liegenden Daten zu erzielen.

3.3 Weiterentwicklung von UR:SMART

Nachdem in Kapitel 3.1 und 3.2 auf den aktuellen Stand des Social-Media Analysetools UR:SMART eingegangen wurde, erfolgt nun ein Einblick in aktuelle, sowie ein Ausblick auf zukünftige Weiterentwicklungen.

Die aktuelle Version von UR:SMART wurde auf Basis des JAVA-Frameworks „Vaadin“ entwickelt, anhand dessen die eigentliche Anwendungslogik sowie Nutzerinteraktionen durch GUI Elemente entwickelt werden können. Aufgrund der Kapselung der kompletten Anwendungslogik sowie der Erstellung der GUI Elemente innerhalb der gleichen Applikation, entstand jedoch eine monolithische Anwendung (Fowler and Lewis, 2015). Aufgrund der starren Architektur, sowie der fehlenden Modularisierung wird die Wartung eines solchen Monolithen deutlich erschwert. Ebenso müssen Anwendungsfälle mehrfach im Code abgebildet werden, da durch die monolithische Architektur keine wiederverwendbaren Komponenten realisiert werden können. Zusätzlich leidet unter der fehlenden Modularisierung der Komponenten ebenso die Erweiterbarkeit (Schreiber et al., 2017).

Um eine Unabhängigkeit vom ursprünglich verwendeten Vaadin-Framework sowie eine striktere Trennung von Front- und Backend des Softwaretools UR:SMART zu erreichen, wird das Social-Media Analyse Tool aktuell auf eine servicebasierte Architektur (siehe Abbildung 10) adaptiert (Fowler and Lewis, 2015).

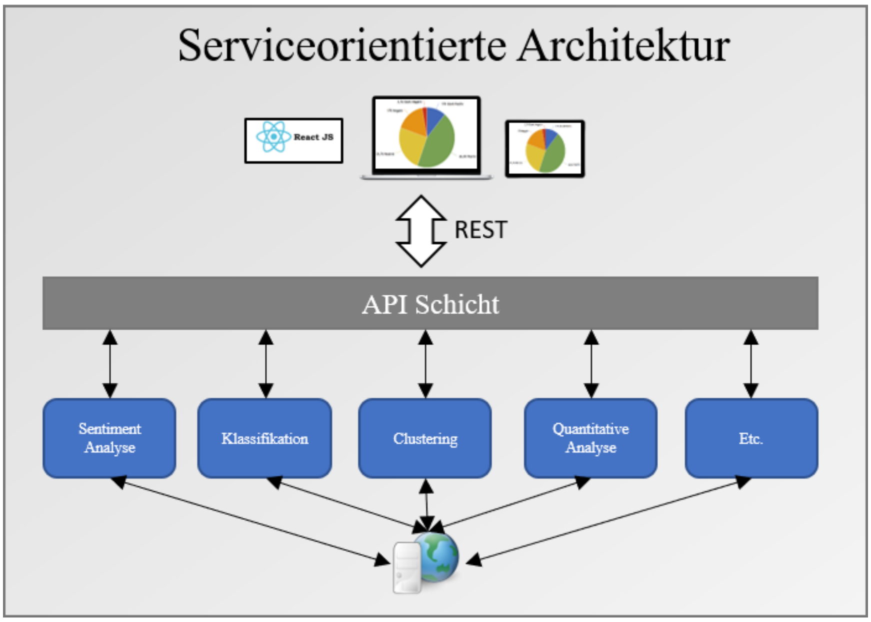

Abbildung 10: Serviceorientierte Architektur von UR:SMART

Die Ablösung des Vaadin-Frameworks erfordert eine grundlegende Umstrukturierung. Die neu entwickelte Anwendung (Backend) wird als Webservice implementiert, der über **RE**presentational **S**tate **T**ransfer (REST) APIs kommuniziert. Einzelne Funktionalitäten lassen sich so modular und wiederverwendbar implementieren.

Die Ausgabe der GUI (Frontend) wird zukünftig mit dem ReactJS[10] Framework realisiert. ReactJS ist eine von Facebook entwickelte JavaScript-Bibliothek zur Erstellung von Benutzeroberflächen. ReactJSs zentrales Konzept sind Komponenten, welche eine modulare Applikationsarchitektur ermöglichen und als Basis für nachvollziehbaren und leicht wartbaren Frontendcode dienen. Das komponentenbasierte Konzept von ReactJS distanziert sich von einem hierarchischen Seitenkonzept, bei welchem alle Funktionalitäten innerhalb einer HTML- und Java-Script Datei enthalten sind. Dies resultiert in sehr übersichtlichem, wartbaren und leicht erweiterbaren Sourcecode.

