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Weiterentwicklung von Methoden und Ansätzen zur automatisierten Informationsextraktion aus Social Networks

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Inhaltsverzeichnis

Abbildungsverzeichnis

Tabellenverzeichnis

Abkürzungsverzeichnis

bez.	bezüglich
bzw.	beziehungsweise
d. h.	das heißt
DS	Design Science
DMR	Dirichlet Multinomial Regression
ESN	Enterprise Social Networks
ggf.	gegebenenfalls
GQM	Goal Question Metric
IS	Information System
IT	Information Technology
LDA	Latent Dirichlet Allocation
OSN	Online Social Networks
PAM	Pachinko Allocation Model
P2P	Peer-to-Peer
S.	Seite
SNA	Social Network Analysis
sog.	sogenannt
u. a.	unter anderem
v.a.	vor allem
vgl.	vergleiche
VoC	Voice of the Customer
WoM	Word of Mouth
z. B.	zum Beispiel

1. Einleitung

Zu Beginn der Arbeit werden zunächst das Thema und der Kontext der Dissertation definiert. Im Zuge dessen werden in Abschnitt 1.1 das zu behandelnde Thema motiviert sowie die zugrundeliegende Problemstellung aufgezeigt. Darauf aufbauend werden in Abschnitt 1.2 konkrete Zielstellungen, die mit der Dissertation erreicht werden sollen, festgelegt. Zudem werden der Dissertation zugrundeliegende theoretische Hintergründe aufgezeigt. Anschließend wird in Abschnitt 1.3 der Aufbau der Arbeit erläutert, um die, in der Dissertation, intendierte Vorgehensweise verdeutlichen zu können.

1.1 Motivation und Problemstellung

In den letzten Jahren stiegen Bekanntheit und Beliebtheit von Social Media Networks stetig an (Kane et al., 2012; Kaplan and Haenlein, 2010; Obar and Wildman, 2015). Dieser kontinuierliche Aufwärtstrend wird besonders deutlich, wenn man den Verlauf der Social Media Nutzerzahlen über die Jahre hinweg betrachtet. Während im Jahr 2012 gerade einmal 1,48 Milliarden Menschen Social Media Networks regelmäßig nutzten, waren es zehn Jahre später, 2022, bereits 4,62 Milliarden Menschen, die aktiv ihre Zeit in Social Media Networks verbrachten (Statista, 2022). Das bedeutet, dass mehr als die Hälfte der Bevölkerung weltweit Social Media Networks derzeit aktiv nutzen. Social Media Networks werden in der aktuellen Forschungsliteratur als internetbasierte Anwendungen definiert, die dem Nutzer die Möglichkeit der interaktiven und dynamischen Kommunikation, Kollaboration und Interaktion bieten (Dwivedi et al., 2021; Kane et al., 2012; Kaplan and Haenlein, 2010). Allerdings wird das Potenzial von sozialen Medien nicht nur von Privatpersonen genutzt, sondern vor allem auch von Unternehmen. Diese verwenden Social Media Networks einerseits als Online Social Networks (OSN) (Kim et al., 2018) zur Kommunikation mit ihren Kunden und andererseits als Enterprise Social Networks (ESN) zur Interaktion innerhalb des eigenen Unternehmens (Hacker and Riemer, 2021).

OSN wie z. B. Facebook, Twitter oder Instagram, als eine von vielen Social Media Arten, sind definiert als Online Communities, die Menschen mit gleichen Interessen, Aktivitäten, Hintergründen und/oder Kontakten miteinander verbinden (AlFalahi et al. 2014; Schneider et al., 2009). Damit ermöglichen sie auch eine neue Art der Kommunikation zwischen Kunde und Unternehmen (AlFalahi et al., 2014; Pal et al., 2014). Wie unterschiedlich diese Kundenkommunikation im Rahmen von OSN gestaltet sein kann und wie Unternehmen davon profitieren können, zeigen Gallaugher und Ransbotham (2010) mit ihrem 3-M-Framework, das folgende drei Ansätze der Kundenkommunikation beinhaltet: Monitor (Dialog zwischen Kunden), Magnet (kundeninitiierter Dialog) und Megaphone (firmeninitiierter Dialog). Demnach kann ein Unternehmen OSN zum einen als sog „Monitor" nutzen, um die Bedürfnisse der Kunden zu identifizieren. Indem die Kommunikation zwischen den Kunden erfasst wird, können Unternehmen Einblicke in die Meinungen von Kunden über das Unternehmen, deren Produkte und Dienstleistungen oder auch Meinungen über Wettbewerber gewinnen (Gallaugher and Ransbotham, 2010). Darüber hinaus bietet der vom Kunden initiierten Dialog (Magnet) dem Unternehmen die Möglichkeit, Kundenfeedback zu erfassen und so einerseits auf individuelle Kundenbedürfnisse zu reagieren und andererseits das Kundenverhalten durch gezielte Kundenkommunikation zu beeinflussen (Gallaugher and Ransbotham, 2010). Neben der direkten Einbindung der Kunden und deren Meinungen können OSN vor allem auch bei der Verbreitung von Marketingbotschaften eingesetzt werden (Megaphone). In diesem Zusammenhang sind gezielte Werbestrategien und elaborierte Kundenbindungsprogramme zum Aufbau und zur Förderung enger Kundenbeziehungen wichtig (Heidemann et al., 2010; Kietzmann et al., 2011). Dies kann zusätzlich zur klassischen Online Werbung auch mittels Peer-to-Peer (P2P)-Marketing erreicht werden. Ziel dieses P2P-Marketing ist die Verbreitung von Werbebotschaften mittels Word-of-Mouth (WoM) (Cha et al., 2010). Persönliche Empfehlungen durch Personen, die im selben Netzwerk agieren, sind hinsichtlich Neukundengewinnung und Kaufentscheidungen oftmals effektiver als herkömmliche Werbung (Brown et al., 2007).

Ob solche Werbebotschaften allerdings effektiv im Netzwerk verbreitet werden können, ist abhängig von der Person, die dabei als Multiplikator eingesetzt wird (Deng et al., 2016; Forestier et al., 2012). In der aktuellen Fachliteratur werden Multiplikatoren bzw. einflussreiche Nutzer als Personen definiert, die ein hohes Maß an Aktivität im Netzwerk aufweisen, Informationen schnell und effektiv verbreiten können und damit zu einer Verhaltensänderung bei anderen Nutzern führen (AlFalahi et al., 2014; Bakshy et al., 2011; Deng et al., 2016; Eirinaki et al.; 2012, Kim and Han, 2009). Der Einsatz einflussreicher Nutzer kann nicht nur die Reichweite der Marketingbotschaft deutlich erhöhen, sondern auch in den Bereichen Innovations- und Produktmanagement wirken. Neben der großen praktischen Relevanz des Themengebiets hat dieses auch in der Wissenschaft eine Vielzahl an Publikationen hervorgebracht. Allerdings gibt es in der aktuellen Forschungsliteratur viele verschiedene Terminologien wie z.B. Hub, Influencer, Key User etc., die der Gruppe der einflussreichen Nutzer zugeordnet werden können. Eine klare Definition und Abgrenzung der Begriffe voneinander fehlt bislang, einige Untersuchungen verwenden diese Begriffe sogar synonym (z.B. Galeotti and Goyal, 2009). Diese eindeutige Definition und Abgrenzung der verschiedenen einflussreichen Nutzer, resultierend aus einer einheitlichen Charakterisierung, ist aber zentral, um die Nutzer identifizieren und auch als Unternehmen davon profitieren zu können. Zudem liegt ein weiteres Problem darin, dass in der aktuellen Forschungsliteratur kaum spezifische Merkmale einflussreicher Nutzer innerhalb eines Social Media Networks definiert werden. Obwohl es viele verschiedene Studien zur Charakterisierung einflussreicher Nutzer gibt, beschreiben sie selten auch diejenigen Merkmale, die den Einfluss im Speziellen festlegen. Aus dieser Problemstellung wird für die vorliegende Dissertation folgende Zielstellung abgeleitet:

Zielstellung 1: Unterscheidung und Charakterisierung verschiedener, in der Literatur vorkommender, einflussreicher Nutzertypen in Social Media Networks

Einflussreiche Nutzer können neben der Verbreitung von Werbebotschaften auch im Zuge der Innovation und Produktentwicklung als sog. Lead User eingesetzt werden. Schwierigkeiten, mit denen sich Unternehmen während des Innovationsprozesses konfrontiert sehen, wie etwa hohe Kosten oder Unsicherheit über die Akzeptanz der Kunden, können diese Nutzer mindern (Ye and Kankanhalli, 2018). Um als Unternehmen allerdings von diesen Nutzern profitieren zu können, ist neben deren Charakterisierung vor allem auch die (automatisierte) Identifikation ein erfolgskritischer Aspekt. Vor allem vor dem Hintergrund der enormen Menge an Social Media Daten ist, laut Literatur, die Identifikation der Lead User der schwierigste und zeitaufwendigste Aspekt innerhalb der Lead User Methode (Brem and Bilgram, 2015). In der aktuellen Forschungsliteratur gibt es viele verschiedene Ansätze zur Identifizierung von Lead User, die jedoch nur einzelne Aspekte des Problems abdecken. Diese konzentrieren sich entweder auf nur ein Lead User Merkmal wie z.B. ein hohes Aktivitätslevel (Martínez-Torres, 2014) oder beziehen eine nur sehr geringe Datenmenge mit ein (Hau and Kang, 2016). Außerdem stützen sich verschiedene Untersuchungen auf Beobachtungen oder Online Fragebögen (Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011), was aufgrund der geringen Stichprobe zu einer eher limitierten Aussagekraft führt und zudem hohe Kosten mit sich bringt. Darüber hinaus werden oftmals Merkmale von Lead User auf Basis von Einschätzungen der Nutzer selbst abgeleitet, was die darauf basierenden Ergebnisse aufgrund subjektiver Beurteilung verzerren kann (Hienerth and Lettl, 2017). Darüber hinaus sind die meisten Identifizierungsmethoden zeitaufwendig, was im Widerspruch zu dem trendabhängigen, kurzfristigen Konstrukt des Lead User steht (Hienerth and Lettl, 2017). Eine Identifizierungsmethode, die große Datenmengen verarbeiten, alle in der Literatur angegebenen Merkmale eines Lead User automatisiert abbilden und auch Gegebenheiten, die durch das Einbeziehen des Innovationsprozesses entstehen, miteinbeziehen kann, fehlt in der aktuellen Forschungsliteratur.

Solche einflussreichen Nutzer lassen sich allerdings nicht nur in OSN feststellen, sondern auch in denen, die die Interaktion innerhalb eines Unternehmens darstellen, d.h. im Bereich ESN. ESN werden mit dem Ziel angewandt, die organisationale Effektivität und Effizienz im Unternehmen zu verbessern (Rossmann and Stei, 2016; Stei et al., 2016). Dabei werden die digitalen Kommunikations- und Interaktionsmöglichkeiten von sozialen Netzwerken auf die interne Unternehmensebene übertragen und an die jeweiligen Bedürfnisse der Unternehmen angepasst (Wehner et al., 2017). Zentral dabei ist, dass die Mitarbeiter dazu motiviert werden, aktiv Inhalte zu erzeugen, ihr Wissen mit anderen zu teilen und das vorhandene Wissen für die Realisierung betrieblicher Ziele zu nutzen (Günther and Spath, 2010). Die Nutzer, die Inhalte innerhalb des ESN konsumieren, produzieren und organisieren, stellen dabei einen der wichtigsten Faktoren dar, um die Möglichkeiten von ESN nutzen und als Unternehmen insgesamt davon profitieren zu können (Oestreicher-Singer and Zalmanson, 2013). In einigen Fällen erfüllen ESN allerdings nicht die Erwartungen der Unternehmen, so dass die Investition in Frage gestellt wird. Ein möglicher Grund dafür ist oftmals die sog. „kritische Masse“ an Nutzern, die nicht erreicht wird und die gleichzeitig aber für die Akzeptanz im Unternehmen unerlässlich ist (Chin et al., 2015). Es ist also absolut notwendig, sich auf ESN Nutzer auszurichten, um deren Verhalten positiv zu beeinflussen insbesondere vor dem Hintergrund, dass diese den Erfolg des ESN gefährden können. Dafür ist es notwendig, solche wertstiftenden Nutzer zu charakterisieren und auch zu identifizieren. Die aktuelle Forschungsliteratur, die sich mit genau dieser Charakterisierung und Identifizierung beschäftigt, stützt sich häufig nur auf die zugrundeliegende Netzwerkstruktur des ESN (Berger et al., 2014; Cetto et al., 2016; Cetto et al., 2018). Durch die Anwendung der sozialen Netzwerkanalyse (SNA) können Nutzer anhand ihrer Position innerhalb eines Netzwerks beschrieben werden. Die Nutzer mit der höchsten

Aktivität und dem höchsten Informationsverbreitungsgrad werden von Berger et al. (2014) als wertstiftende Nutzer bezeichnet. Allerdings lässt die bloße Anzahl an direkten und indirekten Verbindungen zu anderen Knoten keine Rückschlüsse auf die Qualität der Informationen zu, die über das Netzwerk verbreitet werden. Dieses Merkmal ist aber zentral bei der Entscheidung, ob ein Nutzer wertstiftend ist oder nicht. Zentrale Informationen lassen sich v.a. in den Inhalten von Textdokumenten, Posts oder Nachrichten, finden, die ein Nutzer schreibt. Allerdings berücksichtigen nur wenige Studien neben der SNA weitere Ansätze zur Charakterisierung und Identifizierung von einflussreichen Nutzertypen.

Hinsichtlich der eben beschriebenen Problemstellungen zur Identifikation von wertstiftenden Nutzern in OSN und ESN wird für die vorliegende Dissertation somit folgende Zielstellung abgeleitet:

Zielstellung 2: (Automatisierte) Identifikation und Unterscheidung von verschiedenen, einflussreichen Nutzertypen unter Verwendung von diversen Methoden zur Analyse von strukturierten und unstrukturierten Social Media Daten

Die vorliegende Dissertation beschäftigt sich neben der Charakterisierung und Identifikation von Nutzern insbesondere auch mit der Analyse von Social Media Network Daten. Durch deren Analyse können nämlich nicht nur Nutzer identifiziert werden, sondern beispielsweise auch die sog. „Voice of the Customer“ (VoC), also die Meinung von Kunden über bestimmte Produkte (Kitchens et al., 2018; Schwaiger et al., 2017). Die Identifikation der sich entwickelnden und verändernden Anforderungen der Kunden an ein Produkt oder an das Unternehmen selbst ist unerlässlich, wenn ein Unternehmen auf diese Kundenbedürfnisse eingehen will (Hong et al., 2012; Lozano et al., 2017). Das frühzeitige Erkennen von neuen und vielversprechenden Ideen und Trends in den Bereichen Produktentwicklung, Kundenverhaltensanalyse und Markt-/Markenbeobachtung kann zu Wettbewerbsvorteilen für Unternehmen führen (Bhor et al., 2018; Jeong et al., 2019). Verfahren, die innerhalb von Social Media Daten Trends aufspüren, verwenden in der Regel einen schlagwortbasierten Ansatz und liefern Ergebnisse in Form von einfachen Begriffen, Hashtags oder Term-N-Grammen (Lau et al., 2012). Problematisch dabei ist jedoch, dass neue Trends, die nicht in diesem Lexikon gespeichert sind, auf diese Weise nicht gefunden werden können. Um dieses Problem zu lösen, wurden automatisierte Techniken zur Themenfindung und insbesondere das Topic Modelling herangezogen und in der Forschungsliteratur umfassend untersucht (Chinnov et al., 2015; Eickhoff and Neuss, 2017; Hong and Davison, 2010). Das Topic Modelling ermöglicht dabei die Analyse einer großen Menge unstrukturierter Social Media Daten, um zugrundeliegende Themen automatisiert zu extrahieren (Chinnov et al., 2015; Eickhoff and Neuss, 2017; Lozano et al., 2017). Deshalb ist das Topic Modelling eine wichtige Technik, um Trends in Social Media erkennen und nachvollziehen, Inhalte aus Social Media extrahieren und diese auch strukturieren zu können. Durch Topic Modelling können also wertvolle Informationen innerhalb der zugrundeliegenden Daten extrahiert werden, da mithilfe des Topic Modellings verschiedene latente Diskussionsthemen sowie Kundenmeinungen innerhalb der großen Menge an Social Media Daten identifiziert werden können. Dennoch ist die Identifizierung der zugrundeliegenden Themen und Inhalte dieser Dokumente nach wie vor eine schwierige Aufgabe, da eine erfolgreiche Extraktion signifikanter Themeninhalte und -merkmale aus einem Datensatz von der Auswahl der zielführenden Topic Modelling Technik abhängt. Viele theoretische und praktische Untersuchungen verwenden die Standardtechnik Latent Dirichlet Allocation (LDA) (vgl. Blei et al., 2003). Allerdings ist LDA nicht universell einsetzbar und kann beispielsweise nicht alle Anwendungsfälle für marketingbezogene Aufgaben abbilden, so dass Erweiterungen dieser Standardtechnik zahlreich existieren. Das Problem bei deren Umsetzung liegt zum einen aber darin, dass fortgeschrittene technikbezogene Kenntnisse über den geeigneten Einsatz in verschiedenen Anwendungsfällen fehlen, und zum anderen darin, dass eine Vielzahl dieser Topic Modelling Techniken nur theoretisch beschrieben und daher nicht anwendbar sind (Vakansky and Kumar, 2020). Neben der Auswahl der zielführenden Technik ist vor allem auch deren praktische Umsetzung im Hinblick auf verschiedene Einsatzszenarien, v.a. im Bereich der Trend Analyse, ein Problem. Bereits auf dem Markt existierende Topic Modelling und/oder Trend Analyse Tools (z.B. Brandwatch, Meltwater, Symanto) weisen wesentliche Nachteile auf, da sie nicht umfassend die Anforderungen abdecken, die für Trendanalysen in Bezug auf marketingbezogene Anwendungsfälle (z. B. Produkt Entwicklung, Analyse von Kundenverhalten und Marktanalyse) entscheidend sind. Die vorhandenen Tools und Ansätze sind nicht in der Lage, externe Parameter wie z. B. Geolokationen, Zeit und benutzer-bezogene Informationen miteinzubeziehen und sind nicht in der Lage Kookkurrenzen aufzuzeigen, wodurch tiefergehende Analysen und Erkenntnisse nicht realisierbar sind. Um allerdings die VoC nutzen zu können, indem Erwartungen von Kunden erkannt werden, ist neben der Identifizierung der zugrundeliegenden Themen vor allem auch die Analyse des Sentiments zentral. So können beispielsweise durch die

Verbindung der beiden Analysearten Topic Modelling und aspekt-basierte Sentimentanalyse diverse Produktmerkmale und ggf. damit zusammenhängende Mängel festgestellt werden. Das Potenzial der aspekt-basierten Sentimentanalyse für das detaillierte Nachvollziehen von Trends im Zeitverlauf wurde bereits in Praxis und Theorie erkannt (z.B. Tuarob et al., 2015; Tucker and Kim, 2011). Dies hat wiederum zur Entstehung von Trendanalysetools geführt, die zudem Funktionen zur aspekt-basierten Sentimentanalyse enthalten. Die auf dem Markt erhältlichen Trendanalysewerkzeuge weisen jedoch erneut erhebliche Defizite auf, da sie externe Faktoren außer Acht lassen und zusätzlich die Möglichkeit nicht gegeben ist, Trends sowohl mit als auch ohne Vorwissen zu identifizieren (z.B. Tuarob et al., 2015; Tucker and Kim, 2011; Vo et al., 2018). Bei der Erstellung eines Trendanalysetools mit aspekt-basierter Sentimentanalyse kann die Berücksichtigung dieser Aspekte zu einer genaueren Identifikation von Kundenanforderungen führen.

Aus den beschriebenen Problemstellungen bez. des Topic Modelling werden für die vorliegende Dissertation somit folgende Zielstellungen abgeleitet:

Zielstellung 3: Vergleich zwischen verschiedenen Topic Modelling Techniken, um für ausgewählte Einsatzszenarien Handlungsempfehlungen abgeben zu können

Zielstellung 4: Ableitung von Anforderungen an ein Trend Analyse Tool hinsichtlich verschiedener Einsatzszenarien sowie an ein Trend Analyse Tool unter Berücksichtigung aspekt-basierter Sentimentanalyse

Zielstellung 5: Entwicklung und Evaluation von Softwaretools zur automatisierten Analyse von textuellen Social Media Inhalten unter Berücksichtigung verschiedener Anforderungen

Die Untersuchung der Social Media Network Daten insbesondere der zugrundeliegende Stimmung von Nutzern kann aber nicht nur in Bezug auf Veränderungen des Produkts interessante Einblicke bieten, sondern auch im Hinblick auf die unternehmenseigene Strategie bzw. die Social Media Strategie. Positive Resonanz in Social Media kann die Reputation und das Image eines Unternehmens erheblich verbessern. Unternehmen können vor allem profitieren, wenn gesellschaftlich relevante oder aktuelle Themen, wie z. B. die Nachhaltigkeit unternehmerischer Tätigkeit, aufgegriffen werden und sie ihre diesbezüglichen Aktivitäten und Bemühungen in der Öffentlichkeit kommunizieren (Etter 2014; Manetti and Bellucci 2016; Reilly and Larya 2018). Obwohl es für Unternehmen viele Vorteile hat, Nachhaltigkeitsthemen über soziale Medien zu verbreiten, sind es mögliche negative Folgen, die Unternehmen oft verunsichern und davon abhalten, bez. Nachhaltigkeit aktiver in Social Media zu sein (Minton et al., 2012; Lee et al., 2013). In der bisherigen Forschung wurden bereits verschiedene Aspekte dieses Themas erörtert und es wurde festgestellt, dass die negativen Folgen der Nachhaltigkeitskommunikation über soziale Medien verringert werden können, wenn ein Unternehmen seine Motive transparent offenlegt (Kim, 2014) oder einen Dialog mit Kunden und Stakeholdern initiiert, um eine erfolgreiche Kundenbeziehung aufzubauen (Araujo and Kollat, 2018). Um dies erreichen zu können, ist es für Unternehmen sinnvoll, die Themen zu kennen, die in den sozialen Medien in Bezug auf Nachhaltigkeit aktuell relevant und interessant sind. Die bisherige Forschungsliteratur hat dies bereits als wichtigen Aspekt für die Nachhaltigkeitskommunikation über soziale Medien identifiziert, bezieht aber entweder zu wenige Posts in ihre Untersuchung mit ein (Lodhia et al., 2020) oder bewertet die Inhalte und Themen der unternehmerischen Nachhaltigkeitskommunikation anhand offizieller Nachhaltigkeitsberichte, was sich im Ergebnis nicht mit dem Interesse der Social Media Nutzer decken muss (vgl. Reilly and Hynan, 2014). Weitere Studien beziehen ihre Ergebnisse nur auf die rein quantitative Anzahl von Tweets und Followern (vgl. Reilly and Larya, 2018) oder beschränken ihre Inhaltsanalyse auf Facebook- und Twitter-Accounts von Unternehmen (vgl. Manetti et al., 2017) und vernachlässigen damit die Perspektive der Nutzer. Da jedoch dieses Forschungsfeld so breit gefächert ist, sind viele Aspekte und insbesondere die Perspektive der Nutzer noch nicht ausreichend untersucht worden. Zudem fehlen in den Untersuchungen theoretische Implikationen auf die Gestaltung der Social Media Strategie. Aus dieser Problemstellung heraus wird für die vorliegende Dissertation somit folgende Zielstellung abgeleitet:

Zielstellung 6: Ableitung von Gestaltungsansätzen für die Social Media Strategie bei gesellschaftlich relevanten Themen (wie z.B. Nachhaltigkeit) durch die Analyse von Social Media Network Daten

Zusammenfassend lässt sich also festhalten, dass bei der Charakterisierung und Identifikation von einflussreichen Nutzern sowohl in OSN als auch in ESN erhebliches Potenzial liegt, das aufgrund von diversen Forschungslücken nicht ausgeschöpft werden kann. Vor allem auch die tiefergreifende Analyse von Social Media Network Daten, mit deren Hilfe vor allem marketingbezogene Trends identifiziert und untersucht sowie Ansatzpunkte für eine Social Media Strategie im Hinblick auf gesellschaftsrelevante Themen gefunden werden können, soll in der vorliegenden Dissertation durchgeführt werden.

1.2 Forschungsfragen

Basierend auf der in 1.1 beschriebenen Problemstellung und den daraus resultierenden Zielstellungen werden im Folgenden Forschungsfragen aufgezeigt, die in der vorliegenden Dissertation behandelt werden sollen. Diese Forschungsfragen resultieren jeweils aus der Problemstellung sowie den oben beschriebenen Zielstellungen.

Zielstellung 1: Um den aktuellen Stand der Forschung im Hinblick auf einflussreiche Nutzergruppen in Social Media Networks, insbesondere deren Charakterisierung und Unterscheidung, abbilden zu können, ist eine strukturierte Aufarbeitung der Literatur notwendig. Sowohl im Hinblick auf OSN als auch auf ESN stehen Unternehmen vor der Herausforderung, den passenden einflussreichen Nutzer zu finden – je nach Einsatzgebiet bzw. Zielstellung des Unternehmens. So können einflussreiche Nutzer beispielsweise als Multiplikatoren von Werbebotschaften (vgl. Influencer), als Unterstützer im Innovationsprozess (vgl. Lead User) oder auch als Multiplikatoren von Wissen (vgl. Key User oder Experte) eingesetzt werden. Dazu müssen diese einflussreichen Nutzertypen aber zunächst einmal in der aktuellen Forschungsliteratur herausgearbeitet werden. Um in einem ersten Schritt die einflussreichen Nutzertypen voneinander abgrenzen zu können, ist die Unterscheidung hinsichtlich ihres Einsatzgebiets zielführend. Daraus folgt die erste Forschungsfrage der Dissertation:

Forschungsfrage 1: Welche verschiedenen einflussreichen Nutzertypen werden in der aktuellen Forschungsliteratur diskutiert?

Aufbauend auf dieser grundlegenden Frage ist der nächste Schritt die Abgrenzung der verschiedenen einflussreichen Nutzertypen durch die strukturierte Aufarbeitung ihrer nutzerspezifischen Charakteristika. Dabei sollen auch diejenigen Charakteristika identifiziert werden, die den Einfluss, den der jeweilige Nutzer auf andere Personen im Netzwerk hat (was ihn dadurch auch zum <u>einfluss</u>reichen Nutzer macht), herausstellen. Mit Hilfe eines strukturierten Literature Reviews (vgl. Kitchenham et al., 2009; Webster and Watson, 2002; Wohlin et al., 2012), v.a. mit Fokus auf die Literaturanalyse nach Nickerson et al. (2013), sollen Charakteristika von verschiedenen einflussreichen Nutzertypen wie z.B. Influencer, Hub oder Key User gegenübergestellt werden. Dadurch lassen sich Lücken, Redundanzen oder Widersprüche in der Forschungsliteratur bezüglich Nutzertypen aufdecken. Neben der Zuordnung der Charakteristika zu den einzelnen einflussreichen Nutzergruppen im Rahmen eines Frameworks soll zudem ein morphologischer Kasten entstehen, der die Ergebnisse auf eine Metaebene hebt, so dass der Charakterisierungs- und Identifizierungsprozess der verschiedenen einflussreichen Nutzertypen strukturiert werden kann. Um zu dieser systematischen Aufarbeitung gelangen zu können, stellt sich folgende Forschungsfrage:

Forschungsfrage 2: Welche verschiedenen Charakteristika weisen die einflussreichen Nutzer in einem Social Media Network auf und wie können sie strukturiert dargestellt werden?

Neben der Charakterisierung der einflussreichen Nutzer in Social Media Networks ist vor allem auch die **Zielstellung 2**, die (automatisierte) Identifikation und Unterscheidung von verschiedenen, einflussreichen Nutzertypen unter Verwendung von diversen Methoden, zur Analyse von strukturierten und unstrukturierten Social Media Daten, für das Themengebiet der Dissertation elementar. Bisherige Ansätze bei der Identifikation einflussreicher Nutzer kombinieren nur wenige Methoden miteinander sowohl in ESN als auch in OSN. Das führt dazu, dass oftmals nicht alle Charakteristika abgedeckt (siehe auch **Zielstellung 1**) und somit die Nutzer nur eindimensional betrachtet werden. Bezüglich ESN hat sich die bisherige Forschungsliteratur nur auf eine kleine Anzahl an Merkmalen konzentriert – meist zwei –, um den einflussreichen bzw. wertstiftenden Nutzer zu charakterisieren und zu identifizieren. Da davon ausgegangen werden kann, dass die Kombination verschiedener Datendimensionen zu robusteren oder auch gänzlich neuartigen Erkenntnissen für Forschung und Praxis führen kann, sollen verschiedene Ansätze einbezogen werden, damit ein umfassender Ansatz entsteht. Ziel ist es zudem zu zeigen, wie Nutzer zum Wert eines ESN beitragen können, weshalb vor allem derjenige Nutzer identifiziert werden soll, der in dieser Hinsicht am vielversprechendsten ist. Auch in Bezug auf OSN soll bei der Identifikation das Ziel für den Einsatz des Nutzers Ausgangspunkt der Analyse sein. Im Hinblick auf das jeweilige Ziel, wie z.B. die Unterstützung in den einzelnen Phasen des Innovationsprozesses, können die Merkmale eines einflussreichen Nutzers (vgl. Lead User) unterschiedlich miteinander kombiniert werden, um den geeigneten Nutzer identifizieren zu können. Unterschiede zwischen den Lead User in den beiden Innovationsphasen (Ideengenerierung und Produktentwicklung) sollen aufgezeigt werden, um damit die Legitimität der Unterscheidung hinsichtlich phasenspezifischer Merkmale hervorzuheben. Damit folgt die Dissertation sowohl in den Bereichen ESN als auch OSN folgender Forschungsfrage:

Forschungsfrage 3: Wie kann ein einflussreicher Nutzer unter Berücksichtigung seines Einsatzziels durch die Kombination von unterschiedlichen Methoden identifiziert werden?

Um eine effektive und ressourcensparende Vorgehensweise zur Identifikation von Lead User entwickeln zu können, müssen die in der Literatur gefundenen typischen Charaktereigenschaften dieses Nutzers, wie z.B. dem Trend voraus sein, ein hohes Aktivitätslevel, etc., zunächst mit Hilfe von automatisierten Identifikationsmethoden abgebildet werden. Dies ist vor allem vor dem Hintergrund wichtig, dass das Lead User Konstrukt trendspezifisch ist. Das bedeutet, dass die Identifikation eines Lead User kurzfristig und schnell realisiert werden muss, da ein Nutzer, der heute Lead User ist, dies nicht auch in naher Zukunft bleibt. So sollen also die verschiedenen Analysemethoden wie z.B. SNA, Topic Modelling und Sentimentanalyse zur Identifikation des Lead Users automatisiert durchgeführt und miteinander kombiniert werden. Bezüglich der Realisierung dieses Ziels soll ein Softwaretool zur automatisierten Lead User Identifikation entwickelt werden. Dieses muss in der Lage sein, erstens unterschiedliche Lead User in den beiden Phasen des Innovationsprozesses zu identifizieren, zweitens automatisiert alle zuvor identifizierten Merkmale abzubilden und drittens eine große Menge an Online Community Daten zu verarbeiten. Um die Anwendbarkeit des entwickelten Artefakts und damit des Identifikationsprozesses zu belegen, wird das Tool auf reale Daten einer Online Community für Kitesurfen angewendet. Dieser Teil der Dissertation folgt der Forschungsfrage:

Forschungsfrage 4: Wie kann die Identifikation eines Lead Users durch ein Softwareartefakt unterstützt werden und welche Beiträge für Wissenschaft und Praxis können daraus abgeleitet werden?

Nachdem mit den ersten beiden Zielstellungen die Charakterisierung und Identifizierung von speziellen Nutzertypen betrachtet wurden, sollen im Folgenden die Forschungsfragen aufgezeigt werden, die sich mit der Analyse von Social Media Network Daten näher beschäftigen. Neben einzelnen Beiträgen einflussreicher Nutzer birgt insbesondere die breite Masse an Social Media Posts einen potentiell hohen Informationsgehalt hinsichtlich der Wünsche, Ideen und Kritikpunkte (potenzieller) Kunden.

Damit die in einem Social Media Datensatz zugrundeliegenden Themen und damit diese relevanten Informationen identifiziert werden können, wird zunächst ein Vergleich zwischen verschiedenen Topic Modelling Techniken angestrebt **(Zielstellung 3)**. Ausgehend vom LDA, der vor allem in der IS Forschung aufgrund seiner leichten Anwendbarkeit und der guten Analyseergebnisse verwendet wird (Eickhoff and Neuss, 2017), sollen zwei weitere LDA-basierte Techniken, die Erweiterungen darstellen (Dirichlet Multinomial Regression (DMR) (Mimno and McCallum, 2008)) und Pachinko Allocation Model (PAM) (Li and McCallum, 2006)), miteinander verglichen werden. Dieser Vergleich soll vor allem vor dem Hintergrund der drei Anwendungsfälle (1) Themenextraktion, (2) Trend Analyse und (3) Themenstrukturierung erfolgen. Diese wurden aufgrund ihrer, in der Forschungsliteratur, häufigen Nennung im Hinblick auf das Topic Modelling im Marketing ausgewählt. Damit allerdings ein einheitlicher Vergleich zwischen den Techniken gewährleistet ist, müssen verschiedene Vergleichskriterien herangezogen werden. Durch die Anwendung an einen Real Welt Datensatz können die Unterschiede mit Hilfe der Kriterien herausgestellt werden. Auf Basis dieses Vergleichs leiten sich dann Handlungsempfehlungen für die Auswahl der geeigneten Topic Modelling Technik ab. Die Forschungsfragen, die sich daraus ergeben, lauten wie folgt:

Forschungsfrage 5: Anhand welcher Kriterien lassen sich die verschiedenen Topic Modelling Techniken miteinander vergleichen?

Forschungsfrage 6: Welche Topic Modelling Technik kann für die Anwendungsfälle (1) Themenextraktion, (2) Trend Analyse und (3) Themenstrukturierung verwendet werden?

Um das Topic Modelling für die Trend Analyse anwendbar und somit auch für Unternehmen nutzbar zu machen, soll zudem ein Artefakt, ein Softwaretool, entwickelt werden. Um die **Zielstellungen 4 und 5** erfüllen zu können, müssen dazu zunächst aus der bestehenden Forschungsliteratur Anforderungen abgeleitet werden, die wichtig sind für ein Trendanalyse Tool, das auf Topic Modelling basiert. Die frühzeitige Identifizierung von neuen und vielversprechenden Trends und Ideen in den Bereichen a) Produktentwicklung, b) Kundenverhaltensanalyse und c) Marken-/Marktbeobachtung führt zu Wettbewerbsvorteilen für Unternehmen. Bestehende Trend und/oder Topic Modelling Tools weisen aber diverse Defizite auf. Dadurch, dass sie externe Parameter wie z.B. Geolokationen, Zeit oder nutzerbezogene Informationen nicht berücksichtigen können, werden Trends nur oberflächlich identifiziert. Dadurch sind tiefergehende Analysen, und weitergehende Erkenntnisse über den jeweiligen Trend, nicht möglich. Bei der Erstellung des Artefakts zur automatisierten Trendanalyse für Marketinganwendungen soll der Fokus auf die Kombination von verschiedenen

Datenanalysetechniken im Hinblick auf die Anforderungen der Anwendungsfälle gelegt werden, was zu einer umfangreichen Trendanalyse führt. Vor diesem Hintergrund soll folgende Forschungsfrage beantwortet werden:

Forschungsfrage 7: Wie sieht ein Trendanalyse Tool aus, das Anforderungen der marketingbezogenen Anwendungsfälle (a) Produktentwicklung (b) Kundenverhaltensanalyse und (c) Markt-/Markenbeobachtung umsetzt und welche Beiträge für Wissenschaft und Praxis lassen sich dabei ableiten?

Ein zentraler Bestandteil der Trendanalyse und damit auch des Trendanalysetools ist die Sentimentanalyse, damit nachvollziehbar wird, ob das jeweilige Trendthema, wie z.B. ein Produkt von einem Unternehmen, positiv oder negativ behaftet ist. Um diese Produkte allerdings zielgerichteter an die Vorstellungen der Kunden anpassen zu können, ist es für Unternehmen nicht nur zentral zu wissen, ob ein Produkt gut ankommt oder nicht, sondern v.a. auch welche Produkteigenschaften positiv oder negativ bewertet werden. Durch die Integration einer aspekt-basierten Sentimentanalyse lassen sich solche Einblicke in die VoC und damit in die Kundenerwartungen gewährleisten. Auch hier hat eine Analyse von bereits bestehenden Trendanalysetools ergeben, dass diese die Anforderungen nicht ausreichend an ein solches Tool erfüllen. Deshalb soll ein Softwareartefakt erstellt werden, das die Defizite bestehender Tools behebt (fehlende Integration von externen Parametern, Identifikation von Trendthemen mit und ohne Vorwissen). Dieses Artefakt dient der automatisierten Trendanalyse unter besonderer Berücksichtigung und Implementierung der aspekt-basierten Sentimentanalyse. Dadurch kann eine automatisierte Lösung zur Identifizierung von Ideen als Grundlage für (inkrementelle) Produktinnovationen und -verbesserungen präsentiert werden. Folgende Forschungsfrage liegt dem zugrunde:

Forschungsfrage 8: Wie könnte ein aspekt-basiertes Sentimentanalysetool aussehen, das die Trendanalyse für die Produktentwicklung unterstützt, und welche Anforderungen sollte ein solches Tool erfüllen?

Für das Erreichen der **Zielstellung 6,** der Ableitung von Gestaltungsansätzen für die Social Media Strategie bei gesellschaftlich relevanten Themen (wie z.B. Nachhaltigkeit) unter Verwendung der Analyse von Nutzerdaten, wird vor allem die Social Media Kommunikation bez. Nachhaltigkeitsaktivitäten von Unternehmen und die daraus folgenden Reaktionen der Nutzer analysiert. Davon lassen sich erste Erkenntnisse über eine effektive Nachhaltigkeitskommunikation ableiten, wobei die Nutzerperspektive explizit in die Analyse einbezogen werden soll. Dazu werden Twitter-Posts ausgewählter Unternehmen (Walmart, Target und Amazon), die mit dem #sustainability verknüpft sind, über einen Zeitraum von zehn Jahren extrahiert und analysiert. Dabei werden zum einen die Häufigkeit der Posts bez. Nachhaltigkeit festgehalten und zum anderen die jeweiligen Reaktionen der Nutzer mit Hilfe einer Sentimentanalyse untersucht. Zum Vergleich wird ein Ranking von „The Newsweek“ herangezogen, das auch Unternehmen hinsichtlich ihrer Nachhaltigkeitsaktivitäten bewertet. So werden die drei Dimensionen Ranking, Social Media Aktivität und Sentiment der Nutzer miteinander verglichen, was ermöglicht, etwaige Diskrepanzen zwischen den Dimensionen und Gründe dafür zu identifizieren. Darauf aufbauend sollen Konsequenzen für die Gestaltung einer Social Media Strategie abgeleitet werden. Dabei stellen sich folgende Forschungsfragen:

Forschungsfrage 9: Welches Sentiment lässt sich bei den Nutzern in Bezug auf Nachhaltigkeitsthemen von Unternehmen, die über Social Media verbreitet werden, messen?

Forschungsfrage 10: Inwiefern deckt sich diese Wahrnehmung der Nutzer mit den Nachhaltigkeitsaktivitäten der Unternehmen, gemessen an einem Ranking?

1.3 Aufbau der Dissertation

Um das Thema der Dissertation „Weiterentwicklung von Methoden und Ansätzen zur automatisierten Informationsextraktion aus Social Media Networks“ adressieren zu können und somit die vorgestellten Forschungsfragen und Zielstellungen behandeln zu können, ist die Dissertation wie folgt aufgebaut: In Kapitel 1. Einleitung, wird das Thema der Dissertation motiviert und die zugrundeliegenden Problemstellungen, die auf Forschung und Praxis basieren, werden aufgezeigt. Darauf aufbauend werden sowohl die Zielstellungen der Dissertation formuliert als auch konkrete Forschungsfragen, die mit Hilfe der vorliegenden Arbeit beantwortet werden sollen, abgeleitet. Im zweiten Kapitel („2. Wissenschaftliche Beiträge“) werden die Ergebnisse der kumulativen Dissertation in Form von bereits angenommenen sowie im Begutachtungsprozess befindlichen Publikationen vorgestellt. Dieses Kapitel umfasst sieben Beiträge, wobei je Beitrag (Abschnitt 2.1 bis 2.7) eine oder mehrere Zielstellungen sowie damit zusammenhängende Forschungsfragen behandelt werden. Auf Basis der vorgestellten Ergebnisse werden im anschließenden Kapitel 3. diese zusammengefasst, weiter diskutiert und ihr Beitrag zu Wissenschaft und Praxis herausgearbeitet. Des Weiteren erfolgt ein Ausblick auf weitere Forschungsarbeiten und -felder. Abbildung 1 gibt einen komprimierten Überblick über den Aufbau der Arbeit, v.a. werden die Zusammenhänge zwischen Zielstellungen, Forschungsfragen und Forschungsbeiträgen abschließend erläutert.

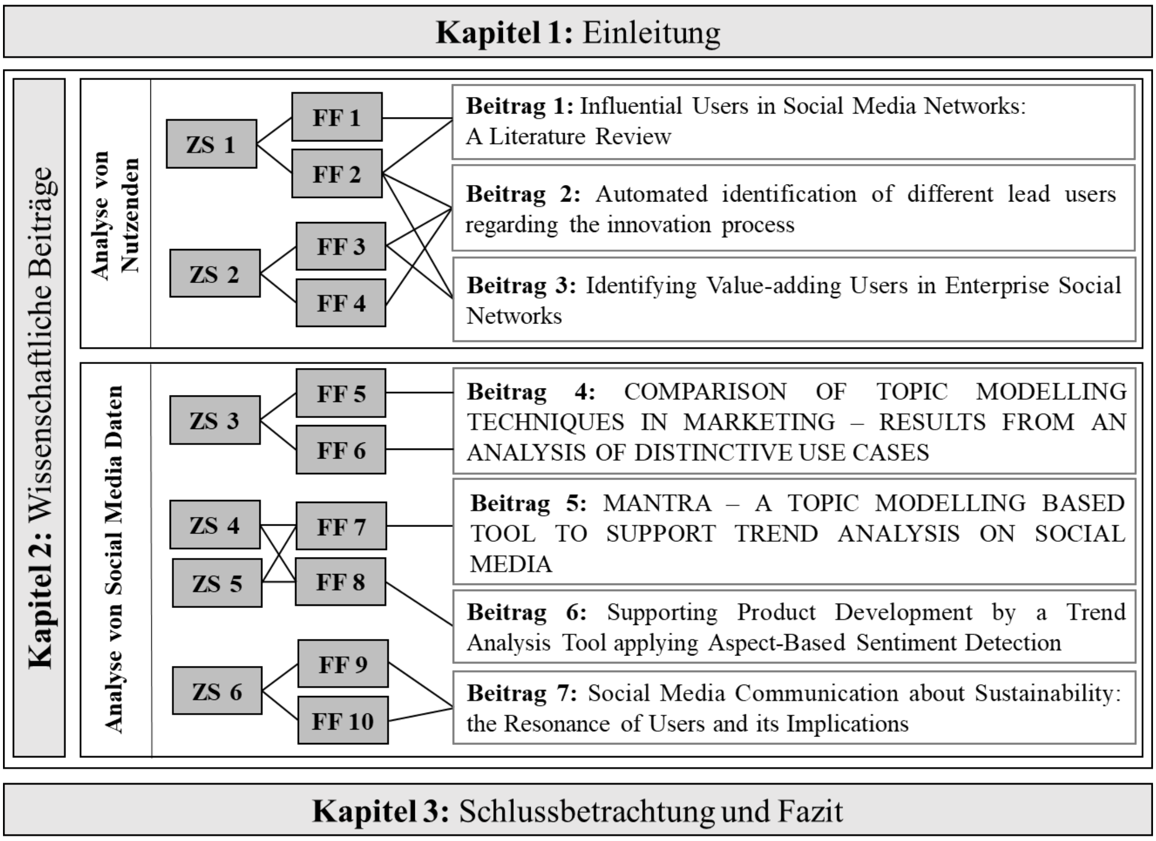

Abbildung 1: Überblick Dissertation

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:

Ab-schnitt	***Typ der Veröffentlichung***	***Status***	***Zitation***
2.1	Konferenzbeitrag	Veröffentlicht	(Schmid, 2020) Schmid, I.M. (2020). “Influential Users in Social Media Networks: A Literature Review.” *Proceedings of the Twenty-Eighth European Conference on Information Systems, An Online AIS Conference 2020.*
2.2	Journalbeitrag	Under Review	(Schmid et al., 2022) Schmid, I., Wörner, J., and Leist, S. (2022). “Automated identification of different lead users regarding the innovation process.” *Electronic Markets Journal*.
2.3	Konferenzbeitrag	Veröffentlicht	(Schmid et al., 2022) Schmid, I., Wehner, B., and Leist, S. (2022). “Identifying Value-adding Users in Enterprise Social Networks.” *Proceedings of the 55th Hawaii International Conference on System Sciences, Online 2022.*
2.4	Konferenzbeitrag	Veröffentlicht	(Wörner et al., 2021) Wörner, J., Konadl, D., Schmid, I.M., and Leist, S. (2021). ”COMPARISON OF TOPIC MODELLING TECHNIQUES IN MARKETING-RESULTS FROM AN ANALYSIS OF DISTINCTIVE USE CASES.” *Proceedings of the Twenty-Ninth European Conference on Information Systems, A Virtual AIS Conference 2021*.
2.5	Konferenzbeitrag	Under Review	(Wörner et al., 2022) Wörner, J., Schmid, I., Konadl, D., and Leist, S. (2022). “MANTRA – A TOPIC MODELLING BASED TOOL TO SUPPORT TREND ANALYSIS ON SOCIAL MEDIA.” *Proceedings of the Forty-Third International Conference on Information Systems, Copenhagen 2022.*
2.6	Konferenzbeitrag	Zur Veröffentlichung angenommen	(Wörner et al., 2022) Wörner, J., Konadl, D., Schmid, I., and Leist, S. (2022). “Supporting Product Development by a Trend Analysis Tool applying Aspect-Based Sentiment Detection.” *Proceedings of the 17th International Conference on Design Science Research in Information Systems and Technology 2022.*
2.7	Journalbeitrag	Under Review	(Schmid et al., 2022) Schmid, I., Hammerl, T., and Leist, S. (2022). “Social Media Communication about Sustainability: The Resonance of Users and its Implications.” *Communications of the Association for Information Systems.*

Tabelle 1: Übersicht zu den wissenschaftlichen Beiträgen

2.1 Beitrag 1: Influential Users in Social Media Networks: A Literature Review

Adressierte Forschungsfrage	**Forschungsfrage 1:** Welche verschiedenen einflussreichen Nutzertypen werden in der aktuellen Forschungsliteratur diskutiert? **Forschungsfrage 2:** Welche verschiedenen Charakteristika weisen die einflussreichen Nutzer in einem Social Media Network auf und wie können sie strukturiert dargestellt werden?
Zielsetzungen	• Unterscheidung und Charakterisierung verschiedener, in der Literatur vorkommender, einflussreicher Nutzertypen in Social Media Networks • Erstellung eines morphologischen Kastens als Ausgangspunkt für die Auswahl eines einflussreichen Nutzers im Hinblick auf die unterschiedlichen Stufen der Wertschöpfungskette • Exemplarische Anwendung des morphologischen Kastens bei zwei Nutzergruppen (Influencer und Lead User), um Anwendbarkeit und Mehrwert aufzuzeigen
Forschungsmethode	**Literature Review** nach (Kitchenham et al., 2009; Webster and Watson, 2002; Wohlin et al., 2012) • Beschreibung der Literatursuche, des Reduktionsvorgangs und der Literaturauswahl • Literaturanalyse: Erstellung (1) einer Taxonomie nach Nickerson et al. (2013) und (2) eines morphologischen Kastens nach Zwicky and Wilson (2012)
Kernergebnisse (Überblick)	• Erstellung eines Frameworks mit den zwei übergreifenden Dimensionen „Charakteristika eines einflussreichen Nutzers“ und „Nutzertyp“ anhand der aktuellen Forschungsliteratur • Übersicht über die verschiedenen Merkmale mit direkter Zuordnung zu dem jeweiligen Nutzertyp anhand des Frameworks • Strukturierte Aufarbeitung der identifizierten Merkmale anhand eines morphologischen Kastens • Konkrete Unterscheidung des Lead User und des Influencer (durch Analyse von Instagram Daten) zeigt auf, inwiefern die unterschiedlichen Merkmale zu unterschiedlichen Stufen der Wertschöpfungskette beitragen
Publikationsort	Proceedings of the Twenty-Eighth European Conference on Information Systems, An Online AIS Conference 2020.
Ranking VHB JQ 3	B
Autor:innen und Anteile	**Isabel Schmid** **100%**

Tabelle 2: Fact Sheet Beitrag 1

INFLUENTIAL USERS IN SOCIAL MEDIA NETWORKS: A LITERATURE REVIEW

Research paper

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Abstract

The importance of social media networks has been increasing in both private and business contexts over the last decade. Companies have recognised the potential of online as well as enterprise social networks. Whether a company can benefit from the usage of social media networks depends on the respective users. Especially the influential user type is able to mobilise and propagate information and marketing messages across the network and is therefore in the centre of attention. In current research literature, different groups of influential users can be identified, but they are not characterised and defined consistently. We approach this research gap and perform a literature review to provide a structured overview of the different influential user types. To this end, we elaborate a morphological box, an artefact that serves as an overview of the multiplicity of the characteristics of influential users and as a starting point for structuring the different characteristics of influential users.

Keywords: social media networks, user types, influential users

1 Introduction

Social media networks such as Facebook or Twitter have become increasingly important for communication and interaction in both private and business contexts (Kaplan and Haenlein, 2010, Kim et al., 2018). This continuous upward trend becomes particularly evident when looking at the daily number of users of the world's largest online social network (OSN): Facebook. Whereas, in 2012, just 618 million people used Facebook every day, in 2019, 1.62 billion people spent their time using Facebook on a daily basis (Facebook, 2019). To the end user, social media networks offer a possibility of interactive and dynamic communication, collaboration and participation (Obar and Wildman, 2015). However, the potential of social media networks is not only taken advantage of by individuals but also by companies that use social media, on the one hand, as OSN to communicate with their customers and, on the other hand, for interaction within the company as Enterprise Social Networks (ESN).

OSN, as one hyponym of social media networks, are often used for a company's external communication with (potential) customers in terms of advertising (AlFalahi et al., 2014, Kim et al., 2018). In this context, targeted advertising strategies are important for establishing and promoting close customer relationships (Heidemann et al., 2010, Kietzmann et al., 2011). In addition to classic online marketing, these advertising messages can also be distributed via peer-to-peer marketing (Cha et al., 2010, Liu and Chen, 2019). Personal recommendations by people operating on the same network are often more effective than traditional advertising in attracting new customers and bringing about buying decisions (Brown et al., 2007, Erkan and Evans, 2018). Before people buy products or make decisions, they communicate and exchange experiences. Thus, a person's activity depends directly on another person's opinion and suggestion (Agarwal et al., 2008, Liu and Chen, 2019). As social influence can affect buying decisions and sales figures, companies are interested in identifying people who trigger this process (Deng et al., 2016, Forestier et al., 2012). However, benefits of social networks can also be determined in the capacity of ESN. ESN, as another hyponym of social media networks, are used to improve organisational effectiveness and business efficiency (Stei et al., 2016). Digital interaction possibilities are transferred from social networks to the internal company level and adapted to the respective company's needs (Richter and Riemer, 2013, Schwade and Schubert, 2019, Wehner et al., 2017). It is important that employees are motivated to actively create content, to share knowledge with others and to use the existing know-how for the realisation of operational goals (Günther and Spath, 2010). Here, different user groups can be identified among employees, too. In both domains, OSN and ESN, a company has to face one major challenge: the identification of influential users who can act as multipliers, on the one hand, of advertising messages and, on the other hand, of knowledge. In current research literature, there are many different terminologies which can be allocated to influential users. Therefore, consistent and uniform definitions of user groups such as influencers, key users, lead users, hubs and experts do not exist. In fact, some investigations even use these terms equivalently (Galeotti and Goyal, 2009). Another problem is that the current research literature barely develops specific characteristics of influential people within a social media network. Although there are a lot of different studies to identify influential users, they rarely describe characteristics that define what influence means in this particular context. In order to determine the state of the art of influential user groups in research, a literature review including a detailed analysis of the characteristics is necessary. Comparing the user group characterisation allows for the identification of gaps and redundancies. As a result of the problem description, this paper addresses these two research questions:

RQ1: What different influential user types are discussed in literature?

RQ2: What different characterisations does an influential user in a social media network exhibit?

The impact of social media networks for organisations represents an important area for information systems research. With this investigation, we seek to outline the differences between influential user groups in social media networks by establishing a morphological box. This morphological box can serve as a starting point for practitioners to choose and apply the proper influential user types with regard to different stages of the organisational value chain and the organisation´s objectives. The exemplary comparison between influencer and lead user shows the applicability and the benefit of this morphological box. The remainder of this paper is organised as follows. Section 2 provides a theoretical background by introducing important terms and definitions as well as foundations of social influence. In section 3, we perform a literature review. Section 4 presents the results of our literature review on the basis of the two research questions. In section 5, we discuss the results and draw boundaries between lead user and influencer by applying the morphological box. Furthermore, we show the additional benefit of the results for practice. Finally, in section 6, we draw an overall conclusion.

2 Conceptual Basics

In the following section, the conceptual basics will be introduced. Various terms that are essential for our investigation will be introduced in chapter 2.1. Chapter 2.2 defines the influential user by presenting related work.

2.1 Terms and Definition

Social media networks can be defined as internet-based applications that offer opportunities for interactive and dynamic communication, collaboration and participation (Kane et al., 2012, Kaplan and Haenlein, 2010, Obar and Wildman, 2015). As people use social media to support their social relationships, a closer look on social media networks is necessary. According to Kane et al. (2012), social media networks feature four characteristics allowing users (1) to have an exclusive user profile, (2) to consume digital content and be able to protect it from different search mechanisms applied by the platform, (3) to arrange a list of other users with whom they are connected and (4) to observe their connections. In a business context, social media networks can be used to assemble social relationships in two different ways. On the one hand, social media networks can represent the relationship between companies and customers (c.f. OSN), on the other hand, they can represent the relationships between employees within an organisation (c.f. ESN). Therefore, the term social media networks is used as a hypernym for ESN and OSN in the following sections. OSN, as one of many social media types, are online communities that connect people with the same interests, activities, backgrounds, and/or friendships (AlFalahi et al., 2014, Schneider et al., 2009). Users of OSN are able to communicate with other people and join groups or networks in the fields of their interests (Schneider et al., 2009, Wehrli, 2008). The active use of OSN enjoys particularly great popularity in private use. But, additionally, companies have also adopted OSN to achieve different business objectives in areas such as marketing, innovation, human resources and strategy (Deng et al., 2016). Therefore, OSN as for instance Facebook or Twitter serve as an important interface between companies and customers. Social media applied by a company to support knowledge transfer, collaboration and communication between employees has received increasing attention as well as fast diffusion, especially in large multinational organisations (Ellison et al., 2015, Oettl et al., 2018). An example for a category of internal applications is ESN, which can be seen as the internal counterpart of OSN (Wehner et al., 2017). Based on previous research, ESN can be defined as (1) internal web-based social platforms that allow employees to communicate and share knowledge with colleagues, (2) a means to enable users to find and access digital content created by other users and (3) a medium to provide users with the possibility of connecting to other users (Behrendt et al., 2014, Ellison et al., 2015, Kane, 2015, Leonardi et al., 2013).

To understand and analyse human social interactions within social media networks, research has established social network analysis (SNA), which relies on the network as a suitable central construct (Kane et al., 2012). Such a network can be illustrated by a graph whose nodes represent the members of the network (users or entities), and the links between the nodes that show relationships (Forestier et al., 2012, Tang et al., 2009). Several studies have shown that through SNA and different centrality measures important nodes can be identified (Ilyas and Radha, 2011). Some of the most commonly used centrality measures include degree centrality (DC), betweenness centrality (BC), closeness centrality (CC) (Freeman, 1979) and eigenvector centrality (EVC) (Bonacich, 1972). SNA enables to show the relations in a structured network via nodes and ties to state quantitative characteristics of an influential user. But the number of ties to other nodes has no bearing on the quality of the information that is spread across the network. A high level of centrality does not necessarily mean that a user is an influential individual, since centrality is based on the structure of a network, while influence should be based on the dynamics and changes that occur in the social network's connections and links (AlFalahi et al., 2014). If a user e.g. posts many messages without meaningful content, this user will be a node with a high level of centrality, without, however, being an influential user. Hence, a person is described by SNA via the location in the network as well as the number of relationships a user has. Therefore, SNA does not suffice to fully characterise and describe an influential user, as additional attributes are necessary to specify this type of user. Thus, further research is necessary to answer our research questions.

2.2 Definition of influential users

Social influence has been studied in different disciplines such as sociology, economics or marketing and has its roots in the fields of opinion formation and diffusion of innovations (AlFalahi et al., 2014). In the 1950s and '60s, authors as for instance Katz and Lazarsfeld (1955) and Lazarsfeld et al. (1965) stated in their investigations of the role of media influence that individuals may be more affected by the exposedness to each other than by the mass media. According to them, influential people are defined by their impact on other people's decisions either by their example or their advice. Their theory states that information from mass media circulates through leaders to their followers (Katz and Lazarsfeld, 1955). Hence, the definition that people are able to shape opinion and trends across persons in their (immediate) environment has remained unchanged until today and can be transferred to social media (Borrego et al., 2019). Thus, social influence can be defined as a process of affecting the behaviour of others (AlFalahi et al., 2014). Watts and Dodds (2007) add that social influence not only derives from the simple connection to other people but also from a high level of information a member holds. Sharing this information can change an individual's behaviour, a consumer's decision-making process and the attitude towards a product based on a friend’s recent action or recommendation (Brown et al. 2007; Zhu et al. 2015).

Moreover, in literature, an influential user can also be defined by means of a network. The nodes can be seen as users of this network, whereas the links represent the relationships between individual people. As mentioned before, the importance of a user depends on the opinion of other actors, shown by their ties to the node (Eirinaki et al., 2012). According to Agarwal et al. (2008), a high number of in-links and a low level of out-links among others characterise an influencer. In contrast to that, Yang and Leskovec (2010) state that the users of an OSN with the most followers are not the most influential ones in terms of information propagation. In fact, their study shows that users with medium numbers of followers have a much higher influence. Goldenberg et al. (2009) emphasise furthermore in their study that a link between two people does not automatically indicate influence. Hinz et al. (2011) agree with this statement, namely that a high number of ties does not automatically mean that a user is influential. Moreover, user actions and past behaviours are of major interest when measuring a user’s influence (AlFalahi et al., 2014). Still other investigations emphasise that not only the frequency of an action is relevant for the characterisation of an influential user but also the content of a post. Users who are influential in one topic have to post high quality content and have to express themselves eloquently (Agarwal et al., 2008, Forestier et al., 2012). All in all, there is neither a consistent definition of what influence means nor a concrete way to measure influence, which is why it is difficult to identify and characterise an influential person (Cha et al., 2010). But, in general, it becomes evident that just considering influential users and their characteristics is not enough. Looking at characteristics of an influential user’s environment as well as at the user´s relationship to its environment are also essential.

3 Research Method

To provide full transparency of our research the relevant steps are demonstrated in the following. As it is our aim to guarantee a comprehensive and valid picture of the existing literature and our literature review at the same time, the following procedure includes steps of three different, eminently respectable, papers (cf. (Kitchenham et al., 2009, Webster and Watson, 2002, Wohlin et al., 2012).

3.1 Literature Search

First, the **review scope** was defined in accordance with our research questions (cf. (Cooper, 1988), see section 1). As a next step, we **specified search strings** and applied them to databases (Wohlin et al., 2012). Our key word identification was a multistage, iterative process (Kitchenham et al., 2009, Wohlin et al., 2012). We began our search with very broadly conceived search terms such as “social networks” and “user roles”. As we found many interesting results including a literature review on a similar topic (cf. (Probst et al., 2013)), we adopted search terms such as “influential user”, “influencer” and “key user”, bringing to light further primary studies. Additionally, the consultation of seminal works was used to define not only search terms and key concepts but also the databases and the time period for the literature search (see table 1). These databases were selected in view of the quality of the papers, meaning that a prerequisite for selecting the database was that peer-reviewed journals and conferences were included in these databases.

Time period	2005-2019		
Databases	Google Scholar, EBSCOhost Business Source Premier, dblp, AIS electronic library and ACM digital library		
Search Fields	Full-text		
Search Terms	influential user	AND	(online/enterprise) social network(s)
	influencer, hub,		social media networks
(all combina-tions)	expert, lead user, key user		online/virtual community/-ies
	central user(s), user (role/position)		social network sites

Table 1. Search Parameter

The year 2005, which marks the beginning of social media, especially of OSN and ESN to become a global phenomenon, seemed to be a suitable starting point for our literature search. Indeed, the first work was published in that year (Nolker and Zhou, 2005). As IS is an interdisciplinary field of research (Webster and Watson, 2002), we identified major contributions not only in the area of IS but also in the fields of marketing, sociology and psychology. As the focus of this paper is on the characterisation of influential users, we added these aforementioned disciplines which focus mainly on human beings and their behaviour.

The subsequent literature search was conducted in three steps. First, we searched publications using the previously defined search terms and filtered the results for the relevant literature. The second step included the reviewing of the citations of articles identified in step 1 (backward search). Furthermore, we conducted a forward search to identify publications citing these papers (cf. (Vom Brocke et al., 2015)). To conduct a successful literature search, we focused on leading journals and selected conference proceedings, especially those with a high reputation for quality (cf. (Webster and Watson, 2002)). To that purpose, we concentrated on peer-reviewed conferences and journals which require a strict review process and are listed in various rankings. Initially, this literature search resulted in a total of 2,256 publications. But, based on our research questions, we only selected articles with a direct reference to online or enterprise social networks based on their title, the provided keywords and their abstract. Publications investigating social networks in the offline area were not considered. As we included in our search terms also the keyword “social network” in order not to limit our investigation to either only enterprise or only online social networks, we received many wrongly positive results (cf. (Mattia and Weistroffer, 2010, Qin et al., 2005, Suh et al., 2008)). Therefore, almost two thirds of the articles were excluded (remaining: 752 articles). Furthermore, a time span was established with 2005 as a starting point. Moreover, duplicates found in the databases were eliminated (remaining: 411 articles). In order to apply the following inclusion and exclusion criteria to the selected literature, we downloaded all of these articles and examined the full-text of each article manually. Hence, in a next step, the relevant publications were analysed with regard to their definition and description of an influential user. Articles that did not explicitly focus on influential users but e.g. only on active users were not included in our investigation (remaining: 219 articles). In addition, articles with a focus only on the identification process of individual users and no reference to characteristics were excluded (remaining: 138 articles). Literature of the fields of sociology or psychology with no direct link to social media networks was also excluded. Furthermore, only peer-reviewed, full papers were considered. So, 89 articles were analysed in detail. A total of 52 articles were selected for a further in-depth topic analysis in connection with a literature review. Initially, the literature search was conducted by a leading researcher. But, to reduce subjectivity and to avoid biases, two other researchers who are familiar with this research area were also included in the literature search to check both the included and excluded papers.

3.2 Literature Analysis

The next step in the procedure was the literature analysis with the aim to structure the literature and the resultant characteristics of influential users logically. To this aim, we divided the literature analysis into two different steps: 1) a topic analysis based on the method for taxonomy development according to Nickerson et al. (2013) and 2) the compilation of a morphological box according to Zwicky and Wilson (2012), with the second step being based on the first step. The morphological box lifts the results onto a meta-level, thus we are able to structure the identification and characterisation process of the different influential user types. All in all, we follow the Nickerson et al. (2013) concept of a taxonomy, as our framework (see table 2) should be explanatory, not descriptive. Furthermore, we aim to establish an artefact (the framework) for classifying the results of our literature review, which speaks even more for Nickerson´s approach. This iterative approach begins with the determination of meta-characteristics that are based on the purpose of the framework (Nickerson et al., 2013). As we are intent on showing that different influential user groups have different characteristics, we set, on the one hand, the influential user types and, on the other hand, the different characteristics of an influential user. The next step in the approach is the determination of ending conditions. Objective as well as subjective ending conditions were defined in our investigation. For the objective ending conditions, we determined that 1) all objectives were examined, 2) no dimension was added in the last iteration and 3) each cell (combination of characteristics) was unique and not repeated (i.e. there is no duplication). For the subjective ending conditions, we set up that the framework had to be concise, robust and comprehensive. The third step in the approach of Nickerson et al. (2013) stipulates to choose one approach, either the empirical-to-conceptual one or the conceptual-to-empirical one. Initially, we went for the empirical-to-conceptual approach and applied it to our literature review. As we identified several characteristics in the existing literature, we followed the inductive category development and created our own categories to structure the characteristics appropriately (Mayring, 2014). Even though the theory about influential users as introduced in section 2 exhibits similar characteristics, the literature analysis we conducted was independent thereof. In a second search, we identified different user types in the current research literature, followed by the deductive category development including e.g. literature that subdivides user groups in online social networks into different types (Forestier et al., 2012). As, however, this subdivision was not completely suitable for our investigation, we added and replaced further categories defined as influential in literature (inductive category development). The next step of the literature analysis consisted in the allocation of the characteristics to the different user types. To reduce subjectivity, the categorisation approach (the division of the attributes as well as of the user types and the allocation process) was carried out in the same way as the literature search. Thus, the leading researcher consulted two other researchers in order to discuss the categorisation approach and, afterwards, reach a consensus. To that purpose, both the subjective and the objective ending conditions were met. This framework (see table 2) is the starting point for the compilation of the morphological box. This assignment follows the specification of Zwicky and Wilson (2012) who divided the process into the following three steps: 1) formulation of the problem, 2) definition of the parameters and 3) construction of the morphological box (Zwicky and Wilson, 2012).

4 Results

4.1 Classification of articles

In our research, we gathered essential characteristics of influential users in the literature. To that effect, we identified the characteristics of both an influential user and of a user´s environment. Altogether 43 different characteristics could be identified. Derived from the 52 identified articles, we developed a framework to classify the articles in the first place. The aim of this framework was to structure the literature along the lines of the main perspective of our investigation. To categorise the different characteristics of influential users, we identified two major dimensions and five sub-dimensions as shown in table 2.

On the one hand, **the characteristics of an influential user** include all characteristics that are directly related to a single user, thus the node of a network. The different influential user types can be subdivided by consulting their central position in a social network, their personal characteristics and the features of their posts. The central position in a social network includes centrality measures such as CC, BC or DC primarily. Some investigations use a directed graph for their analysis, thus differentiating between in-degree and out-degree (cf. (Adamic et al., 2008, Aral and Walker, 2012, Zhang et al., 2007)). The cited investigations show varying levels of centrality in reference to the different influential user types. Furthermore, personal characteristics must be included when defining influential users, which include individual responsibilities as well as the skills of a person and can be subdivided into 19 different personal characteristics. It is the most considered characteristic in our literature review. In addition to the personal characteristics, features of posts are furthermore important for the characterisation of an influential user. Thus, the focus is not on posts as a flow of information to other users but rather on the different features of the posts written by a user. The relevant content (Araujo et al., 2017, Forestier et al., 2012, Luo et al., 2019, Ríos et al., 2019, Uzunoğlu and Kip, 2014, Vogiatzis, 2013, Vollenbroek et al., 2014) as well as the originality and uniqueness of the post (Agarwal et al., 2008, Casaló et al., 2018) matter in the definition of an influential user. For instance, Casaló et al. (2018)

state that an influential user has to post content that is unusual, new and sophisticated. Agarwal et al. (2008) also state that an influencer is often eloquent. As this characteristic is often difficult to measure with appropriate statistics, the authors argue that the length of a post can serve as a heuristic measure to determine if a user is eloquent. According to Agarwal et al. (2008), there is a positive correlation between the length of a post and the number of comments. This means that in this investigation longer posts attract more people. Forestier et al. (2012) confirm this statement and add that a high quality and a relevant issue are important for an influential post as well. To be able to phrase a high quality post about a special topic, it is necessary that users have a high level of knowledge in their field of interest (Balog and De Rijke, 2007).

On the other hand, the **characteristics of influential users´ environments** focus on the nodes and links around the influential user. Thus, the effect of nodes on the network does not only depend on their own characteristics but also on their neighbours´ positions in a network as well as on their neighbours' change of behaviour. The centrality of direct and indirect neighbours matters in defining influential users because a node´s importance within a social media network also depends on the importance of its neighbours (Pal et al., 2014). Zhang et al. (2007) e.g. propose "ExpertiseRank" as a new measure, a PageRank-based measure that does not only consider how many people are reached by an answer, but also for whom this answer is helpful. A user´s ExpertiseRank does not rise only because s/he makes a post, but because a user is able to answer a question posted by someone else who also has a high level of expertise (Zhang et al., 2007). Further measures such as the EVC are assigned to this sub-dimension by definition (Berger et al., 2014, Ilyas and Radha, 2011). Moreover, the change of behaviour in the influential user´s environment is crucial for the characterisation of an influential user. This change of behaviour can emerge in many different ways: from a change of other people´s opinions in relation to already existing products (Agarwal et al., 2008, Forestier et al., 2012) as well as in relation to new trends (Agarwal et al., 2008, Goldenberg et al., 2009, Ilyas and Radha, 2011, More and Lingam, 2017) to the change of their log-in data (Trusov et al., 2010) or to the change of awareness about products or services (Heidemann et al., 2010). Often, the relevant studies do not feature the precise method of measuring the change of behaviour. In order to categorise the high number of articles dealing with the impact of a node on its neighbours, we followed distinction made by Agarwal et al. (2008). Therefore, we created one category that relates to innovations (innovation-related) and another category with a change of behaviour not related to innovation (non-innovation-related), a stream of research focusing influential nodes exhibiting the strongest influence on others in disseminating information (Kimura et al., 2007, Nguyen et al., 2015, Saito et al., 2012). Through the diffusion of information, a change of opinion and therefore in behaviour is supposed to be achieved. The more nodes are affected by the information the more influential a node is.

4.2 Allocation of user types

The second dimension of the framework, user types, is based on the different designations identified in the research literature, making a distinction of influencers, key users, lead users, hubs and experts possible. Each of these influential user types exhibits different characteristics that can be directly allocated. All in all, we combined the dimensions of different influential user types and their characterisations into a 5x5 framework (see table 2) to provide a structured overview of the latest state of research.

Remarkably, the **influencer** is the most studied type of user in the current literature. All of our identified characteristics of an influential user were found in 31 different investigations. Even the features of a post (Agarwal et al., 2008, Araujo et al., 2017, Forestier et al., 2012, Ríos et al., 2019, Uzunoğlu and Kip, 2014, Vogiatzis, 2013, Vollenbroek et al., 2014) and the position in the network of an influential user's environment (Pal et al., 2014, Scripps et al., 2007, Smith et al., 2009, Weng et al., 2010) were examined, which are not considered for most other user types. The literature agrees on different characteristics such as personal characteristics as for instance high activity level, high knowledge, etc. The situation is different when the central position in a social network is the subject of investigation. Here, the authors of different investigations disagree regarding the level of in-degree centrality.

User Types		Attributes of an influential user				
		Characteristics of an influential user			Influential user´s environment	
		Central position in a social network	Personal characteristics	User´s post	Position of the neigbours	Change of behaviour (influence)
User Types	Influencer	• High DC (3, 11, 16, 29, 30, 38, 44, 45, 47, 48,) • Intermediate in-degree (50) • High in-degree (2, 6, 18, 41, 42) • High level of Retweets & Mentions (5, 14, 44) • Low out-degree (2) • High BC and CC (3, 42, 44, 47) • Strong edge strength (3, 7) • High TwitterRank (49) • High PageRank (44, 47)	• **High activity level** (3, 6, 16, 17, 18, 29, 48, 49) • High knowledge (19, 39, 47, 48) • High level of trust and credibility (11, 19, 45, 47, 48, 52) • High affinity & sensitivity (17) • High popularity and reputation (11, 16, 18, 19) • High status (30) • **Spreading information** (5, 17, 30, 31, 34, 36, 39, 40, 43, 44, 50) • Opinion leadership (13, 16)	• Eloquence (2) • Relevant content (5, 19, 39, 45, 47, 48,) • Originallity and uniqueness (13)	• High Diffusion Degree (38) • High community score (41) • Neighbours´ Mean Degree (42) • High EVC (42) • High influence of the neigbours (49)	• Innovation-related (2, 34, 50) • **Non innovation-related** (2, 3, 4, 5, 6, 7, 13, 16, 17, 19, 29, 30, 36, 39, 40, 41, 43, 45, 47, 48, 52)
	Key User	• High in-degree (10, 12) • High BC and CC (10, 46) • High DC (46) • High PageRank (22) • High level of Repost (32)	• High activity level (10, 12, 22) • High knowledge (10) • Spreading information (12, 32)	• Relevant content (32)	• High EVC (10)	• Non innovation-related (22)
	Lead User	• High DC (25, 37) • High BC (27, 28, 37)	• High activity level (9, 25) • Suggesting solutions (33) • **Ahead of trends and dissatisfaction** (9, 21, 25, 27, 33) • **High (product/innovation related) knowledge** (9, 21, 25, 27, 28, 33, 35, 37) • Opinion leadership (9, 21) • Spreading information (9, 27, 28) • Strategic alignment with the brand identity (35)			• **Innovation-related** (9, 21, 25, 27, 28, 33, 35, 37)
	Hub	• High DC (23, 24) • High BC (23, 24) • High in- & out-degree (20)	• Adoption and diffusion of innovations (20, 26) • **Spreading information** (20, 23, 24, 26)		• High EVC (26)	• Innovation-related (20, 26) • No affection of others (24)
	Expert	• **High out-degree** (1, 51) • High in-degree (15, 51)	• **High knowledge** (1, 8, 15 19, 39, 45, 51) • High level of trust and credibility (19)	• **High quality answer posts** (1, 8, 51)	• Expertise Rank (51)	

Legend: [1] Adamic et al., 2008 [2] Agarwal et al., 2008 [3] AlFalahi et al., 2014 [4] Aral and Walker, 2012 [5] Araujo et al., 2017 [6] Bakshy et al., 2011 [7] Bakshy et al., 2009 [8] Balog and De Rijke, 2007 [9] Belz and Baumbach, 2010 [10] Berger et al., 2014 [11] Borrego et al., 2019 [12] Canali and Lancellotti, 2012 [13] Casaló et al., 2018 [14] Cha et al., 2010 [15] de Toni and Nonino, 2010 [16] De Veirman et al., 2017 [17] Deng et al., 2016 [18] Eirinaki et al., 2012 [19] Forestier et al., 2012 [20] Goldenberg et al., 2009 [21] Hau and Kang, 2016 [22] Heidemann et al., 2010 [23] Hinz et al., 2009 [24] Hinz et al., 2011 [25] Hung et al., 2011 [26] Ilyas and Radha, 2011 [27] Kratzer and Lettl, 2011 [28] Kratzer et al., 2016 [29] Kim and Han, 2009 [30] Kim et al., 2018 [31] Kimura et al., 2007 [32] Luo et al., 2019 [33] Mahr and Lievens, 2012 [34] More and Lingam, 2017 [35] Marchi et al., 2011 [36] Nguyen et al., 2015 [37] Nolker and Zhou, 2005 [38] Pal et al., 2014 [39] Ríos et al., 2019 [40] Saito et al., 2012 [41] Scripps et al., 2007 [42] Smith et al., 2009 [43] Trusov et al., 2010 [44] Tsugawa and Kimura, 2018 [45] Uzunoğlu and Kip, 2014 [46] Viol et al., 2016 [47] Vogiatzis, 2013 [48] Vollenbroek et al., 2014 [49] Weng et al., 2010 [50] Yang and Leskovec, 2010 [51] Zhang et al., 2007 [52] Zhu et al., 2015

Table 2. The framework: Allocation of the attributes to the different user types

On the one hand, authors as for instance Agarwal et al. (2008) and Bakshy et al. (2011) state that a high level of in-links indicates that a lot of people recognize the post. This means it is more likely to be influential. Yang and Leskovec (2010) disagree with this opinion arguing that a high level of in-degree is not necessarily an indicator of an influencer. Other characteristics have to be considered, e.g. the impact on the behaviour of other people. This change of behaviour is approached in 21 of 31 investigations about influencers, and therefore it is one of the most used attributes to characterise an influencer. As for the **key user**, all of the four included studies concentrate on the central position in a social network, with one also considering the centrality scores of the key user's neighbours (Berger et al., 2014). In contrast, none of the articles includes the features of a post. Key users are thus described by different personal characteristics as well as by their central position in a network. Lead users as well as hubs are described in a similar way. Whereas **lead users**, mentioned in eight different investigations, are characterised by personal characteristics as a result of the traditional lead user research and a high level of DC as well as BC, other categories as for instance features of a post are totally missing. Concerning **hubs** (four investigations), the characteristic "change of behaviour" is analysed, but with conflicting results. Ilyas and Radha (2011) state that a hub creates and adopts as many trends as possible. According to them, the spread of trends in social networks is modelled as a process of influence. In contrast to that, Hinz et al. (2011) state that hubs are not more persuasive than other nodes. All investigations agree with the fact that a hub is a node with a high level of centrality. The centrality of the hub's neighbours is also important. However, the **expert** (seven investigations) is mostly analysed in regard to the high knowledge level and the related high quality of the answers posted. Contrary to the investigations of the other influential user types, studies about experts do not consider the impact on others.

Considering the allocation of the characteristics of influential users to the different user types, it is noticeable that fewer research activities have been undertaken in terms of the influential user´s environment as well as the influential user´s posts. As no information can be found for hubs, key and lead users, the respective cells in table 2 remain empty, with these gaps also pointing to gaps in the current research literature.

5 Interpretation and Discussion

5.1 Delineation of the characteristics

The current research literature shows considerable disagreement and inferences regarding the description and characterisation of an influential user. As a result, many different characteristics of one user type and no homogenous characterisations of different user types are found. Hence, in the following section, we are intent on separating the different types of influential users from each other and ensuring that there is no overlap or duplication. Characteristics that are mutually contradictory in the current research literature are not considered in the following, because we cannot ascribe superiority to any of the studies. However, there are only two characteristics that contradict each other – the level of in-degree of influencers and the ability of hubs to change the behaviour of others. As these two characteristics constitute only a small minority of the 43 identified characteristics, they do not affect our results. Instead, we focus on those characteristics that are identified by the majority of the investigations. The characteristics described in the following are printed in bold in table 2. To structure this identification and characterisation process, we developed a morphological box based on our literature review. We chose the five different sub-dimensions of an influential user as vertical dimensions (the same order as in table 2) and their particular characteristics as horizontal dimensions. All of them result in the multi-dimensional matrix as shown in table 3. With regard to our aim, namely the differentiation and characterisation of the different influential user types, none, one or more characteristics of each dimension can be selected. Depending on the combination of the dimensions, and therefore depending on how the morphological box is filled, different influential user types can be identified and characterised. This morphological box serves, on the one hand, as a structured overview of the plurality of the characteristics of influential users and, on the other hand, as a starting point for structuring the different characteristics of influential users. To show the applicability of the morphological box, we apply it to two different influential user types by way of example: the influencer and the lead user.

Central position	High degree-centrality	Intermediate in-degree-centrality	High in-degree centrality	High level of Retweets & Mentions	Low out-degree	High out-degree	High Betweenness Centrality	High Closeness Centrality	Strong edge strength	High PageRank
Personal characteristics	High activity level	High knowledge	High level of trust and credibility	High popularity	Spreading information	Ahead of trends	High level of affinity and sensitivity	Opinion leadership	Adoption and diffusion of innovations	
User´s post	Length	Relevant content	High quality answer posts							
Network position of the neighbours	High Diffusion Degree	High community degree	High level of Neighbors´ Mean	High Eigenvector Centrality	High Expertise Rank					
Change of behaviour	Innovation-related	Non innovation-related	No affection of others							

Legend: the grey shaded cells represent influencers; the small boxes represent lead users; the white boxes represent the characteristics that are representative neither for a lead user nor for an influencer

Table 3. Morphological Box

Influencer: One of the major research streams to identify an influencer is the SNA. 19 out of 31 investigations dealing with the characterisation of an influencer describe this type of user as a central node regarding **DC, CC, BC, retweets and mentions**, **strong edge strength, TwitterRank as well as PageRank** (Agarwal et al., 2008, AlFalahi et al., 2014, Araujo et al., 2017, Bakshy et al., 2011, Bakshy et al., 2009, Borrego et al., 2019, Cha et al., 2010, De Veirman et al., 2017, Eirinaki et al., 2012, Kim and Han, 2009, Pal et al., 2014, Scripps et al., 2007, Smith et al., 2009, Tsugawa and Kimura, 2018, Uzunoğlu and Kip, 2014, Vogiatzis, 2013, Vollenbroek et al., 2014, Weng et al., 2010, Yang and Leskovec, 2010). Some studies contradict each other regarding the level of in-degree centrality (intermediate level versus high level), and, as it is not possible to ascribe superiority to any of these studies, we do not consider in-degree centrality in the morphological box. This does, however, not apply to **out-degree**, which is according to (Agarwal et al., 2008) at a low level. Furthermore, it is not possible to characterise influencers only by means of their own centrality measures. The network position of their neighbours has to be considered as well by calculating further centrality measures such as **diffusion degree, community degree, neighbours´ mean**, **EVC** or the **overall influence of the neighbours** (Pal et al., 2014, Scripps et al., 2007, Smith et al., 2009, Weng et al., 2010). Furthermore, user activity is one of the critical aspects when evaluating a node's influence (Bakshy et al., 2011, Deng et al., 2016). Therefore, influencers can be described as users with a **high level of activity** showing the vitality of the node over a defined period of time (AlFalahi et al., 2014, Bakshy et al., 2011, De Veirman et al., 2017, Deng et al., 2016, Eirinaki et al., 2012, Kim and Han, 2009, Vollenbroek et al., 2014, Weng et al., 2010). Different activity parameters can be distinguished: the number of posts includes activities such as updating photo albums, videos, the postage of a link or the number of status updates (Bakshy et al., 2011, Eirinaki et al., 2012, Kim and Han, 2009). Thus, the community gets to know active users, they catch more attention and hence have the possibility to influence others (Eirinaki et al., 2012). Deng et al. (2016) divide user activity into two groups, user-positive activity and user-passive activity. User-positive activity is helpful in the identification of people who serve as information sources (**spreading information**). Diffusion of information can achieve a change in opinion and behaviour. The more nodes are infected with information, the more influential an individual node is. Therefore, influencers are users who have an effect on other people's decision making processes (**non-innovation-related**) or even on their behaviour, also because of their high level of **trust and credibility** as well as their **high level of affinity and sensitivity** (Borrego et al., 2019, Deng et al., 2016, Forestier et al., 2012, Uzunoğlu and Kip, 2014, Vogiatzis, 2013, Vollenbroek et al., 2014, Zhu et al., 2015). Furthermore, the content of a post is highly relevant for the characterisation of an influencer. It has to be **relevant** as well as **original** and **unique** (Araujo et al., 2017, Forestier et al., 2012, Ríos et al., 2019, Uzunoğlu and Kip, 2014, Vogiatzis, 2013, Vollenbroek et al., 2014). Forestier et al. (2012) add that high quality is furthermore important for an influential post. An intention to devise a high-quality post about a relevant issue requires a **high level of knowledge** (Forestier et al., 2012, Ríos et al., 2019, Vogiatzis, 2013, Vollenbroek et al., 2014). Another personal attribute of an influencer is the aspect of **popularity** and **reputation** within a social media network. This attribute depends on the network position of the neighbours and can be divided into several parameters such as number of friends, community outreach, number of active friends, ratings of other users, quality of friendship, etc. (Eirinaki et al., 2012).

Lead User: The characterisation of a lead user in social networks is closely associated with the traditional research on this user type (cf. (Lüthje, 2004, Urban and Von Hippel, 1988, Von Hippel, 1986)). As lead users foresee needs and trends often months or years before others do, they can be seen as innovators (**ahead of trends**) (Belz and Baumbach, 2010, Hau and Kang, 2016, Hung et al., 2011, Kratzer and Lettl, 2011, Mahr and Lievens, 2012). These innovations conceived by lead users are often triggered by dissatisfaction. When lead users are discontented with existing products or services they try to find new solutions for their specific problems, and concomitantly, they create new features of a product or even new trends (**innovation-related**). Therefore, lead users can also be deployed as researchers during concept generation and testing phases. To incorporate their needs into a new product or service, a **high product-related knowledge** is required (Belz and Baumbach, 2010, Hau and Kang, 2016, Hung et al., 2011, Kratzer and Lettl, 2011, Kratzer et al., 2016, Mahr and Lievens, 2012, Marchi et al., 2011, Nolker and Zhou, 2005). Furthermore, due to their advance in knowledge and their central position (**high level of BC and DC**), the diffusion of information across the network by lead users is fast and easy (**spreading information & diffusion of innovations**), which is why they can also serve as **opinion leaders** during the launch of a product (Belz and Baumbach, 2010, Hau and Kang, 2016). Belz and Baumbach (2010) add that lead users are among the most active users in a social media network (**high activity level**). As the characterisation of a lead user and consequentially of the morphological box are based on the current research literature, the dimensions user´s post and network position of the neighbours are not filled for this type of user.

5.2 Interpretation and Contribution of the Results

The difference between lead users and influencers becomes clear by applying the morphological box. Companies can benefit from lead users in terms of user innovations as they are ahead of trends and know about the needs of organisations´ communities. In contrast to influencers, lead users can be seen as innovators and shapers of new products (Belz and Baumbach, 2010, Kratzer and Lettl, 2011, Kratzer et al., 2016, Nolker and Zhou, 2005). Influencers, however, are characterised by their own as well as their neighbours´ central position within a network. Influencers are individuals with a high level of connectivity, represented by delineated with high centrality measures, and they are able to change other users´ opinions or behaviours (Agarwal et al., 2008, Forestier et al., 2012). As influencers are more focused on being active than on creating something new, they do not need to have the same high product-related knowledge as lead users.

In order to show the applicability of the morphological box, we identified an influencer and a lead user of a leading manufacturer of sporting goods. In the OSN Instagram, the identified influencer had 2.4 million followers at the time of our investigation, thus confirming her central position in the network. As she is an international model, she has a high popularity especially in German-speaking countries. Furthermore, the network position of the neighbours was overall central as well. The influencer´s followers were partly influencers or persons with a verified badge in Instagram. The verified badge indicates an authentic presence of a notable public figure, celebrity or global brand (Instagram, 2020). During the 12-month period November 2018 through November 2019, she published 329 posts as well as six stories per day on average (=high activity level). Of the 329 analysed posts, 9.4% (31 posts) had a clear link to the sporting goods manufacturer (=relevant issue). All of them were non-innovation related, as the influencer did not specify any attributes of the presented products or explained to her followers why the product was better than others. With her posts, she only showed how the brand of the manufacturer of sporting goods fitted into her lifestyle. On average, these 31 posts received 56,295 likes and 299 comments. Only 6.26 comments were related to the sporting goods manufacturer on average, the larger part of the comments were on the influencer herself and her appearance. Furthermore, we also analysed the length of the posts and found them to have an average length of 16.8 words.

In contrast to the influencer, the chosen lead user is a successful marathon runner and takes part in the company´s manufacturing process of several sporting goods on an official basis. He had 16,800 followers and published a total of 182 posts last year. In comparison to the influencer, he had a much more decentralized position in the network. All in all, 105 (57.7%) posts were directly related to the sporting goods manufacturer (=relevant issue), whereas 7.6% of them were innovation-related. In these posts, the lead user introduced new products and, in contrast to the influencer, his focus was much more on details and the specification of single products. Via comments, the lead user talked with his followers, due to his product-related knowledge, about the latest trends in the sporting industry and discussed e.g. how particular components of a running shoe can improve the runner's performance. In such discussions, the lead user could be seen as an opinion leader. As we were intent on comparing the lead user with the influencer, we also analysed the lengths of the posts. The posts of the lead user contained 44.8 words on average which may be seen as due to the fact that when the lead user presented products, detailed information was given. Therefore, length and eloquence are not only important in the description of an influencer but even more so in the characterisation of a lead user.

This example shows that, depending on the choice of the product and marketing message, the differentiation between lead user and influencer is necessary for the success of the company´s marketing goals. So, when the sporting goods manufacturer introduces new marathon running shoes, the distribution of the marketing message via lead users will be more credible. The situation is different for example for the presentation of new sport tights for an amateur athlete. Here, marketing via an influencer is the better alternative. Thus, companies can provide influencers with additional information about a product that is interesting for them. An influencer is then able to post news about the product and promote it. As influencers are able to change the opinions and even the purchase decisions of people in their direct and indirect environments, the influencers´ posts can possibly result in increasing sales. In contrast, lead users can be applied by companies to develop as well as introduce new products, services or processes, due to their highly product-related as well as innovation-related knowledge (Kratzer and Lettl, 2011, Nolker and Zhou, 2005). As described above, lead users are ahead of trends and know about key concerns of consumers. Thus, customer orientation in the innovation process can be achieved (Belz and Baumbach, 2010). The direct comparison of the lead user and the influencer shows the differences between these two influential user types and highlights why they should be considered individually. In addition, the data confirmed many of the features identified in the literature review. However, the analysis of the lengths of the posts is not completely consistent with Agarwal et al. (2008), for example. Given that both "user´s post" and "position of the neighbours" have not yet been considered with a special and exclusive focus on lead users, further research is needed.