Auf Basis dieser Umstrukturierung ist zudem die zukünftige Erweiterung von UR:SMART um zusätzliche Analyseformen möglich. So ist aktuell ein neuer Ansatz zur Sentiment Analyse von längeren Texten in der Entwicklung, welcher neben kurzen, vorrangig auf Social-Media Kanälen wie Facebook und Twitter vorkommender Social-Media Beiträgen auch die Analyse von längeren Texten, wie beispielsweise Produktbewertungen oder Serviceberichten aus Foren oder Bewertungsportalen ermöglicht. Des Weiteren soll als neue Analyseform das Clustering, also ein unüberwachter Analyseansatz, welcher sich auf den Zusammenstellungsprozess von Daten konzentriert, um automatisch definierte homogene Gruppen durch Identifizierung statistischer Strukturen und Muster zu erkennen, in UR:SMART integriert werden (Dayan, 1999). Mit Hilfe des Clusterings soll es möglich werden, auch neue, bisher nicht relevante oder unbekannte Themengebiete zur Kategorisierung der Social-Media Inhalte zu identifizieren und in die Analyse zu integrieren.

Durch die stetige Erweiterung der verfügbaren Analyseformen in UR:SMART werden zudem die Möglichkeiten der hybriden Analyse ausgebaut. So ergeben sich durch die Integration neuer Analysemethoden auch neue Kombinationsmöglichkeiten und Anwendungsfälle. Beispielsweise können durch die neue Sentiment Analyse von längeren Texten auch Produktrezessionen oder Serviceberichte ausgewertet und in

[10] vgl. https://reactjs.org/

Kombination mit dem Clustering neue Kundenbedürfnisse oder Produktschwachstellen identifiziert werden.

4 Schlussbetrachtung und Fazit

Dieses Kapitel fasst zunächst die Forschungsergebnisse der Dissertation in Kapitel 4.1 zusammen. In Kapitel 4.2 wird der Beitrag der Dissertation für Wissenschaft und Praxis nochmals hervorgehoben. Eine kritische Würdigung (Kapitel 4.3) sowie ein Ausblick (Kapitel 4.4) schließen diese Dissertation ab.

4.1 Zusammenfassung der Forschungsergebnisse

Die Zusammenfassung der Forschungsergebnisse erfolgt für jede der sechs wissenschaftlichen Publikationen separat.

Die Zielstellung des **ersten Beitrags** „UR SMART: Social-Media Analysis Research Toolkit“ (Kapitel 2.1) lässt sich in drei Bereiche gliedern: (1) Die Identifikation von Anforderungen an ein Social-Media Analyse Tool für KMU; (2) Die Identifikation von generalisierbaren Klassen für die Klassifikation von Social-Media Posts bei KMU; (3) Entwicklung eines Konzeptes des Software-Prototyps UR:SMART, der eine automatische Sentiment Analyse und eine Klassifizierung von Kundenbeiträgen in Social-Media Plattformen, speziell auf die Bedürfnisse von mittelständischen Unternehmen in Süddeutschland abgestimmt, ermöglicht. Zur Erreichung dieser Zielstellung wird ein Design Science Projekt nach (Hevner et al., 2004) durchgeführt. Dabei werden Interviews und Workshops mit fünf Partnerunternehmen aus dem KMU Bereich durchgeführt. Für die Analyse der textuellen Social-Media Inhalte der Partnerunternehmen kommt die allgemeine Methode der Textanalyse nach (Aggarwal and Zhai, 2012a) zum Einsatz.

Als Ergebnisse werden in diesem Artikel 11 spezifische Anforderungen an ein Social-Media Analyse Tool für KMU auf Basis der durchgeführten Interviews und Workshops mit den fünf Partnerunternehmen identifiziert. Zudem erfolgt die Identifikation von 12 Klassen (z.B. Produkt, Service, Prozesse etc.) für die Klassifikation von Social-Media Posts bei KMU, welche aus von den Partnerfirmen bereitgestellten Social-Media Inhalten extrahiert wurden. Abschließend wurde ein speziell auf die Bedürfnisse von mittelständischen Unternehmen in Süddeutschland abgestimmter Software-Prototyp UR:SMART konzipiert und implementiert, welcher die automatische Sentiment Analyse und Klassifizierung von Kundenbeiträgen in Social-Media Plattformen ermöglicht.