6 Conclusion

In this paper, two research questions dealing with influential users in social media networks were defined, with RQ1 and RQ2 focusing on the state-of-the-art regarding influential users and their characteristics. To that effect, we conducted a structured literature review following the procedure of Cooper (1988) and Webster and Watson (2002). We identified 52 relevant publications for further qualitative analyses and conducted a classification in accordance with the approach of Nickerson et al. (2013) and Mayring (2014) and developed a two-dimensional framework containing the dimensions "attributes of an influential user" and "user types". By assembling the different characteristics and the particular user types, we created a foundation especially for the second research question, asking for different characteristics of influential users in a social media network and for how they can be separated from other user groups. Hence, the 5x5 framework serves as an overview of different characteristics with a direct allocation to the individual user types. Furthermore, we specified the characterisation and identification process by means of a morphological box. This morphological box serves, on the one hand, as a structured overview of the plurality of the characteristics of influential users and, on the other hand, as a starting point for structuring the different characteristics of influential users. Therefore, the morphological box enables the delimitation of the different influential user types. To show the applicability of the morphological box, we applied it to two user types, the influencer and the lead user. Especially for practice our results provide additional benefit. Applying the right influential user means to reach their organisational goals for a company, such as the distribution of advertising messages to the ideal target audience or getting to know needs and trends months before others do.

Thus, our analysis contributes in various ways to both research and practice. We have created a framework that classifies the current state of the art for influential users in social media networks enabling researchers to directly identify the gaps in the current research literature. Furthermore, we have shown that there are various terminologies for similar user types resulting in overlaps in their characterisation. Hence, we have supported the research community´s process by taking the first step towards standardised definitions and term consolidation. In this context, the differences between user types can also be explained by the nature of the social media network, meaning that influential users as for instance key users, who are mainly analysed in terms of ESN, exhibit characteristics different from those of lead users who occur mainly in OSN. However, there are also user types, such as the expert, who appear as influential users in both types of social media networks, ESN and OSN, alike. Practitioners can benefit from our findings as well as make use of the capabilities of the different influential user types within a company as described by us. As we distinguished different levels of influence and introduced these into the context of companies, we did not only show how to quantify social influence but also looked at it on a qualitative level, simply by describing it in detail.

However, our findings are not without limitations. Although we conducted a broad, structured research, it is possible that some relevant articles were not identified. Moreover, a literature review captures, due to its nature, a snapshot of investigations. Further research should conduct additional case studies to identify additional attributes for the characterisation of the different user types such as characteristics of a lead user´s environment or a lead user´s post. Moreover, based on our work, the different influential user types could be compared with each other to possibly identify a characteristic all them may have in common. In doing so, uniform definitions without any overlaps of the user types based on the same criteria could be achieved. Also, further empirical validation of our results should be conducted. Based on our present investigation, it would be worthwhile investigating whether our allocation of the different user types to the different stages of a value chain is empirically reasonable or not. Thus, considered in more detail, a further study could empirically analyse at which stage of the value chain, e.g. a lead user or an influencer is most successful and therefore most valuable for a company. Furthermore, our investigation focuses on social influence in the way that someone is able to affect other people´s decisions. We do, however, not consider concepts of influence such as for instance homophily. Future investigations could examine why some users are more influential than other users and how homophily could contribute to explain this distinction.

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2.2 Beitrag 2: Automated identification of different lead users regarding the innovation process

Adressierte Forschungsfrage	**Forschungsfrage 2:** Welche verschiedenen Charakteristika weisen die einflussreichen Nutzer in einem Social Media Network auf und wie können sie strukturiert dargestellt werden? **Forschungsfrage 3:** Wie kann ein einflussreicher Nutzer unter Berücksichtigung seines Einsatzziels durch die Kombination von unterschiedlichen Methoden identifiziert werden? **Forschungsfrage 4:** Wie kann die Identifikation eines Lead Users durch ein Softwareartefakt unterstützt werden und welche Beiträge für Wissenschaft und Praxis können daraus abgeleitet werden?
Zielsetzungen	• Überblick über Lead User Charakteristika in der Literatur • Technische Umsetzung dieser Charakteristika, um eine automatisierte Identifikation zu ermöglichen • Unterschiede zwischen Lead User aufzeigen, u.a. anhand von verschiedenen Phasen im Innovationsprozess • Entwicklung eines Softwaretools, Demonstration anhand von Online Community Daten und Evaluation der Ergebnisse
Forschungsmethode	**Design Science Research** • Design Science Process nach Peffers et al. (2007), der basierend auf der Problem- und Lösungsbeschreibung u.a. die Schritte Entwicklung, Demonstration und Evaluation des Lead User Identifikationstools als Artefakt beinhaltet • Anlehnung der Forschung an Hevner et al. (2004) durch den Design Cycle (Demonstration und Evaluation des Artefakts), Relevance Cycle (Beitrag zur Praxis) und Rigor Cycle (Beitrag zur Kernel Theorie und (Nascent) Design Theorie)
Kernergebnisse (Überblick)	• Lead User Charakterisierung anhand von sechs Merkmalen (trend leadership, dissatisfaction, enjoyment, high activity level, high product related knowledge, opinion leadership) und Differenzierung derer anhand der beiden Phasen Ideen Generierung und Entwicklung im Innovationsprozess • Gestaltung und Entwicklung eines Tools, das die technische Realisierung aller Charakteristika eines Lead User durch Analyseformen wie Sentimentanalyse, SNA und Topic Modelling umsetzen kann • Demonstration des Tools durch die Identifikation von unterschiedlichen Lead User für die beiden Phasen im Innovationsprozess anhand von Online Communtiy Daten • Evaluation der Ergebnisse und des Tools anhand von Lead User Interviews und einem Experteninterview
Publikationsort	Electronic Markets Journal (Under Review)
Ranking VHB JQ 3	B
Autor:innen und Anteile	**Isabel, Schmid 45%** Janik, Wörner 45% Susanne, Leist 10%

Tabelle 3: Fact Sheet Beitrag 2

Automated identification of different lead users regarding the innovation process

Abstract:

Lead users are often established in an organizational innovation process to attenuate the difficulties a company faces, such as high costs or the obscurity of customers' needs. But to benefit from these lead users a major challenge is to characterize and identify them especially in the fast-moving world of social media. Therefore, we aim to design a tool to identify lead users automatically for the two innovation phases ("Idea generation" and "Development") by combining different approaches such as Social Network Analysis, topic modeling and sentiment analysis. Thus, we consulted the design science approach and applied our artifact to 11,481 contributions of an online digital platform. The technical realization of the six different characteristics and their respective weighting according to the different phases of the innovation process resulted in different lead users and showed the necessity of distinguishing between them. Our results were evaluated and confirmed by the identified lead users and an expert. Hence, our investigation contributes to both practice and theory (kernel theories and design theory) alike.

1 Introduction

In today's dynamic environment, innovation is central for the competitiveness of companies. To create competitive advantages a profound understanding of the sources of innovation is necessary (Von Hippel, 2007). New and innovative ideas can be released by both internal and external sources. According to Innovation Theory generating a new idea by consulting the corporate research and development (R&D) department can be seen as the internal way of innovation creation to advance a company's technology (Freeman & Soete, 1997; Marxt & Hacklin, 2005). The external way of innovation creation, however, consults innovation ideas initialized from parties outside the company such as customers, suppliers, universities or individuals (West & Bogers, 2014). Integrating an individual in the innovation process can take place in different ways e.g. in terms of co-creation (Ramaswamy, 2010), crowdsourcing (Poetz & Schreier, 2012) or open innovation (Martínez-Torres, 2014).

In current research literature, there are a lot of documented examples of successful collaboration with external parties in the innovation process. General Electrics, for example, has banded together with a number of venture capital companies to arrange the "Ecomagination Challenge," a $200 million fund for identifying and investing in innovative ideas and business models regarding renewable energy, grid efficiency and energy consumption. They created a platform where different external stakeholders submitted their ideas and in total they attracted more than 5000 ideas (King & Lakhani, 2013). Moreover, Lilien et al. (2002) have shown that in the company 3M the inclusion of external individuals in the innovation process results in ideas that have greater commercial potential than ideas without the inclusion of external persons. Whereas TopCoder arranged a two-sided innovation platform to bring software programmers and companies together in order to fix IT-related problems (Lakhani, Garvin & Lonstein, 2010).

Therefore, new ways of communication such as social media or online communities, a form of digital platforms, provide companies the possibility to access a huge number of users for a new way to innovate (Brem & Bilgram, 2015; Gawer & Cusumano, 2014). Hence, a company can use social media like a magnet to capture customer feedback, improve market research and facilitate innovation (Gallaugher & Ransbotham, 2010). Thus, on the one hand the company benefits from the collaboration with a user as it may result in ideas for extending product varieties, in entirely new products and/or in modifications to existing ones (Al-Zu'bi & Tsinopoulos, 2012). On the other hand, the user also benefits strongly from the innovative products as these are tailored to their own needs (Tuarob & Tucker, 2014; Von Hippel, 1986). In order to realize these benefits, some approaches consult the opinions and suggestions of a crowd of people (cf. open innovation). Although a company thereby receives a lot of input, the ideas are often futile, as they are either not innovative, not feasible or are formulated too superficially. Furthermore, the processing and evaluation of the ideas is very time-consuming as the example of Fiat Mio shows (Saldanha & Pozzebon, 2015). The Fiat Mio team aimed to create a concept car by composing a collaborative website where they received 21,000 ideas and 45,000 comments. The whole process took 15 months and a lot of resources – both human and capital – to screen all the posted ideas and suggestions. To avoid such an intricate and expensive process it is more constructive to concentrate on single persons who are able, due to their individual characteristics, to support a company's innovation process – so called lead users. Hence, a lead user is a user who identifies needs and trends in the market months or years before other people do and who benefit significantly by obtaining a solution to those needs according to the Lead User Theory (Hienerth & Lettl, 2017; Schaarschmidt, Stol, Walsh & Bertram, 2019; Von Hippel, 1986).

These lead users can attenuate the difficulties a company faces during the innovation process, such as high costs or the unsteadiness of customers' acceptance of a company's innovation (Ye & Kankanhalli, 2018). Therefore, a lead user is often established at the beginning and at the end of an innovation process. In the early phases of this process lead users formulate their needs which can result in new ideas. At the end of the process, a lead user can be incorporated to test the product's functionality and durability (Al-Zu'bi & Tsinopoulos, 2012). But in order to benefit from lead users, one major challenge in both research and practice is to characterize and identify them (Ernst, Brem & Voigt, 2013). Amongst other factors, the tremendous amount of online community data is responsible for the fact that the identification of lead users is the most difficult and time-consuming aspect within the lead user method (Brem & Bilgram, 2015). In current research literature there are a lot of different lead user identification approaches, but these investigations only covered a limited point of view as they either focus on only one lead user characteristic such as the high level of activity (Martínez-Torres, 2014) or include a very small amount of data (Hau & Kang, 2016). Moreover, various investigations base their approach on observations or online questionnaires (Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011), resulting in rather low sample efficiency and high costs. Additionally, lead user characteristics are derived based on self-assessments, which may bias the results due to subjective assessments (Hienerth & Lettl, 2017). Finally, most of the aforementioned identification methods are time-consuming, which contradicts to the trend specific short-term construct of lead users (Hienerth & Lettl, 2017).

With this work at hand, we address these aforementioned problems by following the Design Science (DS) approach suggesting an automated and effective approach for the lead user identification. Therefore, this research seeks to answer the following research questions informed by the Lead User- and Innovation Theory and is thus built on a descriptive knowledge base:

RQ1: What different characteristics does a lead user in an online community exhibit?

RQ2: How can the identification of a lead user be supported by a software artifact?

With this investigation we seek to cover the major characteristics of a lead user found in the literature. We aim to identify this user type automatically by means of combining different analysis approaches such as social network analysis (SNA), topic modeling and sentiment analysis. By screening the current research literature, it became obvious that different lead users can be identified in different phases of the innovation process. Thus, we further aim to show the differences between the lead users in these two innovation phases and therefore the legitimacy of the differentiation with respect to the phase-specific characteristics. To cope with this, our goal is to develop a software tool for the automated lead user identification, enabling e.g. the identification of different lead users regarding the two phases of the innovation process, the mapping of all prior identified characteristics in an automated manner and the processing of large amounts of online community data containing relevant information regarding the characteristics of a lead user. To show the applicability of the designed identification approach we apply our artifact to real-world data of an online community for kitesurfing. Kitesurfing is a water sport in which the athlete surfs through the water by pulling a large, controllable kite while standing on a special board. It is a popular example for lead user innovation as this sport was initiated by surfers who - driven by the desire to jump higher and further - experimented with the combination of a surfboard and sails from hang gliding. Moreover, this area of application is further suitable as these individuals in this area are quite active as innovators and kitesurfing is comprised of a young community, essentially all serious participants are active members in some kind of online community (Franke, Von Hippel & Schreier, 2006; Von Hippel, 2005; Wagner & Piller, 2011).

In addition to the instantiated artefact and the results obtained from the demonstration we want to highlight contributions to both practice and theory. Thereby, we want to acknowledge both perspectives of contribution in a design science research project – the artifact school of thought (cf. Hevner, Salvatore, Jinsoo & Sudha, 2004) and the design school of thought (cf. Gregor and Jones, 2007). Furthermore, different knowledge contributions will be taken into account to contribute to theory - the descriptive knowledge base in the course of kernel theories and the prescriptive knowledge base in the course of design theory (by deriving the design principles and evaluating them in the course of applying the artifact). To achieve this goal, our investigation follows the third research question:

RQ3: What different contributions for theory and practice can be derived from our Design Science project?

The remainder of this paper is as follows: the following section "Conceptual Basics" provides a theoretical background by introducing important definitions and related work regarding lead users and their characteristics. Next, the procedure of the research following the DS approach (Hevner et al., 2004; Peffers, Tuunanen, Rothenberger & Chatterjee, 2007) is described in the subsequent section. The section "Design and Development" particularly deals with the technical realization and derivation of the design principles to enable the automated identification of lead users regarding the different phases of the innovation process. The following section "Demonstration, Evaluation and Discussion" shows the application of the demonstrated approach on approximately 12,000 online community data and presents as well as discuss the resulting outcomes, which are additionally evaluated by an interview with our cooperating partner and interviews with the identified lead users. The paper concludes with the contribution for practice and theory and a conclusion.

2 Conceptual Basics

2.1 Online Communities

Social media are defined as internet-based applications that offer opportunities for interactive and dynamic communication, collaboration and participation (Kaplan & Haenlein, 2010; Obar & Wildman, 2015). Thus, different types of social media can be identified: whereas social network sites (SNS) especially enable users to connect with other people by creating personal profiles, online communities, as a further hyponym of social media, focus on sharing content between users (Kaplan & Haenlein, 2010). Therefore, online communities can be defined as internet-based platforms for communicating and exchanging content among users who are interested in a given product or technology (Autio, Dahlander & Frederiksen, 2013; Breitsohl, Roschk & Feyertag, 2018; Preece & Maloney-Krichmar, 2003). Online communities as digital, multisided platforms benefit mainly from so called “network effects”: the more users the platform access, the more valuable the platform becomes for both users and companies (de Reuver, Sørensen & Basole, 2018; Gawer & Cusumano, 2014).

For online communities, which have become increasingly popular due to the rise of social media, various characteristics were defined early and are still relevant today: such as (1) users follow a shared goal, interest or need (Breitsohl et al. 2018; Preece & Maloney-Krichmar, 2003; Tuunanen, Bragge, Haivala, Hui & Virtanen, 2011) (2) users participate actively, interact with each other and build up ties (Dahlander & Frederiksen, 2012; Fisher, 2019; Füller, Jawecki & Mühlbacher, 2007; Preece & Maloney-Krichmar, 2003) and (3) users have access to shared resources (like knowledge or information) (Breitsohl, Kunz & Dowell, 2015; Breitsohl et al., 2018; Preece & Maloney-Krichmar, 2003). The communication in online communities is established around discussion threads. This means that users initialize new threats in order to start a new discussion, issue or call for advice (Autio et al., 2013). Thus, as online communities often cover one main topic (e.g. mountain biking or kitesurfing), this sub-type of social media focus more on connecting people with the same interests than SNS.

Moreover, companies can also benefit from the broad dissemination of digital, multisided platforms in terms of online communities because of social media’s reach (via social media a lot of people can be reached) and richness (social media platforms provide various types of information) (Shang, Wu & Li, 2017). This kind of communication medium gives a company the opportunity to communicate and engage with (potential) customer communities (Fisher, 2019). Thus, as users discuss their experiences, news, improvements or ideas, companies become aware of the customers’ needs (Autio et al., 2013; Kaplan & Haenlein, 2010; Tuunanen et al., 2011). Especially in brand communities, excited users group together and share brand-related content (Breitsohl et al., 2015; Breitsohl et al., 2018). However, a company can not only benefit from online communities in terms of nurturing brand commitment and the awareness of customers’ needs but also from the fact that these digital platforms can serve as a source of innovation (Dahlander & Frederiksen, 2012; Fisher, 2019). In terms of the discussions taking place in online communities, users also provide new ideas, offer solutions for problems, work out details and test new product ideas (Füller et al., 2007). Thus, these platform-based new product developments can be consulted to increase product variety, meet diverse customer requirements and business needs (Gawer & Cusumano, 2014).

All in all, online communities allow communication and interaction between users and companies in different ways. Gallaugher and Ransbotham (2010) take this on in their 3-M framework including the three different customer dialog approaches: Megaphone (firm-initiated dialog), Monitor (customer-to-customer dialog) and Magnet (customer-initiated dialog). From this follows that a company can use digital platforms in terms of online communities not only as a megaphone (in terms of spreading marketing messages) but also especially as a monitor to get to know customers' needs. Thus, by monitoring customer-to-customer dialogs companies can gain insights in customers' opinions or market intelligence (Gallaugher & Ransbotham, 2010). Furthermore, a company can also use online communities as a magnet, the customer-initiated dialog, to capture customer feedback, improve market research and facilitate innovation (Dahlander & Frederiksen, 2012; Fisher, 2019; Gallaugher & Ransbotham, 2010).

2.2 Lead User Innovation

Innovation is a central construct for organizational competitiveness and effectiveness (Wolfe, 1994). It can be seen as an essential process for driving economic growth (Chen, Yin & Mei, 2018). In general, innovation can be defined as a process that includes the generation, adoption and implementation of new ideas, practices, or artifacts in organizations (Axtell et al., 2000; Ye & Kankanhalli, 2018). So, innovation is a complex issue that comprises many theories, each with a different focus (Wolfe, 1994). In addition, there are also many innovation process models that describe how innovations can be implemented step by step. Cooper (1996), for example, established the so-called stage-gate model and divided the innovation process into the following five different phases (stages): 1. preliminary investigation, 2. detailed investigation, 3. development, 4. testing and validation, 5. full production and market launch. The stage-gate model describes a conceptual and operational model for moving new product projects from idea to launch. Other widely spread innovation process models (cf. Crawford, 1994; Herstatt, 1999; Ulrich & Eppinger, 1995) are similar to the process of Cooper's (1996) approach.

By scanning further research literature about innovation and keeping the process models in mind, exemplarily the stage gate model, it became apparent that most innovation approaches identify two comprising key phases: (A) the idea generation which means the "awareness" of an innovation and incorporates therefore the preliminary and detailed investigation phases of the stage gate model, and (B) the development of an innovation incorporating the development as well as the testing and validation phases of the stage model (Amabile, 1988; Axtell et al., 2000; Unsworth, Brown & McGuire, 2000). We follow this approach and concentrate on the two phases "Idea generation" and "Development". Consequently, we excluded in our investigation e.g. the step "market launch" as here another user type – the influencer – can be applied to support this phase optimally (Schmid, 2020). According to the definition of an influencer, this user type is applied by companies for disseminating information, for spreading marketing messages, and for changing the opinions and even the purchase decisions of people in its direct and indirect environments (Schmid, 2020). If an influencer would be involved in upstream value creation stages respectively innovation related phases (such as "Idea Generation" or "Development"), the user would feature characteristics of lead users (e.g., ahead of trends, etc.) and would therefore be – in addition of being an influencer – also a lead user.

So, as our overall goal of this paper is to identify users who can support a company in their innovation process, we focus the characteristics of a lead user who can also appear in other phases as other type of user.

In the last decades, it has become conventional that consumers or users themselves support one or even both phases of the illustrated innovation process. Hence, this user innovation can be conveyed from the shift of traditional firm-centered innovation to user-centered innovation (Von Hippel, 2005). Prior research highlights that users, rather than firms, are frequently the ones who initiate new product ideas and product developments (Dong & Wu, 2015). Thus, user innovation can be defined as innovative activities undertaken by users who are the source of innovative ideas and who engage actively in developing and modifying products also to meet their own needs (Zheng & Zhou, 2017). These users can invent, prototype, and test new innovations (Roy, 2018). The advantages of user innovations can be mainly attributed above all to the nature of digital innovation platforms.

From a company's point of view, the most important driver for user innovation is to overcome information stickiness. Innovation requires both information about the problem and problem-solving information or, in other words, need-related and solution-related knowledge (Von Hippel, 1994, 2005). Often the information about user's needs and the information used in problem solving is costly to acquire and therefore "sticky" (Piller, 2006; Von Hippel, 1994). Hence, the acquisition as well as transferring costs of the information that is decisive for initiating innovation have tremendous influence on where innovation is created (Idota, 2019). Therefore, as users with highly sticky information can create innovation, organizations should include them in their innovation process to get to know the user's needs, to solve (product) problems and to reduce R&D costs. Thus, User Innovation Theory postulates i.a. that "*innovation among users tends to be concentrated on lead users (people with high lead userness) of those products or services*" (Ye & Kankanhalli, 2018). This means that those users who carry out user innovation are so-called lead users (Von Hippel, 1986).

In current research literature there is no consistent definition of a lead user, but the Lead User Theory of Von Hippel (1986) is often used as a starting point for defining them: "*Lead users face needs that will be general in a marketplace – but face them months or years before the bulk of that marketplace encounters them, and – Lead users are positioned to benefit significantly by obtaining a solution to those needs*." (Von Hippel, 1986, p.796). Thus Lead User Theory states that lead users can be used as a source of innovative and commercially attractive ideas about products and services and are characterized by two distinct characteristics: ahead of trend and high benefits from innovation (Hau & Kang, 2015; Von Hippel, 1986; Von Hippel, 2005). Hence, lead users are able to invent, prototype and field test innovations (Roy, 2018). Therefore, they can either be applied for the entire innovation process (cf. Ye & Kankanhalli, 2018) or can be applied for only one part of the innovation – either need or solution related tasks (cf. Von Hippel & Katz, 2002). As lead users can constrict the challenges a company faces during the innovation process and as they are simultaneously able to disclose new ideas, lead users can be seen as a valuable resource for companies in terms of different phases of the innovation process (Al-Zu'bi & Tsinopoulos, 2012; Ye & Kankanhalli, 2018). Several studies have shown that their involvement in this process, especially in the early and late phases, can enhance product success (Brem, Bilgram & Gutstein, 2018b; Schreier, Oberhauser & Prügl, 2007). Hence, an intensive collaboration with lead users can increase the product variety as well as the rapidness of a new product development process (Al-Zu'bi & Tsinopoulos, 2012).

Furthermore, as the lead user is the only user type who can be applied in terms of user innovation and therefore support a company in their innovation process, we focus on this type of user. To benefit from a lead user, one major challenge in both research and practice is to characterize and identify him/her (Ernst et al., 2013) – the second step in Von Hippel (1986) 4-step process of utilizing lead users (1. identification of the trend, 2. identification of a lead user, 3. analyze lead user need data, 4. project lead user data onto the general market). Here, the identification of adequate lead users is mostly accompanied by horrendous monetary, time and human resources (e.g. Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011). Therefore, to reduce the devoted resources regarding the characterization and identification of lead users, we aim to design a software tool, enabling the automated identification of lead users based on their descriptive characteristics. This tool is intended to automate the identification process which is described in current research literature as the most difficult and time-consuming aspect within the Lead User Theory (Brem & Bilgram, 2015). However, to automate the identification process we need to characterize the lead user in detail first.

2.3 Characterization of lead users in online communities

In order to characterize lead users in online communities, we conducted an extensive literature search. This resulted in 18 investigations (see table 1) that focus on the characterization of lead users in terms of online communities. A minority of the 18 investigations (3 out of 18) examines lead users within SNS rather than explicitly in online communities. Nevertheless, since these investigations specify SNS with the same characteristics as online communities and since the authors of these three investigations also base their research primarily on identifying lead users in online communities, these investigations are also included here. Numerous research papers that are not related to the online area were excluded as well as those that do not focus on the identification or characterization process.

However, the description of lead users by Von Hippel (1986) in the course of the description of the Lead User Theory (see section: “Lead user innovation”), were used as a starting point for the characterization of lead user as almost every investigation mentioned in the following relate to these two major lead user characteristics: (1) trend leadership/being ahead of trend and (2) the high expected benefit from innovative solutions, meaning that lead users benefit strongly from adopting new products tailored to their needs (Brem et al., 2018b). Prior research about the identification and characterization of lead users in the social media sphere have shown that these two characteristics of the basic model of the Lead User Theory remain valid (Pajo, Vandevenne & Duflou, 2017; Schaarschmidt et al., 2019; Tuarob & Tucker, 2014; Ye & Kankanhalli, 2018).

(1) Trend leadership incorporates the degree to which a user can be seen as a leading edge with respect to a certain trend (Franke & von Hippel, 2003). That means lead users have prevailing information and expertise about major trends of products and services as well as future demands for them in the market (Hau & Kang, 2016; Tuarob & Tucker, 2014). Hence, a lead user is a consumer of a product that identifies problems and unmet needs that will later be experienced by the public. This means that the innovations lead users strive for often do not exist on the market (Franke & von Hippel, 2003). Therefore, as lead users recognize what the mass desires months or years before others do, they are ahead of trends (Brandtzaeg, Haugstveit, Lüders & Følstad, 2016; Pajo et al., 2017; Pajo, Verhaegen, Vandevenne & Duflou, 2014; Tuarob & Tucker, 2014; Ye & Kankanhalli, 2018).

(2) In addition, the characteristic **high expected benefit** is broken down into further sub-characteristics in the current research literature to make this characteristic more tangible and (especially against the background of the large amount of social media data) more measurable (Ye & Kankanhalli, 2018). We agree with this approach and focus on these sub-characteristics (e.g. dissatisfaction) when defining and characterizing a lead user in the following section. Thus, a lead user does not only come up with attractive innovations to help others but they also benefit strongly from the adoption of new or improved products (cf. high expected benefit) (Schreier et al., 2007; Von Hippel, 1986). Often it is not the financial benefit that motivates a lead user to innovate, but e.g. the chance to execute their sports more effectively. By undertaking their sports, users become aware of the mismatch of expected and experienced performance of the products which can lead to **dissatisfaction** (Lüthje, 2004). Therefore, the discrepancy between the users' needs and the solutions available on the market leads to dissatisfaction. Given the nature of the kitesurfing or mountain bike community and their genesis, it was through the dissatisfaction of the athletes that the sport emerged, which leads to this proxy measure for users' expected benefit (Belz & Baumbach, 2010; Pajo et al., 2017; Pajo et al., 2014; Schaarschmidt et al., 2019). The unmet needs and the relating dissatisfaction of a user lead to the expectation to benefit significantly from an innovative solution (Pajo et al., 2017; Ye & Kankanhalli, 2018). Although this characteristic is prevalent in the current research literature, a discrepancy can be determined. Chen, Hu, Wang and Tao (2019) e.g. introduce a new model (ITF model) for determining a user's index of innovativeness including the three dimensions of involvement, thinking and feeling. The last dimension "feeling" is related to the extent of a user's **enjoyment**, exploration and creativity, which in turn enables the users to make full use of their potential innovativeness. Therefore, the authors refer to the emotional attachement and the preference for the product by users and therefore state that a lead user exhibits positive sentiment rather than negative sentiment such as dissatisfaction (Chen et al., 2019).

Additionally, with regard to the topic of lead users in online communities, multiple other characteristics, beside the abovementioned, can be identified e.g. the **high level of activity** with regards to the involvement. According to various investigations (Martínez-Torres, 2014; Miao & Zhang, 2017; Pajo et al., 2017) lead users are more active in a community than the rest of their members. Moreover, the authors Hung, Chou and Dong (2011) emphazise the lead user's creative and active participation in order to facilitate effective innovations and to encourage innovation communication. The more a lead user's participation level is, the more they get involved in the community. High involvement of users usually implies that there will be high effort made by the users in interacting with the product (Chen et al., 2019). This active involvement is necessary to disclose the sticky information that resides in a lead user. This information can only be valuable in terms of innovations when a user exhibits a high **product related knowledge** (Franke et al., 2006; Li & Tang, 2016). According to Schaarschmidt et al. (2019) a lead user differs most "*from `typical` consumers as they also have considerable levels of solution knowledge*" (Schaarschmidt et al., 2019, S. 4). This kind of product-related knowledge contains expertise about the product architecture, the used materials and the technologies as this is the basis for creating new ideas (Franke et al., 2006; Schreier et al., 2007). Only by having high product related knowledge, a lead user is able to formulate the needs into concrete innovation ideas and/or concrete specifications of new products (Chen et al., 2019; Marchi, Giachetti & De Gennaro, 2011; Pajo et al., 2017; Pajo et al., 2014; Tuarob & Tucker, 2014).

As lead users not only have ideas for realizing innovation but also diffusing them, a lead user can also be described by the characteristic **“opinion leadership”.** Opinion leadership is the ability to enable the flow of information and especially to diffuse it. Strong social relationships and a high level of engagement are premises for a functioning exchange of ideas and innovation (Pajo et al., 2017; Pajo et al., 2014).

However, lead users can be defined not only in terms of these different characteristics but also – as already mentioned in the section “Lead user innovation” – in terms of the different phases of the innovation process where a lead user can be applied. Therefore, to support the identification of lead users regarding these different innovation phases, we further allocate the aforementioned characteristics to the respective innovation phase.

Lead users can be applied in the phase **“Idea generation”** of the innovation process and are therefore more problem-oriented (Belz & Baumbach, 2010; Miao & Zhang, 2017). Lead users in this phase of the innovation process describe problems and unmet needs with the already existing products (cf. **dissatisfaction**) (Belz & Baumbach, 2010; Hau & Kang, 2016). Furthermore they bring forward new ideas which might help to fix the problem described before (cf. **trend leadership**). These ideas tend to be unique and can possibly be useful for the development of the next generation (Tuarob & Tucker, 2014). In online communities lead users can share their innovative ideas and other community members can comment and evaluate these ideas. The users offer suggestions on the one hand about modifications and adaptions regarding product attributes, positioning, etc.. On the other hand, lead users formulate innovative ideas about completely new products which can be realized afterwards by a company’s R&D team (Marchi et al., 2011; Martínez-Torres, 2014). Therefore, lead users are incorporated in a very early phase in the innovation process (Hung et al., 2011). This phase “Idea generation” can be seen as a venue for brainstorming to make the free exchange of ideas possible (Muller et al., 2012; Paulus, Putman, Dugosh, Dzindolet & Coskun, 2002). When brainstorming, people are encouraged to generate as many ideas as possible and therefore a high participation as well as a **high activity level** is necessary here (Chen et al., 2019; Hung et al., 2011; Miao & Zhang, 2017))

Lead users are not only able to provide new ideas but can also be integrated into the **“Development”** phase of the innovation process. Because of their **high product related knowledge** and their vast experience lead users are able to suggest concrete solutions instead of describing problems or stating customer needs (Mahr & Lievens, 2012). Hence, scientific articles which characterize and identify lead users in terms of the “Development” phase focus on users e.g. who have already done security-related modifications to a web server software (Franke & von Hippel, 2003) or who have already developed applications for different plattforms (Schaarschmidt et al., 2019). Hence, Mahr and Lievens (2012) summarize it and state that lead users are best suited for improvements pertaining to functionality. Thus, lead users in this second phase of the innovation process are able to support companies in order to develop new products and solutions with the aim of meeting rapidly changing consumer needs and to stay competitive (Pajo et al., 2014). This can diminish failure rates of new product introduction. So utilizing this high-product related knowledge combined with the high level of **trend leadership**, a lead user can be conducive in strengthening a company’s innovation competitive advantage (Li & Tang, 2016).

The assignment of the characteristics to the different phases in the innovation process and thus the difference made by the lead users in the two innovation phases can be detected in table 1.

		Trend leadership	Sentiment		High Activity Level	High product related knowledge	Opinion leadership
			Dissatisfaction	Enjoyment			
Idea generation	(Belz & Baumbach, 2010)	X	X		X	X	X
	(Chen et al., 2019)	X		X	X	X	
	(Miao & Zhang, 2017)				X		
	(Marchi et al., 2011)	X			X	X	
	(Martínez-Torres, 2014)				X		
	(Hau & Kang, 2016)	X	X			X	
	(Hung et al., 2011)	X	X		X		
	(Pajo et al., 2017)	X	X		X	X	X
	(Tuarob & Tucker, 2014)	X				X	
Development	(Brandtzaeg et al., 2016)	X					
	(Chen et al., 2019)	X		X	X	X	
	(Franke & von Hippel, 2003)	X				X	
	(Franke et al., 2006)	X				X	
	(Li & Tang, 2016)	X				X	
	(Miao & Zhang, 2017)				X	X	
	(Mahr & Lievens, 2012)	X				X	
	(Pajo et al., 2014)	X	X		X	X	X
	(Pajo et al., 2017)	X	X		X	X	X
	(Schaarschmidt et al., 2019)	X	X			X	
	(Schreier et al., 2007)	X				X	X
	(Tuunanen et al., 2011)	X			X		

Table 1: Prior research on lead users

2.4 Related Work

The review of the research literature has shown that, in addition to the two characteristics from the basic model of the Lead User Theory, there are many different characteristics to describe and characterize lead users in the online environment (see table 1), whereby different approaches such as screening (Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011), pyramiding (Von Hippel, Franke & Prügl, 2009), SNA (Martínez-Torres, 2014), or netnography (Belz & Baumbach, 2010; Mahr & Lievens, 2012) have been used. However, these studies on lead user identification covered only a limited point of view as they either focus only on one characteristic of a lead user, like the high level of activity (Martínez-Torres, 2014), or they include a very small amount of data (Hau & Kang, 2016). Furthermore, investigations are based on observations or (online) questionnaires (Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011) which results in a low sample efficiency and high costs. In addition, lead user characteristics are thereby based on the self-assessment of respondents, which means that the results can be affected by subjective assessments (Hienerth & Lettl, 2017). Another problem within the current research literature is the aspect of time (Brem, Bilgram & Gutstein, 2018; Hienerth & Lettl, 2017). Most of the aforementioned identification methods are time-consuming. This contrasts with the fact that the concept of "lead userness" is not a long-term construct but it is trend specific and can change over time. A lead user today may or may not be a lead user in distant future (Hienerth & Lettl, 2017).

Furthermore, as already mentioned, lead users can be identified in both innovation phases: the "Idea generation" and "Development" (Füller et al., 2007). However, in current research literature it is common practice to identify a lead user for one of the two phases (Marchi et al., 2011; Martínez-Torres, 2014; Schaarschmidt et al., 2019). Moreover, only a minority of the investigations incorporates an innovation process but identifies a lead user for all of its phases (Miao & Zhang, 2017; Pajo et al., 2017). Consequently, the current research literature is incomplete here as there is no approach that identifies different lead users for every phase of the innovation process and so an overall approach is missing. Thus, we aim to show the differences between the lead users in the two innovation phases and the legitimacy of the different identification processes, although we have seen in our summary table 1 that there are no large differences between the two phases.

All in all, in order to avoid these negative aspects of the prior research literature, we have come to the conclusion that a tool for automated lead user identification is needed. This tool should meet the following design requirements and should therefore be able to:

- map all prior identified characteristics,
- process a large amount of online community data,
- apply objective identification methods,
- repeat the identification process for lead users at any time as lead users are trend specific, and
- identify different lead users regarding the two phases of the innovation process.

3 Procedure of the research

In order to make the development of a systematic approach for the automated identification of lead user comprehensible, we applied Design Science (DS) research. Research projects that follow the DS paradigm are concerned with the design, development, implementation, use, and evaluation of socio-technical systems in organizational contexts. Design scientists produce and apply knowledge of tasks or situations to create effective artifacts (March & Smith, 1995). These artifacts are delineated in different structured forms such as software, formal logic, and rigorous mathematics to informal natural language descriptions (Hevner et al., 2004).

An important step in DS research is to prove the utility, quality, and efficacy of the artifact via well-executed evaluation methods. Since the artifact's performance is related to the environment in which it is used, an incomplete understanding of the environment can induce inappropriately designed artifacts (March & Smith, 1995). Therefore, Hevner's "design cycle" (Hevner, 2007) substantiates the importance of constructing and evaluating the artifact, and suggests balancing the efforts spent on both activities, which must additionally be convincingly based in relevance and rigor (Hevner, 2007). Consequently, DS research is based on and contributes to scientific knowledge by performing the research process rigorously (e.g., by reflecting the construction or/and evaluation of the artifact) which is represented by Hevner's "rigor cycle". DS research additionally uses practical knowledge and leads to several practical contributions which constitutes Hevner's "relevance cycle" and which can be seen as self-evident objectives of a DS research project (Hevner, 2007).

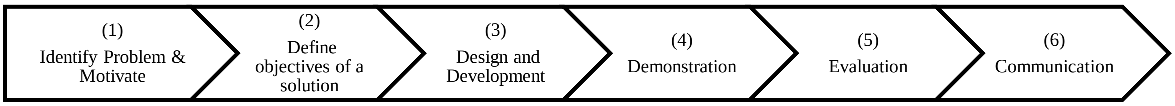


Figure 1: Design science process

We followed the DS research paradigm (Gregor & Hevner, 2013; Hevner et al. 2004) and aligned our research activities with the procedure as proposed by Peffers et al. (2007) (see figure 1). This procedure provides a commonly accepted framework for conducting research based on DS principles. In addition, Peffers et al. (2007) designed the procedure as a result of a consensus-building approach, which comprises well-agreed process elements (Peffers et al., 2007). As a first step, (1) **corresponding problems** and drawbacks of already existing approaches to identify lead users in online communities were identified (see sections "Introduction" and "Conceptual basics"). Hence, in current research literature there are a lot of different lead user identification approaches, but these investigations only cover a limited point of view as they either focus only on one lead user characteristic, they include a very small amount of data or their approach is reliant on the self-assessment of users. Consequently, our (2) **objective** is to provide and combine a set of methods, based on the characteristics of a lead user, in order to identify this type of user automatically in an online community (see sections "Conceptional basics" and "Design and Development"). The third step of the DS process model contains the (3) **design and development** (see section "Design and Development") of a solution or an artifact, respectively. Such artifacts can be constructs, models, methods or instantiations. In order to fill the gaps identified within phase (1), we focus on the design of the technical realization of the tool by means of the combination of different methods such as SNA, topic modeling and sentiment analysis. Thus, our approach was established to support and simplify the lead user identification process and to eliminate the existing disadvantages. In the next step, the (4) **demonstration**, we show the application of the demonstrated approach on approximately a data set of about 12,000 contributions from an online community about kitesurfing. Kitesurfing is a suitable area of application as individuals in this area are quite active as innovators. Furthermore, kitesurfing comprises a young community, essentially all serious participants are active members in some kind of online communities (Franke et al., 2006; Von Hippel, 2005; Wagner & Piller, 2011). The overall results of the application of the analysis are shown in this chapter, consolidated in a summary table and discussed in detail. These results are additionally **evaluated** (5) by conducting both interviews with lead users and an in-depth interview with an expert (head of marketing of our cooperating partner) in the field of kitesurfing. In terms of these interviews, we evaluated our artifact and showed that our approach provides an added value. We have further discussed the results of the evaluation as well. Finally, the results are then (6) **communicated**.

The orientation towards the procedure by Peffers et al. (2007) also makes it possible to align our research with the guidelines of Hevner et al. (2004) or Hevner (2007), respectively. According to the design cycle, we present our artifact as the result that has gone through the process of demonstration (application of our approach to an online community about kitesurfing and evaluation with several interviews (see section "Demonstration, Evaluation and Discussion")). In view of the relevance cycle, we identified several design requirements (from literature including several case studies (see section "Conceptual Basics")) that guided the design of the artifact, and so the practical application of our artifact brought up several contributions for practice (e.g. identifying relevant users for innovation/trends (see section "Discussion of the Results of Demonstration")). In view of the rigor cycle, we used several methods and techniques to rigorously construct and evaluate our artifact (e.g. topic modeling, SNA, frequency analysis) and derived initial findings as contributions to theory, both kernel theory (Lead User- and Innovation Theory) and Design Theory (see section "Contribution for Practice and Research"). Thus to contribute to a rather general and abstract knowledge base – "nascent design theory" (Gregor & Hevner, 2013) – and in order to design a purposeful artifact in a comprehensible way, we first established both, a set of meta-requirements and design principles (Gregor & Jones, 2007; Heinrich & Schwabe, 2014). Thus, the design of the lead user identification tool is grounded on design requirements retrieved from seminal works on Lead User- and Innovation Theory. In a next step, we then describe our prototypical implementation that demonstrates the feasibility of the design principles and meta-requirements in the tool.

4 Design and development

4.1 Design principles for a lead user identification tool

First, the composition of meta-requirements (MRs) that describe "*what the system is for*" (Gregor & Jones, 2007, p.325) is based on the purpose and scope of the identification tool that has been discussed in the introduction. Thus, we define the solution objectives based on the class of problems our paper addresses and present them in Figure 2. These MRs established to be suitable for a class of artifacts and are based on the current research literature (Gregor & Jones, 2007; Heinrich & Schwabe, 2014; Walls, Widmeyer, El Sawy, 1992). Besides the MRs, the design principles are synthesized in a next step. Design principles are defined as prescriptive statements that show how to do something to achieve a goal (Gregor et al., 2020). The design principles that we dispose fall into the category of action and materiality-oriented design principles that describe what an artifact should enable users to do and how the artifact should be built in order to do so (Chandra, Seidel, Gregor, 2015). Regarding companies (=users) who are interested in identifying lead users in online communities (=boundary conditions) and keeping our design requirements for our artifact in mind, we derive four design principles for (lead) user identification tools:

1. **The principle of comprehensive characteristics consideration.** In order to identify specific user types in online communities, e.g. a lead user, it is necessary to precisely define and describe their characteristics. Thus, the automated identification of a lead user requires a technical implementation of its characteristics that we have derived from the current research literature. Therefore, the tool should be able to incorporate and technically realize all relevant lead user characteristics (trend leadership, sentiment, high activity level, high product related knowledge and opinion leadership) to obtain precisely targeted results.
2. **The principle of using inter-subjectively verifiable identification methods.** In order to counteract the subjective self-assessment of respondents of (online) questionnaires different inter-subjective methods should be consulted and combined to identify a lead user. Therefore, the tool should use comprehensible and inter-subjectively verifiable identification methods to make the identification process traceable.
3. **The principle of contextual adaptability.** Since lead users are applied in terms of innovations in a company, the identification of a lead user must also take into account the different phases of the innovation process the user supports. Therefore, the tool should be able to adapt the weights of the characteristics according to the different circumstances of the companies and their aim to apply lead user in different stages of the innovation process.
4. **The principle of repeatability.** As lead userness is a short-term construct, which means that lead users can change over time, the identification process should be executable often and in a resource-saving way. Therefore, the tool should allow repetition of the identification process at any time to react quickly to changing circumstances such as trends.

These design principles are deduced from the design requirements that are further based on kernel theories and prior research literature. Gregor & Jones (2007) state that these kernel theories disclose "*an explanation of why an artifact is constructed as it is and why it works*" (p.328). So, these kernel theories include the body of knowledge that is necessary to meet the design requirements (Böckle, Bick & Novak, 2021). Hence, based on the discussion of the kernel theories and thus the related work, we derive design requirements our tool should meet. These design requirements offer guidance by designing the artifact and advise the design principles (Böckle, et al., 2021; Gregor & Jones, 2007). These principles refer to at least one requirement and serve as an abstract "blueprint" of our artifact (Böckle, et al., 2021; Gregor & Jones, 2007; Heinrich & Schwabe, 2014). By establishing these design principles, we made sure that they follow the value grounding (reference to the requirement) and the explanatory grounding (design principles are based on the current literature and thus on kernel theories) (Heinrich & Schwabe, 2014).

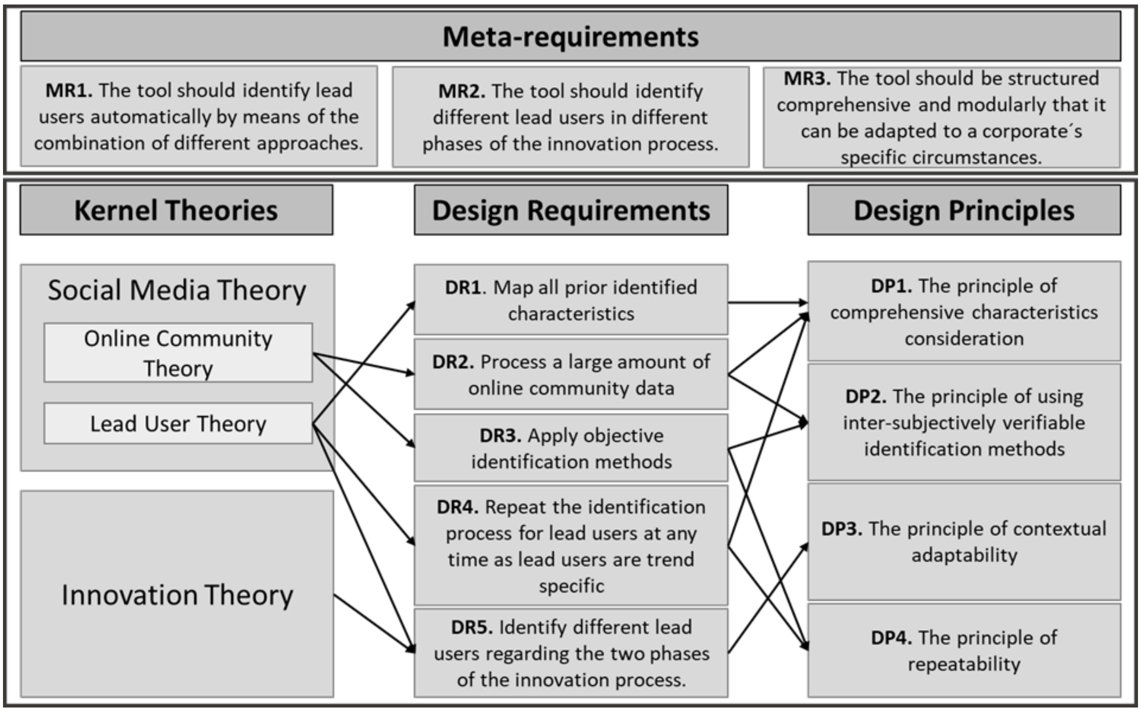


Figure 2: Overview of the design phase

For each of the design principles, its instantiation in the artifact is described in the following sections.

4.2 Weighting of the according lead user characterizations

To address the shortcomings of the prevailing research and therefore consider the derived design principle 1. The principle of comprehensive characteristics consideration, we aim to compose an automatic identification approach including all characteristics identified in literature. Furthermore, to account for the different circumstances of the two innovation phases (see section "Lead User Innovation"), we also distinguish between lead users associated to the phase “Idea generation” and lead users associated to the phase “Development” of the innovation process. Therefore, to consider the different relevancies related to the identified characteristics with respect to each innovation phases, the characteristics are weighted accordingly (see table 2) based on their occurrences within the current research literature (see table 1). In addition, with respect to the derived design principle 3. The principle of contextual adaptability, companies are enabled to adapt the respective weights to their circumstances and thus to apply lead users in different stages of the innovation process.

Characteristics	Weight by occurrence in literature	
	Idea generation	Development
Trend leadership	5	5
Dissatisfaction	3	2
Enjoyment	1	1
High activity level	5	3
High product related knowledge	4	4
Opinion leadership	2	2

Table 2: Weighting the relevance of each characteristic for both innovation phases

Table 2 summarizes the characteristics' accompanied relevancies in the context of the respective innovation phases. Here, the weights illustrate that the respective focus of the innovation process within the activity of the users (Idea generation) as well as their product-specific knowledge (Development) differs considerably. Additionally, users also differ in the mood they exhibit. Here, the characteristic dissatisfaction is given greater meaning in the "Idea generation" phase since users express their unmet needs of a product or service within negatively afflicted communication. These differentiations enable to adequately consider the circumstances of the two innovation phases, resulting in the determination of precisely fitting and goal-oriented lead users.

4.3 Technical realization

To enable the automated identification of lead users based on the above determined relevancies, the previously identified characteristics (see table 1) must be mapped in an automatic manner. Therefore, we have implemented each identified characteristic in the programming language Python. As the underlying data (e.g. online community posts, network interactions, etc.) are mainly represented in a textual way, we focused on finding computer-based procedures from the research field of text mining to map the identified characteristics. Text mining enables an automatic identification of hidden structures or patterns within a corpus of textual data (Feldman & Sanger, 2007; Heyer, Quasthof & Wittig, 2006). In addition, we conducted the SNA, which best suits the identification of users within a potentially high influence to be solved, as SNA enables us to show the relations in a structured network via nodes and ties to state quantitative characteristics of users. Furthermore, due to the different nature of each characteristic (see table 3), the values must be normalized to make them comparable. Therefore, we have conducted the Min-Max normalization (Han, Pei & Kamber, 2006) to rescale each characteristic into a value range between [0;1]. In the course of normalization, the specific values of all users were related to each other. Thus, the higher the respective value, the more the respective user exhibits the specific characteristic. By this, all values are located at the same scale and therefore can be weighted by their allocated relevance (see table 2). To give an overview of the characteristics and their technical realization, they are further summarized in table 3. Here, to consider the derived design principle 2. The principle of using inter-subjectively verifiable identification methods and therefore ascertain an adequate analysis process, all technical realizations are based on broadly known and prevalent quantitative and qualitative content analysis methods. To further meet the particular needs associated to the respective characteristic, the methods used have further been adapted as described in the following.

Characteristics	Technical realization	Implementation	Outcome
Trend leadership	Latent Dirichlet Allocation (LDA)	Gensim; Mallet (McCallum, 2002)	Probability
Dissatisfaction	Sentiment Analysis	VADER (Hutto & Gilbert, 2014)	Classification
Enjoyment	Sentiment Analysis	VADER (Hutto & Gilbert, 2014)	Classification
High activity level	Frequency Analysis	Self-created	Frequency
High product related knowledge	Frequency Analysis	Self-created	Frequency
Opinion leadership	Closeness, Betweeness and Degree centrality	NetworkX (NetworkX, 2020)	Centrality measure

Table 3: Technical conception of the identified characteristics

With respect to the characteristic of **trend leadership**, the aim is the identification of users who talk about trends before they became general, community-wide discussed topics. To meet these requirements, we mainly had to split the automation into two separate sub-sequences: (1) identify trends (e.g. frequently discussed product issues or service properties), based on UGC; (2) identify users who talked about one or multiple of these previously identified trends, before they became discussed community-wide. With regard to these two identified sub-sequences, we focused on the use of text mining methods, enabling the automatic processing of unstructured, unlabeled data such as online community posts. More specifically, as trends represent frequently emerging topics as well as the advantage of topic modeling compared to other text mining techniques to operate directly on the textual data instead of solely comparing their underlying structure (Aggarwal & Zhai, 2012), we have chosen topic modeling for the automatic identification of trends. Topic modeling can project the textual corpus of contributions into a topical space by reducing the dimensionality and attaching different weights, which results in semantically coherent groups of words (topics), which represents our trends (Crain, Zhou, Yang & Zha, 2012; Xie & Xing, 2013). Specifically, because of LDA's simple applicability but also its satisfactory analysis results within the topic modeling (Eickhoff & Neuss, 2017), the choice was made for LDA. For the implementation of LDA within the automated identification approach, the established python library Gensim was used in combination with Mallet (see table 3). In order to achieve the highest quality of results possible, we further automatically prepared the data for the analysis by applying tokenization, stop word removal and case folding (cf. Boyd-Graber, Mimno & Newman, 2014). Furthermore, in order to take the characteristics of trends into account (1), we adapted LDA to only consider contributions of the last eight weeks to extract the trending topics. By this adaption, the identification of those user who were already talking about these trending topics within their contributions at an earlier point in time than eight weeks ago (2) is feasible. The identification takes place through statistical inference and reflects the cumulated probability with which a user talks about one of the identified trending topics.

Considering the characteristic of **dissatisfaction** or **enjoyment** aims to identify users with either negative or positive mood. Therefore, the global mood of each user within their contributions has to be identified. The automatic identification of moods within textual data is summarized under the term "sentiment analysis". Through this, for instance, it is possible to identify users who have unfulfilled expectations and thus show a significant potential for improvement of a product or service (Pajo et al., 2017). To determine the mood of each post by a user, we implemented the "Valene Aware Dictionary for sEntiment Reasoning" (VADER) (Hutto et al., 2014) technique. VADER is a lexicon and rule-based sentiment analysis technique that is specifically attuned to sentiments expressed in social media and has achieved remarkable results compared to other prominent sentiment analysis techniques (Hutto et al., 2014). To determine the sentiment value, VADER uses a labelled dictionary adapted to the contextual characteristics of social media data. Hereby, VADER is able to combine the positive and negative inflections and generates a single sentiment score within the range of -1 to +1. In order to determine the global sentiment value of each user, we further adjusted the technique to build a consolidated sentiment score for each user reflecting its global mood by setting the individual scores of each contribution into relation to the total amount of contributions of a user. This results in the mean value of all mood-bearing contributions of a single user, which reflects their average mood.

To measure the **activity level** of a user, we further determined the amount of user interactions within the community. For this purpose, the number of posts and transacted comments per user within the analyzed period was identified to attain information about the activity level of a user (Miao & Zhang, 2017).

In the case of **high product related knowledge**, the aim is to identify users who have an immense knowledge of product specific information. To accomplish this, we considered splitting the determination of the characteristic into two parts. In the first step, a dictionary of product-specific terms was extracted from product and service descriptions e.g. product brochures. Secondly, following the generation of the product-specific dictionary, the occurrence of the extracted product-specific words in the contributions were determined. Therefore, matching word candidates from the contributions are identified and reflected against the product-related dictionary. If an entity matches with a product-specific word, the total sum of the user's usage of product-related words will be increased. After all contributions of the related user have been analyzed, the number of product-specific words is divided by the total number of all words used by the specific user. The resulting value reflects the average use of product-related words by a user and allows conclusions to be drawn about the product knowledge of a user.

With regards to the determination of the user's ability to enable the flow of information and especially diffuse it, which are prerequisites for **opinion leadership**, we have considered several centrality measurements which best suit the identification of strong social relationships within a social network (Pajo et al., 2017). These measures are those of *degree*, *closeness* and *betweenness centrality*, and are fundamentally related to the concept of social influence in terms of the structural effects of different connections within a network of users (Aggarwal, 2011). Degree centrality σ_D is used to determine the number of direct interactions of a participant within the network, which represents an indicator of quality for the member's interconnectedness. Through the use of an adjacency matrix $A = (a_{ij})$, the degree centrality can be formulized as follows:

$$\sigma_D(x) = \sum a_{ix} . \quad (1)$$

As a consequence, the higher the centrality score $\sigma_D(x)$ is, the more contacts a node x has. Thus, by implementing the degree centrality, we are able to identify those users who have the most interactions with other network participants (Aggarwal, 2011). The closeness centrality σ_C is based on the idea that nodes with a short distance to other nodes can disseminate information very productively in the network. To calculate $\sigma_C(x)$ of a node x, the distances between node x and all other nodes in the network are summed up. By using the reciprocal value, the closeness increases when the distance to another node decreases, i.e., when the integration into the network is improved. The closeness centrality can be formulized as follows:

$$\sigma_C(x) = \frac{1}{\sum_{i=1}^{n} d_G(x,i)} \tag{2}$$

In this respect, through the implementation of the closeness centrality, we are able to identify those users who distribute information among other network participants as efficiently as possible (Latora & Marchiori, 2007). In case of the third centrality measure - the betweenness centrality σ_B - a network member is well connected if it is located on as many of the shortest paths as possible between pairs of other nodes. The underlying assumption of this centrality measure is that the interaction between two non-directly connected nodes x and y depends on the nodes between x and y. The betweenness centrality for a node x can therefore be formulized as

$$\sigma_B(x) = \sum_{i=1,i\neq x}^{n} \sum_{j=1,j<i,j\neq x}^{n} \frac{g_{ij}(x)}{g_{ij}} \tag{3}$$

with g_{ij} representing the number of shortest paths from node i to node j, and $g_{ij}(x)$ denoting the number of these paths which pass through the node x. Through this, we are able to identify those situated on the shortest path distance between various actors, showing that a user has fast access to and control over network flows (AlFalahi, Atif & Abraham, 2014; Freeman & Soete, 1997). By these centrality measures, we are able to subdivide the users on the basis of their network characteristics. Regarding the calculation of the respective centrality measurements, the well-known and widely used python library *NetworkX* found application (see table 3). Besides the plain calculation of the centrality measures of each user, we further adapted the technique to normalize the calculated values into the range of [0;1]. Based on this normalization, it is possible to consolidate the different centrality measures into a single value by calculating their mean. By this, the respective user´s position in the network and therefore their ability to enable the flow of information is being represented.

Following the calculation of the individual metrics, the automatic identification of the lead users per phases in the innovation process takes place. Therefore, the result per metric is multiplied by the corresponding weight of the respective phases (see table 2) and summed up for each specific user. Finally, the calculated sum is divided by the maximum number of points to be achieved (see (4)). Thus, two resulting scores for each user, one each for the two phases in the innovation process, will be generated. These two resulting scores represent the cumulative relevance of a user with respect to the phases in the innovation process. The higher the resulting score for a respective user is, the more highly the user is defined by his characteristics as a lead user for one of the respective phases: “Idea generation” or “Development”.

$$\text{score}_i = \frac{\sum(x_i * w_i)}{\sum w} \mid w = weight;\ x = metric \tag{4}$$

An identification of lead users according to the described procedure enables the determination of users who show particular strength in terms of relevant characteristics such as their influence on other participants within the community, their product related knowledge or their level of activity. In combination with an individual weighting of these characteristics, the two identified phases of “Idea generation” and “Development” are also considered. In addition, with respect to the derived design principle *4. The principle of repeatability,* the artifact is designed in a modular and generic way. Thus, the underlying data and the respective characteristics’ weighting can be easily adapted, allowing the identification process to be carried out at any time without further restrictions to e.g., react quickly to changing circumstances such as trends. Finally, as our design principles follow our purpose and scope and found consideration within the designed artefact as described above, the derived meta requirements (see figure 2) can be seen as successfully met since they are representing our underlying purpose and scope.

5 Demonstration, Evaluation and Discussion

To demonstrate the applicability of the developed artifact – including the identification approach and the corresponding software tool – we have conducted several steps. In order to verify the consideration of the design principles, the underlying design requirements are examined for their met using our specific use case (see table 4). Subsequently, the artifact was applied on a real-world kitesurfing dataset to ensure its usability for practice. Further, we conducted interviews with our identified lead users and with an expert from our cooperating partner, a market leader in kite- and watersports to evaluate both the usability and the generated added value for practice.

5.1 Review of the identified requirements

In order to verify the derived design principles, we further review whether and how the elicited design requirements of our artifact (see figure 2) were met. Therefore, we specify them in more detail in table 4.

Design Requirements	***Requirements met***
Map all prior identified characteristics	As all identified characteristics of lead users are considered within the artifact (see table 3), we see the requirement as met.
Process a large amount of social media data	The artifact was applied successfully to a real-world dataset of 11,481 contributions (see table 5). Furthermore, by choosing adequate analysis techniques settled in the field of text mining or SNA respectively (see table 3), the analysis of larger data sets is easily possible.
Apply objective identification methods	The implemented characteristics were either implemented by well-known text mining or SNA techniques or by self-developed techniques that build on patterns of well-known analysis methods from text mining (see section "Technical realization").
Repeat the identification process for lead users at any time as lead users are trend specific	As the developed artifact is implemented in a generic way, the underlying data and the respective weighting of the characteristics can be easily adapted, allowing the identification to be carried out at any time without further restrictions (see section "Technical realization") to e.g., react quickly to changing circumstances such as trends. Additionally, the identification of lead users within the real-world application with 11,481 contributions took 1317 seconds, which is why a quick identification based on a new dataset is also easily possible.
Identify different lead users regarding the two phases of the innovation process.	As the proposed artifact differs between lead users regarding the phase "Idea generation" and lead users regarding the phase "Development", we see the requirement as met.

Table 4: Met of the previously identified requirements

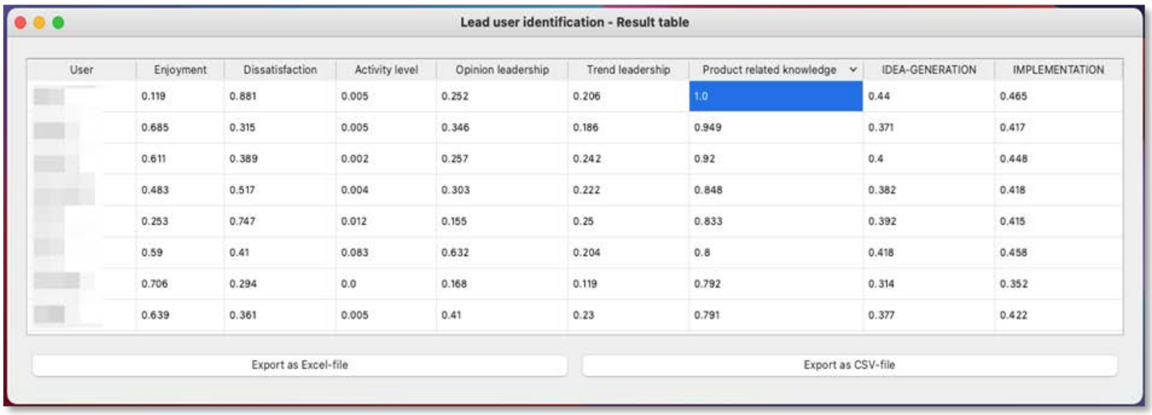
5.2 Demonstration of the artifact

In order to facilitate the accessibility concerning the use of the developed artifact, including the designed identification process, all its customizabilities, as well as the monitoring of the analysis, a graphical user interface (GUI) was developed. To ensure the development of a highly responsive, performant and platform-independent interface, the GUI was developed using the standardized and well-known Python library PyQt5. Figures 3 and 4 show the two main interfaces – namely the configuration and the result table view – of the developed GUI.

Figure 3: GUI - Configuration view

The configuration (see figure 3) represents the initial view when starting the tool and can be used to customize the underlying analysis approach to one's own needs. The layout was designed based on three sections (i) - (iii), following an adaptation of the design principles of Garrett (2010). In section (i), the user can flexibly specify the data to be analyzed as well as the output path for storing the analysis results by selecting the appropriate directories within the native filesystem. Further, in case of not all elicited characteristics being deemed necessary, a subset of them can be individually defined, comprising all specific characteristics relevant to the current circumstances. This ensures that only favored characteristics are considered in the analysis, resulting in a resource-efficient identification of lead users who show particular strength in terms of significant characteristics such as their influence on other participants within the community (opinion leadership) or their level of activity. In addition, to incorporate the two identified phases "Idea Generation" and "Development", they were implemented modularly using dynamic tabs to enable a distinctive configuration (see figure 3, ii). Here, the weightings for each respective phase elicited from literature (see section "Weighting of the according lead user characterizations") are defined as default within the phase's configuration. Nevertheless, to provide maximum flexibility and to be able to react quickly and almost effortlessly to changing circumstances, the pre-defined weighting can also be individualized per phase through the corresponding text fields highlighted in section (ii). The start of the analysis process as well as its monitoring takes place in section (iii). As soon as the process is initiated, all relevant information concerning the process such as the current state or occurring errors will be monitored and logged within the designated text area (see figure 3, iii).

Once the process has finished, the results will be consolidated and displayed by a responsive, sortable table (see figure 4). Here, the results are subdivided into each characteristic as well as the two calculated phase-specific scores, featuring the dispensation of the users to each characteristic or innovation phase, respectively. To facilitate the selection of relevant lead users, it is further possible to filter the identified users based on each calculated value (see figure 4, "Product related knowledge"). This allows companies to select users in an intuitive way based on either a specific characteristic such as product-related knowledge or the overall scores.


Lead user identification - Result table

User	Enjoyment	Dissatisfaction	Activity level	Opinion leadership	Trend leadership	Product related knowledge	IDEA-GENERATION	IMPLEMENTATION
	0.119	0.881	0.005	0.252	0.206	1.0	0.44	0.465
	0.685	0.315	0.005	0.346	0.186	0.949	0.371	0.417
	0.611	0.389	0.002	0.257	0.242	0.92	0.4	0.448
	0.483	0.517	0.004	0.303	0.222	0.848	0.382	0.418
	0.253	0.747	0.012	0.155	0.25	0.833	0.392	0.415
	0.59	0.41	0.083	0.632	0.204	0.8	0.418	0.458
	0.706	0.294	0.0	0.168	0.119	0.792	0.314	0.352
	0.639	0.361	0.005	0.41	0.23	0.791	0.377	0.422

Export as Excel-file | Export as CSV-file

Figure 4: GUI - Resulting table view

To preserve the obtained results for later usage, two functions were implemented to handle the extraction by use of either a Microsoft Excel or a Comma-separated value (CSV) file. These file formats enable a platform-independent presentation of the results for e.g., marketing campaigns (Excel) as well as the automated processing by a proprietary third-party system, such as importing the generated information into the company's active directory (CSV). To demonstrate the practical applicability of our developed tool, a representative real-world dataset was needed. Thus, we extracted data from one of the most popular online communities for kiteboards (*https://www.seabreeze.com.au/*), which comprises a total of 11,481 contributions of 945 users. The data were extracted using the ParseHub extraction tool and span the period from January 1st, 2018 to April 10th, 2020. Based on these data, the analysis was undertaken to identify the respective lead users. Table 5 presents the top five identified users per phases of the innovation process. The values represent the previously identified characteristics by a normalization within a scale of [0;1]. Thus, a high value implies the respective characteristic is strongly distinctive. The identified users are differentiated regarding the two innovation phases. Accordingly, the weights of the characteristics were adapted to the respective needs of the phase (see section "Weighting of the according lead user characterizations"). The "Overall score" represents the affiliation of the respective user in each phase and is determined through the weighting of the characteristics.

		Enjoyment	***Dis-satisfaction***	***High product related knowledge***	***Trend Leadership***	***High Activity Level***	***Opinion leadership***	***Overall Score***
	User / Weight	1	3	4	5	5	2	
Idea Generation	user #1	0.347	0.653	0.367	0.489	1.0	1.0	***0.662***
	user #2	0.395	0.605	0.438	0.374	0.84	0.925	***0.602***
	user #3	0.346	0.654	0.506	0.304	0.353	0.81	***0.472***
	user #4	0.295	0.705	0.291	0.291	0.497	0.743	***0.46***
	user #5	0.364	0.636	0.36	0.3	0.381	0.79	***0.442***
	User / Weight	1	2	4	5	3	2	
Development	user #1	0.347	0.653	0.367	0.489	1.0	1.0	***0.6***
	user #2	0.395	0.605	0.438	0.374	0.84	0.925	***0.557***
	user #6	0.119	0.881	1.0	0.204	0.005	0.252	***0.51***
	user #7	0.611	0.389	0.92	0.24	0.002	0.257	***0.489***
	user #8	0.59	0.41	0.8	0.203	0.083	0.632	***0.478***

Table 5: Top five identified lead users for the specific innovation phases

A cursory glance at table 5 reveals that lead users can be identified in both phases of the innovation process. Thus, the two identified lead users: user #1 and user #2 are identified as lead users exhibiting the highest values compared to all users of the innovation process. We assume that the identification of users present in both innovation phases is a rarely occurring exception resulting from extremely conspicuous users. Here, the two identified users have a significantly higher activity level than the lead users identified for a specific phase, which supports this conclusion. User #1 even has the highest activity level (1.0) among all 945 users. In addition to the identification of users who are present in both phases, lead users, who differ significantly in their descriptive characteristics, were further identified for each innovation phase. User #6 e.g., shows an activity level way below average (0.002), but exhibits remarkable results regarding the presence of product related knowledge (0.92). Therefore, the user is considered as lead user regarding the second innovation phase “Development”.

To be able to identify lead users scaled to the different circumstances of enterprises in a resource-optimized way, a high degree of generalizability was considered in the implementation of the artifact. Therefore, to be able to adequately react to specific circumstances, the weighting of the respective characteristics can be individualized at the beginning of the analysis process. Thus, the identification approach can be specifically geared to users who dominate a single criterion or a combination of criteria and can therefore be easily adapted to different conditions.

Finally worth to mention, the related lead user characteristics (and therefore the lead users themselves) are validated in an intrinsic way by incorporating different evaluation metrics (e.g., topic coherence) during the identification process. In this way, a high information quality is ensured, supporting the practical applicability of both, the identification process and the retrieved lead users. In this regard, by applying our tool, we revealed promising lead users for the specific innovation phases based on their remarkable characteristics exhibited (see Table 5, e.g. user #1). However, as the intrinsic evaluation of probabilistic models such as topic modeling (trend leadership) poses various challenges and drawbacks (Chang, Gerrish, Wang, Boyd-Graber, Blei, 2009), it is not sufficient to verify the elicited results. Thus, we evaluate the identified lead users and their characteristics in an extrinsic way by verifying the identified lead users through an interview with an expert of our cooperating partner (a market leader in kite- and watersports) and respective lead users (see section “Evaluation of the artifact”). Therefore, we will evaluate the derived lead users as well as the identification process by applying them to our specific use case, revealing their meaningfulness and potential regarding their practical applicability in a first step.

5.3 Discussion of the results of demonstration

Our results have shown that our identification approach and the corresponding software tool are working immaculately. The implementation of the design principles was thus feasible, resulting in the identification of lead users for both innovation phases (see table 5). Prior research literature is inchoate here as only a minority of the investigations incorporates an innovation process but identifies a lead user for all of the phases in an innovation process (Miao & Zhang, 2017; Pajo et al., 2017). Thus, we provide a new approach that identifies different lead users for every phase of the innovation process. Most of the identified lead users are better suited for one of the two phases but there are also lead users who exhibit very high values in both innovation phases. We have shown with our results that a clear differentiation of the two phases as well as the separated identification and consideration of lead users is necessary as they have different competencies, characteristics and application areas.

The lead users #3 or #4 are according to our results an adequate choice when searching for a lead user in terms of the innovation phase “Idea generation”. User #3 e.g. features a high value in the dimensions “trend leadership” (0.304) and “high activity level” (0.353). This means that this lead user can be seen as an active member in the kitesurfing-lifestyle scene. His/her creative and active participation in the online discussions shows that this lead user is highly involved in the kite community. Their active participation and involvement additionally lead to the awareness of unmet needs about existing solutions in the kiteboarding scene (see dissatisfaction: 0.654). Because of his/her high value in the dimensions “trend leadership” (0.304), we can assume that this lead user is able to “translate” his/her dissatisfaction into concrete ideas. Against the background of the fact that a company requires many initial ideas from lead users (as only a few of them can be realized anyway) especially the requirement “repeat the identification process for lead users at any time” is important in this first innovation phase. Approaches that are established and discussed in prior research literature such as screening (Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011), pyramiding (Von Hippel, Franke & Prügl, 2009) and other lead user identification procedures are often based on interviews or (online) questionnaires (Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011) which makes it almost impossible to repeat the identification process for lead users at any time. However, most business-to-consumer industries are fast-moving and therefore identifying innovative lead users and their ideas repeatedly with little expenditure of time must be focused on. Thus, with our artifact a company is able, on the one hand, to identify lead users who are currently ahead of trends and, on the other hand, to react to changing circumstances such as trends. Furthermore, with this procedure we also counteract the low sample efficiency and the high costs that results from conducting interviews and online questionnaires.

By examining the detailed results of the phase “Development” it is especially interesting that user #6 and user #7 are determined as lead users although they exhibit very low values in the dimension “high activity level” (user #6: 0.005; user #7: 0.002). This shows that due to the medium weight of the dimension “high activity level” in the phase “Development” a lead user does not necessarily exhibit a high active usage behavior which contradicts the results of Martinez-Torres (2014). This means that in our case the lead users #6 and #7 posted only few contents and therefore they do not participate a lot in these online community discussions. But if they did submit a post, it contained very valuable and detailed content including high product-related knowledge (user #6:1.0 user #7: 0.92). These users suggested concrete solutions based on their broad expertise about the products, the components and how they mesh with each other.

The combination of this “high product related knowledge” with the relatively high value for “trend leadership” (0.204) and the simultaneously low value for the “high activity level” (0.005) led to the assignment of user#6 to the phase “Development”. The results have shown that this combination of characteristics is more decisive than, for example, the dimension “dissatisfaction” as user #6 is the lead user (compared to all other identified users) with the highest value in the dimension “dissatisfaction” (0.881). This high value of “dissatisfaction” would actually speak for being assigned to the “Idea generation” phase as it is weighted higher (Idea generation: 3, Development: 2) here. However, the high level of product related knowledge and the associated ability to suggest concrete solutions for new products or their improvements is the main factor for a promising cooperation in terms of the “Development” phase. Therefore, observing both the individual results of the characteristics and the overall score has shown that not only is

the weighting and selection of the characteristics plausible, but that our software tool is also capable of finding them.
Moreover, we have identified lead users for both phases as they exhibit the highest overall scores: user #1 and user #2. Both users exhibited extraordinary results, especially for the dimensions "high activity level" (user #1: 1.0; user #2: 0.84) and "opinion leadership" (user #1: 1.0; user#2: 0.925). So, their high level of involvement in the kitesurfing scene is characterized by their active participation as well as by their central position in the network. Displaying both strong social relationships and high levels of engagement enable the users to spread information in the online community. Consequently, these users know the overall sentiment and can also identify unmet needs that will later be experienced by the public (see trend leadership and dissatisfaction). Based on this, they formulate and disseminate ideas for new products as well as suggest detailed solutions for the prior identified needs. Thus, they facilitate effective innovation and encourage innovation communication. Only in some dimensions such as "high product related knowledge" other users (e.g. users: #6, #7 and #8) exhibit better results. Nevertheless, the users' overall scores in both phases show their outstanding position as lead users, which we assume, however, that this can be seen rather as an exception. Furthermore, we are convinced, that it makes sense not only to focus on lead users who are suitable for both innovation phases but rather consider for what purpose a lead user should be engaged and to adjust the weighting accordingly. If a lead user is only active in one phase, then s/he can focus on either the objective generating many good and innovative ideas (see Idea generation) or on the objective developing explicit solutions for unmet needs (see Development) and applies his/her strengths accordingly. In other words, if a lead user would act in both phases and thus focuses on both objectives simultaneously, e.g. knowledge about the realization and development could have a negative impact on the creativity in the idea generation phase. Concentrating on lead users for both phases simultaneously also means that lead users who have extraordinary new ideas but only less product-related knowledge would be excluded. This would lead to a loss of new and potentially successful ideas.

In summary, observing both the individual results of the characteristics and the overall score has shown that not only is the weighting and selection of the characteristics plausible, but that our software tool is also capable of finding them. Our results follow from combining, weighting and considering all relevant lead user characteristics. Previous research literature (e.g., Miao & Zhang, 2017; Martinez-Torres, 2014; Tuarob & Tucker, 2014) has often focused on only few characteristics for identifying lead users and thus resulted in many and ambiguous lead users.

5.4 Evaluation of the artifact

To evaluate the generated artifact and our results, we conducted both an in-depth interview with the head of marketing of our cooperating partner and interviews with some of our identified lead users.

The in-depth interview was undertaken by two researchers, recorded, transcribed, and finally condensed to the most important statements. It lasted approximately two hours and we aimed to investigate the artifact´s applicability and its generated added value. In the course of the interview, we presented the expert both an excerpt of our results and randomly selected posts from the identified lead users. Thus, we wanted to find out if he can benefit from the lead users identified by the tool and if the expert agrees with the differentiation of the user types. Accordingly, by analyzing the selected posts as well as the excerpt of our results, the interviewee stated first that by means of the software tool he is now able to analyze a huge amount of social media data. Previously, his team only analyzed social media data by hand, which cost a lot of resources (e.g. time, human resources, etc.) and often led to incorrect results.

Second, the expert highlighted the distinction to be beneficial as it allows him to address users for different stages in the innovation process. Ultimately, he was aware of the two lead users that were identified by the tool. As he knew them in advance, he has already incorporated them successfully into the company´s innovation process. However, there are also lead users, and therefore also innovative ideas and content, that were unknown to him so far. To reveal what the users are talking about we discussed randomly selected posts with him. Hence, the aim was to detect whether both the analysis of posts in the context of the innovation process and the differentiation of the lead users made sense from the practitioner's point of view. Consequently, by analyzing and discussing the provided posts, our interviewee already detected some ideas and suggestions for new products or for variations of existing ones. He contemplated the involvement of the users in the company´s internal brainstorming/idea-finding process to talk about ideas for new products or about drawbacks of pre-existing ones. Therefore, he is committed to include the dissatisfaction in the identification approach here. To get a better understanding of how the expert came to this decision, we included a short excerpt of a selected post as an example:

> *"[…] The male velcro is facing the wrong way, which means its going to chaff like 60 grit sandpaper if you don't wear a thick rashie or wetsuit. […]"*

According to the interviewee, from this short excerpt, it can already be recognized that the user is pointing to a certain problem (*"male velcro is facing the wrong way"*) and therefore identify an unmet need. Accordingly, the expert identifies here a starting point for improving a specific product. The expert added that the selected posts also show that these identified lead users seem to be "*passionate individuals who are true ambassadors of the kitesurfing scene*" and can therefore be auspicious, prospective partners for the company´s internal idea-finding process with the aim of uncovering existing problems, unmet needs and new product ideas.

Furthermore, after showing the interviewee the posts that our tool assigned to the phase "Development", he was enthusiastic about the high level of product-related knowledge. According to our interviewee this and the positiveness of user #7 could, for example, support the engagement of a promising cooperation regarding the development of new products. Including a lead user means the incorporation of the user´s vast experience and knowledge. Thus, this cooperation could potentially lead to decreasing failure rates in product innovations. For demonstration purposes we also included here a selected post of a lead user. To exclude potential influence, mentioned competitors were blackened.

> *„Yes it is[,] if you like to ride powered, the early edition was a fave of mine[.] The next imho was completely different, lost all the flex that you want in choppy conditions and a lot of feel by going heavier on build. The newbronq crb 4 is back to the original, been riding the ts from* [redacted]*, great board but* [redacted] *struggle [to] make a non spray board especially in chop conditions, in flat water it isn't an issue, the monk will cover most riders as mentioned. Demo I'd say"*

Phrases such as "*The newbronq crb 4 is back to the original*" led the expert to the assumption that this user exhibits a high product-related knowledge and thus is able to formulate precise solutions, which are both indicators for assigning this post/user to the

"Development" phase. From the analysis of the posts the expert drew the conclusion that these lead users identified here, represent "*progressive riders who are continuously pushing their riding and the sport to new levels*". Therefore, the expert referred to the fact that these users propose to apply new materials and technologies to create constantly better performing products. Moreover, the interviewee stated that not only the identification of promising lead users will be supported with the tool but also analyzing the posts and contents of the respective users, which represents another added value for him.

He further noted that because of these different application areas, it is very constructive to identify lead users regarding the two innovation phases and therefore differentiate between them. The interviewee had already involved some kitesurfers in the company's (innovation) processes and therefore drew the conclusion that he would definitely involve the two lead users who exhibit the highest overall scores in both innovation phases (user#1 and user#2) but he also highlighted that it would be reluctant to focus only on them. He reasoned as follows: First, it is advisable for a company to include more than just two lead users so that multiple perspectives can be included in the company. Second, according to his experience, when a user is part of each innovation phase, the generation of ideas is inhibited if the user always keeps the development and its boundaries in mind. This would limit the venue for brainstorming that should be ensured in the "Idea generation" phase. Moreover, a user can have interesting new ideas, but s/he has too little product related knowledge to implement and develop them. This would also lead to a loss of new and potentially successful ideas. Furthermore, our interviewee noted that the lead users #1 and #2 exhibited good overall scores (and thus he would definitely include them), but he tended to prefer to incorporate the user with the highest level of product-related knowledge (user #6) in the "Development" phase. Overall, the expert confirmed that a clear differentiation between the two phases as well as a separated identification and consideration of lead users is necessary.

In addition to the evaluation with the expert, we discussed our results with three of the identified lead users. To strengthen the results of our tool and to make sure that the identified users are the appropriate lead users for the particular innovation phase we also examine the lead user perspective by conducting short interviews. This should also confirm and, where appropriate, extend the characteristics that we have found in literature. In doing so, the interviewees all confirmed being lead users in this online community and they postulated that they are all aware of making major contributions to idea generation and/or product development in line with our results. In addition, in surprising harmony they all mentioned similar characteristics (enthusiasm for the sport, high activity level in the online community and experience in the field) as essential for lead users. Only on the time needed to be an experienced kitesurfer there was no agreement. Two of the respondent lead users stated a minimum of 3 and 5 years to be an experienced kitesurfer. The remaining one quantified the respective time by the kitesurfing sessions performed and different kitesurfing locations visited.

With these statements our lead users supported the results of our research and in consequence validated the applicability of our approach. Furthermore, the essential characteristics fit to those we have found in literature and thus confirmed the characteristics we have included in our tool. The characteristic "enthusiasm for the sport" is implemented with "opinion leadership" in our approach. According to the current research literature "opinion leadership" is the ability to enable the flow of information and especially to diffuse it. Strong social relationships and a high level of engagement are premises for a functioning exchange of ideas and innovation (Pajo et al., 2017; Pajo et al., 2014). Accordingly, a user who is motivated to build relationships in the community and thus exhibits high centrality scores is highly enthusiastic about the sport. The high activity level in the online community, calculated in our tool by the number of posts and transacted comments per user within the analyzed period, represents the second characteristic the lead users have mentioned. The "Experience in the field" can be partly covered by our characteristic "high product-related knowledge". However, the number of training hours, e.g., could also be included here.

5.5 Discussion of the results of evaluation

The evaluation has revealed not only the applicability but also the added value of our artifact in a practical environment. Thus, the in-depth interview with the head of marketing of our cooperating partner has highlighted that he is enthusiastic about the results as he benefits from them in many ways. First, the interviewee was able to assign the innovation potential to many posts by recognizing trends that were talked about in the posts, months before their realization. Moreover, the content of the comments has already made him aware of ideas on how to improve certain products in the company. Second, our expert has also confirmed that the high level of product related knowledge, vast experience and the associated ability to suggest concrete solutions for new products or their improvements is the main factor for a promising cooperation with a lead user in terms of the "Development" phase. The lead users identified with our tool have suggested concrete solutions based on their broad expertise about the products, the components and how they mesh with each other. As our expert has confirmed, this high product related knowledge can lead to decreasing failure rates in new product introductions or improvements because these users are aware of very specific facts such as every tiny change to a kite's profile can have enormous impact on its flight characteristics. Third, our expert also stated that he would be reluctant to focus only on the lead users who exhibit the highest overall scores in both innovation phases. He further highlighted that he would prefer in the "Development" phase the user with the highest level of product-related knowledge (user #6) and not user #1 or #2 who have higher overall scores. All in all, he confirmed that a clear differentiation of the two phases as well as a separated identification and consideration of lead users are necessary.

Finally, the interviews with the lead user confirm our approach and implicated further interesting perspectives and provided indications on how our approach can be further refined. In future research, these and other possible aspects and characteristics mentioned by the users have to be evaluated additionally.

6 Contribution for Practice and Research

Our investigation contributes to research and practice alike. As a contribution to practice, first companies can benefit from our comprehensive and modular approach. By applying our approach companies can resource-efficiently identify lead users which is an important process as the acquisition as well as the transferring costs of the information that are decisive for initiating innovation have tremendous influence on where innovation is created (Idota, 2019). Therefore, as lead users feature highly sticky information and are able to create innovations, organizations benefit from including them in their innovation process in order to overcome their information stickiness and so get to know the user's needs to solve (product) problems and reduce R&D costs. Thus, we stand out against other approaches that follow more resource intensive approaches (e.g. Brandtzaeg et al., 2016; Hung et al., 2011; Tuunanen et al., 2011).

Second, we created an artifact, respectively a tool, that is able to process a large number of social media data which can be repeated at any time as lead users are trend specific. This counteracts i.a. weaknesses of previous approaches that include only a small amount of data in the identification (Hau & Kang, 2016). By means of our tool, companies are able to start and monitor the current state of the identification process, display the analysis results by an intuitive, sortable table to easily enable either the selection of the overall lead users by the respective overall-scores or specific lead users by their identified results of an explicit characteristic and extract and persist the elicited results to various file formats (Excel, CSV) for later usage.

Third, a high degree of generalizability was taken into account to identify a lead user by considering several characteristics depending on the different circumstances of different companies. Thus, they are able to customize the identification process to their own needs by uploading their own dataset and applying all or a selected set of characteristics either following our pre-defined weights for each of the two innovation phases or individualize them as well. Hence, the weight of the respective characteristic is determined in the beginning of the analysis process. The identification process therefore can be specifically geared to users who dominate a single criterion or a combination of criteria. When a company, for instance, wants to focus more on lead users who express a sentiment of enjoyment in the innovation process, then the company can set the weights for dissatisfaction very low (or even to zero) and for enjoyment very high. Thus, we created an extensive, flexible, and resource-saving approach which can be easily applied by companies and which is based on objective traceable characteristics (different to other approaches that include self-assessment of respondents (Hienerth & Lettl, 2017)).

Fourth, the evaluation of our results has shown their contribution for our cooperating partner and therefore for practice. As the expert has highlighted, the tools enable him to turn away from analyzing social media data by hand, which costed a lot of resources (e.g. time, human resources, etc.) and often led to incorrect results. Further he identified lead users and therefore also innovative ideas and content, that had been unknown to him so far. So, our tool also allows to analyze posts and contents of the respective users and is thus able to detect new ideas and suggestions for new products or for variations of existing ones. For practice this can mean decreasing failure rates in product innovations.

In summary, companies aiming to identify different lead users for the particular phases in the innovation process can benefit from our comprehensive and modular artifact, since they are enabled to autonomously analyze large amounts of data and therefore automatically identify respective lead users adapted to the corporate's specific circumstances. Thus, we automated the lead user identification process, the most difficult and time-consuming aspect within the lead user method (Brem & Bilgram, 2015).

Furthermore, as outcomes of our DS research project we achieved theoretical contributions to research that go beyond the technical contribution (i.e., the artifact) and which are explained in more detail in the following. In terms of the DSR knowledge contribution framework of Gregor and Hevner (2013) the enhancements of our artifact over existing ones in the literature can be classified in the group of improvement (development of new solutions for known problems). DSR improvement projects make contributions to both prescriptive theory i.e. Design Theory (Gregor, 2006) and descriptive theory i.e. kernel theories (Gregor & Hevner, 2013). Thus, first, in terms of prescriptive theory our artifact contributes to a rather general and abstract knowledge base – "nascent design theory" (Gregor & Hevner, 2013). Therefore, design principles based on kernel theories and resulting design requirements were formulated and proposed in the section "Design principles for a lead user identification tool". By applying them in the course of the design and development of the artifact followed by the demonstration and evaluation, an implicit empirical grounding of the design principles was achieved here (Heinrich & Schwabe, 2014). Our design principles capture design-related knowledge and can therefore support the development of further IS (design) theories and new artifacts. For designing further (identification) tools in related areas our design principles can be applied as we have formulated them generally by describing what the artifact should enable users to do and how the artifact should be built. By considering e.g. the design principle 3. Contextual adaptability, the importance of the context is highlighted in which the respective tool should be created. Since the context has a direct impact on the definition and implementation of the requirements, the alignment with the context also will lead to a more targeted identification tool. So, with the compilation of the design principles, we made a first step towards contributing to Design Theory in terms of theory for design and action (Gregor, 2006) as we comply with conditions as March and Smith (1995) and Hevner et al. (2004) pointed out under which a contribution to knowledge in DS has occurred: utility to a community of users, the novelty of the artifact and the persuasiveness of claims that it is effective. To take a next step towards mature Design Theory, according to Gregor and Jones (2007), a total of eight components are necessary. We have shown the "Purpose and scope" by means of the meta-requirements and the "Principles of form and function" by means of the design principles (see both figure 2). Furthermore, the latter is based on kernel theories (Lead User Theory and Innovation Theory) which entails the inclusion of a further component – "Justificatory knowledge". Also, the "Constructs" that are described as the most basic levels of the theory are involved with the alignment to the characteristics of a lead user and the two phases of the innovation process. These components resulted in the "Expository instantiation", i.e. in the application of the designed tool in a real world setting. However, the inclusion of the "artifact mutability", the "testable propositions" and the "principles of implementation" explicitly and aligning the investigation on these eight components in general, as for example Böckle et al. (2021) have done, would need to be undertaken as a next step towards a mature contribution to Design Theory.

Beside that, our results also contribute to the kernel theory knowledge base regarding the social media theory as well as the innovation related theory. Moreover, our results contribute to different kernel theories by providing the following useful implications which previous investigations have barely considered until now. First, this study sheds a new light on the lead user construct itself – the core of Lead User Theory – as our investigation has shown that it is meaningful to differentiate lead users according to the different innovation phases as they have different competencies, characteristics and application areas. Until now, no distinction has been made in defining and characterizing lead users in terms of the innovation process. The basic model of Lead User Theory (Von Hippel, 1986) indicates indeed a distinction between lead users, but only against the background of whether the product innovation supported by the lead user is a novelty or one that requires commercially viable modifications and enhancements (Von Hippel, 1986). Our results highlighted that a separated consideration implicates a more targeted identification. If a lead user is active in one phase, then s/he can focus on either the objective generating many good and innovative ideas (see Idea generation) or on the objective developing explicit solutions for unmet needs (see Development) and applies his/her strengths accordingly. When lead users are examined and identified separately in the two phases, the generation of ideas is not inhibited by keeping the development and its boundaries in mind. Additionally, our approach takes also into account who have extraordinary new ideas but only less product-related knowledge and would therefore be excluded from prior identification approaches. Thus, our approach contracts a loss of new and potentially successful ideas. So, our study has revealed a new point by defining a lead user against the background of the purpose of its use (based on the innovation process) whereby we introduce a new dimension to the Lead User Theory. This can constitute an important new implication which includes that the definition of a lead user should not only focus on Von Hippels' characteristics but also on the purpose of its use (Von Hippel, 1986).