Für den **zweiten Beitrag** „Assessing the accuracy of sentiment analysis of Social-Media posts at small and medium-sized enterprises in Southern Germany" (Kapitel 2.2) lassen sich folgende Zielstellungen nennen: (1) Die Identifikation der spezifischen Eigenschaften von Social-Media Posts bei KMU; (2) Die Identifikation von Algorithmen zur automatisierten Sentiment Analyse von Social-Media Inhalten bei KMU; (3) Implementierung und Evaluierung eines geeigneten Algorithmus zur Sentiment Analyse bei KMU. Zur Erreichung dieser Zielstellungen wurde wiederum ein Design Science Projekt nach (Hevner et al., 2004) durchgeführt. Dabei wurde zum einen eine Literaturanalyse zum Thema „automatisierte Sentiment Analyse" nach (Vom Brocke et al., 2009) durchgeführt, um geeignete Algorithmen für die automatische Sentiment Analyse von Social-Media Inhalten bei KMU zu identifizieren. Zum anderen wurde ein geeigneter Algorithmus implementiert, demonstriert und evaluiert.

Als Ergebnisse werden in diesem Artikel verschiedene Besonderheiten von Social-Media Beiträgen bei KMU, z. B. spezielle Branchen- und Produktsprachen, themenfremde Diskussionen, branchenspezifische Komponenten (z. B. Slang, Jargon) und firmenspezifische Ausdrücke (z.B. Surferjargon im Fun- und Wassersport oder spezielle Fahrzeugteile) identifiziert. Zur Sentiment Analyse von Social-Media Inhalten bei KMU wurden 17 potentielle Algorithmen zur Sentiment Analyse von Social-Media Inhalten bei KMU aus der Literatur identifiziert. Eine Implementierung und Evaluation eines lexikonbasierten Sentiment Analyse Algorithmus, welcher speziell an die Charakteristika der jeweiligen KMU angepasst wurde, ergab eine Genauigkeit bis zu 88% bei der Anwendung an konkreten Social-Media Inhalten des jeweiligen Partnerunternehmens.

Die Zielstellungen des **dritten Beitrages** „"What does the customer want to tell us?" An automated classification approach for Social-Media posts at small and medium-sized enterprises" (Kapitel 2.3) lässt sich in zwei Bereich unterteilen: (1) Die Identifikation von Algorithmen zur automatisierten Klassifikation zur Analyse von Social-Media Inhalten bei KMU; (2) Die Implementierung und Evaluierung eines geeigneten Algorithmus zur Klassifikations-Analyse bei KMU. Zur Erreichung dieser Zielstellungen wurde analog zum letzten Beitrag ein Design Science Projekt nach (Hevner et al., 2004) durchgeführt.

Dabei wurde zum einen eine Literaturanalyse zum Thema „automatisierte Klassifikation“ nach (Vom Brocke et al., 2009) betrieben, um geeignete Algorithmen für die Klassifikation von Social-Media Inhalten bei KMU zu identifizieren. Zum anderen wurde ein geeigneter Algorithmus implementiert, demonstriert und evaluiert.

Als Ergebnisse des Artikels werden 9 potentielle Algorithmen zur Klassifikation von Social-Media Inhalten bei KMU aus der Literatur identifiziert. Auf Basis der analysierten Social-Media Inhalte der Partnerfirmen geht hervor, dass die Zielstellung des Social-Media Kanals des jeweiligen Unternehmens eine entscheidende Rolle bei der Klassifizierung von Social-Media Beiträgen darstellt. Zudem ist die unternehmensspezifische Anpassung der wichtigsten Kategorien entscheidend für ein hohes Maß an Genauigkeit. Eine Implementierung, Demonstration und Evaluation eines geeigneten Ansatzes zur Klassifikation von Social-Media Inhalten bei KMU resultierte in den folgenden Mittelwerten: Precision (53,28%); Recall (80,45%); F-Measure 62,75%.

Für den **vierten Beitrag** „A hybrid approach combining various Social-Media analysis methods” (Kapitel 2.4) lassen sich ebenfalls zwei zentrale Zielstellungen nennen: (1) Die Konzeption und Entwicklung eines hybriden Ansatzes, der verschiedene Analysemethoden von Social-Media Daten (z. B. Sentiment Analyse, Klassifizierung, Clustering, Social-Media-Insights usw.) kombiniert und somit deutlich detailliertere sowie zielgerichtetere Analysen im Vergleich zu einer einschichtigen Auswertung bietet; (2) Die Demonstration und Evaluation des entwickelten hybriden Ansatzes auf Basis von Social-Media Inhalten von zwei kooperierenden KMU. Zur Erreichung dieser Zielstellung wurde ein kombinierter Design Science Ansatz nach (Peffers et al., 2007) und (March and Smith, 1995) angewendet. Dabei steht vor allem die Synthese der Aktivitäten „Build / Development“ und „Justify / Evaluate im Vordergrund, mit dem Ziel ein Organisationsproblem durch die Entwicklung eines IT-Artefaktes, in diesem Fall die zu entwickelnde hybride Social-Media Analysemethode, zu lösen. Dabei wurde zum einen auf Basis einer Marktstudie von bereits erhältlichen Social-Media Analyse Tools der Bedarf sowie die Potentiale von hybriden Analysen im Bereich der Social-Media Analyse erhoben. Zum anderen wurde ein Ansatz zur freien Kombination verschiedener Social-Media Analysemethoden entwickelt.

Als Ergebnis des Artikels lässt sich ein hybrider Ansatz nennen, welcher die freie Kombination von Sentiment Analyse, Klassifizierung, Clustering, Social-Media Insights usw. erlaubt. Dabei werden die vier konkreten hybriden Analysemethoden “*Sentiment of reactions”, “Ranking of reactions within a sentiment”, “Distribution of categories vs. Distribution of reactions”* und *“Fan growth per category”* vorgestellt und detailliert beschrieben. Zudem erfolgt eine Demonstration und Evaluation des hybriden Ansatzes anhand von Kooperationsunternehmen zur Verfügung gestellten Social-Media Daten. Aus der Auswertung der Analyseergebnisse geht hervor, dass die Kombination verschiedener Social-Media Analysemethoden einen deutlichen Mehrwert gegenüber alleinstehenden Analysemethoden bietet und zielgerichtete und detailliertere Informationen über die aktuellen Meinungen, Bedürfnisse und Interessen der Kunden liefert.

Die Zielstellungen des **fünften Beitrages** „Analyzing social-media content from a qualitative and quantitative perspective - design and development of a hybrid approach“ (Kapitel 2.5) lassen sich wie folgt beschreiben: (1) Die Identifikation von Anwendungsszenarien für die hybride Analyse von Social-Media Inhalten; (2) Die Evaluation des Artefaktes UR:SMART im Unternehmenseinsatz bei KMU im süddeutschen Raum; (3) Durchführung und Auswertung einer SUMI Usability Studie des Artefaktes UR:SMART. Um diese Zielstellungen zu erfüllen, wurde eine Design Science Untersuchung nach dem Vorbild von (Sonnenberg and vom Brocke, 2012) durchgeführt. Der Evaluationsprozess wird dabei in eine Ex-ante- und Ex-post-Evaluation aufgeteilt was zu einer separaten Evaluation der Problemstellung, des Artefaktdesigns und des konstruierten Artefakts führt. Im Rahmen der Evaluation werden sowohl Interviews mit verschiedenen kooperierenden KMU zur Verifizierung der Problemstellung, als auch Workshops zur Identifikation verschiedener Anwendungsszenarien für die hybride Analyse von Social-Media Inhalten durchgeführt. Zudem erfolgt eine Demonstration des Social-Media Analyse Tools UR:SMART und der Anwendungsszenarien bei einem Kooperationspartner.