Second our investigation contributes to the process of utilizing lead users included in the Lead User Theory. Von Hippel (1986) introduced a 4-step process – which has often been taken up in other studies (cf. Hung et al., 2011) –, including (1) the identification of an important market or technical trend, (2) the identification of a lead user leading that trend, (3) analyzing the lead user need data and (4) project lead user data onto the general market (Von Hippel, 1986). Our approach and results have shown that the (1) identification of a trend before (2) identifying a lead user for that respective trend is no longer deemed necessary as the identification of trend(s) can be included within the identification of corresponding lead users. Thus, the initial step (1) identification of trends is no longer considered as a necessary sequential premise for the (2) lead user identification, since the emerging trend is identified and considered simultaneously, resulting in a more flexible and easier-to-use process. Moreover, our approach provides the opportunity to consider multiple trends simultaneously, rather than being limited to one previously identified trend (Von Hippel, 1986). Therefore, multiple trends reflected in the underlying data can be dynamically considered when identifying lead users, enabling the identification of target-oriented lead users associated with each trend. Thus, the 4-step process can be enhanced in terms of its applicability and ease of use by enabling the automated identification of underlying trends when identifying accompanying lead users, as well as in terms of its functional scope by including multiple trends instead of solely considering the previously, manually identified trend.

Third, this study sheds another light to Lead User Theory and contributes to the automated identification of lead users in online communities in more specific (and thus a further contribution to the identification process). With this work at hand, we provide initially a comprehensive and structured overview of lead user characteristics based on the current research literature. Beyond that, we further technically realized these characteristics by means of an adaption of several machine learning methods (see section "Technical Realization") and enriched the related Lead User Theory by establishing synergies of these research areas. Thus, future research in Lead User Theory will benefit from the advantages of automated analysis techniques and will therefore be supported by our concrete techniques for the identification of lead user characteristics. In addition, we distinguish ourselves from investigations that define and identify lead users by including only one or two characteristics (cf. Miao & Zhang, 2017; Tuarob & Tucker, 2014; Tuunanen et al., 2011), as our identification process enables an identification of lead users considering all identified characteristic. This enables the consideration of each relevant characteristic, allowing lead users to be identified in a more target-oriented and fine-grained manner. Moreover, to take a step further in the identification of respective lead users and in order to account the differentiation of them in the innovation process, we have adapted the identification process to incorporate priorities (weights) regarding the characteristics with respect to the different innovation phases. Consequently, contrary to the current research literature which treats all characteristics equally, we assign different weights to different lead user characteristics in the course of the identification process to make this process even more targeted.

Finally, for innovation theories our research identified relevant characteristics of users who can contribute to the different stages of the innovation process. Our results have shown that it is important to consider for what purpose a lead user should be engaged and to adjust the weighting of the identified characteristics accordingly. This has implications for the theories dealing with the process of innovation, e.g. the stage gate model. By applying specific lead users within the stages preliminary and detailed investigations as well as in development, testing and validation, the rigid sequence of stages and gates can be broken up. By integrating the user's and therefore the external point of view the assessments at the go/kill checkpoints (i.e. gates) become less elaborate as the alignment with the external requirements is maintained constantly. This results in a more agile and target group-oriented approach. Based on this, the innovation process must be specified more concretely in terms of interactive value creation, especially the open innovation. Thus, including different lead users adds new tasks for companies in the innovation process. These different lead user types can be taken into account by introducing process variants.

7 Conclusion

In the existing literature there are a lot of different lead user identification approaches, but these investigations only covered a limited point of view as they either focus on only a few lead user characteristics (Martínez-Torres, 2014), include a very small amount of data (Hau & Kang, 2016) or base their approach on the self-assessment of users (Hienerth & Lettl, 2017). This problem is further compounded by the tremendous amount of online community data which makes it even more difficult, costly and time-consuming to identify lead users. We approached this research gap by introducing an automated and – according to our interviewed expert – effective method for identifying lead users. After consulting the research literature, we focused on two main phases of the user innovation process (A) the "Idea generation" of an innovation and (B) the "Development" of an innovation. In both cases (A and B), a lead user is a valuable resource for companies. Furthermore, we have demonstrated that six different characteristics (trend leadership, dissatisfaction, enjoyment, high level of activity, product related knowledge, opinion leadership) are prevalent in existing research literature regarding lead user identification in online communities (see RQ1). Based on this, we further designed and implemented a tool that, on the one hand, combines all of the aforementioned characteristics and, on the other hand, considers the fact that lead users can be applied in different phases of the innovation process (see RQ2). To demonstrate the applicability of our artifact we applied it to 11,481 contributions of 945 users from a popular online forum for kiteboarding. After identifying the lead users, we evaluated our results by interviewing the respective lead users as well as an expert. In conclusion, following the DS research, we derived numerous contributions for both, theory (kernel theories: Innovation- and Lead User Theory; Design Theory: Design Principles) and practice (e.g., the artifact) (see RQ3).

In the previous section (see "Contribution for Practice and Research") we have shown that companies can benefit from our comprehensive and modular artifact, with which large amounts of data can be analyzed adapted to the corporate's specific circumstances with the aim of identifying different lead users for the particular phases in the innovation process. Thus, we automated the lead user identification process, the most difficult and time-consuming aspect within the lead user method. Furthermore, we have highlighted how our investigation made a first step towards contributing to Design Theory (theory for design and action (Gregor, 2006)) by formulating four design principles. These design principles (comprehensive characteristics consideration, using inter-subjectively verifiable identification methods, contextual adaptability and repeatability) can support the design of further user identification tools. Beside that we also highlighted our contribution to the kernel theories: Our study has revealed a new point by defining a lead user against the background of the purpose of its use (based on the innovation process) whereby we have introduced a new dimension to the Lead User Theory. Moreover, we enhanced Von Hippel's 4-step lead user utilization process in terms of its applicability and ease of use by enabling the automated identification of underlying trends when identifying accompanying lead users, as well as in terms of its functional scope by including multiple trends instead of solely considering the previously, manually identified trend. Finally with respect to the current Lead User Theory which treats all characteristics equally, we have assigned different weights to different lead user characteristics in the course of the identification process to make it even more targeted. Regarding the Innovation Theory the rigid sequence of stages and gates can be broken up and further parallelized by applying specific lead users within the different stages. However, our research is not without limitations. We have identified the characteristics that are decisive for a lead user in the current research literature. It is possible that there are further characteristics distinctive for a lead user that we have not considered. During our research we came upon areas of further research. In terms of a further evaluation of our results, we are intent on carrying out a study to assess the completeness and usefulness of our approach with other cooperating partners. Further, as the users noted in the interviews that experience in the respective field of application is important and we only partially cover this with the characteristic "product-related knowledge", the question "At what point can a lead user be seen as experienced?" may be subject of future work.

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2.3 Beitrag 3: Identifying Value-adding Users in Enterprise Social Networks

Adressierte Forschungsfrage	**Forschungsfrage 2:** Welche verschiedenen Charakteristika weisen die einflussreichen Nutzer in einem Social Media Network auf und wie können sie strukturiert dargestellt werden? **Forschungsfrage 3:** Wie kann ein einflussreicher Nutzer unter Berücksichtigung seines Einsatzziels durch die Kombination von unterschiedlichen Methoden identifiziert werden?
Zielsetzungen	• Aufzeigen des Wertes, den ein Nutzer in einem ESN generieren kann • Extraktion der Charakteristika von „Value-adding Users“ aus der Literatur und Erstellung einer Übersichtstabelle im Hinblick auf verschiedene Datendimensionen • Vor dem Hintergrund von verschiedenen Zielen, Kombination der Datendimensionen und Anwendung an einem Real Welt Datensatz • Identifikation von unterschiedlichen Value-adding Users
Forschungsmethode	**Single Case Study** nach Yin (2009) • Ausgangspunkt: Literature Review zum Thema „Value-adding Users in ESN” (Kitchenham et al., 2019; Vom Brocke et al., 2015) • Durchführung der Single Case Study am Beispiel eines Data Warehouse Consulting Unternehmens
Kernergebnisse (Überblick)	• Strukturierte Zusammenfassung der Charakteristika eines value-adding users anhand der Datendimensionen Netzwerkstruktur, Nachricht/Post, Verhalten und Social Network Affinität • Unterschiedliche Ziele (Wissensverbreitung, Lebhaftigkeit des Netzwerks und Feedback in Echtzeit) führen zu unterschiedlicher Kombination der Dimensionen und somit auch zu unterschiedlichen wertstiftenden Nutzern • Adaption der Identifikationsmethoden an die speziellen Ziele des Unternehmens (Ziel Wissensverbreitung: zusätzlich Themenidentifikation und Ziel Feedback in Echtzeit: Themen- und Emotionsidentifikation)
Publikationsort	Proceedings of the 55th Hawaii International Conference on System Sciences, Online 2022.
Ranking VHB JQ 3	C
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Tabelle 4: Fact Sheet Beitrag 3

Identifying Value-adding Users in Enterprise Social Networks

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Abstract

Enterprise Social Networks (ESN) have been gaining increasing attention both in academia and practice. In previous works, different user types were identified in ESN. However, there is no clear definition of value-adding users, their characteristics and how this type of user can be identified. Based on a literature review, we show that value-adding users are defined in different ways in respect to different objectives, for example spreading knowledge, vivacity of the network or real-time feedback. Each of the value-adding users shows different characteristics that are allocated to the following dimensions: network structure, message, behavior, and social network affinity. Based on the objectives and characteristics, we conduct a single case study, analyze a dataset of a cooperating company, conduct several interviews, and thereby identify value-adding users with respect to objectives. So, we can show that our approach is applicable, useful and that it is a valuable means to take decisions.

1. Introduction

Nowadays, in the globalized world, technology is continuously establishing new ways for communication. Especially large organizations face the challenge of spreading information throughout time and space [1, 2]. Systems that can facilitate networked communication and foster collaboration are so-called Enterprise Social Networks (ESN) [3, 4]. Prior research in this field showed that ESN provide employees with an effective possibility to share knowledge [5, 6], with an easy way to organize meetings and manage teams [7, 8]. Likewise, they can support the process of innovation [9, 10] and facilitate a better connection of the employees [11, 12]. To take advantage of these opportunities, organizations depend on different factors such as technological (e.g. ease of use), organizational (e.g. top management commitment), social (e.g. contribution quality) and individual factors (e.g. enjoyment of helping others) [13]. Users who consume, organize, and produce content within the ESN constitute one of the most important factors [14]. However, in some cases, ESN do not fulfil the company's expectations making it question the investment [15]. Possible reasons are that the so-called "critical mass" of users or content could not be reached, which is indispensable for ESN acceptance in a company [13]. So, it is necessary to focus on ESN users to influence their behavior in a positive way. Especially considering the users' characteristics is of particular importance contributing to the success of ESN. Research dealing with the identification and characterization of users often draws on the network structure of the underlying ESN [16-18]. Thus, a user´s behavior can be evaluated by applying social network analysis (SNA). This delineates, on the one hand, the overall shape and size of a network and, on the other hand, the relation pattern of all nodes in a network [18]. The users with the highest connectivity, the highest activity and the highest information diffusion degree are designated as value-adding users by [16]. However, only few studies consider, in addition to the SNA, further measurement approaches to describe and distinguish user types. But the mere number of ties to other nodes does not allow to draw a conclusion on the quality of the information that is spread across the network and in addition, most of the organization's information can be found in the content of text documents [19]. Thus, various studies combine centrality measures with either the content of a post [20-22] or other measures, e.g., the level of sentiment [23]. As a matter of fact, they are mostly applied on limited views based on different individual data dimensions. Research has also tended to focus on a small number of characteristics – mostly two – to characterize a value-adding user. Thus, as we want to provide a comprehensive approach, we decided to take a closer look at various measurement approaches, reasoning that further investigations give us a deeper insight into the characteristics of users. Further, the combination of different data dimensions will lead to more robust or novel insights for researchers and managers [24]. With this paper, as we want to show how users who contribute to the value of ESN can be characterized, we focus on the users who are most promising in these terms, the value-adding users, and seek to answer these research questions (RQ):

1. Which characteristics of a value-adding user can be distinguished?
2. How can value-adding users be identified by comprehensively applying various measurements?

The remainder of this paper is organized as follows: in section 2, we give a brief introduction in conceptual basics. In section 3, the research procedure following the case study approach [25] is explained in detail. Section 4 deals with the procedure and the results of the literature review. Next, section 5 shows the results of the case study and section 6 discusses them. Finally, we draw an overall conclusion.

2. Conceptual Basics

2.1 Terms and Definition

Social Media applied by a company is typically used for the communication with external parties. But social media can also be used for internal communication, often referred to as ESN [26]. ESN have been gaining increasing attention, especially in large multinational organizations [22, 27]. Based on previous research [24, 26] ESN can be defined as digital platforms that facilitate employees to communicate with everyone in the organization, to post, edit, and sort texts and files linked to themselves or others and to connect users via various features. So, these platforms are used to improve organizational effectiveness and efficiency [28]. Investigations have shown that ESN are information-sharing platforms, areas for developing crowdsourcing ideas, spaces for receiving expert knowledge and platforms for communication [3, 26, 29]. There are two central capabilities that are fundamental in organizational application of ESN. The first one is the ability to establish and manage social networks, the second one is the ability to find and access digital content [30]. ESN allow users to visualize and navigate the relational structure of their own networks including all connections to other users [30, 31]. Furthermore, accessing digital content like information means a competitive advantage for organizations.

2.2 Value in terms of ESN

In literature, different fields of research such as economics or business administration focus on value as a central construct [32]. Thus, the concept of value is considered from different perspectives so its definition can vary widely. The definition regarding the value of a product e.g. includes the two concepts “value in use” (value can be perceived via the use to be deduced from a product) [33] and “value in exchange” (value is (ac)countable) [32, 34]. Another definition of value can be established regarding customer valuation. The value of a company´s customer incorporates the profit that a company expects to earn with a customer. With regard to ESN a different perception of value can be found, too.

Value in terms of ESN can further be determined from three different perspectives: First, investigations focus on users who evaluate what drives the value of ESN for them [35-37]. Thus, value is defined here as the user´s evaluation of the benefits of applying ESN for receiving and spreading information against the costs caused by the usage [36]. But these benefits and thus the value in terms of an ESN can not only be evaluated by users but also from organizations. This second perspective includes i.a. the utilitarian value of an ESN for a company. Therefore, an ESN is valuable for a company when it enables e.g. the increase of task performance [38] or when organizations´ expectations are met [27, 39]. The third perspective on value in terms of ESN focuses on the value that is generated in an ESN. Users of a social network are seen as a “tool” for creating value. Thus, a consumer´s active participation in a social media network, including the creation of valuable UGC, is central in value creation [40-42]. Taking this to the internal point of view, a user of an ESN can create value. [22] has included this idea and highlighted that different user types can generate different aspects of value as a user can act as enabler of new methods of working together whereas another user can be valuable as s/he gives high business-related task support. Value-adding users are therefore employees who are rising the challenge of constantly changing business circumstances and go beyond their job obligations, which is also discussed in the research field of organizational citizenship behavior (OCB) [62-64]. So, every perspective defines value differently. It became apparent that discrepancies in the definitions result from different objectives. This applies to all above mentioned perspectives. Specifically, in terms of ESN it depends on the alignment of the objectives whether a user can e.g., be valuable or not. Only if one is aware of the objective, one can determine if someone is valuable or not [39]. Furthermore, as different types of value can be differentiated (due to different objectives), a distinction of the users who create this value must be identified as well. By scanning the literature, it became obvious that few investigations focus on user types in ESN that are in fact valuable. So, little research has focused on the value-adding user, although a company benefits especially from this user as s/he makes a positive contribution. The actual value and the characteristics of a value-adding user vary widely, resulting in an inconsistent definition.

3. Research Method

To ensure the understandability and applicability of the development of a systematic model for the distinction of users, we applied the research method "single case study" and went by the approach of [25]. In the process of planning the case study, we conducted both interviews with the case company and a research literature review about value adding users and their objectives, which resulted in the formulation of our RQs (see section 1). The structured procedure and the results of this literature review are explained in the following section (see section 4). The RQs serve as a basis for the definition of the unit of analysis – the value-adding user – which is central in the design phase. As 'every network context produces its own culture of intersubjectively shared expectations' (p.53 [61]), we determined the single case study design [25, 57]. It allows us to carve out connections between constructs with the aim of highlighting theoretical insights. Afterwards we prepared the collection of case study evidence. Therefore, we developed a protocol to increase the reliability of our study. Thereby, we noted an overview of our case study project including background information (see section 5.1), the project objective (characterization of value-adding users within an ESN regarding different objectives) and the case study issues (value-adding users, ESN, SNA, sentiment, content analysis). The case study protocol also includes the field procedures (schedule of data collection activities) and our case study questions. After these preliminary considerations, we collected case study evidence. To guarantee the reliability and validity of our results we used multiple sources of evidence, which is why the analysis (see section 5.3) comprises both the detailed analysis of network data and conducting interviews with a board member and two department managers. The purpose of the analysis is to recombine evidence so we can draw conclusions.

4. Literature Review

4.1 Procedure of the Literature Review

To start the literature review, first, we defined the review scope in accordance with the research questions (cf. [43]). Consulting promising papers dealing with value-adding users in ESN and their different objectives (e.g. [19, 22]) led us to key concepts in the current literature as well as to key words such as "user types", "value-adding user(s)", "user roles" in combination with "enterprise social *" and "objective" (in any combination) necessary for the further search. The consultation of seminal works was not only destined for search terms but also to define meta-databases (dblp, AIS electronic library, ACM digital library) and the time period of the literature search (2005-2020). The literature search, including study selection criteria, was conducted by two researchers simultaneously to avoid biases [44]. First, we searched for publications that use the previously defined search terms then we conducted a forward and backward search (cf. [45]) before we filtered the results to concentrate on the relevant literature. The initial literature search resulted in a total of 467 publications. In view of the aim of our paper, we selected investigations with a direct reference to user types in ESN in their title, the provided keywords and the abstract. As a result, almost three quarters of the articles had to be discarded. We also eliminated duplicates and only peer-reviewed full papers have been selected (58 remaining) which were analyzed in detail. 36 publications analyzing user types in other online social networks such as Facebook were eliminated. Additionally, we removed investigations without direct reference to the value-adding user and their objectives. Finally, we identified 16 articles as relevant. The literature analysis is based on the qualitative content analysis according to [46].

4.2 Results of the Literature Review

In literature, there is neither a consistent definition nor a homogeneous characterization of the value-adding user within an ESN. [20] e.g. define value-adding users as users who post both work-related and non-work-related content in an ESN on a balanced level to stimulate the ESN. However, [16] identify value-adding users in their investigation likewise but focus on expert identification. Therefore, they define value-adding users as users who share knowledge in ESN to support others [16]. Although both user types are value-adding for a company, they mainly differ in their overall value (thus also in their objectives) and in the specification of different data dimensions. Both the structured review of the literature regarding the characteristics (cf. table 1) and the objectives/ value will be presented and discussed in more detail here:

- **Network structure**: The network position is an often-consulted metric in the distinction of different user types. This structure can be illustrated by "a set of nodes interrelated by dyadic ties" [47]. Value-adding users are amongst the best-connected users [17-19, 48-50]. They can be described via four different centralities: degree, betweenness, closeness, and eigenvector centrality. While degree centrality shows the number of direct links a user has [51, 52], betweenness centrality indicates how often a user is situated on the shortest path distance between various actors [51, 53]. When users have a high level of closeness centrality, they have fast access to information within the entire network [51]. By means of eigenvector centrality one can determine a node's status by investigating both the number of direct connections and how well its contacts are connected [47, 51]. Thus, the status of the users depends on who they are tied to [18]. Value-adding users are amongst the best-connected users and add value to the organization in terms of **spreading knowledge** [16, 17]. They exhibit the highest centrality measures in the social graph [17-19]. When ESN become very large the situation can change: users with lots of connections can no longer be generally rated as value-adding as they are seen as persons who want to build friendships rather than using ESN professionally [21].

- **Message:** Literature has distinguished between a professional purpose leisure posts [16, 19, 20, 22, 54]. However, it is not possible to infer directly from the content of a post to the user type. Value-adding users can be described as employees who communicate knowledge and help others by posting merely work-related content [16, 19, 22]. Moreover, the proportion of work-related to non-work-related content is also important. Work-related blogging allows users to bring out their expertise, whereas a high number of readership of non-work-related content only shows that its authors are popular among their colleagues. More popular users are mostly also happier at work [20]. So, from an organizational perspective, one can state: when companies restrict non-work-related blogging, the spread of work-related knowledge decreases as well. So, if a company is interested in the **high vivacity of a network**, users who post non-work-related content can also be seen as value-adding users, especially as there is a positive spillover effect from non-work-related posts to work-related posts [20, 55]. Based on the usage of textual data, the contents of messages and posts can be tagged as positive, neutral or negative [23]. To intervene adequately if necessary, companies therefore need to take a closer look at users who exhibit a very negative or very positive sentiment. Moreover, ESN provide new possibilities for employees to express themselves [23], providing users with the opportunity to **give real-time** (both positive and negative) **feedback**. A value-adding user may also be a person who posts constructive and criticism, with the impact on the overall health of a company, understanding its reputation as an employer.
- **Behavior**: A differentiation between active and passive user behavior within an ESN can easily be made [17, 19, 22]. Focusing on the user's active behavior - a value-adding user is amongst the most active users [18, 49, 50, 54-58] - different activities such as writing and reading articles, writing, reading or tagging in messages, etc. can be distinguished [54]. Hence, value-adding users exhibit the highest centrality measures in the activity graph [17-19, 21]. The more network connections employees have within the ESN, the more they can exchange expertise. Hence, ESN can enable firms to trace employees' expertise as well as the dispersion in general based on their social connections [21]. Value-adding users communicate knowledge and help others by posting merely work-related content [16, 17]. Other users show their appreciation by giving likes or shares. However, further research has shown that value-adding users who are willing to support others also want to receive help in return [19]. The high activity level is directly tied with the utilization frequency: Depending on how often users are logged-in, the utilization frequency is high, as their ESN usage goes from several times a day to permanent use [22, 54].
- **Social Network Affinity:** This dimension includes the analysis of a user´s affinity towards ESN usage. Value-adding users are extremely open for using social networks in general. They are highly familiar with the usage of ESN in their routines. Furthermore, they are curious which leads to the user´s ability to motivate other people´s ESN usage [22, 50, 58].

As a result, the conducted literature review showed that there are many different characteristics of a value-adding user (cf. table 1) and that no homogeneous definition can be found. Consequently value-adding users were essentially examined regarding different objectives. Depending on the respective objective, the different studies result in different characterizations of a value-adding user. This is in line with our previous remarks in section 2.2. So, value, and thus a value-adding user, cannot be defined isolated but only against the background of a specific objective. Thus, in the current research literature we have identified the following objectives: (1) spreading knowledge, (2) increasing the vivacity of a network and (3) giving real-time feedback.

(1) According to the literature, users who are most value-adding regarding the objective **spreading knowledge** are the ones who have a high level of centrality in both the social and the activity graph and spread their knowledge by posting merely work-related content [19, 21, 22]. Thus, a combination of the following characteristics of data dimensions is to be conducted to meet this objective: centrality, active posting behavior and work-related content.

(2) Value-adding users who support and provoke the **vivacity of a network** are, according to [20], users who are on a central position, post both work – related

and non-work-related content on a balanced level. Thus, a combination of the following characteristics of data dimensions is to be conducted to meet this objective: centrality measures and both work-related and non-work-related content.

(3) Regarding the third objective, **real-time feedback**, a value-adding user is a user who posts negative as well as work-related content. These posts that seem, at first glance, destructive can help an organization to identify their internal weaknesses and react to negative but constructive and change-oriented contents [23]. Thus, a combination of the following characteristics should be conducted to meet this objective (cf. table 1): active behavior, negative sentiment, and work-related content.

These objectives represent the contribution of a value- adding user to the network. To prove the applicability of our approach, we conducted a case study to show how different value-adding users can be identified (combination of characteristics of the data dimensions) with reference to the different objectives.

5. Case study results

5.1 Data collection

Our case study takes place in a Data Warehouse consulting company. As an international company it has about 130 employees. To keep them all connected and up-to-date, the management decided to introduce Yammer, a leading ESN platform. Within the first three months 93% of their employees registered.

Table 1. Value-adding user

Data dimensions	**Characteristics of the data dimensions**	**Characteristics of a value-adding user**
(I) Network Structure	Analysis of the centrality measures within a network: • Degree centrality • Betweenness centrality • Closeness centrality • Eigenvector centrality	• Central position an ESN: best-connected user in the network [17 - 19, 49, 50, 60] • High status in a network: contacts are well connected and central, too [17 – 19] • Large ESN: the more connections the less one is classified as a value-adding user [21]
(II) Message/ Post	Analysis of the messages/posts sent by a user: • Content of a post o Leisure posts versus work-related posts o Sentiment of a post: general temper (positive, negative, neutral)	• Has a high level of knowledge: merely work-related posts, original content [16, 17, 19, 21, 22, 54] • Keeps network alive: equal proportion of work-related to non-work-related posting [20, 49] • Sends messages that are very detailed when they reply to questions [55] • Sends posts of change-oriented work-related criticism (negative sentiment) [23]
(III) Behavior	Analysis of the users´ behavior within an ESN: • Participation within a network o Passive/Active o Read/Post	• Content creator and highly active user (including writing/reading articles, writing/reading/ tagging in messages, helping others, posting status updates) [17 - 19, 49, 50, 54 – 58] • Person who is willing to help: o More likely to share than to seek knowledge [17, 60] o Equal level of sharing and seeking knowledge [19, 55] • Helpful person: receives most likes and bookmarks [16] • Exchanges information between different working groups effectively and rapidly [19] • Behaves like an opinion leader [21]
	• Utilization frequency	• Exhibits a medium to high utilization frequency: o Uses ESN several times a day [18, 22] o Has created 10 posts in the previous 12 months [54]
(IV) Social Network Affinity	Analysis of the individual affinity towards an ESN: • Attitude towards ESN	• Open-minded towards the introduction of ESN [22, 50] • Motivates colleagues to use ESN [22] • Curiosity, anticipation, and enthusiasm [22]
	• Ability to use ESN	• Familiarity with using a social network and ability to take advantage of it [22]
	• Opinion about future potential	• High level of promotion and support of the system [22, 50, 58]

Besides promoting the interaction among the employees and providing a place for criticism, various further benefits were expected, e.g. in the fields of knowledge or by establishing discussion groups. After a few months, the management realized that there were significant differences in the ESN usage. Posts of several employees popped up frequently, others posted only in groups and many employees did not post at all. The question arose how these different usage patterns could be identified and how employees could be characterized and clustered based on their behavior in the ESN, leading to the final question which type of user was value-adding. To answer these questions, we conducted two in-depth interviews with each of three interviewees, a board member and two department managers. All interviews lasted about two hours each and were structured as follows: in the first interview, we discussed the initial situation taking into consideration the results of the literature review. In a second interview, as we had already applied the metrics, we were able to discuss the results with them. These second interviews resulted in adapting and sharpening the identification approaches regarding the different objectives. The interviews were conducted by two researchers, recorded, transcribed, and finally reduced to the most important statements. Additionally, we analyzed a full data excerpt of seven months of ESN tool usage. The data were provided in csv-files, containing for each employee: subsidiary, department, job role, hierarchy level, and date of registration. In total, the data excerpt comprised 670 posts by 122 employees in the given timeframe. We are aware that the number of posts seems to be small at first glance. However, this number must be seen against the background that the ESN has only recently been introduced. Furthermore, the company wants to carry out the analyses about the identification of value-adding users precisely because these users should increase the value and thus the success of the network.

5.2 Data cleansing and preparation

First, the data had to be prepared. Thus, we set up a Jupyter Notebook (Python). We then removed posts that were created by the ESN itself (technical post). 511 posts were the basis for the upcoming analysis. While most columns contained structured data, we also processed the unstructured posts. In this regard, we removed symbols, special characters and stopwords [59]. As explained above, we also wanted to extract the sentiment of each text corpus. The sentiment score is a numeric value ranging from -1.0 (negative) to 1.0 (positive), with a value of 0.0 indicating a neutral sentiment. As we were also intent on distinguishing posts containing business and/or private matters, we manually classified each post as being a business or a private post. To make this differentiation more understandable, we provide an example each: business post "*Since now, we´ve got version 3.3.0, updated themes and bunch of new plugins.*" versus private post "*What about to drink some beer?*". In some cases, the posts contained business and private topics. To analyze the network structure of the employees, we modeled the interaction network by using the networkx library in Python. While employees are considered as nodes, their interactions are represented by the edges. Consequently, the social graph equals the activity graph and we cannot distinguish between network structure and behavior in our analysis. This means that an active user is central in the network, since we can calculate the following measures: closeness, degree, betweenness, eigenvector centrality for each user. The last data dimension, social network affinity, comprises i.a. a person´s attitude towards ESN. As described above 93% of all employees registered within the first three months. This indicates that the registered persons are early adopters [50]. Furthermore, more than 80% of all employees have an IT-related qualification which speaks for a high level of ability to use ESN.

5.3 Results of the data analysis

As a first step we present a short analysis of each variable to create a solid basis for separating the value-adding users from other users in the network. Looking at the network structure, the 511 posts were sent by 48 nodes, in the following referred to as active users. The active users build a coherent network, on which the centrality measures are calculated. Looking at them in detail and calculating the Pearson correlation coefficient, we see that all centrality measures are highly correlated, with all values being higher than 0.82, meaning e.g. that an employee who has a high (low) betweenness centrality value also has a high (low) degree centrality value (r= 0.951). Thus, we can distinguish different employee groups regarding their network positions. We chose the degree centrality, as it has a high correlation with the other centrality metrics. Looking at the sentiment values of all posts, we saw a wide range from very negative to very positive values. Moreover, the results indicated that far more posts had a positive sentiment value, enabling us to finally state that the general sentiment in the ESN was positive. When aggregating these values per employee it turned out that, on average, all users had a positive posting-behavior. Looking at the business and/or private characteristics of a post, we saw that

56.9% of all posts had a business and 59.7% a private character. 16.6% of the posts had both business and private contents. After presenting the analysis of each variable, we combine them based on the literature to meet the objectives spreading knowledge and real-time feedback. During the first interviews it turned out that the company wanted to focus primarily on value-adding users in the context of these two objectives and wanted to exclude vivacity of a network.

First, a value-adding user regarding the objective **spreading knowledge** is defined as a person sharing knowledge from a central network position. Thus, following the research literature we combined the data dimensions (cf table 1): Message (work-related) and Network structure/Behavior (centrality measures). After applying these two dimensions we presented our first results to the interviewees. It turned out that this procedure was too superficial here. For them it is interesting who is value adding in which area of knowledge. Thus, we came to the decision to differentiate not only between work-related and non-work-related but also between different work-related topics. So, we first filtered for work-related posts, as we only wanted to focus business-relevant knowledge. Then, we further identified the specific topics (three detail levels) with the help of Natural Language Understanding V1 of IBM Watson to differentiate the areas of knowledge. Thus, we aggregated the posts of each topic and, subsequently, of each employee to identify the topic a particular employee addressed most frequently. To identify which content was spread most, we finally analyzed the network position, as the knowledge of employees is more widely spread if posted by a central node. We chose the degree centrality due to its high correlation with other centralities. Looking at the topic categories, we found out that among the work-related posts 21 different topics were addressed by 40 employees on the whole. Further, as every employee addressed different topics, 146 combinations of employees and topics could be identified. However, for each topic, we were able to identify those employees who contributed most to a topic. Continuing this analysis on a higher detail level (topic_cat2) made it possible to also identify the knowledge spread on more specialized topics such as technology and computing/internet technology. In total, 88 detailed topics were identified across the 40 employees. On this detail level, 210 combinations of topics to employees could be identified. But did this knowledge also reach many other employees? Looking at the network positions of the employees and at the topics that were addressed most often (top 25% of the 88 detailed topics), it could clearly be stated that all of them were among the central nodes. Hence, we were able to identify different value-adding users depending on the different topics. For each topic (topic_cat1), we identified two to three value-adding users and therefore experts in this knowledge area. So, all interviewees agreed to combine the dimensions business-related content, topics and centrality.

Second, regarding the objective **real-time feedback**, a value-adding user actively gives feedback in terms of change-oriented criticism. This is in line with our results of the literature review: a user who actively posts negative and work-related content. After applying this identification approach to our data, we discussed our results with the interviewees. The concurrent opinion was that these dimensions were helpful in a first step but were not fully enough for identifying a value-adding user in terms of the objective "real-time feedback". The board member argued that further analysis was needed as not every negative post contain constructive feedback. Posts that contain e.g. furious invectiveness had to be excluded. So, to fulfil the requirement of the board member we additionally included the emotion detection. it is possible to identify the emotional sentiment of a user's written text. Hence, by applying the Tone Analyzer V3 of IBM Watson Developer Cloud we drew a distinction between six emotional levels: anger, disgust, fear, joy, analytical and sadness. This allows us to check the emotional aspect of the criticism expressed by the employee. The distribution of the emotions can be seen in figure 1 (left).

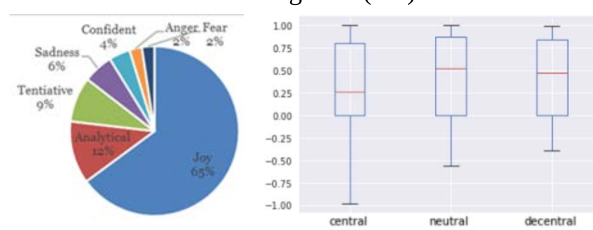

Figure 1. Left: tone analysis; Right: Sentiment analysis and centrality measures

In a first step, we focus on the negative emotion "sadness" to identify the subliminal criticism. Moreover, we excluded emotional posts (e.g. posts with high values of anger) that are so decidedly negative that a user who exhibits these kinds of emotions is not able to give constructive feedback. Further, one of the department managers pointed out that it would be important to include the centrality measure as criticism may not be realized if dispatched by decentral nodes because of their weak connectivity. As the case company wanted to react quickly to the negative feedback that spread fast across the network, we included the centrality measures. In addition, the other department manager stated that it would be further helpful to identify the topics a value-adding user gives feedback about. As we stated above, the network position of the employees plays a decisive role in meeting this objective. Thus, we split the employees into central, neutral and decentral nodes and provided boxplots based on the sentiment values of work-related posts (see figure 1: right). Comparing the three groups central, neutral and decentral, we saw that in all of them the inter quartile range started at 0.0, indicating that 75% of all posts had a neutral or positive and 25% of them a negative sentiment. Differences could especially be seen when comparing the median of the central nodes (0.56) to the other groups (0.51, 0.47) as it was much lower and the group of central nodes had a lower skewer (-0.98) than the neutral (-0.55) and decentral nodes (-0.39). Our results show that the posting behavior of central nodes generally had a more negative sentiment than that of the other nodes. Furthermore, looking at the negative posts and analyzing their emotion, the largest share of the negative posts exhibited the emotion "sadness" with 41.7%, e.g. "*Status update: It's endless. We can barely see our monitors*", posted at 04:11am. Afterwards, we additionally analyzed the topics of the negative posts. Here, we saw that most negative posts contained the topic "technology and computing", especially "technology and operating systems", e.g. "*Yes, we are still here and we screwed only two of our seven gateways.*" We saw that across these negative posts, subliminal feedback in terms of criticism prevailed. As can be seen above, the employees complained about their workload and working hours. As the same employees repeatedly wrote similar posts, it was possible to identify them as valuable.

6. Discussion of the results

Drawing on the literature was a starting point for identifying value-adding users. Advantageously, the results of the literature summarized in table 1 covers various dimensions that can be combined to meet the three identified objectives. Moreover, these data dimensions can be combined differently to meet other objectives a company may have. But, they can be further sharpened to identify more targeted value-adding users, too. First, regarding the objective spreading knowledge, we were able to identify value-adding employees and estimate – according to their network positions – how knowledge spreads across the network, based on the assumption that knowledge provided by central nodes spreads faster and wider than knowledge provided by e.g. decentral nodes, which was already proven correct by [19]. But as there are also topics that are initiated by decentral users, specific incentives need to be identified that stimulate the employees' needs to influence goal achievement and therefore their helping behavior in a positive way (cf. [62]). Their knowledge, even if relevant for other employees in the company as well, does not spread fast or reach the persons of interest although they exhibit individual initiative. The question is what a company or the employees themselves can do to facilitate access to this knowledge, e.g. how employees can shift their network position from decentral to central, a problem network science literature deals with (cf. [65]). Certain software functionalities e.g. could be implemented to provide employees with the information that their posts are barely seen, which they may not be aware of, or central employees could share these posts identified as relevant but invisible to other employees. Second, regarding the objective real-time feedback (cf. [23]), we were able to identify value-adding users by combining the dimensions centrality, work-related posts, sentiment, emotion and topics. According to our interviewees this is a huge advantage for the case company. However, it is counter-intuitive to classify employees who complain about internal conditions as value-adding users, as it is of course also probable that these users spread a disadvantageous atmosphere in the company [23]. But, in the long run, it is better for the management to know of rumors and problems within the company and be aware of who is discontent with the prevailing situation. Identifying these users creates the opportunity to counteract dissatisfaction promptly and change things. Being aware of problems and reacting accordingly is by far better than ignorance. We discovered that employees complain about their workload after working late. When the board member became aware of this, the company decided to reward such employees. The identification of value-adding users based on the company´s objectives thus seems promising in terms of serving as a basis for deriving measures that are crucial to make an ESN successful. So, we saw that along the two objectives presented, value-adding users could be identified properly. We were also able to show that in an ESN there are different types of value-adding users, depending on their particular objectives.

7. Conclusion

The aim of this paper is to identify value-adding users in ESN. Based on the literature with rewarding results, it was not only possible to clearly define the characteristics of a value-adding user. Instead, we identified that different authors provide different characteristics relating to different objectives [19-23]. Even though the objectives define a value-adding user in different ways, we identified intersections that we dissolved in table 1. In the existing literature, a clear definition of value-adding users could not be found.

Instead, we concluded that value-adding users must be defined in the context of distinguishable objectives. To answer RQ1, we compiled the characteristics of a value-adding user resulting in a set of dimensions: network structure, message, behavior and social network affinity. So, we can provide a comprehensive overview of how to identify and define value-adding users. Further, we examined the applicability of the dimensions and the objectives in a case company by analyzing the dataset of the ESN and by conducting several in-depth interviews, enabling us to identify value-adding users in a practical context. Within these interviews the case company formulates further requirements a value-adding user should meet to be valuable. Thus, regarding the objective spreading knowledge the case company wanted to identify those users who spread knowledge in a specific topic area across the network. Therefore, in our analysis we included topic detection to identify the value-adding user per topic. Regarding the objective real-time feedback, the interviewees agreed that the first results were too broad, so we included further measurement approaches (emotions, topics). Including them, and highlighting objectives is an indispensable step with regards to identifying value-adding users and, from a company´s point of view, applying them effectively (see RQ2). With the help of the interviewees, we were also able to confirm the value-adding users. Our research contributes to theory and practice alike. First, as a contribution to theory, we provide a comprehensive view in terms of value-adding users in ESN, identifying well-defined objectives and dimensions. Second, we contribute to theorizing how value can be generated within an ESN, which is hardly considered in literature. As a contribution to practice, first, we show the applicability of various dimensions and the combination of these dimensions in a real-life setting. Second, we identify measures to influence employee behavior, eventually influencing the network structure towards an achievement of the goals. However, our research is not without limitations. In the case study, we had to restrict ourselves to a limited number of values and objectives that were aligned to the case company. In other practical settings, different values and objectives may have to be set. Thus, for further research we are intent on carrying out a study by analyzing a larger data set. So, we plan to evaluate whether our approach applied on an extended network results in more value-adding users because of further objectives, whether these users can be distinguished more precisely, and whether further characteristics can be derived. Furthermore, since the value-adding users show characteristics that are also important dimensions of the research direction of OCB, such as helping behavior or individual initiative, we aim to investigate to what extent the other five dimensions [62] can also be applied in the field of ESN and how this research field can be support to structure user types in ESN.

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2.4 Beitrag 4: COMPARISON OF TOPIC MODELLING TECHNIQUES IN MARKETING – RESULTS FROM AN ANALYSIS OF DISTINCTIVE USE CASES

Adressierte Forschungsfragen	**Forschungsfrage 5:** Anhand welcher Kriterien lassen sich die verschiedenen Topic Modelling Techniken miteinander vergleichen? **Forschungsfrage 6:** Welche Topic Modelling Technik kann für die Anwendungsfälle (1) Themenextraktion, (2) Trend Analyse und (3) Themenstrukturierung verwendet werden?
Zielsetzungen	• Identifizierung von Anforderungen an eine Topic Modelling Technik hinsichtlich der Anwendungsfälle (1) Themenextraktion, (2) Trend Analyse und (3) Themenstrukturierung • Vergleich der Topic Modelling Techniken LDA, PAM und DMR anhand von Metriken wie Zeit, log-likelihood, coherence, word und topic intrusion • Aufzeigen von Unterschieden zwischen den einzelnen Topic Modelling Techniken, um Handlungsempfehlungen für die drei Anwendungsfälle abgeben zu können
Forschungsmethode	**Goal Question Metric** nach Basili et al. (1994) • Goal: Vergleichsparameter definieren, um Topic Modelling Techniken vergleichen zu können • Question: Inwieweit erfüllen die drei Topic Modelling Techniken (LDA, PAM, DMR) die Anforderungen der verschiedenen Anwendungsfälle? • Metric: Metriken werden aus der Forschungsliteratur identifiziert

Kernergebnisse (Überblick)	• Identifikation von elf Anforderungen an Topic Modelling Techniken und fünf verschiedenen Vergleichsmetriken
	• Zuordnung der Anforderungen und Metriken zu den drei, in der Literatur identifizierten, Anwendungsfällen (1-3)
	• Vergleich von LDA, PAM und DMR anhand eines Facebook Datensatzes mit 4,1 Mio. Posts unter Anwendung der Vergleichsmetriken
	• Handlungsempfehlungen für Auswahl der Technik:
	  o Themenextraktion: LDA (v.a. bei kleineren Dimensionen) oder DMR (v.a., wenn mehrere Themen extrahiert werden)
	  o Trend Analyse: DMR
	  o Themenstrukturierung: PAM

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Tabelle 5: Fact Sheet Beitrag 4

COMPARISON OF TOPIC MODELLING TECHNIQUES IN MARKETING - RESULTS FROM AN ANALYSIS OF DISTINCTIVE USE CASES

Research paper

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Abstract

Currently, topic modelling is an effective analytical tool for the automated investigation of text data. However, identifying the underlying topics is still a challenging task that is dependent on the selection of the proper technique. Moreover, due to the considerable number of topic modelling techniques reported in the literature, uncertainty about the application of the techniques arises for both researchers and practitioners. Therefore, we conducted a comparison of three different topic modelling techniques (LDA, PAM, DMR) to give recommendations for three use cases identified in the literature: content extraction, trend analysis and content structuring. For each of them, we identified several requirements and by conducting the method 'Goal Question Metric', we derived several comparison metrics. We applied these metrics to a real-world Facebook data set (4,155,992 posts) to highlight the differences between the three topic modelling techniques and to give recommendations for our defined use cases.

Keywords: topic modelling, social media analysis, text analysis, marketing use cases

1 Introduction

Topic modelling is a prevalent kind of probabilistic generative model for extracting latent variables from large unstructured data sets (Liu et al., 2016). This can be applied to analyse different data such as bioinformatics data (Coelho et al., 2010), environmental data (Girdhar et al., 2013), and text data (Vayansky and Kumar, 2020). Thus, topic modelling has been studied in different disciplines and is also prevailing in information systems (IS) research, mainly focusing on Latent Dirichlet Allocation (LDA) (Blei et al., 2003) because of its simple applicability and good analysis results (Debortoli et al., 2016, Eickhoff and Neuss, 2017). With the continuous growth of social media and the consequential transformation of the way individuals interact with each other, increasing amounts of written data are created that can be analysed i.a. to support marketing related decision-making (Ghosh and Guha, 2013). Thus, social media data are increasingly used to enrich marketing tasks, such as complaint management (Einwiller and Steilen, 2015, Grégoire et al., 2015), innovation management (Mount and Martinez, 2014, Piller et al., 2012), or sales (Guesalaga, 2016, Marshall et al., 2012). However, the huge amount of written social media contents (Statista, 2020) complicates manual content analysis.

To solve this problem, automated topic discovery techniques and – in particular – topic modelling have been widely investigated (Chinnov et al., 2015, Eickhoff and Neuss, 2017, Hong and Davison, 2010). Topic modelling enables the analysis of a large amount of written social media data to extract embedded topics. Therefore, topic modelling has facilitated addressing marketing related questions and problems that have exceeded the feasibility of in-depth qualitative analysis (Eickhoff and Neuss, 2017). Thus, marketing related problems that refer to (1) content extraction, (2) trend analysis and (3) content structuring have often been discussed in the literature. Companies are required to base their products and services on customer requirements. Therefore, (1) content extraction with topic modelling is an appropriate application to extract customers' praise and criticism for product planning purposes (Irawan et al., 2020, Rathore et al., 2018). To be aware of evolving trends concerning their own products and services, marketing departments conduct (2) trend analysis. Tracking evolving and changing requirements of customers is imperative to fulfil customers' wishes (Hong et al., 2012, Lozano et al., 2017). Moreover, (3) content structuring can help marketing departments to gain deeper insights into topics and their interrelatedness (Anoop et al., 2015, Srijith et al., 2017). Extracted hierarchical structures can reveal relationships between topics (e.g. price and product quality) and support more coordinated and sounder decision-making. Nevertheless, identifying the underlying topics of these documents is still a challenging task as the reasonable extraction of significant statistics and features from a dataset is dependent on the selection of the proper technique (Vayansky and Kumar, 2020).