Die Ergebnisse des Artikels gestalten sich wie folgt: Zunächst wird der aktuelle Stand der Social-Media Analyse inkl. spezifischer Problemstellungen in der Praxis auf Basis von elf Interviews bei KMU, welche sowohl im B2C- als auch im B2B-Bereich tätig sind, erhoben. Hieraus wird die Notwendigkeit von hybriden Social-Media Analyseformen konkret ersichtlich. Anschließend werden die zwei Anwendungsszenarien „*Product Commendation/Criticism*“ und „*Topic Identification*“ für die hybride Analyse von Social-Media Inhalten entwickelt und vorgestellt. Diese Szenarien werden im weiteren Verlauf des Artikels mit Hilfe von UR:SMART auf 635 Datensätze eines Partnerunternehmens angewendet. Nach der Demonstration erfolgt eine Evaluation der Analyseergebnisse auf Basis von Interviews mit Social-Media Verantwortlichen bei den Kooperationsunternehmen, woraus ein deutlicher Mehrwert der hybriden Analyseszenarien ersichtlich wird. Abschließend wird die Usability der Software UR:SMART mit einer SUMI Studie untersucht, welche der Software mit einem SUMI Score von 60.31% (“efficiency”, 58.83%; “graphical user interface”, 60.46%) gute Usability Werte bescheinigt.

Der letzte **Beitrag 6** „Measuring the Success of Social-Media: Matching Identified Success Factors to Social-Media KPI” (Kapitel 2.6) hat wiederum zwei Zielstellungen: (1) Die Entwicklung eines Ansatzes zur Kategorisierung von CSFs von Social-Media Anwendungen; (2) Das Matching von CSFs mit entsprechenden KPIs zur Erfolgsmessung von Social-Media. Zur Lösung dieser Zielvorgaben kommt die Design Science Research Methodology nach (Peffers et al., 2007) zum Einsatz. Dabei wurden zwei Literaturanalysen zum Thema CSFs & KPIs von Social-Media nach dem Vorgehensmodell von (Vom Brocke et al., 2009) durchgeführt, um geeignete CSFs sowie KPI von Social-Media aus der Literatur zu identifizieren. Diese CSFs wurden im Anschluss mit Hilfe einer Klassifikation in Kategorien eingeteilt. Abschließend erfolgte eine Zuordnung der identifizierten KPIs zu den klassifizierten CSFs, um Erfolgsfaktoren im Social-Media Bereich konkret mit Hilfe von zugehörigen KPIs messbar zu machen.

Als Ergebnis dieses Artikels wurden im ersten Literature Review zum Thema „Kritische Erfolgsfaktoren für Social-Media“ 42 Critical Success Factors für Social-Media identifiziert. Diese 42 CSFs wurden im Rahmen einer Klassifikation in fünf Cluster *User, Content, Management (Mgmt), Determining Factors (DF)* und *Team* eingeordnet. Im zweiten Literature Review zum Thema „KPIs im Social-Media Bereich“ wurden 99 KPIs zur Erfolgsmessung von Social-Media identifiziert. Anschließend konnten 55 dieser KPIs zu konkreten CSFs zugeordnet werden und erlauben so die Messung des Erfolges des Einsatzes von Social-Media im Unternehmensumfeld im allgemeinen sowie der Erfolgsmessung von bestimmten Maßnahmen im Social-Media Bereich.

Zusammenfassend lässt sich hervorheben, dass auf Basis der Ergebnisse der sechs wissenschaftlichen Beiträge die in Kapitel 1.1 erhobenen Zielstellungen (Z1-Z3) vollständig erfüllt wurden.

4.2 Beitrag für Wissenschaft und Praxis

Durch die Forschungsergebnisse in dieser Dissertation ergeben sich verschiedene Beiträge sowohl für die Wissenschaft als auch für die Praxis.

Ein Beitrag für die Wissenschaft ist die Bereitstellung eines Wörterbuches für sprachliche Besonderheiten von Social-Media Inhalten im süddeutschen Raum. Die Dissertation behandelt nicht nur eine mehrsprachige Auswertung sowohl englischer als auch im speziellen deutscher Social-Media Posts, sondern erlaubt weiterhin eine Anpassung der Analyse auf die einzigartigen regionalen und branchenabhängigen Anforderungen wie Dialekt, Slang und branchenspezifische Ausdrucksweisen. Diese Besonderheiten von Posts werden in einem Wörterbuch gesammelt und dienen damit als Ausgangspunkt für weitere Forschungsvorhaben im genannten Bereich.