As mentioned above, a growing number of IS-related investigations are currently using LDA. However, the basic LDA cannot represent all use cases (e.g. mapping hierarchies) for marketing related tasks so that extensions of LDA are essential. Therefore, not only do the numerous existing techniques for topic modelling hinder practical applications, but also the necessity of advanced technique-related knowledge. Liu et al. (2016) have divided various extensions of LDA into three areas: (I) extension of topic attributes (II) extension of document attributes and (III) extension of word attributes. Although numerous techniques are presented in these three areas, such as the Partially Labelled LDA (PLLDA) (Ramage et al., 2011), the Dirichlet Multinomial Regression (DMR) (Mimno and McCallum, 2008), or the Pachinko Allocation Model (PAM) (Li and McCallum, 2006), these extensions are scarcely applied. Due to the large number of topic modelling techniques in the current research literature, uncertainty about the selection of the right technique can arise. Vakansky and Kumar (2020) addressed this problem by conducting a theoretical comparison of different topic modelling techniques based on a structured literature review. Although this serves as a good overview of various topic modelling approaches and as a starting point for selecting a technique, differences only become obvious when applying them to a real-world data set. Furthermore, the results do not give clear suggestions which problem should be addressed with which technique. We addressed these problems by conducting a comparison between three different topic modelling techniques to give recommendations regarding the three use cases of (1) content extraction, (2) trend analysis, and (3) content structuring. We contribute to close this identified gap by comparing the practical application of the three techniques. This leads to the following research questions:

RQ1: Which criteria can be used to compare the different topic modelling techniques with each other?
RQ2: Which topic modelling technique can be recommended for the marketing related use cases (1) content extraction, (2) trend analysis, and (3) content structuring?

Topic modelling, both in general and especially regarding the analysis of companies´ social media posts, represents an important area for IS research. Accordingly, against the background of marketing we uncover various corporate use cases in the context of social media. By applying and comparing the three topic modelling techniques LDA, DMR, and PAM and by using build time, log-likelihood, coherence, word and topic intrusion as evaluation measures, we want to show differences between these techniques, identify advantages, disadvantages, and various potentials to enhance topic modelling techniques. Hence, we apply LDA, DMR, and PAM to a real-world data set. The remainder of this paper is as follows: section 2 provides a theoretical background. Then, we refer to the derivation of the three use cases and the respective requirements from literature. The transformation of them into topic modelling related metrics is also described here. Next, the procedure of the research 'Goal Question Metric' (cf. Basili, 1994) is described in section 3. Section 4 deals with the selection of the topic modelling techniques that are used for our comparison. The data analysis in section 5 achieves this comparison and further explains the data collection, the preparation of the data and the data analysis. Afterwards, in section 6, we present and discuss our results. Finally, section 7 draws an overall conclusion.

2 Theoretical Background

2.1 Social media

Social media can be 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 User Generated*

Content (UGC)' (Kaplan and Haenlein, 2010, p.61). Social media connects people with the same interests, activities, backgrounds, or friendships (AlFalahi et al., 2014, Schneider et al., 2009). The active utilisation of social media enjoys particularly great popularity in private use. However, companies have also adopted social media to support value-creation (Hanna et al., 2011, McDonald and Aron, 2012). In particular, many companies apply these Internet-based applications such as content communities (e.g. YouTube), blogs, or social networks (e.g. Facebook or Twitter) to enable communication mainly with external stakeholders (Kietzmann et al., 2011). Thus, companies adopt social media to achieve different business objectives such as branding, including advertising, marketing, and content delivery for creating brand awareness (Culnan et al., 2010, Di Gangi et al., 2010, Kietzmann et al., 2011). Therefore, social media such as Facebook or Twitter serve as an important interface between companies and customers. This interface generates large amounts of data that need to be analysed and interpreted, as a company can strongly benefit from these data. In addition to structured social media data (e.g. timestamps, like counts, etc.), especially unstructured text data contain interesting contents for companies. Posts and comments often include an user´s major wishes, ideas, and expectations towards products, services, or a company in general (Hienerth et al., 2011, Sigala, 2012a, Sigala, 2012b). The so called 'Voice of the Customers' can be used to adjust marketing campaigns, to identify and support the position in the market and to adjust product features on customers´ favourability. However, to uncover this useful information from the large amount of data requires considerable effort (Dahal et al., 2019, Kumar and George, 2007, Womack and Jones, 1996). To avoid this problem, automated analysis of social media data such as social network analysis, sentiment analysis, and topic modelling can be conducted. Especially through the latter one, valuable information for companies can be extracted, as this technique is able to identify various (discussion) topics, perceptions, and opinions (Dahal et al., 2019, Lozano et al., 2017). However, automated analysis such as topic modelling are often complicated, as many companies are not familiar with the applied techniques, its implementation, and its purpose (Dai et al., 2011).

2.2 Topic modelling

Topic modelling aims to determine content structures in underlying document collections. Hereby, topic modelling refers to the use of generative probability models for determining latent relationships within a corpus of text data. The dataset under investigation is to be seen as a mixture of individual documents, where each document affects several corpus-wide topics, that in turn consist of frequently occurring words within the dataset (Blei, 2012). LDA can be considered as one of the most fundamental works in the topic discovery research area, wherefore a growing number of investigations currently uses this technique proposed by Blei et al. (2003). The authors describe their probabilistic model as *'a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics'* (p. 993). This means that LDA is a generative model that is based on the assumption that documents are represented by a collection of different, latent topics. Each topic will be represented as a probability distribution over all words of a corpus (Krestel et al., 2009). LDA is frequently used in marketing to identify important issues for the adaptation of marketing campaigns or to identify product and service features currently being discussed (Chae and Park, 2018, Gao et al., 2012, Jeong et al., 2019, Ko et al., 2017, Luo et al., 2015, Xu and Xiong, 2020, Yu et al., 2019). However, the LDA as proposed by Blei et al. (2003) cannot represent all use cases (e.g. mapping hierarchies).
Thus, there are adaptations and extensions that are based on the probabilistic model of Blei et al. (2003). Generally, it can be differentiated between (I) topic-based extensions, (II) document-based extensions and (III) word-based extensions (cf. Liu et al., 2016). (I) Topic-based extensions derive structures and dependencies within the latent topics of a document (cf. Rathore et al., 2018, Rathore and Ilavarasan, 2017, Tuarob and Tucker, 2015). (II) Document-based extensions have the ability to incorporate an additional parameter into the model building (cf. Cheng et al., 2020, Lozano et al., 2017, Zhang et al., 2016). (III) The word-based extensions compute n-grams instead of Bag of Words (BoW) to incorporate the order of words in a document within the model generation procedure (cf. Wallach, 2006).
As can be concluded from previous research, the LDA approach is the predominantly applied technique (cf. Eickhoff and Neuss, 2017). Vakansky and Kumar (2020) provide a good overview of existing topic modelling techniques and accordingly develop a decision tree model supporting the selection of a

technique. These authors also include adaptations and extensions of the basic LDA for recommending an appropriate technique. However, their recommendations are theoretical in nature and not derived from practical applications of the techniques. There are numerous topic modelling techniques in the literature, but the number of papers comparing them is scare. Further, it is not clear if the theoretical overview and the decision tree of Vakansky and Kumar (2020) can withstand empirical investigations. The authors only conditionally contribute to the operational application of topic modelling as recommendations should ideally be deduced from the analysis of real-world social media data.

2.3 Corporate use cases and requirements of marketing

Within the prevailing literature, we identified papers that deal with utilising topic modelling techniques in marketing. These applications of topic modelling described in the identified papers cover a wide range of marketing tasks. In particular, three main use cases could be identified: (1) content extraction is concerned about consolidating insights of topics discussed in written social media data. By investigating brand-related content from social media, (1) content extraction enables marketing representatives to develop an understanding of topics and themes, e.g. sustainability or product feature favourability, that are discussed by customers and parties of interest. Thereby, companies can improve their external presentation by, e.g. emphasising the ecological superiority of the own products in brand communications (Chae and Park, 2018), and guide future product planning initiatives by putting more focus on product features that are appreciated by customers (Cirqueira et al., 2017, Irawan et al., 2020, Ko et al., 2017, Rathore et al., 2018). Providing a current overview of customers' major wishes, ideas, and thoughts is therefore a central requirement for these techniques as the ever-increasing amount of social media data along with the breadth of the user base may hinder marketing departments to focus on the essential aspects (cf. Cirqueira et al., 2017, Ko et al., 2017, Lee et al., 2016, Liu et al., 2017, Rathore et al., 2018, Rathore and Ilavarasan, 2017). Hereby, (1) content extraction is of a retrospective nature and is less concerned with speed. Because of the abundance of information provided by social media and the necessity to cover as much useful information as possible, the main aim is to cover the relevant and most frequent topics embedded in social media texts (cf. Gao et al., 2012, Ibrahim and Wang, 2019, Irawan et al., 2020, Wang et al., 2016, Yang et al., 2016). Therefore, we assume training time of the topic modelling techniques as secondary, because there are the two central quality dimensions, relevance and dominance of topics, as the basis for well-funded decisions. Furthermore, techniques for (1) content extraction need to support comparisons with competitors, assessments of a company´s position in the market (Aiello et al., 2013) and effectively support product and service opportunities generation (Ko et al., 2017, Rathore et al., 2018, Rathore and Ilavarasan, 2017).

The second use case we could identify is (2) trend analysis. It has in common with (1) content extraction that it deals with extracting topics from large amounts of written social media data. However, (2) trend analysis focuses on keeping track of emerging trends and their development, while the results of (1) content extraction, are instead point-in-time snapshots of the contents that do not illustrate the dynamic courses of the topics. Marketing representatives applying (2) trend analysis related techniques strive to track how certain topics (e.g., product favourability or customer satisfaction) evolve geographically and temporally (Hong et al., 2012, Jeong et al., 2019, Lozano et al., 2017, Zhang et al., 2017). Thereby, marketing departments can enhance the effectiveness of brand message placement and the allocation of appropriate resources to marketing campaigns depending on geographical and temporal developments. Furthermore, linking topics and contents to groups of interested parties and customers enables companies to adapt brand messages to meet the respective target groups´ expectations and attitudes (Zhang et al., 2016). Therefore, topic modelling techniques for (2) trend analysis need to flexibly incorporate different parameters like authors (Zhang et al., 2016), locations (Cheng et al., 2020, Hong et al., 2012, Lozano et al., 2017, Wang et al., 2007), or time (Cheng et al., 2020, Wang et al., 2012, Zhang et al., 2017) into the model building procedure. Ideally, it should even be possible to include implicit parameters such as places or times mentioned in the texts (Lozano et al., 2017). Since trends describe current issues that influence customers' decision-making, companies want to respond to the resulting customer demands to adapt e.g. marketing campaigns (cf. Luo et al., 2015, Rathore et al., 2018, Zhang et al., 2015, Zhong and Schweidel, 2020). Compared to (1) content extraction, especially with fast sequenced social media data and topics of interests changing quickly, it is necessary to keep track of trends and topic transitions (cf. Wang et al., 2012, Zhang et al., 2017). The requirement to be able to react as quickly as possible is further intensified by reduced product lifecycles and globalised business environments that have made customer needs more dynamic (Jeong et al., 2019). For this reason, the applied topic modelling techniques must provide short training times (cf. Cheng et al., 2020, Wang et al., 2012, Zhang et al., 2017) and as well support quick comprehension of the extracted topics (cf. Jeong et al., 2019, Lozano et al., 2017) in order to keep up with the speed of the trends.

Compared to (3) content structuring, (2) trend analysis captures the dynamic courses of topics and do not collect hierarchical relationships and correlations. Topic modelling techniques for (3) content structuring enable deeper insights from textual social media by extracting not only the topics (cf. (1) content extraction) but also relationships and connections between them. In this way, (3) content structuring supports decisions that need to connect different aspects with each other (e.g. identifying the influence of different product features on customers´ favourability) (Rathore et al., 2018). Mining the inter-relatedness of individual topics can help to detect subtopics (Anoop et al., 2015, Nolasco and Oliveira, 2019, Park et al., 2015, Rathore and Ilavarasan, 2017, Shahbaznezhad, 2016, Srijith et al., 2017) that can be investigated more closely as driving or inhibiting factors. Hereby, it is also possible to identify niche topics at a finer level of granularity of the topical structure. In line with that, recognising the properties of subevents can enrich the understanding of the main event and to create a powerful knowledge about the scenario (Nolasco and Oliveira, 2019, Srijith et al., 2017). In general, corresponding techniques need to extract topics and at the same time establish connections between them. In line with that, the relationships identified between the topics should be understandable and applicable.

In the next step, the identified requirements (cf. tab. 1) are transformed into corresponding metrics that are necessary for evaluating and comparing the topic modelling techniques in section 5.3.

	Requirements	**Sources**	**Metrics**
(1) Content Extraction	(a) Cover all relevant and the most frequent topics embedded in textual social media data	Gao et al. 2012, Ibrahim and Wang, 2019, Irawan et al. 2020, Lee et al., 2016, Liu et al., 2017, Wang et al. 2016, Yang et al. 2016	log-likelihood
	(b) Provide a current overview of events and insights about customers' wishes and complaints	Aiello et al., 2013, Chae and Park, 2018, Cirqueira et al., 2017, Ibrahim and Wang, 2019, Ko et al., 2017, Lee et al., 2016, Liu et al., 2017, Rathore et al., 2018, Rathore and Ilavarasan, 2017	
	(c) Support comparisons with competitors and assessments of one's position in the market	Aiello et al., 2013, Ko et al., 2017, Rathore et al., 2018	
(2) Trend Analysis	(d) Contextualise the extracted topics with additional parameters	Cheng et al., 2020, Hong et al., 2012, Lozano et al., 2017, Luo et al., 2015, Wang et al., 2007, Wang et al., 2012, Zhang et al., 2016, Zhang et al., 2017, Zhong and Schweidel, 2020	build time, coherence, word intrusion
	(e) Support a flexible inclusion of different parameters (e.g. authors, locations or time)	Cheng et al., 2020, Lozano et al., 2017	
	(f) Support quick information provision	Cheng et al., 2020, Wang et al., 2012, Zhang et al., 2017	
	(g) Support quick comprehension of contents	Jeong et al., 2019, Lozano et al., 2017	
	(h) Support continuous tracking of trends and developments	Wang et al., 2012, Zhang et al., 2016, Zhang et al., 2017, Zhong and Schweidel, 2020	
(3) Content Structuring	(i) Identify niche topics at a finer level of granularity of the topical structure	Anoop et al., 2015, Nolasco and Oliveira, 2019, Park et al., 2015, Rathore et al., 2018, Rathore and Ilavarasan, 2017, Shahbaznezhad, 2016, Srijith et al., 2017	topic intrusion
	(j) Identify meaningful relationships and the inter-relatedness of topics		
	(k) Cover all aspects that are semantically related to the extracted topics		

Table 1. Identified corporate use cases and their requirements

When evaluating a model with respect to (1) content extraction, the ability of the respective technique to (a) cover all relevant and the most frequent topics embedded in textual social media data is required. An excessive number of topics leads to the generation of not only relevant but also irrelevant topics. If the number of topics is too small, however, the given overview of topics will lack relevant content (cf. Liu et al., 2017, Yang et al., 2016). Therefore, the researcher must ensure that all relevant topics within an underlying dataset are considered within the analysis and thus integrated within the resulting extraction, which (b) provides a comprehensive and current overview of customers' wishes and complaints. This results in a comprehensive, decision driven base of information which supports (c) comparisons with competitors and assessments of one's position in the market. In order to evaluate this descriptive ability, the metric of log-likelihood is used. Using this, it is possible to quantify how accurately a model can represent the underlying data and thus models all relevant information (cf. Daud et al., 2010, Wallach et al., 2009). Furthermore, the evaluation has to consider different circumstances regarding the number of topics to be identified. Therefore, the evaluation of each technique takes place multiple times, with a continuously increasing number of topics. Thus, the strengths and weaknesses in modelling low (high) numbers of topics and thus lowly (highly) differentiated contextual information can be assessed.
When evaluating a model with regard to the described use case of (2) trend analysis, (d) the ability to contextualise the extracted topics and (e) hereby flexibly include different additional parameters (e.g. authors, location or time) is mentioned. Furthermore, corresponding techniques need to enable time-critical reactions to emerging circumstances so that (f) the provision of the topics should be as quick as possible. Therefore, the analysis of the different techniques is twofold. On the one hand, authors refer to the coherence measure (Dahal et al., 2019, Paul and Girju, 2009, Wang et al., 2007), which describes the property of the respective technique to generate topics that correlate well with the human understanding of semantically coherent topics. This results in a semantically meaningful and sound analysis output that (g) supports time-critical decisions and does not need further investigations to be applicable. On the other hand, to validate the calculated reasonability of the respective analysis output, we incorporate word intrusion (Chang et al., 2009). Thus, multiple subjects evaluate the consistency of the extracted topics by analysing the associated words. The objective is to identify the so-called 'intruder' within the topic, which is represented by a single word without contextual relevancy regarding the intruded topic. If the subjects are able to identify the respective intruder, the evaluated topic is consistent with the human understanding of a meaningful and sound topic. Besides the unhindered applicability of the analysis results, we also classified the build time as a time-critical evaluation metric. So, a short build time results in a timely output supporting faster decision-making. Beyond the aforementioned time-critical requirements, the ability to contextualise the extracted topics and (h) to continuously track their development is also required. To assess the possibility of accounting for further contextual information such as geological or time-based data, we qualify the ability to incorporate external information.
Concerning an evaluation of a model with regard to the described use case of (3) content structuring, the ability of the techniques to reveal the underlying structure within the data is focused. Thus, (i) to be able to extract hidden niche topics to identify relationships between the discussed topics, the ability of the respective technique to identify relationships within the data is qualified. Besides the pure ability to identify relationships, the assessment of the (j) meaningfulness of the identified relations is also required. In this regard, we opted to use the topic intrusion approach, which measures how well a topic model's decomposition of a document as a mixture of topics agrees with human associations of topics related within a document (Chang et al., 2009). Using these techniques, the (k) coverage of all aspects within the extracted topics as well as their interrelationships in the relevant document are analysed. The procedure of the analysis is similar to that of word intrusion. Specifically, the subjects are presented the document title alongside a short extract thereof. In addition to the document information, the subject receives four topics, of which three are the most probable topics assigned to the document and the remaining topic embodies the intruder topic to be identified. If the subjects are able to identify the erroneously listed topic, the topics and their contextual relationship to one another are meaningful and sound. A more detailed insight into the tasks of word and topic intrusion can be found in section 5.2.
As our review shows, different use cases and corresponding requirements have been reported in line with the literature that provide insights into the application of topic modelling techniques in marketing. However, the used data sets and the applied topic modelling techniques vary across the different papers,

so that recommendations made on this basis may not be sufficiently reliable. Therefore, within the research at hand, three different topic modelling techniques are applied to the same data set to give recommendations that are not only theory-driven but also based on the results of a data analysis.

3 Procedure of the Research

Our investigation follows the '*Goal Question Metric*' (GQM) approach outlined by Basili et al. (1994) for a systematic development of metrics for conducting a comparison of topic modelling techniques. The GQM approach is based on the idea that measurements in an organisational context depend on a thoroughly defined goal firstly operationalised by relevant enterprise data, which are then interpreted regarding the goal (Basili et al., 1994). Thus, this approach focuses on which informational needs a company exhibit in order to quantify them and consequently examine if the quantified information meets the goals or not. Especially for our investigation, the GQM approach is well qualified as it assures a systematic research procedure in which reproducible results are achieved. According to Basili et al. (1994) the GQM approach is divided into three different levels:

1. Conceptual level (**GOAL**): We set our goal as the development of means to compare different topic modelling techniques with each other regarding different use cases. Therefore, with this investigation we seek to highlight differences in the organisational application between the three different topic modelling techniques LDA, DMR, and PAM.
2. Operational level (**QUESTION**): In order to characterise how the assessment of our goal is performed, we formulate a question. In our study, the requirements of the different use cases for the techniques identified in the literature form the basis for our questions of the GQM approach: 'To what extent do the three topic modelling techniques (LDA, DMR, PAM) meet the requirements of the different use cases (a-k) (cf. tab. 1)?'
3. Quantitative level (**METRIC**): To answer this question, we conducted a quantitative analysis of the topic modelling techniques, that helps us to evaluate to what extent a selected topic modelling technique can meet the requirements. Subsequently, in order to meet these requirements, that we have already identified in a previous step, we now need proper metrics. Therefore, we consulted the research literature and established specific metrics for the requirements to enable a comprehensible comparison. Consequentially, we will be able to formulate recommendations for the allocation of the topic modelling techniques to the use cases.

4 Selection of the Topic Modelling Techniques

As mentioned above, the field of topic modelling has many different techniques, which all try to identify specific topics within large sets of text data by reducing the dimensionality and attaching different weights to the specific data set (Crain et al., 2012). In order to optimally meet the identified use cases, the selection of the techniques to be used is critical to success. Besides the aforementioned LDA with its extensions, a variety of different categories of topic modelling techniques like Latent Semantic Analysis, Probabilistic Latent Semantic Analysis, Correlated Topic Models, Dynamic Topic Models, or Topic Evolution Model exist (cf. Alghamdi and Alfalqi, 2015). Although they potentially could offer benefits in terms of different applications, most approaches lack a ready-to-use implementation or require an advanced technique-related knowledge and therefore suitable applicability for companies is not given. Differently LDA, where a clear dominance in the use has become apparent, as it offers simple applicability and good analysis results (Eickhoff and Neuss, 2017). Due to the multifaceted challenges to be mastered in the analysis of text data, different extensions of the basic LDA procedure have been developed over time which are suitable for the solution of different scenarios depending on their extending characteristics. Generally, a distinction is made between three expanding properties: (I) extension of topic attributes, (II) extension of document attributes, and (III) extension of word attributes (cf. Liu et al., 2016). In order to answer **RQ2**, the identification of topic modelling approaches for processing certain corporate use cases, we decided to compare LDA as well as selected extensions with respect to the identified use cases. Therefore, to achieve optimal coverage of different techniques, we selected one specific technique for each extension class.

The (I) topic-based extensions deal with the mapping of relations within the latent topics of a corpus. In this context, a variety of techniques is highlighted in literature (cf. Griffiths et al., 2004, Liu et al., 2016). The focus is on the identification of relationships between the inferred topics allowing a hierarchical representation of them. Mimno et al. (2007) compared the ability of their PAM algorithm to represent a hierarchical data structure and to predict a topic distribution for new data not included in the training set with a variety of techniques of the same extension class (cf. Mimno et al., 2007). Since PAM was characterised by better evaluation results, we decided to choose PAM as the topic-related extension. PAM represents the relationships among the topics as directed graphs, which allows the representation of a hierarchical structure within the topics.
The extension based on documents (II) enables the consideration of document-specific meta-information such as authors, document titles, points in time, or geographical information (cf. Liu et al., 2016). In this context, approaches such as the author-topic model (cf. Rosen-Zvi et al., 2012), Topics over Time (cf. Wang and McCallum, 2006), embedded topic model (Dieng et al., 2020) as well as DMR (cf. Mimno and McCallum, 2008) are highlighted in the current research literature. Because the technique presented by Mimno and McCallum (2008) is more flexible with respect to the incorporation of additional information as well as performs remarkable in terms of information quality, DMR is chosen for the implementation of (II) extension of document attributes. DMR is an upstream topic model with a particularly attractive technique for integrating any document features. Instead of defining specific random variables in the graphical model for each new document feature, DMR treats the document annotations as features in a log-linear model. The log-linear model parameterises the Dirichlet before the document's topic distribution, making the Dirichlet's hyperparameter document-specific. Since no assumptions are made about the model structure of new random variables, DMR is flexible to include various types of features, resulting in a flexible use of DMR (Benton and Dredze, 2018).
The above-mentioned topic modelling techniques, which are all based on the BoW approach, do not consider the order of words within a document. This resulted in extension (III), attempting to eliminate the interchangeability of words. Therefore, Wallach (2006) argued that the consideration of word orders in the form of bi-grams can lead to improved results when using a topic modelling approach. Since the consideration of word orders in the form of bi-grams did not show any difference with regard to the generated topics and the underlying topic quality compared to LDA, it will be equated with the use of the basic technique in the following. By choosing these techniques, a selection was made which considers each extension class of the basic approach, whereby a broad spectrum of different techniques is compared with regard to their applicability against diverse use cases.

5 Data Analysis

5.1 Data collection

To identify the potential of the different techniques with regard to the applicability to different use cases, an existing data set of Facebook posts was used (cf. Martinchek, 2017). This comprises 4,155,992 documents from the 15 most popular news services in the United States of America for the period from 2012 to 2016. The raw text dataset contains information such as the respective picture URL or the like count, which are not relevant for the application of the implemented topic modelling approaches. Therefore, to reduce the dimensions of the data, a custom converter was developed and applied to the data. The resulting data set contains three parameters after conversion: the ID of the respective document, the respective year – which serves as feature input to determine the topic relevance at different points in time within the analysis via DMR – and the description – which reflects the actual text of the contribution. The following excerpt from the training data set gives an insight into the data (cf. tab. 2).

ID	Year	Description
52921	2016	Dow Drops More Than 300 Points Following Market Rout...
21049	2014	How to Greet People During Flu Season: Handshake, ...

Table 2. Structure of training data

5.2 Data cleansing and analysing

In order to compare the topic modelling techniques empirically on the basis of their analysis results, the data must first be prepared. With respect to this, we applied tokenisation, stopwords removal and case folding as proposed by Boyd-Graber et al. (2014). As the use of stemming procedures does not improve the interpretability of the results, but can potentially even deteriorate the topic stability (Schofield and Mimno, 2016), we did not incorporate stemming.

By conducting this comparison between LDA, DMR, and PAM based on the mentioned evaluation measures, we aim to reveal the strengths and weaknesses of the different techniques in terms of identifying embedded topics within written social media data. As it is necessary to provide similar conditions for a comparison to be valid, all techniques were configured with their default parameters and trained with iteratively increasing numbers of topics. Accordingly, the selected topic range includes 10, 30, 50, 100, and 300 topics (*k*). Furthermore, all evaluation metrics were validated by cross-validation to eliminate the choice of a potentially non-representative test dataset (Bramer, 2007). The evaluation approach is further distinguishing between intrinsic and extrinsic measures. Intrinsic evaluations measure the performance of a component on its defined subtask, usually against a defined standard in a reproducible laboratory setting. Extrinsic evaluations focus on the component's contribution to the performance of a complete application, which often involves the participation of a human in the loop (Resnik et al., 2006).

#	log-likelihood measurements ($\cdot 10^6$)			coherence measurements			build time (min)		
k	LDA	DMR	PAM	LDA	DMR	PAM	LDA	DMR	PAM
10	- 4.86	- 5.03	- 4.85	- 197.96	- 198.50	- 208.34	342	363	832
30	- 4.49	- 4.61	- 4.41	- 232.84	- 220.75	- 236.81	571	634	1,264
50	- 4.29	- 4.40	- 4.19	- 244.29	- 217.90	- 251.17	912	1,083	1,992
100	- 4.06	- 4.10	- 3.88	- 241.74	- 213.03	- 254.92	1,407	1,732	3,481
300	- 3.91	- 3.62	- 3.67	- 215.02	- 186.95	- 241.52	3,180	3,821	6,984

Table 3. Intrinsic evaluation measurements

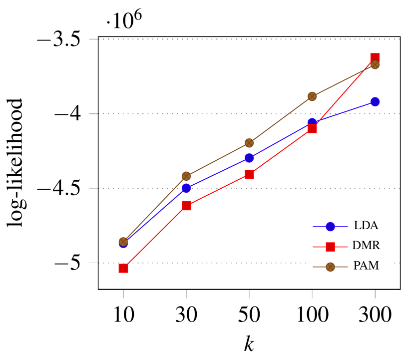

Figure 1. log-likelihood

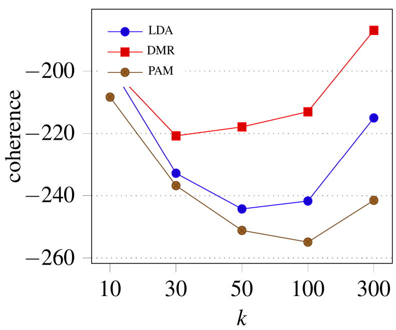

Figure 2. coherence

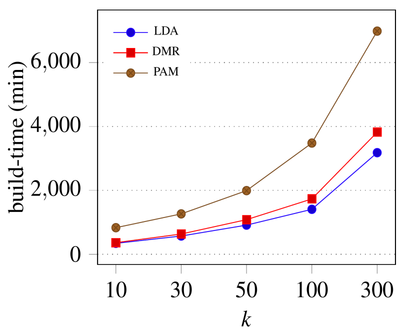

Figure 3. build time

In the first step of the evaluation, the models are compared according to their ability to represent the underlying data. Therefore, the metric of log-likelihood was applied (cf. tab. 3, fig. 1). A higher value represents a better model with regard to the ability to adequately represent the underlying data. The best model here is DMR, with k = 300 (-3.62). LDA performs better than DMR (e.g. k = 30 ≙ -4.86 > -5.03) and worse than PAM (e.g. k = 30 ≙ -4.49 < -4.41) until the number of topics exceeds 100. PAM and LDA have in common that, as the number of topics increases, the log-likelihood improves iteratively (cf. fig. 1). The increase in the number of topics for DMR results in a continuous improvement of the log-likelihood as well. Nevertheless, DMR always outperforms PAM and LDA when k >~ 300. This result implies that DMR is the technique that can be recommended when tasks require many different topics to be identified. However, within tasks that require a lower number of topics to be generated, our results indicate that PAM and LDA may be superior to DMR.

Besides the general ability of the models to adequately represent the underlying data, the semantic quality of the generated topics was evaluated. For that reason, the coherence measure was applied (cf. fig.

2). Therefore, we conclude that DMR generates topics, that are more coherent in general. LDA has a slightly better coherence for k = 10. However, any modelling of k > 10 is outperformed by DMR. Further, PAM performed worst in terms of coherence. Here, all different circumstances of topics are dominated by the other techniques. Nevertheless, PAM generated its most relatable topics for k = 10, which leads to the conclusion, that PAM, similar to LDA, exhibits its strength in modelling low topic dimensions.
To react in a time-critical manner to changing circumstances, it is also necessary to acquire supporting information as quickly as possible. Therefore, to measure the time an approach needs to extract the required information (cf. fig. 3), the build time of each technique is tracked. The respective build time includes data preprocessing, the actual model building and cross-validation. A lower build time indicates a quicker model training, which results in faster information provision. In this regard, LDA outperforms the other two techniques in terms of information extraction time. The difference between LDA and DMR in the lower range of topics is negligible (21 min), but the higher the value of topics, the larger the difference. The difference in the context of k = 300 amounts to 641 minutes. Because of the hierarchies to be modelled by PAM, it generally takes much longer to extract the respective information in comparison to LDA and DMR. Here, PAM needs at least twice as much time under almost all circumstances.
Besides the intrinsic measurements of log-likelihood, coherence and build time, the topic modelling techniques were further assessed by humans to evaluate the semantic quality of the generated topics as well as their interrelationships. Therefore, word and topic intrusion procedures were performed. The respective survey was undertaken by two researchers and administered to 18 participants, all of whom evaluated the semantic coherence of three randomly selected topics (word intrusion) and the decomposition of a single document into its topics and the corresponding relationships (topic intrusion). Each survey ranged between 38 and 51 minutes. The topics as well as the respective excerpts of a document were extracted randomly for each trained model. Further, to account the inter-rater reliability of the results, all participants evaluated the same set of topics or documents respectively for each trained model. Regarding the word intrusion task, the subjects had to identify the intruder within the topics that did not cohere to the semantics of the other presented words. The corresponding results for word intrusion are calculated as the sum of the correctly classified intruders by the test subjects in relation to the total number of tests per model. By analysing three topics per trained model, a total of 810 individual observations were carried out. Regarding the topic intrusion task, the participants had to identify the intruding topic by reading a document title alongside a short extract thereof. The respective document was randomly extracted for each trained model. All participants evaluated the decomposition of the same documents. By this, a total of 270 individual observations are accomplished. The respective results of the topic intrusion task are calculated as the amount of correctly classified intruder topics in relation to the total number of observations per model.

	Word intrusion (%)			Topic intrusion (%)		
k	LDA	DMR	PAM	LDA	DMR	PAM
10	74.0	85.1	53.7	83.3	72.2	83.3
30	72.2	79.6	57.4	66.6	61.1	72.2
50	62.9	75.9	51.8	72.2	72.2	72.2
100	64.8	70.3	48.1	55.5	66.6	55.5
300	55.5	77.7	46.2	55.5	72.2	44.4

Table 4. Extrinsic evaluation measurements

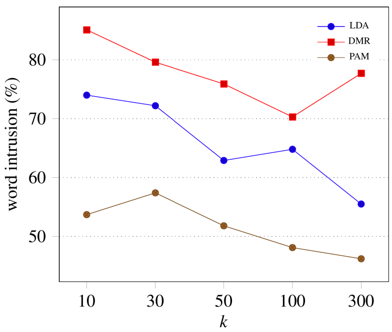

Figure 4. Word intrusion

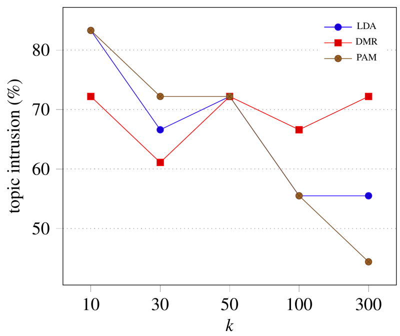

Figure 5. Topic intrusion

Regarding the word intrusion task, it becomes apparent that the previously determined values of coherence are in line with human understanding so DMR generates the most semantically coherent topics. Specifically, the best topics are generated by DMR with k = 10 (cf. fig. 4). The achieved model precision is 85.1% for k = 300. The evaluated minimum precision of DMR is 70.3%. As the results for word intrusion do not show any distinct extremes for different values of k, every model of DMR seems to produce a coherent word-topic distribution. Besides that, LDA also proves to generate the most coherent topics for k = 10 (74.0%). The higher the number of topics to be generated, the more difficult it becomes for the subjects to determine the intruder. This leads to the assumption, that the topics generated by LDA will be increasingly difficult to interpret with a rising number of k, thereby losing their semantic coherence and therefore their meaningfulness. The minimal precision of LDA is recorded for k = 300. Here, only 30 of 54 measurements are classified correctly, resulting in a model precision of 55.5%. There is a clear discrepancy in the quality of topics generated by PAM. The semantically most coherent topics are determined by the model with k = 30. The model precision achieved is 57.4%. The minimum semantic coherence of the topics is with k = 300, with a precision of 46.2%. Thus, it can be concluded that PAM, similar to LDA, has its strength in modelling a smaller number of topics but is clearly inferior to DMR for larger numbers. Besides the evaluation of the topic quality, their decomposition and interrelationships were evaluated. Therefore, topic intrusion tasks were conducted, where the best results were obtained with 83.3% for LDA and PAM with k = 10. Further, it is remarkable, that all techniques achieve the same score with k = 50 (cf. fig. 5), which leads to the conclusion, that all techniques generate consistent topic decompositions for a medium number of topics. The higher the number of topics to be generated, the worse LDA and PAM perform. The worst result is achieved by PAM with k = 300. That decrease of PAM for larger numbers of topics to be generated can be traced back to the formation of the many hierarchical levels, since a high number of k also means that a correspondingly large number of relationships between the different topics must be inferred.

6 Discussion

By evaluating the different techniques, the strengths and weaknesses (cf. tab. 5) of them were identified, that provide information about the applicability of the techniques related to the identified corporate use cases (1) content extraction, (2) trend analysis as well as (3) content structuring settled in marketing.

	Requirements	LDA	DMR	PAM
(1) Content Extraction	(a) Cover all relevant and the most frequent topics embedded in textual social media data	●	●	◗
	(b) Provide a current overview of events and insights about customers' wishes and complaints	●	●	◗
	(c) Support comparisons with competitors and assessments of one's position in the market	●	●	◗
(2) Trend Analysis	(d) Contextualise the extracted topics with additional parameters	○	●	○
	(e) Support a flexible inclusion of different parameters (e.g. authors, locations or time)	○	●	○
	(f) Support quick information provision	●	●	○
	(g) Support quick comprehension of contents	●	●	○
	(h) Support continuous tracking of trends and developments	◗	●	○
(3) Content Structuring	(i) Identify niche topics at a finer level of granularity of the topical structure	○	◗	●
	(j) Identify meaningful relationships and the inter-relatedness of topics	○	○	●
	(k) Cover all aspects that are semantically related to the extracted topics	○	◗	●

Table 5. Results of the comparison ●: applies fully ◗: applies partly ○: applies not

For the first use case – (1) content extraction – the models′ ability to provide an adequate overview of customers' major wishes, ideas, and thoughts to cover all relevant topics embedded in a collection of written social media data was evaluated. Therefore, we applied the metric of log-likelihood, which describes the ability of a model to represent the underlying data as appropriately as possible. This guarantees that the generated output contains all necessary information and that no relevant topics are missing. The standard procedure of LDA as well as that of PAM present their strength compared to DMR in the extraction of topics in the lower range of generated topics. DMR, in contrast, has its strength in the representation of large numbers of topics. This leads to the conclusion that the selection of the best fitting technique depends on the needs to be fulfilled within the extraction task:

- If the content must be very specific, e.g. to support a comparison with competitors and assessments of one's position in the market, a high number of topics is required. So, DMR should be considered.
- If the task requires an extraction on a more abstract level, a low number of topics will mostly be satisfying. If so, the usage of LDA and PAM could be considered. Due to the higher semantic coherence within the topics generated by LDA (cf. tab. 3, tab. 4, fig. 2, fig. 4), the use of LDA is recommended with respect to (1) content extraction for small dimensions.
- The use of PAM is considered as partly applicable, but not recommended, as it is outperformed by LDA and DMR for the criteria being evaluated.

Regarding the second use case (2) trend analysis, the ability of the techniques to generate immediately meaningful and sound output was analysed, which results e.g., in a quick decision supporting information base. This is indispensable regarding the need of time-critical actions within the volatile characteristic of trends. Hereby, DMR shows an advantage leading to the conclusion, that it generates the most reasonable topics (cf. tab. 3, fig. 2). To validate the collected intrinsic evaluation results, the techniques were further evaluated by humans regarding their semantic quality and soundness in an extrinsic way. Here, DMR could be confirmed to generate the most comprehensible output (cf. tab. 4, fig. 4). Further, LDA and PAM show their strength for modelling low numbers of topics as both techniques achieve their best results in the range of 10 (LDA) and 30 (PAM) topics. In addition to direct applicability, the time required for a technique to provide the necessary information was also accounted for. In this respect, LDA provides the fastest output, followed by DMR. The measured discrepancy between these two techniques is negligible for a small number of topics ($k = 10 \triangleq 21$ min.), but the larger the number of topics, the larger the gap ($k = 300 \triangleq 641$ min.). Since the focus of trend analysis is on identifying individual trends and tracking their development, the number of topics will not be that high. Therefore, LDA and DMR are considered capable of reacting to rapidly changing circumstances. PAM, however, requires at least twice as much time for each condition and is therefore not suitable. The strengths and weaknesses of the techniques in the context of (2) trend analysis are represented as follows:

- DMR provides the most reasonable and meaningful topics and is further able to provide them quickly. Additionally, DMR has the advantage of taking external parameters into account. This allows, e.g., tracking the development of topics over a certain period of time or based on geolocation data. Therefore, DMR should be considered regarding (2) trend analysis.
- If the contextualisation of topics does not apply, LDA can also be used for tracking trends and their development, as it can be used to quickly identify meaningful and sound analysis results. Therefore, LDA can be seen as partly applicable regarding trend analysis.
- PAM is not suitable due to the amount of time required and the lack of ability to contextualise topics.

Regarding the last identified use case – (3) content structuring - the ability of the techniques to reveal meaningful relationships and the inter-relatedness of topics was evaluated. Therefore, the extrinsic evaluation metric of topic intrusion was applied. By doing so, it could be guaranteed that all semantically related aspects were extracted. Here, PAM shows a slightly better result than the two remaining techniques for a small number of topics to be generated (cf. tab. 4, fig. 5). Further, DMR underlined its strength in the representation of a high number of topics. A large advantage of using PAM is represented by its ability to model hierarchical structures within the topics themselves. Thus, it is possible to extract general topics as well as their respective subtopics, whereby the topics can be divided into different, thematically consistent groupings that can support the identification of niche topics at a finer level of granularity. The elicited strengths and weaknesses of the techniques are listed in the following:

- As the best evaluation results regarding the topic intrusion task were achieved by PAM, we recommend this technique as an approach to support (3) content structuring.
- Besides that, DMR can also be applied if the number of topics to be generated reaches a comparatively high number. Thus, the applicability is considered partial.
- Since LDA is surpassed by the two techniques here, the application is not considered suitable.

In summary, all the investigated techniques have different strengths and weaknesses in their applicability to the identified use cases. Nevertheless, LDA showed its strength in modelling low-dimensional topics. In comparison, DMR showed to be superior in representing high-dimensional topics. Regarding trend analysis, DMR showed its strength within the generation of semantically meaningful results. For content structuring tasks, PAM showed superior results in extracting meaningful relationships compared to LDA and DMR.

7 Conclusion and Outlook

Analysing written social media data with automated techniques has massively gained in importance as being aware of customers' wishes is no longer sustainable with manual analysis due to the sheer volume of available posts. Topic modelling has shown to be an adequate instrument to support these tasks by extracting the topics discussed within documents (e.g. Eickhoff and Neuss, 2017, Vayansky and Kumar, 2020). However, it can be observed that especially LDA has been given particular attention for marketing-specific applications. Furthermore, since LDA cannot cover all fields of the identified use cases, marketing tasks may only be supported to a limited extent by automated approaches.

Within this work, the use cases (1) - (3) were identified from the literature due to the frequency that the identified papers related to them. For each of these use cases, corresponding requirements were identified and assigned to different metrics (log-likelihood, coherence, build time, word and topic intrusion) for evaluating these topic modelling techniques (cf. **RQ1**). Thus, LDA, DMR and PAM were applied to a real-world data set, evaluated and compared with each other. Thereafter, this work gives recommendations regarding which topic modelling technique could be applied for which use case (cf. **RQ2**).

Through our comparison of topic modelling techniques, practitioners are given means to select a technique that can best support their daily business activities. Decision makers in marketing can classify their concrete task into one of the three identified use cases and derive a recommendation for a suitable technique. Tasks in marketing, which can be enriched by topic modelling, can thus be supported more optimally and thus the performance of this division, which is so important for companies, can be increased. Beyond creating value for practitioners, theoretical contributions in the research area of IS are also provided. First, based on the use cases we derived several requirements for topic modelling techniques and assigned several evaluation criteria to each of them. Second, in order to provide recommendations, we compared LDA, DMR, and PAM with each other regarding five different evaluation metrics by analysing a real-world data set. This comparison is based on the GQM approach and assures therefore a systematic research procedure in which reproducible results are achieved. Based on this comparison potentials for further enhancements (e.g. considering a faster build time for PAM when $k > 50$) could be evolved. Third, we further deduced strengths (such as DMR should be considered regarding trend analysis, cf. section 6) and weaknesses (such as PAM is not suitable for trend analysis due to the amount of time required and the lack of ability to contextualise topics) of the three topic modelling techniques which is valuable for both researchers and practitioners.

There are some limitations to this study: first, the number of papers we incorporated in identifying use cases and related requirements for topic modelling within marketing is limited. Nevertheless, these requirements enabled the central metrics of topic modelling techniques to be assigned and generally valid recommendations for appropriate procedures to be derived. Second, the number of topic modelling techniques being compared is limited to three. Although the extensions proposed by Liu et al. (2016) could thus be covered to a large extent, we plan to include further techniques in future analysis for each extension and thereby further refine our recommendations.

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2.5 Beitrag 5: MANTRA – A Topic Modeling-Based Tool to Support Trend Analysis on Social Media

Adressierte Forschungsfrage	**Forschungsfrage 7:** Wie sieht ein Trendanalyse Tool aus, das Anforderungen der marketingbezogenen Anwendungsfälle (a) Produktentwicklung (b) Kundenverhaltensanalyse und (c) Markt-/Markenbeobachtung umsetzt und welche Beiträge für Wissenschaft und Praxis lassen sich dabei ableiten?
Zielsetzungen	• Identifikation von Anforderungen an ein Trend Analyse Tool basierend auf Topic Modelling hinsichtlich der drei Anwendungsgebiete (a-c) • Entwicklung eines Softwaretools, das alle drei Anwendungsgebiete und deren Anforderungen durch die Kombination von verschiedenen Social Media Analyse Methoden abbilden kann
Forschungsmethode	**Design Science Research** • Design Science Process nach Peffers et al. (2007), der basierend auf der Problem- und Lösungsidentifikation u.a. die Schritte Entwicklung, Demonstration und Evaluation des Trend Analyse Tools als Artefakt beinhaltet • Anlehnung der Forschung an Hevner et al. (2004) durch den Design Cycle (Demonstration und Evaluation des Artefakts), Relevance Cycle (Beitrag zur Praxis) und Rigor Cycle (Beitrag zur Kernel Theorie und (Nascent) Design Theorie)
Kernergebnisse (Überblick)	• Ableitung von Design Requirements aus der Literatur zur strukturierten Entwicklung des Artefakts • Entwicklung und Validierung von sechs Design Prinzipien für ein Trend Analyse Tool • Durch Trend Analyse Tool basierend auf Topic Modelling: Identifikation von Trendthemen sowie Darstellung des Verlaufs im Hinblick auf Sentiment • Vergleich der beiden Trends „Vegane Cuisine“ und „Global Cuisine“ über den Zeitverlauf inkl. Unterscheidung von Sentiment und Geolokationen (Massachusetts, Texas und Oregon) • Sentimentanalyse: Aufzeigen von möglichen Verbesserungen eines Produkts • Einbeziehen von externen Parametern, wie z.B. Geolokationen liefert tiefere Einblicke in VoC
Publikationsort	Proceedings of the Forty-Third International Conference on Information Systems, Copenhagen 2022 (Under Review)
Ranking VHB JQ 3	A
Autor:innen und Anteile	Janik Wörner 30% **Isabel Schmid 30%** Daniel Konadl 30% Susanne Leist 10%

Tabelle 6: Fact Sheet Beitrag 5

MANTRA – A Topic Modeling-Based Tool to Support Trend Analysis on Social Media

Abstract. *The early identification of new and auspicious ideas and trends leads to competitive advantages for companies. Thereby, topic modeling is effective for the automated investigation of trends within social media. However, existing topic modeling-based trend analysis tools do not meet the requirements regarding the common use cases (a) Product Development, (b) Customer Behavior Analysis and (c) Market-/Brand-Monitoring reflected by the extant research literature. Therefore, based on these requirements for each of the use cases (a)-(c), we derived design principles following the design science research and instantiated an artefact called "MANTRA" (MArketiNg TRend Analysis). Subsequently, we demonstrated MANTRA on a real-world social media data set (~1.03 million Yelp reviews). Hereby, remarkable trends regarding vegan and global cuisine can be confirmed. In particular, the importance of meeting all specific requirements of the respective use cases and especially to flexibly incorporate external parameters into the trend analysis is exemplified.*

Keywords: Topic Modeling-Based Tool, Design Science, Social Media Analysis, Trend Analysis, Marketing

1 Introduction

Social media such as Facebook, Twitter and online communities have become increasingly important for communication and interaction in both private and business contexts (Kaplan and Haenlein 2010; Kim et al. 2018). As social media is a channel for the exchange of user-generated content and unfiltered voices about companies as well as products and services, it contains the so-called "Voice of the Customer" (VoC). VoC provides companies deep and valuable insights into the customers' current behaviors and expectations. To monitor how opinions regarding their products, services and competing brands evolve, marketing departments conduct trend analysis. Tracking customers' evolving and changing expectations is thereby essential so that companies are able to meet their customers' wishes and expectations (Hong et al. 2012; Lozano et al. 2017). Thus, the early identification of new and auspicious ideas and trends regarding the development of products and services, the analysis of customers' behaviors and the monitoring of markets and competing brands leads to competitive advantages for companies (Bhor et al. 2018; Jeong et al. 2019).

However, assessing people's opinions about a particular event and its future impact is especially difficult given the tremendous amount of social media data (Oghaz et al. 2020; Wörner et al. 2021). Applications that track trends usually apply a keyword-based approach and result in outcomes in form of distributions and frequencies of simple terms or hashtags (Lau et al. 2012). But this is insufficient as new trends which are not stored in existing keyword lists cannot be found thereby. Moreover, the trends that can be identified in this way are limited to these previously known keywords. Trends that are semantically related to the applied keywords remain undiscovered. To solve this problem, automated topic discovery and – in particular – topic modeling, have been widely investigated as they are capable of extracting these embedded topics from large amounts of texts (Chinnov et al. 2015; Eickhoff and Neuss 2017; Hong and Davison 2010). Therefore, it has facilitated addressing marketing-related questions and problems that have exceeded the feasibility of in-depth qualitative analyses (Eickhoff and Neuss 2017).

Nonetheless, most approaches require advanced technique-related knowledge, thus people who are not familiar with topic modeling cannot take advantage of this automated content analysis. Additionally, as a large number of topic modeling techniques are often only described in theory, they lack ready-to-use implementations and are therefore not applicable (Wörner et al. 2021). This has already been recognized in practice and science, having led to the emergence of topic modeling and trend analysis tools. Anyways, these existing tools show many drawbacks as they do not cover the comprehensive requirements deemed crucial for trend analysis for different marketing-related use cases. Thus, these tools lead to a superficial identification of trends, making deeper insights unfeasible.

With this work at hand, we address these problems. We suggest the design of a trend analysis tool by means of design principles (DPs) that describe what such an artefact should enable users to do and how the artefact should be built in order to do so (Chandra et al. 2015). Further, we show a concrete instantiation of an artefact for automated trend analysis regarding the common and distinctive marketing-related use cases (a) Product Development, (b) Customer Behavior Analysis and (c) Market-/Brand-Monitoring. Thereby, we want to focus especially on the combination of different data analysis techniques regarding the particular design requirements (DRs) of the use cases, which leads to the trend analysis being constructive. Thus, this paper seeks to answer the following research questions:

- **RQ1:** Which DRs should a trend analysis tool meet that supports the marketing-related use cases (a) Product Development, (b) Customer Behavior Analysis and (c) Market-/Brand-Monitoring?

- **RQ2:** How can such a trend analysis tool be designed and implemented and which contributions (practice, IS-theory) can be derived?

With this research, we seek to identify several DRs that are relevant for a topic modeling-based trend analysis tool. Through the design and implementation of this tool (by establishing and realizing several DPs) we aim to offer a solution to identify and analyze trends regarding (a)-(c). Hereby, we combine different social media analysis techniques to meet the particular DRs. The remainder of this paper is structured as follows: the following section provides the conceptual basics and related work. Subsequently, the research procedure, following the Design Science (DS) approach (Hevner et al. 2004; Peffers et al. 2007), is described. The next section deals with the compilation of the DPs that we derived from DRs. Then we report on the technical realization of the tool. Subsequently, we show the application of the tool on about (~) 1.03 million online customer reviews (OCRs) and present the resulting out-comes. The paper concludes with a discussion and conclusion.

2 Conceptional Basics and Related Work

2.1 Conceptual Basics

Companies use social media such as social networks (e.g., Twitter) or content communities (e.g., Yelp) to enable communication mainly with external stakeholders (Kietzmann et al. 2011). In this way, social media serves as an important interface between companies and customers. In content communities, users can evaluate e.g., companies' products and services, by disseminating their opinions in terms of OCRs. These OCRs do not only support customers to make the right decision, but they can also be beneficial for companies (Hösel et al. 2019) as they include customers' experiences and expectations of products, services, or a company in general (Hicks et al. 2012; Sigala 2012). Therefore, by analyzing OCRs, companies are able to identify customers' opinions, unfiltered and in real-time (Yan et al. 2014). Keeping track of the evolution of these opinions is central for trend analysis. Thereby, marketing departments can enhance the effectiveness of brand message placement and the allocation of appropriate resources to marketing campaigns depending on geographical and temporal developments (Hong et al. 2012; Lozano et al. 2017). Furthermore, linking topics and contents to groups of interested parties and customers enables companies to adapt brand messages to meet the respective target groups' expectations and attitudes (Zhang et al. 2016). To reveal these topics and contents, marketing representatives can apply topic modeling. Topic modeling refers to the use of generative probability models for deter-mining latent relationships within a corpus of text data. Hereby, Latent Dirichlet Allocation (LDA) (cf. Blei et al. 2003) can be considered as one of the most fundamental techniques in this research area as it is frequently applied to identify important issues to adapt marketing campaigns or to identify currently discussed product and service features within social media (Jeong et al. 2019; Xu and Xiong 2020).

2.2 Use Cases and Design Requirements of Topic Modeling-Based Trend Analysis

We have searched and consolidated the extant literature to identify distinctive marketing-related use cases of topic modeling-based trend analysis for textual social media posts. Based on attention and im-portance received within literature, in particular three main use cases could be identified: (a) Product Development (cf. Bae et al. 2018; Irawan et al. 2020; Jeong et al. 2019; Tucker and Harrison 2011), (b) Customer Behavior Analysis (cf. Bhor et al. 2018; Chen et al. 2012; Tang and Yang 2012; Zhang et al. 2016) and (c) Market-/Brand-Monitoring (cf. Endo et al. 2015; Lozano et al. 2017; Qu et al. 2015; Zhao et al. 2019).

By applying topic modeling for (a) Product Development, marketing representatives can develop an understanding of how customers perceive their products, services and corresponding features. As an example, the topics identified from OCRs may indicate existing shortcomings regarding the packaging of the product (e.g., ecologically unfriendly packaging). Harnessing these OCRs may bring up the idea of replacing the plastic packaging with paper packaging so that customers' expectations regarding the packaging are subsequently met (cf. Park et al. 2020). As the prevailing literature shows for use case (a), customers' product and service expectations can differ across geographical markets. To be successful and competitive in a targeted market, marketing representatives need to know which features should be designed in which way to meet the local customers' expectations. Therefore, topic modeling requires enabling (DR1) the incorporation of geolocation data as an external parameter (Bae et al. 2018; Endo et al. 2015; Ha et al. 2017) that matches the generated topics with the corresponding geographical locations. Furthermore, customers' self-reported opinions of products and services play an important role. Marketing representatives aim at retaining features evoking positive customer perceptions, while features evoking negative sentiments need to be improved to meet customers' expectations. Therefore, a trend analysis tool needs to (DR2) incorporate the sentiment of social media posts (Irawan et al. 2020; Jeong et al. 2019). Thereby, numerous opportunities for improving products and services can be deter-mined, and certain features are given greater importance than others. With this in mind, it is not feasible to address all the identified issues because of limited resources in marketing departments. Thus, it is necessary to additionally support marketing representatives with means (DR3) to assess the product and service topics' favorability. Accordingly, it is imperative for a trend analysis tool to support marketing representatives in (DR4) linking anticipated customer preferences with new features (Axtell et al. 2000; Jeong et al. 2019; Tucker and Kim 2011; Ye and Kankanhalli 2018). In line with that, e.g.

Production Theory and Innovation Theory can serve as foundations here. Thereby, Innovation Theory proposes how to develop new (i.e., disruptive innovation) or improve existing products (i.e., incremental innovation) (Axtell et al. 2000; Ye and Kankanhalli 2018) by following, e.g., the stage-gate model (Cooper 1996).

In contrast to (a), the focus in (b) Customer Behavior Analysis is laid on the authors of the social media posts. Marketing representatives responsible for customer targeting must know how customer behaviors and associated trends differ for certain customer characteristics like age or gender (Bhor et al. 2018; Chen et al. 2012; Tang and Yang 2012). With this in mind, Customer Behavior Analysis can for example reveal that older people perceive comfort as an essential property. To increase favorability among the older customers, the company needs to communicate their superiority regarding comfort to this target group (cf. Duncan and Moriarty 1998). For certain customer characteristics, there are different customer behaviors. For example, particular needs for online shopping platforms distinguish be-tween males (e.g., accurate description of products) and females (e.g., fair pricing) (cf. Ulbrich et al. 2011). In this vein, Customer Focus Theory, can be applied as it proposes companies to increase their customer focus by aligning their actions to customers' needs, characteristics and identities (cf. Gulati and Oldroyd 2005). To establish these topic-person connections, topic modeling needs to (DR5) include user-related information and customer characteristics as external parameters. Based on this, marketers can tailor marketing messages with offers that individual customer groups appreciate most. As (b) is about analyzing customer behavior, (DR6) a functionality to filter posts is essential so that company posts can be excluded from the generation of customer-related topics (Saha and Sindhwani 2012). Further, fast execution times (DR7) are particularly important for topic modeling applied to Customer Behavior Analysis. This is because customer perceptions can change rapidly (Bhor et al. 2018; Sasaki et al. 2014) and, while identified concerns about products or services require a certain time for refactoring, customers can be rapidly contacted and appeased.

The third use case (c) Market-/Brand-Monitoring is about investigating how brands and companies act and which strategies they deploy. Therefore, (c) is concerned with the companies and brands in-stead of (a), their products and services. Applying trend analysis to social media posts of competitors can for example reveal that competing brands include reporting about their sustainable acting within public communications. Use case (c) captures dynamic courses of topics and incorporates geolocation data as an external parameter. To support decisions on the market-/brand level (e.g., planning a communication strategy or market positioning), the topics must be generated for the respective companies or brands. Thus, beyond generating topics according to geographical markets (DR8), the topic modeling technique must be capable of incorporating brands (e.g., Endo et al. 2015; Lozano et al. 2017; Qu et al. 2015). By doing so, marketers can gain insights on how brands performed and which perceptions they have raised in social media. Consequently, a company may e.g., adapt its own market strategy to focus on certain niche markets that other brands have paid little attention to. Brand Communication Theory is thereby applied as it points out the necessity that companies need to assess the way in which competitors shape their public communications (Lozano et al. 2017). Therefore, corresponding tools (DR9) need to support the identification of competitors and how they place themselves within respective markets (Lozano et al. 2017; Tirunillai and Tellis 2014; Zhao et al. 2019). Beyond this, marketers need not only support in identifying emerging competitors but also in understanding the behaviors (e.g., communication patterns or discount strategies) of current competitors. To enable this explorative analysis, (DR10) filter criteria like time periods, geolocations and brands should be applicable to narrow down the data set (Valdez et al. 2018; Zhao et al. 2019).

Beyond these use case specific DRs, we have as well identified DRs that apply to (a)-(c). One theory that poses implications for all three use cases as it turns to the properties to be considered when conducting trend analysis on social media data is the Social Media Theory (cf. Stieglitz et al. 2014). Therefore, when applying techniques from the fields of computer science and statistics for trend analysis, one necessity for a trend analysis tool is (DR11) dealing with a huge number of social media posts (e.g., Lozano et al. 2017; Jeong et al. 2019; Stieglitz et al. 2014). Furthermore, it is essential to provide opportunities to include (DR12) historical data so that past developments of trends can be considered when assessing the current state of a trending topic (e.g., Bhor et al. 2018; Lozano et al. 2017). Because trends constitute dynamic developments and not solely static points in time, the applied topic modeling technique needs to integrate temporal parameters into the topic model generation (e.g., Naveed et al. 2011; Sohn et al. 2019; Qu et al. 2015). Marketing representatives require (DR13) support in assessing the course of topics over time and in identifying emerging and declining trends (e.g., Lau et al. 2012; Zhong and Schweidel 2020). In general, applying the results of topic modeling requires advanced technique-related knowledge. Thus, (DR14) the results need to be visualized (e.g., by charts and plots) so that marketing representatives are supported in making sense of the derived topics (Bae et al. 2018; Ha et al. 2017).

Use Cases	Design Requirements	Sources
(a) Product Development	**(DR1)** Incorporation of geolocation data as external parameters	Bae et al. 2018; Endo et al. 2015; Ha et al. 2017
	(DR2) Consideration of sentiment	Irawan et al. 2020; Jeong et al. 2019
	(DR3) Providing means to assess the importance of a product or service feature	Jeong et al. 2019; Tucker and Kim 2011
	(DR4) Linking of newly discovered preferences with new features	Axtell et al. 2000; Jeong et al. 2019; Tucker and Kim 2011; Ye and Kankanhalli 2018
(b) Customer Behavior Analysis	**(DR5)** Incorporation of different customer characteristics as external parameters	Bhor et al. 2018; Chen et al. 2012; Hidayatullah et al. 2019; Naveed et al. 2011; Qu et al. 2015; Shi et al. 2018; Tang and Yang 2012
	(DR6) Provide means to filter out social media posts being posted by the company itself	Saha and Sindhwani 2012
	(DR7) Provide a fast execution time	Bhor et al. 2018; Sasaki et al. 2014
(c) Market-/ Brand-Monitoring	**(DR8)** Incorporation of different brands and geolocation data as external parameters	Endo et al. 2015; Gulati and Oldroyd 2005; Lozano et al. 2017; Qu et al. 2015; Zhao et al. 2019
	(DR9) Identify differences in the way enterprises communicate and how they place themselves in markets	Tirunillai and Tellis 2014; Valdez et al. 2018; Zhao et al. 2019
	(DR10) Be able to apply time periods, geolocations, and brands as filter criteria	Valdez et al. 2018; Zhao et al. 2019
Use Case Independent Design Requirements	**(DR11)** Dealing with large numbers of social media posts	Jeong et al. 2019; Lozano et al. 2017; Luo et al. 2015; Stieglitz et al. 2014; Yan et al. 2015
	(DR12) Capability of analyzing historical data	Bhor et al. 2018; Ha et al. 2017; Hidayatullah et al. 2019; Lau et al. 2012; Lozano et al. 2017; Sohn et al. 2019; Zhong and Schweidel 2020
	(DR13) Identification of trends over time (topic evolution)	Ha et al. 2017; Lau et al. 2012; Lozano et al. 2017; Luo et al. 2015; Naveed et al. 2011; Tang and Yang 2012; Tucker and Kim 2011; Zhang et al. 2015; Zhong and Schweidel 2020
	(DR14) Visualization of the results	Bae et al. 2018; Ha et al. 2017; Yang et al. 2017

Table 1. Identified Use Cases and Corresponding Design Requirements

2.3 Assessment of available Tools for Trend Analysis on Social Media

To identify the shortcomings of available tools in the context of trend analysis for social media posts, we have identified in a first step providers of corresponding tools. For that purpose, the “Google” search engine and the most popular “social media analytics tools” groups within social networks (i.a., LinkedIn) were drawn upon. In this way, we could take an up-close look at the most popular tools (e.g., Brandwatch, Hootsuite, Sprout Social). Based on the DRs that we derived from literature (see Table 1) a questionnaire was designed to assess to which degree current trend analysis tools cover the posed DRs. In the next step, this questionnaire was then validated by the involved researchers and subsequently applied within the data collection, either asynchronously when the tool providers filled in the questionnaires on themselves and sent it back via e-mail, or otherwise synchronously via online chats with sales representatives of the tool providers. In addition, we have also investigated demo versions of these trend analysis tools. Thereby, the questionnaire served as an evaluation basis for assessing the tools regarding the posed DRs. In this way, we could ensure consistency and comparability of our observations across the diverse tools involved.

As could be confirmed, there is a lack of a software tool that meets all the specific DRs of the identified marketing-related trend analysis use cases (a)-(c). There are analysis tools, that determine trends based on the number certain keywords appear within social media posts. However, these social listening tools (e.g., Brandwatch or Sprout Social) do not consider co-occurrences between terms or the se-mantic relatedness of terms as topic modeling techniques do. There are also trend analysis tools available that provide topic modeling (e.g., MineMyText or Synthesio). However, none of the available topic modeling-based tools integrates all three common marketing-related use cases (a)-(c). In particular, the available tools lack to flexibly integrate different external parameters (see Figure 1).

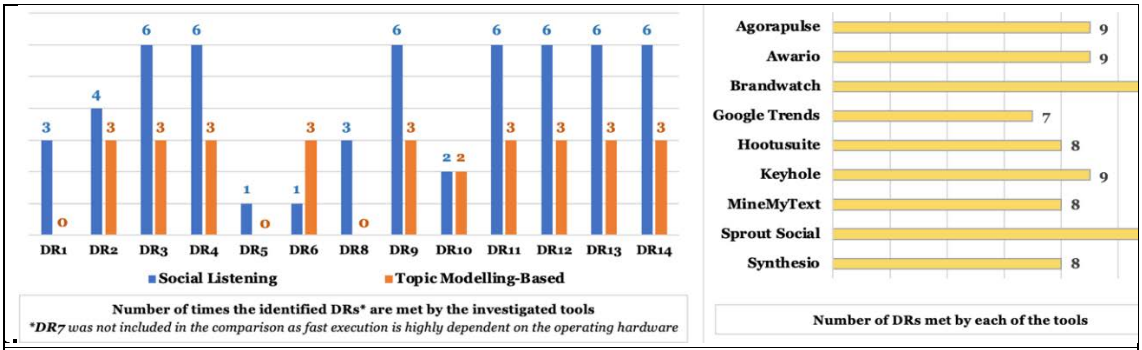

Figure 1. Results of the Tool Assessment

Nevertheless, the use cases (a)-(c) explicitly demand different contextualizations. Perceptions of products and services do differ across continents and countries because of locally differing customer expectations. Customer behaviors do differ for certain customer characteristics (e.g., age or gender). Without the ability to flexibly integrate different external parameters (time, geolocations and user-related in-formation), a topic modeling-based trend analysis tool does not optimally support the use cases (a)-(c). However, literature unveils the need for such a comprehensive topic modeling-based tool that supports all three use cases.

3 Research Procedure

To accomplish the development of a systematic approach for the automated trend analysis in marketing, we applied Design Science (DS) research. 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 designing an IT-artefact to address an organizational problem (see Figure 2) (Cleven et al. 2009; von Alan 2004).

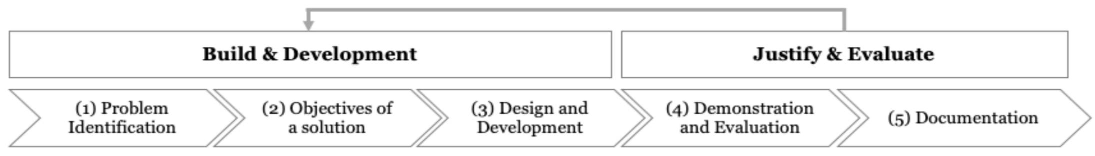

Figure 2. Procedure of the Research (own representation based on Peffers et al. (2007))

As a first step, (1) corresponding problems and drawbacks of already existing approaches regarding trend analysis in marketing-related use cases were identified (see section “Introduction” and Figure 1). Hence, approaches that deal with trend analysis are neither based on topic modeling nor do they meet the requirements that are indispensable to the successful application of trend analysis. Consequently, our (2) objective is to provide and combine a set of techniques, based on the DRs, to facilitate trend analysis regarding marketing-related use cases based on topic modeling (see section “Introduction”). The third step of our DS process contains the (3) design and development (see section “Design and Development of the Artefact”) of a solution or an artefact. In order to fill the gaps identified within step (1), we focus on the design of the technical realization of the tool by establishing DPs and combining different machine learning techniques. Thus, our approach was established to support and simplify the trend analysis and to eliminate the existing disadvantages. In the next step, the (4) demonstration and evaluation of our artefact (see section “Demonstration and Evaluation of MANTRA”), we show the application of the demonstrated approach on ~1.03 million Yelp OCRs. Thus, we showed the instantiation of the DRs identified in literature. However, evaluating emerging trends in general is out of scope here as a large-scale survey with interviews about upcoming trends would be necessary. Furthermore, a SUMI study (cf. Kirakowski et al. 1993) to assess the usability of the tool will be conducted later on. Nevertheless, we confirm our results by two trend reports. Finally, we (5) documented and communicated our results.

With this procedure we align our research also with the guidelines of Hevner et al. (2004) or Hevner (2007), respectively. According to the design cycle, we present our artefact as the result that has gone through the process of demonstration (application to a Yelp data set) and evaluation by a survey by a panel of experts from the National Restaurant Association Board (NRAB) (see section “Demonstration and Evaluation of MANTRA”). In view of the relevance cycle, we identified several DRs from research literature and theory (see Table 1) that guided the design of the artefact, and so the practical application of our artefact brought up several contributions for practice (e.g. trend analysis of social media content for marketing representatives (see section “Disussion and Contributions of the Results”)). In view of the rigor cycle, we used several techniques to rigorously construct and evaluate our artefact (e.g. topic modeling, sentiment analysis). In this way, we derived initial findings as contributions to theory, both kernel theory (e.g., Innovation-, Social Media Theory) and design theory. Thus to contribute to a rather general and abstract knowledge base – “Nascent design theory” (Gregor and Hevner 2013) – and in or-der to design a purposeful artefact in a comprehensible way, we first deduced both, a set of meta-requirements (MRs) and DRs (Gregor and Jones 2007; Heinrich and Schwabe 2014) for a trend analysis tool grounded in seminal works, resulting in the DPs. In a next step, we then describe our prototypical implementation that demonstrates the feasibility of the DPs and MRs in the tool.

4 Design and Development of the Artefact

4.1 Design Principles for a Trend Analysis Tool

First, the composition of MRs that describe “what the system is for” (Gregor and Jones 2007, p. 325) is based on the purpose and scope of the trend analysis tool that has been discussed in the introduction. Thus, we define the solution objectives based on the investigations’ problems our paper addresses. These MRs established to be suitable for a class of artefacts and are based on the current research literature (Gregor and Jones 2007; Heinrich and Schwabe 2014; Walls et al. 1992). Besides that, DPs are synthesized in a next step. DPs are defined as prescriptive statements that show how to do something to achieve a goal (Gregor et al. 2020). The DPs that we dispose fall into the category of action and materiality-oriented DPs that describe what an artefact should enable users to do and how the artefact should be built in order to do so (Chandra et al. 2015). For companies (=users) who are interested in conducting trend analysis (=boundary conditions) and keeping our DRs for our artefact in mind, we derive six DPs for trend analysis tools:

- **DP1:** The principle of finding trends autonomously. To track customers’ evolving and changing requirements in social media it is necessary to retrace the evolution of topics and identify therefore trends over time. Thus, the tool should be able to find trending topics in large amounts of social media data autonomously, so users do not need to have any prior knowledge about the trends.
- **DP2:** The principle of contextual adaptability. Since external parameters (e.g., geolocations or customer characteristics) directly influence how a trend is pronounced these must be included in the trend analysis tool. Therefore, it should provide the possibility to incorporate external parameters as well as filters, so the users can tailor the trend identification to their peculiarities.
- **DP3:** The principle of incorporating sentiment. To meet customers’ expectations, it is necessary to identify features evoking positive customer perceptions to retain them as well as features evoking negative customer perceptions to be improved. Therefore, the tool should be able to assign polarities to the individual trends and differ them over time and per use case specific external parameter to show the evolution of the corresponding trend.
- **DP4:** The principle of comparison. To be competitive in the future, a comparison is necessary that identifies the extent to which the existing products meet customer expectations (in-ternal comparison) on the one hand and allows a comparison with competitors (external comparison) on the other hand. Thus, the tool should possess a functionality to provide the retrieved analysis results to enable users conducting internal and external comparisons.
- **DP5:** The principle of visualization. To obtain added value from the results and to benefit from the derived trends, they must be refined approachable. Thus, the tool should be able to visualize the trends and sentiment values so that users are aided in interpreting the derived results.
- **DP6:** The principle of repeatability. As a trend is a short-term construct, which means that it can change over time, the identification process should be executable

often and in a resource-saving way. Therefore, the tool should allow repetition at any time (including both historical and current data) to react quickly to changing circumstances.

These DPs are deduced from the DRs that are further based on current research literature. Gregor and Jones (2007) state that this reference to theory and literature disclose “an explanation of why an artifact is constructed as it is and why it works” (p.328). Hence, based on the discussion of related work, we derive DRs our tool should meet. These DRs offer guidance by designing the artefact and advise the DPs (Böckle et al. 2021; Gregor and Jones 2007). These DPs refer to at least one DR and serve as an abstract “blueprint” of our artefact (Böckle et al. 2021; Gregor and Jones 2007). By establishing these DPs, we made sure that they follow the value grounding (reference to the DRs) and the explanatory grounding (DPs are based on current literature and kernel theories) (Heinrich and Schwabe 2014). Further, following Gregor and Jones (2007) we have also defined Implementation Principles (IPs) to support “the implementation in practice of an abstract, generic design method or development approach” (Gregor and Jones, 2007, p.329).

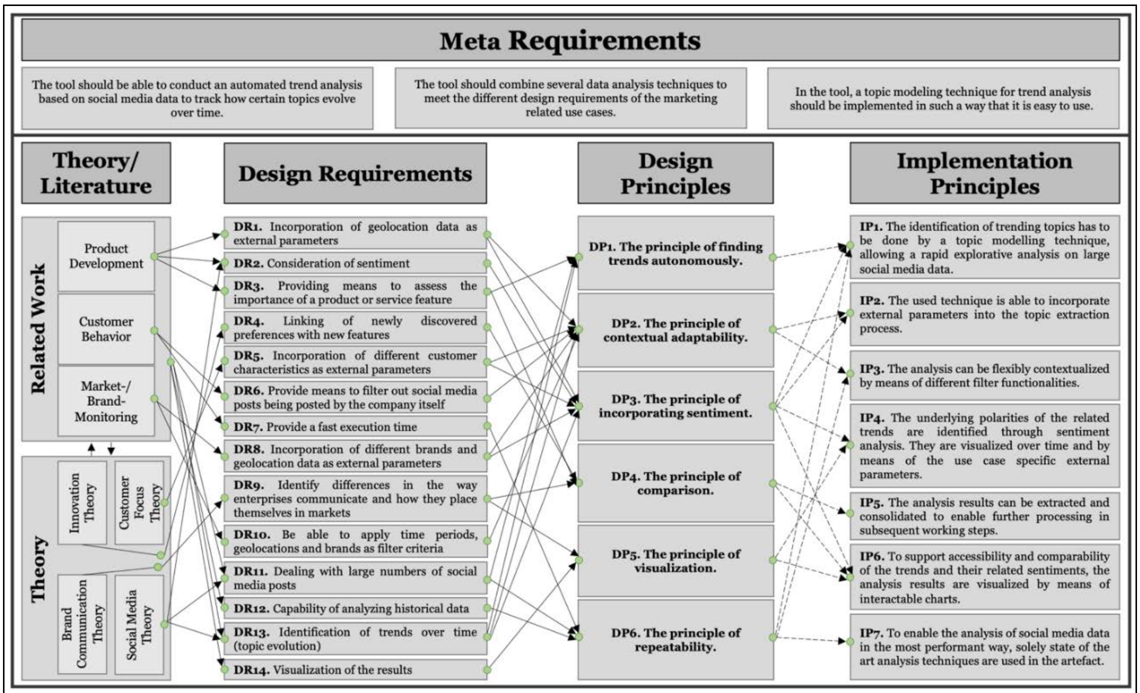

Figure 3. Design of a Trend Analysis Tool on Social Media Data

4.2 Technical Realization

To address the shortcomings of the prevailing research, we have designed and developed an artefact called MANTRA (MArketiNg TRend Analysis) in Python. To disclose the technical realization of MAN-TRA, the selection of the topic modelling technique used will be explicitly highlighted initially as it builds the foundation of MANTRA. Subsequently, the instantiation of the DRs will be described as they depict the required features in the most detailed way. Since the derived DPs and IPs depicting a generic and prescriptive statement of how something should be done, they capture design-related knowledge and can therefore support the development of further IS (design) theories and new artefacts focusing trend analysis. To reveal the association of the derived DPs/IPs to the respective DRs, their relation will be pointed out as well.

Regarding the autonomously identification of trends (DP1), the selection of the topic modeling techniques to be used is critical to success. As trends are time-dependent constructs, a rapid and explorative analysis must be provided. With this respect, unsupervised topic modeling techniques (e.g., LDA) are conceivable to enable an explorative analysis. However, in view of DP2 (the principle of contextual adaptability), the incorporation of external parameters (DR1, DR5, DR8) is not feasible using unsupervised techniques such as LDA. In addition, as stated by Chang et al. (2009) the potential of unsupervised techniques is stymied by their purely unsupervised nature, which often leads to topics that are neither entirely meaningful nor effective at extrinsic tasks such as conducting a marketing campaign. To counteract this weakness, semi-supervised topic modeling techniques have arisen, retaining the flexibility of unsupervised techniques while facilitating an effective way to incorporate external parameters to learn topics of interests specific to a user (Jagarlamudi et al. 2012). Thus, using semi-supervised techniques, the possibility to identify trends in an autonomous and performant way while maintaining the possibility to incorporate external parameters such as geolocation information (DR1, DR8), brands or products (DR8) and user-related external information (DR5) is enabled. Concerning the implementation of a semi-supervised topic modeling technique within MANTRA, GuidedLDA is applied as it achieves convincing analysis results (Jagarlamudi et al. 2012). With GuidedLDA, the topics can be con-textualized through seed words, biasing the generated topics into the respective semantic direction. By choosing seed words such as a specific product/brand name or words related to an area such as the global food industry, the topics will converge to gravitate into the contextual direction of those seed words. The degree of biasing within the topic generation is defined by the seed confidence $[0 \leq x \leq 1]$, where a value close to 0(1) evokes a weak(strong) consideration of the respective seeds.

Furthermore, in view of use case (a) Product Development, the identification of trends and their matching with corresponding geolocations is required. Besides the incorporation of geolocation information through respective seed words, we therefore enabled MANTRA to pre-define different geolocations by applying a filter function, gaining maximum flexibility regarding the incorporation of external geolocation information (DR1, DP2, IP3). The use case (a) stipulates further the inclusion of sentiments within the analysis to determine the positive or negative tonality of the OCRs (DR2, DP3, IP4). Therefore, we implemented the "Valene Aware Dictionary for sEntiment Reasoning" (VADER) (Hutto and Gilbert 2014) technique. VADER is a lexicon and rule-based sentiment analysis technique that is specifically attuned to sentiments expressed in social media and has achieved remarkable results (Hut-to and Gilbert 2014). VADER is able to extract positive, neutral and negative inflections within the range of -1 to +1. Additionally, the importance of a respective product or service feature has to be taken into account (DR3, DP1, IP1). As probabilistic topic modeling techniques such as GuidedLDA infer their resulting topics based on various probabilistic distributions, depicting the relevance of the under-lying topic words and thus the resulting topics (Crain et al. 2012), the assessment of the importance of the specific topic is met through the nature of topic modeling itself. Moreover, the linking of newly dis-covered preferences with new features (DR4, DP4, IP5) is compulsory regarding (a). To develop an artefact that is suitable for various applications in marketing, including the processing of heterogeneous datasets, an automated linking of newly discovered preferences will not be feasible. Nevertheless, to take DR4 into account, a function was implemented to extract the respective results using a Microsoft-Excel file. With this, the results are consolidated and condensed and thus can be used to manually map the identified preferences with new product or service features. The second use case (b) Customer Behavior Analysis deals i.a., with identifying behavior changes regarding different kinds of customers. Besides the consideration of customer-related information by biasing the generated topics through defining meaningful seed words, users can pre-define customer groups based on a dynamic set of at-tributes such as gender or age (DR5, DP2, IP2). In this way, maximum flexibility when analyzing trends based on external customer information is provided. Additionally, it is necessary to filter out posts created by the company itself to inhibit a bias in the analysis results (DR6, DP2, IP3). Thus, MANTRA provides the possibility to dynamically define an identifier that is used to filter out associated data entries. DR7 (DP6, IP7) reflects a fast execution time when analyzing data with respect to customer behavior. Here, MANTRA implements multi-threading, resulting in parallel processing of independent tasks. Besides the incorporation of different brands and geolocation data through respective seed words (DR8, DP2, IP2), the third use case (c) Market-/Brand-Monitoring requires to identify differences in the way companies communicate and place themselves within markets (DR9, DP4, IP6) by applying diverse filter criteria such as time periods, geolocations or specific brands (DR10, DP2, IP3). Therefore, a filter function was implemented, handling the generation of different subsets of data with respect to a specific time period or brand name. This allows a comparison based on diverse dimensions such as topics of interest or specific products or services.

Aside from these use case specific DRs, literature defines further use case independent DRs with respect to MANTRA. Here, to enable the processing of large amounts of unstructured data (DR11, DP6, IP7), only adequate analysis techniques settled in the field of text mining are considered. Regarding the capability to view historical data (DR12, DP6, IP7), a flexible incorporation of different datasets including different periods is feasible. Along with this, the identification of trends over time (DR13, DP2, IP2) is considered by the possibility to determine specific periods, resulting in a flexible identification of time specific trends and their evolution over time. Finally, the trends and their use case specific peculiarities, all customizabilities and results are visualized (DR14, DP5, IP6) by a developed graphical user interface (GUI).

5 Demonstration and Evaluation of MANTRA

To examine MANTRA's ability to identify meaningful and sound trends, we applied it to a real-world dataset. Therefore, we consulted the academic Yelp dataset (Yelp 2021), represented by a subset of real-world reviews and businesses in the US. The dataset comprises ~ 8.6 million OCRs concerning 160,585 businesses and spans the period from October 13th, 2004 to January 28th, 2021. Since the evaluation of prospective trends is not feasible, we aimed to identify former trends retrospectively to verify our artefact. Therefore, we narrowed our demonstration to the multi-faceted field of the food and restaurant industry, resulting in a dataset of ~1.03 million reviews. According to a 2018 survey by a panel of experts from the NRAB, vegan cuisine and global cuisine are likely to gain popularity in the US through 2030 (Statista 2019). To identify these trends and thus verify our artefact, we analyzed the data by applying MANTRA (*see Figure 4*). Thus, we have defined two topics of interest, which are associated with the 2018 forecast: global cuisine, containing Asian and Italian food-related words as well as vegan cuisine, containing vegan and plant-based food-related words. In the following, we demonstrate the elicited results with respect to the use case (a) Product Development. We also applied MANTRA to the use cases (b) and (c) in a first step, but refrain from explicitly demonstrating the results as the demonstration on (a) depicts all relevant features. A detailed demonstration and evaluation of (b) and (c) will take place in future work within a larger field study.

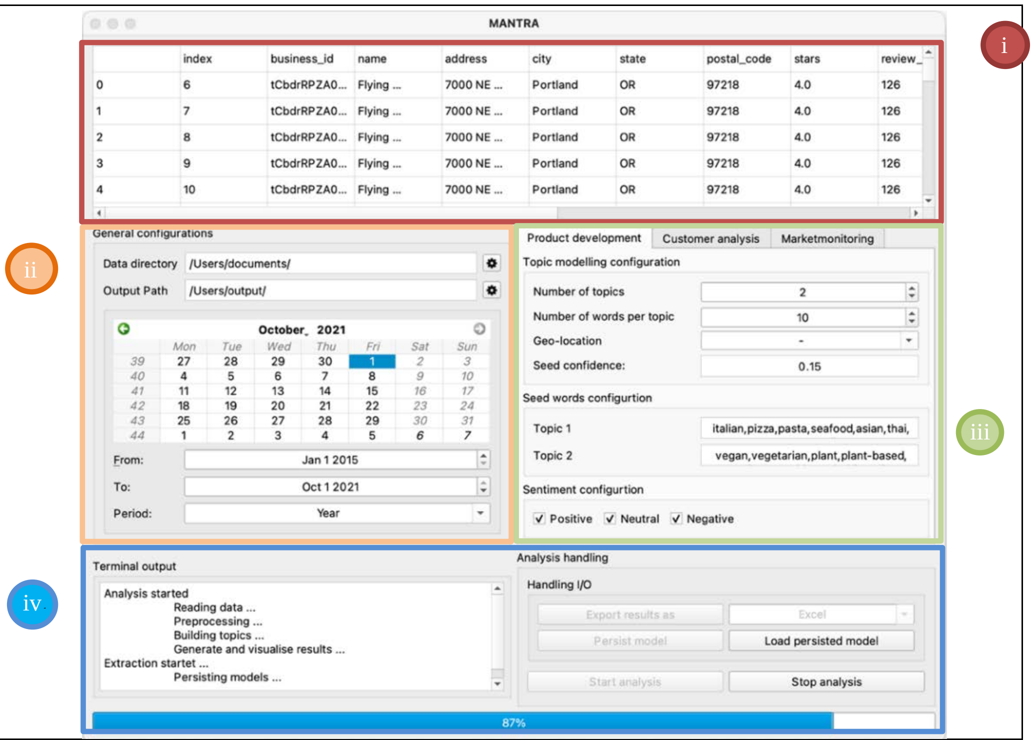

Figure 4. MANTRA – Configuration View

The configuration (see Figure 4) represents the initial view when starting the tool and can be used to customize the underlying analysis to one's own needs. The layout was designed based on four sections (i)-(iv), aligned to the GUI design suggestions of Garrett (2010). The data shown in section (i) represent an excerpt of the dataset used, including the actual reviews and the accompanying business data (e.g., state or name). To consider a representative analysis period with respect to our demonstration, the analysis uses data from 2015 to 2021 (ii), as the related NRAB survey was conducted in 2018. To incorporate the identified use cases, they were implemented in section (iii) using modular, dynamic tabs to enable a distinctive configuration. Here, regarding (a), the number of topics (2), words per topic (10), the respective external parameters of geolocation (none) and contextualized seed words (e.g., topic 1: italian, asian; topic 2: vegan, vegetarian) were defined. Moreover, all sentiment levels (pos, neg, neu) were considered. The start of the analysis, the handling of input and output (I/O) operations and the monitoring take place in section (iv). As soon as the demonstration has been initiated, all relevant information concerning the process such as the current state, occurring errors or the progress made were monitored and logged. Once the process has finished, the results will be consolidated and displayed by responsive, interactive charts (see Figure 5 and 6).

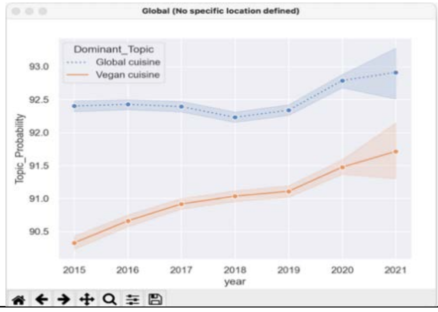

Figure 5. MANTRA – Identified Trends

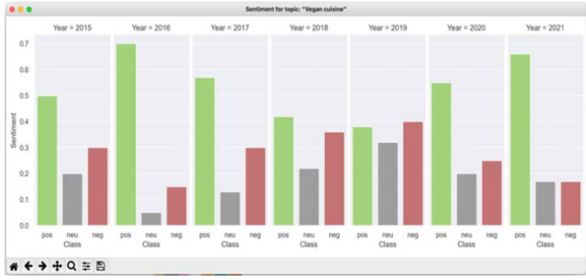

Figure 6. Corresponding Sentiment (Vegan)

Figure 5 represents the determined topic probabilities with respect to the years, resulting in the tracking of the topic evolution based on their relevance within the period analyzed. Here, both identified trends are continuously increasing in terms of their relevance. The trend global cuisine appears to slightly decrease within the period of 2015 to 2018, but continuously increases from 2018 to the present. The trending topic vegan cuisine increases steadily within the analyzed period. These results provide convincing evidence that both mentioned trends are on an upward trajectory and exhibit a consistency to the findings described in the 2018 NRAB forecast. Moreover, the 2020 Food & Health survey conduct-ed by the International Food Information Council (IFIC 2020) shows that a significant percentage of US residents are turning to a vegetarian/vegan diet relative to the previous year. As our tool detects a significant increase compared to the previous years of 2019 to 2020, convincing evidence is provided that our tool can identify even small deviations within the evolution of a trend. In addition, Figure 6 comprises the trend specific sentiment per year, by which a trend can be deconstructed to gain insights into specific customer wishes and demands. All in all, these results confirm the practical applicability of MANTRA, as the elicited trends are consistent with the aforementioned survey results.

Trend topics	***Products/Features (noun)***	***Descriptive characteristics (adj., verb)***
vegan cuisine	food, restaurant, vegan, service, gluten...	good, great, delicious, best, unfriendly, free ...

Table 2. Excerpt of the Resulting Excel

Besides the presented charts, the analysis also comprises an adapted Excel file to link the elicited in-formation to new products/features. Table 2 shows an excerpt of the resulting Excel file, containing the trend words and their classification into the part of speech for the topic vegan cuisine. This breaks down the trends into their constituent parts, enabling the identification of specific products/features and related characteristics. As our tool MANTRA depicts co-occurrences within the elicited trends by the means of topic modeling instead of solely conducting a frequency analysis of respective trending key-words such as prevailing social listening tools do, the identification of sub-trends is enabled. Here, our analysis reveals that e.g., customers eating vegan also refer to gluten-free food in a vast frequency (see Table 2).

Since (a) Product Development refers to examining geolocation-based differences in the corresponding needs of customers settled in the respective locations, we further tested our artefact on sub-datasets referring to three different U.S. states: Massachusetts (MA), Texas (TX) and Oregon (OR). Figure 7 rep-resents the corresponding analysis results. The results provide convincing evidence that MANTRA is able to identify geolocation-based discrepancies within the evolution of trends. Thus, it can be clearly seen that the topic of vegan cuisine differs across the respective locations, as it consistently increases in MA but remains steady respectively decreases in TX and OR.