Des Weiteren erfolgt ein systematischer Vergleich von Ansätzen zur Sentiment Analyse und zur Klassifizierung von textuellen Social-Media Daten. Dabei werden die Bewertungskriterien offen dargelegt, was eine Wiederverwendung der Ergebnisse für andere Anwendungsgebiete ermöglicht. In der Umsetzung der angestrebten Softwarelösung werden bestehende Verfahren zur Sentiment Analyse und zur Klassifizierung erweitert und weiterentwickelt. Die entstehenden Konzepte und die praktischen Umsetzungen in Form des Softwaretools UR:SMART dienen als Ausgangpunkt für weitere Forschungsarbeiten. Weiterhin werden die umgesetzten Ansätze evaluiert und somit der Nutzen und die Anwendbarkeit von Ansätzen zur automatischen Sentiment Analyse und Klassifizierung von textuellen Social-Media Daten bei KMU im süddeutschen Raum gezeigt.

Zudem wurde verdeutlicht, dass die Kombination verschiedener, zunächst eigenständiger Analyseansätze im Bereich der Social-Media Analyse anwendbar und sehr vorteilhaft ist. Daher wurden verschiedene hybride Analysemethoden vorgestellt, die es ermöglichen, tiefe Einblicke in die aktuellen Meinungen, Bedürfnisse und Interessen der Kunden zu gewinnen. Mit dem vorgestellten Ansatz bietet sich eine Lösung, die sich nicht nur zum Extrahieren aller zugrunde liegenden Social-Media Daten (einschließlich Metadaten) und zur Sentiment Analyse sowie zur Klassifizieren dieser eignet, sondern auch eine freie und zielgerichtete Kombination der Analyseformen bietet, um die gewonnenen Erkenntnisse noch weiter zu verbessern und zu vertiefen.

Des Weiteren leistet die Dissertation verschiedene Beiträge für die Praxis. Zum einen kann der Aufwand und die benötigten Ressourcen für die Durchführung von Social-Media Analysen, die von immer mehr Unternehmen im Zuge ihrer Digitalisierungsbemühungen eingeführt werden, durch die automatisierte und zielgerichtete Analyse der vorgestellten Software UR:SMART erheblich reduziert werden. Dabei können die identifizierten Anwendungsszenarien verwendet und spezifisch erweitert werden, um individuelle Social-Media Analysen durchzuführen. Zudem liefert die Anwendung eines hybriden Social-Media Analyseansatzes nützliche Erkenntnisse, die den Ergebnissen einer einseitigen qualitativen oder quantitativen Analyse überlegen sind. Beispielsweise können durch die zielgerichtete Kombination von Analyseansätzen nicht nur Nutzerstimmen gebündelt werden, um das Produkt- oder Dienstleistungsportfolio zu verbessern (qualitative Analyse), sondern auch um auf einfache Weise eine Priorisierung dieser Aussagen abgeleitet werden z. B. basierend auf der Anzahl oder der Steigerungsraten von „Likes“ und „Shares“ (quantitative Analyse). Auf diese Weise erhalten die Mitarbeiter eine fundiertere Entscheidungsgrundlage auf Basis der aus den Social-Media Posts extrahierten Informationen und können individuell und ressourcenschonend auf Problemstellen reagieren.

Somit kann der Einsatz von UR:SMART zur automatisierten Analyse von Social-Media Inhalten im Unternehmen dazu beitragen, Schwachstellen aufzudecken und die zugrundeliegenden Probleme zu identifizieren. Beispielsweise kann eine große Anzahl an negativen Posts zum Thema Produktqualität oder Lieferzeit auf ein ernsthaftes Problem innerhalb der Produktions- oder Lieferprozesse hinweisen. Basierend auf diesem, aus den Social-Media Inhalten extrahierten Wissen, können nun kritische Faktoren identifiziert und konkrete Verbesserungsprojekte angestoßen werden (Pande et al., 2000, Snee and Hoerl, 2003). Die Auswahl kritischer Unternehmensbereiche und das Finden von Ansatzpunkten zur Qualitätsverbesserung stellt Firmen vor große Probleme (Thawesaengskulthai and Tannock, 2008). Die von der Softwarelösung unterstützte Filterung der Posts nach Unternehmensbereichen stellt hier einen Lösungsansatz bereit. Beispielsweise können mit Hilfe der zu entwickelnden Software besonders negative Kundenmeinungen über bestimmte Geschäftsbereiche spezifisch ausgewählt und genauer betrachtet werden. Somit können potentiell problematische Bereiche leichter identifiziert und Gegenmaßnahmen angestoßen werden.

Ein wichtiger Aspekt um die Wirksamkeit von Gegenmaßnahmen nachzuweisen ist die regelmäßige Messung und Überwachung der Effektivität. Die Softwarelösung soll daher eine zeitabhängige Auswertung von Social-Media Posts ermöglichen. Darauf basierend können Unternehmen den Einfluss durchgeführter Verbesserungsmaßnahmen (z.B. Schulung der Servicemitarbeiter) direkt anhand der Kundenmeinungen innerhalb der Social-Media Kanäle messen. Auf ein längeres Zeitfenster bezogen, können mit Hilfe von zeitabhängigen Analysen zudem Veränderungen und Schwankungen von Kundenmeinungen und Kundenerwartungen beobachtet bzw. verfolgt werden. Beispielsweise kann ein sprunghafter Anstieg von Beiträgen zum Produktportfolio eines Unternehmens ein Indikator für veränderte Kundenbedürfnisse sein (Mukerjee, 2013). Viele Unternehmen nutzen ihre Social-Media Auftritte für Marketing und Werbekampagnen. Gerade in diesem Anwendungsgebiet ermöglicht die genannte zeitabhängige Analyse, Kundenreaktionen auf spezifische Kampagnen zu erfassen und erfolgreiche Themen auch in nachfolgenden Aktionen einzusetzen (Castronovo and Huang, 2012).

Zusammenfassend stellt die vorliegende Dissertation also eine branchenspezifisch anpassbare Lösung zur Auswertung von Social-Media Inhalten für KMU im süddeutschen Raum bereit. Durch die Forschungsergebnisse in dieser Dissertation profitieren sowohl die Wissenschaft als auch die Praxis.

4.3 Kritische Würdigung

Die in dieser Dissertation vorgestellten Forschungsergebnisse sollen im folgenden Kapitel kritisch hinterfragt werden, was in Form von Limitationen erfolgt.

Als erste Limitation lässt sich die Einschränkung der Analyse von Social-Media Inhalten auf fünf kooperierende KMU im süddeutschen Raum nennen, was eine Beschränkung für die Generalisierbarkeit der Ergebnisse darstellt. Die Fokussierung auf eine bestimmte geografische Region ermöglicht es, detailliertere Ergebnisse für dieses bestimmte Gebiet zu erzielen. Jedoch ist eine zukünftige Erweiterung der Zielgruppe sinnvoll, um die allgemeine Anwendbarkeit der Social-Media Analysesoftware UR:SMART sicherzustellen. In Anbetracht der Tatsache, dass Social-Media Inhalte von zusätzlichen Kooperationsunternehmen weitere sprachliche Besonderheiten beinhalten können, ist die Erweiterung der Anwendungsfälle und somit die Ergänzung der in UR:SMART integrierten Feature-Lexika wünschenswert.

Eine weitere Limitation liegt in der Subjektivität, welche bis zu einem gewissen Grad der manuellen Sentiment Analyse und Klassifikation von Social-Media Inhalten zugrunde liegt. Die Evaluation der Genauigkeit der automatischen Analyseansätze wurde auf Basis manuell gelabelter Daten beurteilt. Mit Hilfe des Einsatzes von sechs Forschern, welche die manuelle Analyse der Social-Media Inhalte individuell durchgeführt haben und einer anschließenden Konsolidierung der Ergebnisse wurde die genannte Subjektivität abgeschwächt. Eine vollständige Objektivität kann jedoch nicht gewährleistet werden.

Weiterhin beschreibt die Analyse von Social-Media Inhalten immer nur einen momentanen Zustand, da der Social-Media Bereich allgemein als ein sich schnell veränderndes Feld bekannt ist. In Bezug auf die Klassifizierung bedeutet dies, dass die zuvor definierten Klassen den aktuellen Stand widerspiegeln, potenzielle zukünftige Themen jedoch vernachlässigen. Daher erscheint eine Kombination aus Klassifizierung und Clustering zur Identifizierung neu aufkommender Themen vielversprechend. Zudem ist die Abgrenzung der Kategorien während der Klassifizierung schwierig und kann zu Mehrdeutigkeiten führen. Wenn beispielsweise die Firma "B" einen Post veröffentlicht, der sich mit einem neuen Chat-Service für App-Kunden befasst, kann der Post entweder in die Kategorien "Service" oder "Technologie" eingeteilt werden. In diesem Fall ist die entsprechende Zuordnung der Reaktionen zwangsläufig ungenau.

Obwohl die Genauigkeit der verwendeten Ansätze mit einem Durchschnittswert von bis zu 94% hoch ist, ist eine vollständig fehlerfreie Analyse aufgrund sich schnell ändernder Spezifika in Bezug auf die verwendete Sprache (z. B. Slang oder Ironie) und nicht standardisierte Sprachelemente wie Emojis und Abkürzungen nicht erreichbar (Laboreiro et al., 2010, Petz et al., 2013). Daher treten gelegentlich falsch klassifizierte Datensätze auf. Bei der Kombination letzterer mit weiteren Analysemethoden oder quantitativen Metadaten werden die ungenauen Ergebnisse übertragen, was möglicherweise Managemententscheidungen aufgrund von Fehlinterpretationen beeinflusst.

Des Weiteren wurde der hybride Analyseansatz bisher nur in einem Unternehmen eingehend evaluiert. Dem hybriden Analyseansatz liegen jedoch keine branchenspezifischen Voraussetzungen zugrunde, weswegen sich die eingesetzten Mechanismen branchenübergreifend anwenden lassen. Daher ist eine Ausweitung der Anwendung und Evaluation auf weitere Unternehmenspartner sinnvoll, um eine generelle Anwendbarkeit sicherzustellen.

4.4 Ausblick auf weitere Forschungsfelder

Nachdem die Limitationen der Forschungsergebnisse erläutert wurden, schließt diese Kapitel die vorliegende Dissertation mit einem Ausblick auf weitere interessante Forschungsfelder ab.

Zunächst sollte genauer untersucht werden, wie Unternehmen die auf Basis der Social-Media Analysen erhaltenen Informationen für unternehmerische Entscheidungen nutzen können. In diesem Zusammenhang ist zu untersuchen, inwieweit es möglich ist, aus den Analyseergebnissen automatisch Handlungsempfehlungen abzuleiten, z. B. den Start von Initiativen zur Prozessverbesserung oder Marketingkampagnen, um bestimmte Kundengruppen direkt anzusprechen. Darüber hinaus steht die Integration von Social-Media Datenanalysen in die strategische Entscheidungsfindung im Fokus.

Weiterhin ist die Integration neuer, innovativer Analysemethoden ein interessantes Forschungsfeld. Neben textuellen Social-Media Daten ist aktuell ein stetiger Trend in Richtung multimedialer Social-Media Plattformen wie Instagram, Youtube oder Pinterest erkennbar (Statista, 2020a). Daher sollten neue Analyseformen wie eine bildbasierte Sentiment Analyse, eine automatische Objekterkennung oder auch die Analyse von Videoinhalten näher erforscht und integriert werden, um umfängliche Analysen dieser Social-Media Inhalte zu gewährleisten. Auf Basis dieser neuen Analysemethoden können zudem neue und nützliche Anwendungsszenarien für hybride Social-Media Analysen definiert werden.

Abschließend sollte UR:SMART in weiteren Usability-Studien unter Einbeziehung von Praktikern, aber auch in realen Social-Media Projekten mit Unternehmen unterschiedlicher Größe und branchenübergreifend weiter eingesetzt und evaluiert werden. Hierbei ist der Beitrag von UR:SMART zur Unterstützung der Erhebung geschäftsrelevanter Informationen für verschiedene Fälle genau zu prüfen. Dabei sollten die Projektteilnehmer den SUMI-Fragebogen nutzen, um die Software auf der Grundlage der fünf Dimensionen e*fficiency, affect, helpfulness, control* und *learnability* zu bewerten (Kirakowski, 1996). Auf diese Weise ergeben sich Möglichkeiten zur Weiterentwicklung der Software, möglicherweise in Bezug auf die Einbeziehung weiterer erklärender Informationen, der Unterstützung des Benutzers bei der Interaktion mit dem Werkzeug oder seiner visuellen Neugestaltung.

Literaturverzeichnis

Hinweis: Die hier angegebene Literatur wird in den Kapiteln 1, 3 und 4 referenziert. In Kapitel 2 wird je Forschungsbeitrag die referenzierte Literatur im Anschluss an den Beitrag gelistet.

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