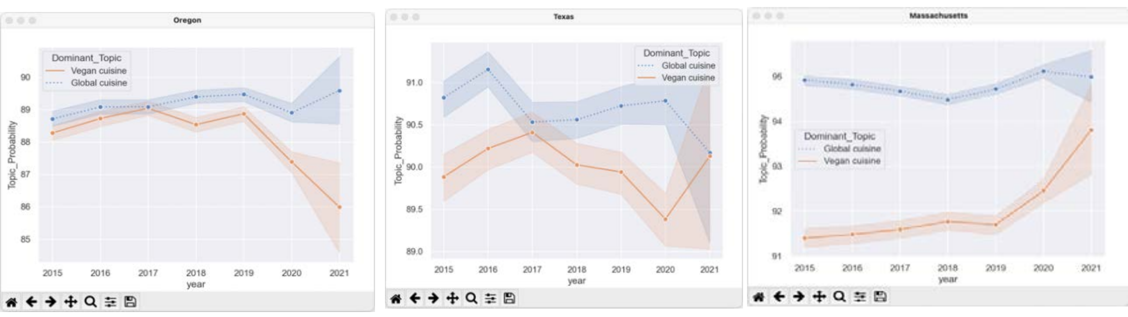

Figure 7. MANTRA - Identified Trends (From Left to Right: MA, TX, OR)

Furthermore, global cuisine declines since 2015 with respect to TX, while slightly increasing in MA and OR. Deeper insights into the ascertained sentiment distributions of MA and TX reveal further that – although the relevance of the vegan trend is vigorously increasing in TX from 2020 to 2021 – the respective reviews are negative connotated (pos: 0.27; neg: 0.61, neu: 0.12). In MA, the trend also increases sharply from 2019 to 2021, but is predominantly characterized by positive reviews on average (pos: 0.56; neg: 0.3; neu: 0.14).

Generally, the development of our tool was based on the DRs, which were all met as described in section “Design and Development of the Artefact”. Accordingly, all expectations posed regarding MANTRA were technically realized. In addition, the 2018 and 2019/2020 trends could be identified and verified by applying our tool on a representative real-world dataset, validating its functionality and therefore its practical applicability by means of an identification of meaningful trends.

6 Discussion and Contribution of the Results

The implementation of the DRs and DPs has provided interesting results. As we have included the sentiment in our trend analysis tool, we can identify positive as well as negative aspects about the trends and how these sentiment values evolve over time. Thereby, numerous opportunities for improving products and services can be identified, and certain features can be given greater importance than others (Irawan et al. 2020; Jeong et al. 2019). Figure 6 shows, that users spoke very positively about the vegan trend in 2016. This decreased through 2019. In 2020 and 2021, however, the positive comments now clearly predominate again. So, our demonstration reveals that, although the vegan trend is consistently rising over the years (see Figure 5), the sentiment is distinctively different. Without including the sentiment, one would not know that especially in 2019 ambivalent opinions were prevalent about the vegan trend and that an opening of a vegan restaurant would not have yielded the expected success implicated by the upward trend. Keyword-based tools determine trends on the occurrences of certain keywords – regardless of whether they have positive or negative connotations. Therefore, the first practical contribution of our research is that our tool enables a company to identify the VoC based on social media data. Thus, as tracking evolving and changing customer requirements is imperative to meet customers’ wishes (Hong et al. 2012; Lozano et al. 2017), companies can respond to them quickly as huge amounts of social media data can be processed effectively with our tool. With the current solutions, which often involve a manual examination, a comprehensive analysis of VoC and its implications e.g., for (a) Product Development is not possible.

Furthermore, including geolocation data and therefore considering geolocation-based discrepancies can also create significant benefits. Customers' requirements can differ across different geographical markets. To be successful and competitive in a targeted market, marketing representatives need to know which features should be designed in which way to meet the local customers' expectations (Bae et al. 2018; Endo et al. 2015; Ha et al. 2017). This becomes particularly evident when comparing the three states of MA, TX and OR (see Figure 7). While both trends in MA have been growing steadily since 2015, especially the vegan trend, the situation in TX and OR is quite different. In TX, it can be seen that the vegan trend has declined between 2017 and 2020. Since 2020, however, it has increased in importance again. This is in contrast to the global cuisine trend which peaked in 2016 but has since (and especially from 2020 onwards) dropped sharply. The state of OR exhibits a completely different picture of the two trends. While the vegan trend initially remains stable and drops sharply from 2019, the global trend remains stable over the years. The comparison of the three figures shows clearly that the inclusion of geolocation information has a considerable influence on the trends. While aligning a restaurant to the vegan trend is (based on these analyses) advisable in MA, this is not the case in OR. Due to the very unsteady trend in TX, a clear conclusion cannot be drawn. To better assess these trends in TX and MA we have combined the two alignments – geolocation and sentiment – because, as mentioned above, disclosing an upcoming trend does not directly mean that the trend exhibits also positive connotations. We resulted in further interesting insights for the vegan trend: whereas the trend in TX increases in importance since 2020 the sentiment is predominantly characterized by negative contributions (neg.: 0.61). This could mean either that the vegan food offered so far does not meet the customers' expectations or that vegan food is not well received in TX in general. Also, in MA the vegan trend has increased during the last years (esp. since 2019). Different to TX, in MA the trend is predominantly characterized by positive reviews on average (pos: 0.56). In this case the upward trend goes hand in hand with the positive sentiment. Without the inclusion of the geolocation data and also the sentiment values, these aforementioned discrepancies in the results would not have been revealed. Existing tools for trend analysis on social media posts lack the possibility to flexibly integrate the different external parameters the use cases (a)-(c) demand (see section "Assessment of Available Tools on the Market") especially associated with sentiment analysis. As our approach meets these DRs and is able to integrate different ex-ternal parameters which are highlighted in research literature as important (Bae et al. 2018; Endo et al. 2015; Ha et al. 2017), marketing representatives are provided an analysis tool that can optimally sup-port them in their daily working routines which can serve as another practical contribution.

Moreover, we also included the possibility to link future customer preferences with new features (Jeong et al. 2019; Tucker and Kim 2011). Thus, as our tool MANTRA depicts co-occurrences within the elicited trends by the means of topic modeling instead of solely conducting a frequency analysis of respective trending keywords such as prevailing social listening tools do, the identification of sub-trends is enabled. Table 2 shows an excerpt of the resulting Excel file, containing the trend words and their classification into the part of speech for the trend topic vegan cuisine. This allows trends and their constituent parts to be analyzed in more detail. A company can align its products and services with these. For ex-ample, a company that has analyzed the trends that emerged in section "Demonstration and Evaluation of MANTRA" could recognize that customers eating vegan also refer to gluten-free food in a vast frequency, enabling restaurants to extend their offer by gluten-free meals. Thus, companies are enabled to identify relevant aspects related to the elicited trends and therefore gain deeper insights into the wishes and demands of customers. Thus, as we have designed a tool which is able to identify the VoC, even with regards to unknown customer demands and design features, our results (and our artefact) also contribute to research theories such as Innovation Theory. Here, our approach can be included e.g., in the stage-gate model of the innovation process that describes a conceptual and operational model for moving new product projects from idea to launch (Cooper 1996). Thereby, our results have shown that it is important to distinguish trends based on external parameters (e.g., geolocation), as customer perceptions and corresponding demands may differ across varied circumstances. By incorporating specific trend-related information within the different stages of the stage-gate model, the rigid sequence of stages and gates can be broken up. By integrating the identified trends and therefore a tailored external point of view, the assessments at the go/kill checkpoints (i.e. gates) become less elaborate as the alignment with the external requirements is maintained constantly.

As trends and especially customer perceptions can change quickly (which in turn is reinforced by the fast-moving settings of social media) (Bhor et al. 2018; Sasaki et al. 2014), a quick identification of concerns and criticism about a company's products and services can mean a competitive advantage over other companies (Bhor et al. 2018; Jeong et al. 2019). Furthermore, MANTRA has been developed in a modular way, enabling a user to define various customized settings through the corresponding GUI elements tailored to its individual case. Therefore, e.g., the time period for a specific trend can be set to conduct the analysis resource-efficiently. Equally the use case specific DRs were also implemented by offering modular and dynamic tabs to react quickly and almost effortlessly to changing circumstances. Thus, as we have combined different machine learning approaches and designed our tool modularly, every company can adapt the analysis to their own individual circumstances. Furthermore, a company that is not aware of any prior knowledge regarding underlying trends can still identify them by using MANTRA. No seed words given, MANTRA depicts the underlying topics without the consideration of any contextual information by the mean of topic modeling, resulting in an identification of general pre-vailing trends. This is a significant advantage over social listening tools as trend-related keywords are indispensable regarding the identification of trends. Moreover, Social Media Theory (especially concerning the research of trend analysis) states that the automated analysis of social media contents still holds various challenges when it comes to practical application (Stieglitz et al. 2018). Thus, with the design and development of our automated, modular tool, we purposefully combined various analysis techniques (e.g., topic modeling, sentiment analysis) and ensured the incorporation of the related use cases and their DRs, which enriches the Social Media Theory by a need-fitted automated approach of analyzing social media contents regarding the identification of trends.

The discussed results have shown how our tool stands out from existing ones, placing our DS research project in the group of improvements (development of new solutions for known problems) in terms of the DSR knowledge contribution framework of Gregor and Hevner (2013). DSR improvement projects make contributions to both prescriptive theory i.e. design theory (Gregor 2006) and descriptive theory i.e. kernel theories such as Innovation- and Social Media Theory as described above (Gregor and Hevner 2013). Thus, in terms of prescriptive theory our artefact contributes to a rather general and abstract knowledge base – "nascent design theory" (Gregor and Hevner 2013). Therefore, based on the DRs de-rived from literature and kernel theories, DPs were formulated and proposed in the section "Design Principles for a Trend Analysis Tool". By applying them during the design and development of the artefact followed by the demonstration and evaluation, an implicit empirical grounding of the DPs was achieved here (Heinrich and

Schwabe 2014). Our DPs capture design-related knowledge and can there-fore support the development of further IS (design) theories and new artefacts. By considering e.g. the DP2. Contextual adaptability, the importance of the context (e.g. location) is highlighted in which the respective trend analysis should be conducted. Since the context has a direct impact on the results of the trend analysis, the alignment with the context leads to deeper insights. So, with the DPs, we made a first step towards contributing to design theory in terms of theory for design and action (Gregor 2006) as we comply with conditions as March and Smith (1995) and Hevner et al. (2004) pointed out under which a contribution to knowledge in DS has occurred: utility to a community of users, the novelty of the artefact and the persuasiveness of claims that it is effective.

7 Conclusion

Assessing people's opinions about a particular event and its future impact, thus a social media trend, is difficult to identify, especially given the vast amount of social media data. Automated approaches analyzing text-based social media data, such as topic modeling, have gained in importance, as companies need to be aware of customers' expectations. Likewise, the early identification of new and auspicious ideas and trends regarding the common marketing-related use cases (a)-(c) means a competitive advantage. However, prior literature and existing tools do not incorporate topic modeling to identify future trends, do not include external parameters and do not cover specific requirements crucial in the field of social media trend analysis. Thus, by identifying several DRs and deriving DPs, we provide a comprehensive tool by combining several machine learning approaches and transfer these in a highly responsive, platform-independent and intuitive GUI to close the research gaps (RQ1, RQ2). Especially with the demonstration on ~1.03 million OCRs we have shown that considering all DRs is necessary for a target-oriented and feasible trend analysis.

Our investigation contributes to practice and research alike (RQ2). Companies can benefit from our comprehensive and modular artefact, with which large amounts of data can be analyzed in a way best suited to the company's specific circumstances with the aim of analyzing trends for marketing-related use cases. Furthermore, we have highlighted how our investigation made a first step towards contributing to design theory (theory for design and action (Gregor 2006)) by formulating six DPs. Beside that we also highlighted our contribution to the kernel theories. Regarding the Innovation Theory the rigid sequence of stages and gates in the stage-gate model (Cooper 1996) can be broken up and further parallelized by examining external requirements constantly. Moreover, by incorporating the DRs of a trend analysis tool we enrich Social Media Theory by a need-fitted automated approach of analyzing social media contents regarding the identification of trends. Finally, it is worth to mention, that the initial assessments on the practical applicability of MANTRA regarding (b) and (c) revealed promising results. Nevertheless, we are not in a position to determine concrete contributions to further kernel theories (e.g., Brand Communication-, Customer Focus Theory) at the present, as deeper insights regarding (b) and (c) are therefore required. However, given our findings, promising contributions to the underlying kernel theories are to be expected. To investigate to what extent MANTRA contributes to the mentioned theories, a larger field study will be conducted within future work. There are also some limitations to this research: Although we included a large set of investigations, we could identify probably even more use cases in further literature. However, the identified use cases are undoubtedly important for marketing, researchers in other areas could identify other use cases.

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2.6 Beitrag 6: Supporting Product Development by a Trend Analysis Tool applying Aspect-based Sentiment Detection

Adressierte Forschungsfrage	**Forschungsfrage 8:** Wie könnte ein aspekt-basiertes Sentimentanalysetool aussehen, das die Trendanalyse für die Produktentwicklung unterstützt und welche Anforderungen sollte ein solches Tool erfüllen?
Zielsetzungen	• Identifikation von Design Requirements an ein Trend Analyse Tool unter Berücksichtigung von aspekt-basierter Sentimentanalyse • Erstellung eines Softwaretools durch die technische Umsetzung verschiedener Social Media Analyseverfahren
Forschungsmethode	**Design Science Research** • Design Science Process nach Peffers et al. (2007), der basierend auf der Problem- und Lösungsidentifikation u.a. die Schritte Entwicklung und Demonstration des Trend Analyse Tools unter Berücksichtigung der aspekt-basierten Sentimentanalyse als Artefakt beinhaltet • Anlehnung der Forschung an Hevner et al. (2004) durch die Ausgestaltung des Design Cycle (Demonstration des Artefakts), Relevance Cycle (Beitrag zur Praxis) und Rigor Cycle (Beitrag zur (Nascent) Design Theorie durch Design Principles)
Kernergebnisse (Überblick)	• Ableitung von Design Principles auf Basis von in der Literatur identifizierten Anforderungen • Verwendung von verschiedenen Analyseverfahren (z.B. aspekt-basierte Sentimentanalyse, Topic Modelling, Neuronale Netzwerke) zur technischen Umsetzung der Design Principles • Einbeziehung externer Parameter (z.B. Geolokationen) und Berücksichtigung der Identifikation von Trends mit und ohne Vorwissen • Erstellung des aspekt-basierten Trendanalysetools zur Produktverbesserung • Demonstration an einem Yelp Datensatz: o Identifikation von Aspekten (Burger, Fleisch, Sauce), die aus Sicht der Nutzer am wichtigsten sind o Betrachtung der Sentimentwerte der Aspekte im Zeitverlauf o Unterscheidung der Sentimentwerte hinsichtlich Geolokationen, um ortsabhängige Diskrepanzen aufzuzeigen
Publikationsort	Proceedings of the 17th International Conference on Design Science Research in Information Systems and Technology 2022.
Ranking VHB JQ 3	C
Autor(en) und Anteile	Janik Wörner 30% Daniel Konadl 30% **Isabel Schmid 30%** Susanne Leist 10%

Tabelle 7: Fact Sheet Beitrag 6

Supporting Product Development by a Trend Analysis Tool applying Aspect-Based Sentiment Detection

Abstract. Incorporating product trends into innovation processes is imperative for companies to meet customers' expectations and to stay competitive in fiercely opposing markets. Currently, aspect-based sentiment analysis has proven an effective approach for investigating and tracking towards products and corresponding features from social media. However, existing trend analysis tools on the market that offer aspect-based sentiment analysis capabilities, do not meet the requirements regarding the use case Product Development. Therefore, based on these requirements, we implemented an automated artifact by following the design science research. We applied our tool to real-world social media data (37,638 Yelp reviews) from one major fast-food restaurant in the US, and thereby demonstrated that our tool is capable of identifying remarkable and fine-grained product trends.

Keywords: trend analysis tool, aspect-based sentiment, product development.

1 Motivation

Social media such as Yelp or Twitter have evolved rapidly over the last years. These platforms have become increasingly important for interaction in both private and business contexts [1, 2]. As social media is a channel for the exchange of user-generated content and unfiltered voices about products, services and the company in general, social media data contain the so-called "Voice of the Customer" (VoC). Thus, the VoC provides deep insights into customers' current expectations. To meet customers' expectations, marketing representatives need to identify and continuously track trending topics regarding product and service features and incorporate the VoC into product innovation processes. For example, identified product features and correspondingly mentioned opinions may indicate shortcomings (e.g., low battery capacity of a smartphone) and which improvements to be made to meet customers' requirements (e.g., [3]). One possibility to identify these shortcomings in an automated way from social media texts is to conduct aspect-based sentiment analysis [4].

The potential of aspect-based sentiment analysis for tracking fine-grained trends over time has already been recognized in practice and in theory (e.g., [3, 5-9]). This has led to the emergence of trend analysis tools that include aspect-based sentiment analysis functionalities. However, trend analysis tools available on the market have remarkable drawbacks as they do not cover the comprehensive requirements that are deemed essential within the extant literature for the use case Product Development (e.g., [3, 5-9]).

With this work at hand, we make practical as well as theoretical contributions. We address drawbacks of existing software tools by suggesting a comprehensive artifact for automated trend analysis that allows marketing representatives to conduct aspect-based sentiment analysis. To meet several use case-specific requirements, we focus especially on the combination of different data analysis methods regarding the particular requirements, leading to a constructive trend analysis. By this, we aim to propose an automated solution for identifying ideas as the basis of (incremental) product innovation. Summing up, the research at hand is guided by the following research question:

What could an aspect-based sentiment analysis tool that supports trend analysis for Product Development purposes look like, and which requirements should such a tool meet?

The remainder of this paper is structured as follows: In the next section, we provide conceptual basics and related work. Following on this, we turn to the Design Requirements (DRs) and Design Principles (DPs) for implementing our tool, and to the shortcomings of trend analysis tools on the market. Next, we show the research methodology. After a description of the tool's design and development as well as its demonstration, the paper concludes with a discussion and its contributions to theory and practice.

2 Foundations and Related Work

2.1 Conceptual Background

Social media serves as an important interface between companies and customers. In content communities, users can evaluate e.g., products by disseminating their opinions in form of online customer reviews (OCR). In doing so, customers not only rate products as a whole but express their opinions and attitudes towards different features of the rated items (e.g., service quality in a Yelp restaurant review). In this way, OCR not only help customers to make informed decisions but are also beneficial for driving innovations of products within companies. As OCR include customers' experiences and expectations of product features [10], unfiltered and in real-time [11], they can serve as a valuable resource for product innovations. Thus, OCR can be harnessed to identify ideas, to either develop new value propositions (i.e., disruptive innovation) or to improve the performance of existing products (i.e., incremental innovation) [12, 13].

To identify ideas for product improvements as well as product development and therefore to drive incremental product innovations, marketing representatives can conduct aspect-based sentiment analysis. The first step of an aspect-based sentiment analysis deals with extracting aspects from OCR. For this purpose, unsupervised as well as supervised techniques can be applied. Topic modeling techniques (e.g., LDA [14]) suggest a possibility to identify aspects without prior knowledge (i.e., unsupervised) [14]. Compared to that, supervised techniques (e.g., artificial neural networks) need first to be trained on training data (e.g., ontologies) to extract the proper aspects (cf. [4]). Subsequently, the expressed tonalities can be identified for each of the aspects [4] by means of automated sentiment analysis techniques [4, 15]. Therefore, aspect-based sentiment analysis offers benefits in terms of Product Development. For marketing representatives that lack the ability to implement aspect-based sentiment analysis themselves, trend analysis tools on the market offer this functionality in a ready-to-use way. However, these tools show remarkable drawbacks as they do not cover the comprehensive requirements that are deemed essential within the extant literature for the use case of Product Development.

2.2 Design Requirements and Available Tools on the Market

In a first step, we have comprehensively searched and consolidated literature (cf. [16]) to identify DRs of a trend analysis tool that applies aspect-based sentiment analysis for Product Development purposes. Based on the attention and importance received, we could derive several DRs (DR1)-(DR10) (see fig. 2) from the extant literature.

Concerning the identification of product features, the tool (DR1) should be capable of extracting the aspects autonomously from social media posts (e.g., [6-8, 17]). However, if marketing representatives have already knowledge documented about a domain problem (e.g., domain ontologies or product trees), the tool (DR2) should provide the option to include this prior knowledge into the automated identification of aspects (cf. [6, 7, 17, 18]). Beyond that, customers' self-reported opinions of product features play an important role for Product Development. Marketing representatives aim to retain the features that evoke positive perceptions, while features evoking negative perceptions need to be improved. Thus, (DR3) determining the polarity as well as the intensity of the opinions expressed about respective aspects is mandatory [3, 6, 8, 19, 20]. Subsequently, the product features can be adapted so that customers' requirements are met (e.g., increasing smartphone screen size). However, adapting features may influence perceptions of the features customers currently appreciate (e.g., high battery capacity of the smartphone). Therefore, to support informed improvement decisions, the tool (DR4) needs to identify the dependencies between product features [7, 9, 17]. Furthermore, to be successful and competitive in a targeted market, marketing representatives must decide which product features to propose in which way to meet customers' expectations within geographical markets. Product trends do also converge over time as they are dynamic developments and not solely static points in time. It is therefore essential that the tool (DR5) can flexibly match aspect-sentiment relations to different geographical (e.g., continents, countries, federal states) and temporal (e.g., days of a week, phases of a day) parameters [3, 5, 17-20]. The huge volume of available social media posts requires the incorporated techniques (DR6) to deal with vast amounts of textual data [8, 9, 18-20]. As past developments of trends are essential for assessing the current state of trending topics, the tool (DR7) needs to allow the user to consider historical data [3, 17-19]. To support Product Development in prioritizing product improvement decisions, the tool (DR8) needs to output aggregated sentiment values for the identified aspects [3, 6, 8, 19, 20] and (DR9) illustrate the frequency of the identified aspects [3, 8, 20, 21]. To immediately identify the most important aspect-sentiment relations, the tool (DR10) should provide means to rank the results in either descending or ascending order [3, 21].

In the second step, we searched the market for available trend analysis tools. We took an up-close look at the most popular tools (e.g., Brandwatch, Meltwater, Symanto) that offer trend analysis by means of aspect-based sentiments. We analyzed the functionality of these tools by installing demo versions. To verify the drawbacks regarding the DRs for each of the tools, we also turned to sales representatives from these companies to confirm our observations. As it turned out, there is indeed a lack of a software tool that meets all the specific requirements for the use case Product Development. Firstly, these tools lack the ability to flexibly match different temporal and geographical parameters to aspect-sentiment relations. Perceptions of product features differ across geolocations (e.g., continents, federal states), trends are temporal developments (e.g., days of a week, phases of a day), and both require different and flexible contexutalizations. Secondly, existing trend analysis tools that apply aspect-based sentiment analysis extract aspects, either with or without incorporating prior knowledge. However, we could not observe a trend analysis tool that includes both possibilities. Literature unveils the need for a comprehensive trend analysis tool that meets all the requirements for the use case Product Development. With this research, we aim to close this gap.

3 Research Procedure

In order to develop a systematic artifact for the automated trend analysis in marketing, we followed the Design Science (DS) approach [22, 23] and aligned our research activities with the DS procedure as proposed by [23] (see Fig. 1).

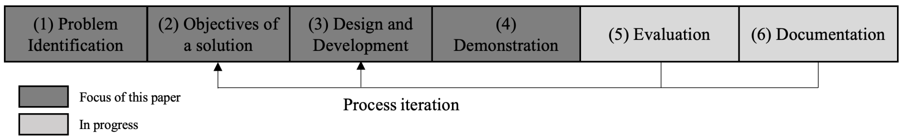

Fig 1. Design Science Research (DSR) Procedure

As a first step, (1) corresponding problems and drawbacks of previously existing approaches regarding the automated trend analysis using aspect-based sentiment analysis were identified (see sections 1 and 2.2). Hence, the revised tools supporting trend analysis by aspect-based sentiment detection do not meet the requirements that are indispensable to the successful application. Consequently, our (2) objective is to address drawbacks of existing software tools by suggesting a comprehensive artifact for automated trend analysis that allows marketing representatives to conduct aspect-based sentiment analysis (see sections 2.2 and 4). The third step of our DS process model contains the (3) design and development (see section 4) of an artifact. To fill the gaps identified within phase (1), we focus on the design of the technical realization of the tool by combining different machine learning techniques, following our derived DPs. Thus, our approach was established to support the trend analysis and to eliminate the existing disadvantages. By (4) demonstrating our artifact (see section 5.1), we highlight the application of our tool on 37,638 Yelp reviews [24]. Thus, we showed the implementation of the requirements identified in literature. In Step 5 the usefulness, applicability and usability of the tool are to be analyzed in a larger field study. Finally, the tool will be further enhanced before it is provided to marketing departments of large companies (6).

The orientation towards the procedure by [23] also makes it possible to align our research with the guidelines of [22] or [25], respectively. According to the design cycle, we present our artifact as the result that has gone through the process of demonstration (application of our approach to a Yelp dataset). In view of the relevance cycle, we identified several DRs from current research literature that guided the design of the artifact, and so the practical application of our artifact brought up several contributions for practice. In view of the rigor cycle, we used several methods to rigorously construct our artifact (e.g., topic modeling, sentiment analysis, neural networks) and derived initial findings as contributions to (nascent) design theory.

4 Design and Development

First, the composition of Meta Requirements (MRs) that describe "*what the system is for*" ([26], p. 325) is based on the purpose and scope of the tool that was discussed in the motivation. Thus, we define the solution objectives based on the investigations´ problems and present them in Figure 2. Besides the MRs, the Design Principles (DPs) are synthesized in a next step. DPs are defined as prescriptive statements that show how to do something to achieve a goal [27]. These DPs are deduced from the Design Requirements (DRs) that are based on current research literature. The DPs we derive from our results fall into the category of "action and materiality-oriented design principles", describing what an artifact should enable users to do and how the artifact should be built to do so [28]. The development of the DPs follows the guidelines of [28] and [27].

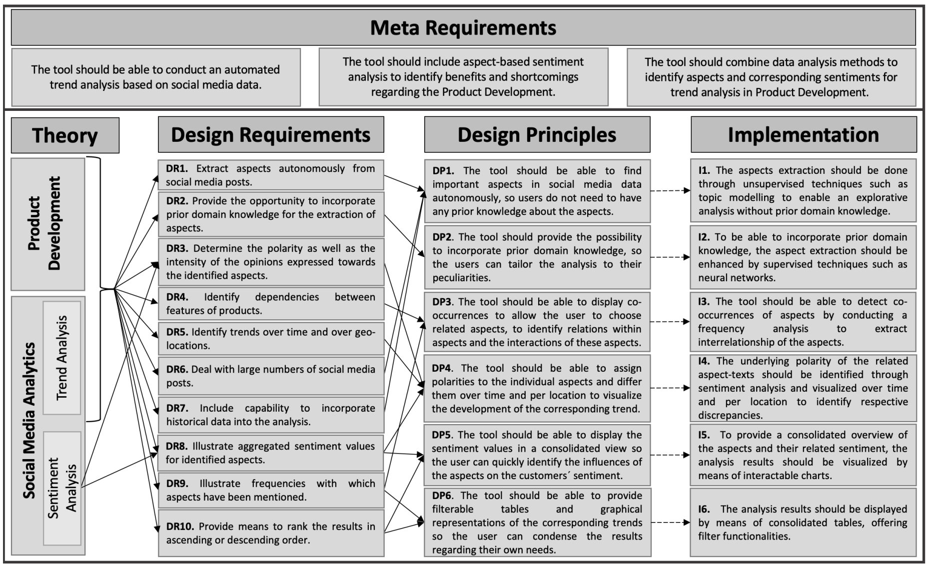

Fig 2. Design of the Artifact

Since no particular machine learning technique is capable of accurately representing all DRs, a combination of techniques was essential. Regarding *DP1*, the autonomous extraction of aspects, unsupervised techniques (e.g., topic modeling) are required to enable an explorative analysis without prior domain knowledge. However, as stated by [29] the potential of totally unsupervised techniques is stymied by their purely unsupervised nature. Thus, semi-supervised techniques have arisen in the past, facilitating an effective way to guide the analysis specific to a user by manipulating the analysis process even without structured prior domain knowledge [30]. Therefore, to take advantages of semi-supervised techniques while maintaining the flexibility of unsupervised ones, the known semi-supervised topic modeling technique GuidedLDA found application as it achieves convincing analysis results [30]. Besides the explorative analysis, the artifact must provide the ability to incorporate prior domain knowledge (*DP2*). Thus, the artifact provides a supervised aspect extraction using deep learning. Specifically, it applies a convolutional neural network (CNN) as proposed by [31], using two types of pre-trained embeddings for the aspect extraction: a general-purpose embedding and a domain-specific embedding, containing domain related information used by the CNN to learn the specific domain peculiarities. Consequently, the analysis can easily be adapted and tailored to the users' own circumstances by changing the underlying domain-embedding, resulting in a highly generic and customizable artifact. With respect to *DP3*, the artifact must depict co-occurrences of the related aspects to detect their interrelationship. As probabilistic topic modeling techniques such as GuidedLDA infer the resulting topics based on various probabilistic distributions, depicting the relations of the underlying topic words (and thus the resulting aspects) [32], the identification of their interrelationships is met through the nature of topic modeling itself. Considering the use of the CNN, the artifact depicts the co-occurrences of the aspects by conducting a frequency analysis. Here, sub-aspects are identified for each extracted (main-)aspect by analyzing their respective occurrence in the context of the related main-aspect, resulting in an n-dimensional occurrence-tree. To determine the tonality of each aspect (*DP4*), the "Valence Aware Dictionary for sEntiment Reasoning" (VADER) [33] technique (a lexicon and rule-based sentiment analysis technique specifically attuned to sentiments expressed in social media) has been implemented. To further consolidate and visualize (*DP5*) the underlying aspects' sentiment as well as its evolution over time, corresponding line-charts are implemented using the well-known python library matplotlib [34]. Finally, to ensure an adequate illustration of the analysis results (*DP6*), the extracted aspects, the corresponding sentiment values and their means, but also specific references to the extracted aspects are displayed using filterable tables and lists as demonstrated in the following section.

5 Demonstration and Discussion of the Artifact

5.1 Demonstration of the Artifact

To examine the tool's ability to identify meaningful and sound trends (including related aspects and their sentiment), we applied it to a real-world dataset. Therefore, we consulted the academic Yelp dataset [24], represented by a subset of real-world reviews and businesses in the US from one of the most popular online communities for crowd-sourced reviews. The dataset, which comprises a total of ~ 8.6 million OCR concerning 160,585 businesses in different fields such as restaurants, cultural sites and sports facilities spans the period from October 13th, 2004 to January 28th, 2021. To demonstrate our tool, we narrowed the data to the multi-faceted field of the food and restaurant industry. Specifically, we narrowed the analysis to the reviews of a fast-food restaurant with multiple franchises in various locations to extract the relevant aspects and associated customer perceptions, resulting in 37,638 reviews. The evaluation of the analysis and the tool's usability will be carried out, as described in section 6, within future work.

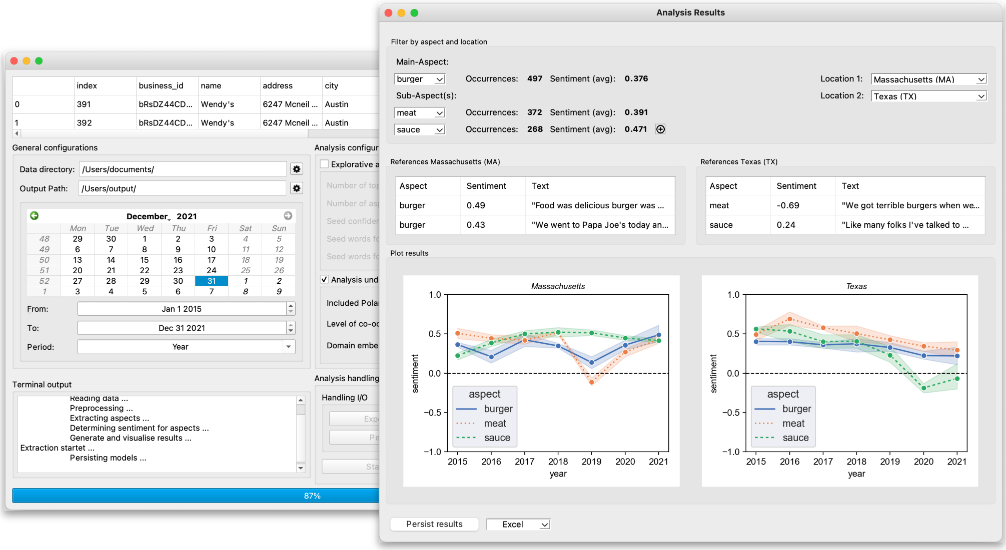

Fig 3. Configuration and Result View of the Artifact

Figure 3 represents the tool's configuration view (left) and results view (right). By the configuration view, the underlying analysis can be customized to the one's own needs. Here, in case of not all periods of time included within the data deemed necessary, a specific period can be individually defined. For the purposes of our demonstration, the analysis was conducted using data spanning the years 2015 to 2021. To further account for the two different analysis settings (with/without the incorporation of prior domain knowledge), both were implemented using dynamic Graphical User Interface (GUI) elements to enable a distinctive configuration. Concerning the demonstration, the analysis under consideration of prior knowledge has been conducted. Therefore, all sentiment levels (*positive, neutral, negative*) are considered. Moreover, the level of co-occurrences has been set to two, resulting in a two-dimensional occurrence-tree. The domain knowledge used was extracted from the renowned dataset of the 2016 SemEval task [35]. By using this appropriate word embedding tailored to the use case of restaurant reviews, the CNN is trained in the domain of the food and restaurant industry.

The result view represents the sentiments of the extracted aspects with respect to the years, resulting in the monitoring of their evolution based on their customer perceptions. Here, both locations refer to the same aspects (main-aspect: *burger*; sub-aspects: *meat, sauce*), facilitating a comparison of their temporal and location-based discrepancies. In Massachusetts (MA), the main-aspect *burger* exhibits slight oscillation across the years but generally remains stable. The worst average customer perception occurs in 2019 and is represented by a slightly positive sentiment score of 0.131. Furthermore, the two sub-aspects *meat* and *sauce* differ strongly in their course in 2019. Here, the course of *meat* collapses drastically (-0.109), while the course of *sauce* remains nearly constant (0.503) compared to the previous year, leading to the assumption that the negative reflections of the *meat* aspect may influence the main-aspect *burger*. Moreover, this assumption is supported by the development of the respective aspects. Here it becomes apparent that the significant improvement of the aspect *meat* also potentially causes an improvement of the main aspect *burger*, supporting the conclusion that our tool is able to identify meaningful and sound trends based on the corresponding aspects and their customer perception. The results provide further convincing evidence that our tool can identify location-based discrepancies in the evolution of trends. Thus, it can be seen that the customer perceptions of the aspects differ across the respective locations, as they overall remain quite constant in MA but consistently decreases in Texas (TX).

Generally, the development of our tool was based on the DPs as shown in Figure 2, which were all implemented as described in section 4. Accordingly, all expectations posed in regard to our artifact were technically realized. In addition, several trends and their evolution could be identified by applying our tool to a representative real-world dataset, validating its functionality. To subsequently evaluate its practical applicability by means of an identification of meaningful and sound trends, an evaluation will be conducted in future work.

5.2 Discussion of the Demonstration

The implementation of both the MRs and the DPs enabled us to design and develop a tool which has provided interesting results. As we establish the opportunity to extract the aspects in either a supervised or an unsupervised way (*DP1, DP2*), we can identify in the first instance aspects and/or product features which are discussed in the social media data under consideration. This allows us to identify those aspects which are most important from the customer´s point of view and, above all, which must be considered in Product Development [3, 8, 20, 21]. Figure 4 shows that the most frequently named aspects in our data are *burger, meat* and *sauce* (497, 372 and 268 occurrences). This means that when reviews about the restaurant are written, customers address mainly these three aspects. In the case of Product Development, the restaurant can start screening these aspects as they are particularly important for the customers. The extraction of aspects is possible on the one hand via a CNN including word embedding, providing the restaurant to incorporate prior domain knowledge (*DP2*) such as aspects about food, drinks, and processes in the restaurant. Therefore, the extraction of the aspects is tailored precisely to the company. But, on the other hand if the restaurant wants to extract aspects without exerting any influence, the tool can also identify them autonomously.

Moreover, the demonstration of the artifact has also shown that the customers have spoken differently about the three aspects. Here, our results show that users spoke about *sauce* more positively (0.471) over the years than about the aspects *burger* (0.376) and *meat* (0.391). However, the results become even more interesting when the related sentiment values are observed over time. Thus, numerous opportunities for improving products can be identified, and certain features can be given greater importance [5, 19]. Figure 4 shows that for MA the values of the individual aspects can change considerably: While in 2015-2018 the sentiment values of *meat* range between 0.40 and 0.52, in 2019 it slipped down into the negative range with -0.12. After this decline, the opinion about *meat* then improved again in 2020-2021. At the same time as the sentiment value of *meat* has fallen, that of the *burger* has fallen too. In this context, it is therefore possible that the negative sentiment about the *sauce* had also influenced the customers' opinion about *burger*. If a company did not have this fine-grained information gained through the aspect-based sentiment analysis and wanted to adjust the product in 2019 based on the negative reviews, it is possible that it would have changed product features which were actually rated positively. Also, in TX, the consideration of the aspects is inevitable as the results show that the *sauce* needs to be changed so that the customer's opinion about it and therefore the opinion of the whole burger can be improved again. Already existing trend analysis tools often include sentiment analysis to show the general tonality about the company or the product over time – without considering that different aspects influence the product's evaluation. However, this leads to a distortion of the results and the benefit for companies is no longer a given.

Furthermore, including geolocations and therefore considering location-based discrepancies can also create significant benefits. Customers' product requirements can differ across different geographical markets. To be competitive in a targeted market, companies need to know which features should be designed in which way to meet the local customers' expectations [17, 36]. This becomes particularly evident when comparing MA and TX (see fig. 4). While we can see in terms of the restaurant in MA that the *burger* exhibits a positively connotated trend over the years, the sentiment over time in TX shows worse values. Especially in 2020 and 2021, the sentiment values of the *burger* differ immensely (MA: 0.35, 0.45; TX: 0.28, 0.22). In both locations, there are different reasons for the burger's better (MA) or worse (TX) rating. While in TX the *sauce* must be adjusted to the taste of the people, this is not necessary in MA due to the steady positive values. Without the inclusion of the geolocations and also the sentiment values, these discrepancies in the results would not have been revealed, which clearly is a benefit in comparison to other existing tools.

6 Conclusion, Contribution and Outlook

Assessing and identifying people's opinions about a particular aspect and its future impact (thus a social media trend), is difficult, especially given the vast amount of social media data. Thus, techniques for analyzing textual social media data, e.g., aspect-based sentiment analysis, topic modeling and neural networks, have gained in importance, as companies need to be aware of customers' expectations regarding products. However, prior literature and existing tools do not incorporate them to identify future trends, do not include external parameters (such as geolocation) and do not cover specific requirements (simultaneous identification of trends with/without prior knowledge) crucial in the field of Product Development (see sections 2.2), although the early identification of new and auspicious ideas and trends means a competitive advantage for companies [19]. Thus, we provide a comprehensive tool by combining several machine learning approaches and transfer these in a highly responsive and platform-independent GUI. Especially with the demonstration of our tool on 37,638 OCR from Yelp we have shown that considering all identified requirements is necessary to analyze trends.

Besides creating value for practitioners, theoretical contributions in the research area of IS are also provided. To acknowledge the importance of different DSR perspectives, we have related our DSR contribution to the category "design artifacts" according to [37], including both: the demonstration of the artifacts practical benefit and design theory contributions [38]. Therefore, by providing a tool for automated trend analysis that can identify aspects that are discussed within social media, we enable companies to gain deep insights into customers' current opinions and future expectations to tailor their products. Hence, to meet these customers' needs, a company has to identify and continuously track product features by incorporating the VoC into internal Product Development processes. Thus, as tracking evolving and changing customer requirements is imperative to meet customers' wishes [36, 39], companies can respond to them quickly and with minimal effort as huge amounts of social media data can be processed with our tool. Compared to already existing trend analysis tools, our tool meets all the specific requirements set out within the extant literature regarding Product Development. In particular, our tool can flexibly match different temporal and geographical parameters to identify aspect-sentiment relations and it provides users the possibility to extract the aspects either with or without prior domain knowledge. Thus, customer perceptions for specific periods or geolocations can be displayed to track fine-grained variabilities. On the one hand, this makes it possible to visualize influences, affecting the sentiment. On the other hand, downward trends in sentiment can be counteracted and upward trends can be strengthened. Hence, this combined with the integration of geolocations can especially support large companies with multiple branches in their efforts to easily perceive location-specific sentiment changes and explicitly react to them. As we have combined different machine learning approaches and designed our tool modularly, companies can adapt the analysis to their specific needs. A further contribution of implementing aspect-based sentiment analysis is that the tool can be supportive in identifying the aspects of the products to be changed to meet the customer's expectations (remove existing aspects of the product, others need to be enhanced). With the realization of (*DP4*)-(*DP6*), we created a tool with which companies can track the overall customer perceptions. In summary, companies can benefit from our comprehensive and modular artifact by analyzing large amounts of data in a way best suited to their circumstances, aiming to analyze trends regarding their aspect-based sentiment values.

Besides our technical contribution (i.e., the artifact), we achieved prescriptive theoretical contributions as a further outcome of our DSR project. Therefore, we formulated and proposed DPs based on the DRs (see section 2.2) derived from current research literature. By applying them in the course of the design and development of the artifact followed by the demonstration, an implicit empirical grounding of the DPs was achieved. Our DPs capture design-related knowledge and can therefore support the development of further IS (design) theories and new artifacts. For designing further (trend analysis) tools in related areas, our DPs can be applied as we have formulated them generally by describing what the artifact should enable users to do and how it should be built. For example, by DP4, the importance of including time, geolocation and/or further external parameters (e.g., customers' characteristics) in a trend analysis tool is highlighted. As these external parameters have a direct impact on the customers' sentiment and therefore on the analysis results (cf. [40]), the alignment to them will lead to a more targeted trend analysis tool. Thus, for researchers that intend to design a trend analysis tool, we suggest considering the influences that are evoked by external factors. So, with the compilation of the DPs, we made a first step towards contributing to nascent design theory. To take a next step towards a more mature design theory, we intend to evaluate our DPs by further evaluating our tool. Therefore, we will first evaluate our tool in a formative and artificial environment (i.e., a laboratory experiment). Here, participants will use the tool to identify relevant aspects and associated customer perceptions in OCR. Subsequently, they will complete a questionnaire to indicate their perceptions of the analysis quality and tool usability. This allows us to identify difficulties and improve our tool (whereby our DPs can be confirmed or adapted) before conducting a more elaborate evaluation in a more natural setting as a further part of the design cycle [41]. This second evaluation will be a field study with a large restaurant chain that plans to integrate a software artifact to support its marketing departments.

However, there are also some limitations to this research: Although we included a large set of investigations, we could identify probably even more requirements the tool should meet in further literature. Nevertheless, the identified DRs are undoubtedly important for Product Development in other areas and other DRs could be identified.

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2.7 Beitrag 7: Social Media Communication about Sustainability: the Resonance of Users and its Implications

Adressierte Forschungsfrage	**Forschungsfrage 9:** Welches Sentiment lässt sich bei den Nutzern in Bezug auf Nachhaltigkeitsthemen von Unternehmen, die über Social Media verbreitet werden, messen? **Forschungsfrage 10:** Inwiefern deckt sich diese Wahrnehmung der Nutzer mit den Nachhaltigkeitsaktivitäten der Unternehmen, gemessen an einem offiziellen Ranking?
Zielsetzungen	• Identifikation von Ansatzpunkten, wie die Social Media Kommunikation gestaltet werden kann, um Themen wie z.B. Nachhaltigkeit effektiv verbreiten zu können • Untersuchung der Social Media Kommunikation über Nachhaltigkeitsthemen von Unternehmen und die Reaktion der Nutzer darauf, v.a. im Hinblick auf das Sentiment in den Social Media Posts • Vergleich der Sentimentwerte mit den Aktivitäten der Unternehmen in Social Media und einem offiziellen Nachhaltigkeitsranking
Forschungsmethode	**Strukturiertes Forschungsvorgehen:** • Kombination von quantitativen und qualitativen Datenanalysen: Interpretation der Ergebnisse des Mixed Method Ansatzes • Social Media Analytics Ansatz basierend auf (Stieglitz and Dang-Xuan, 2013; Stieglitz et al., 2014): (1) Ziel der Analyse, (2) Datenanalyse (Datenextraktion, Preprocessing, Multi-label Klassifikation, Sentimentanalyse), (3) Dateninterpretation basierend auf den Mixed Methods
Kernergebnisse (Überblick)	• Identifikation der am häufigsten diskutierten Themen bez. Nachhaltigkeit (Darstellung in Wordclouds) • Häufigkeitsverteilung: ökologische Dimension dominant • Vergleich der Analyseergebnisse der drei Handelsunternehmen: o Target: wenig Social Media Aktivität, sehr positive Sentimentwerte und gute Werte im Ranking; ganzheitliche Strategie und Fakten führen zum Erfolg o Walmart: sehr schwach positiv ausgeprägtes Sentiment, trotz hoher Social Media Aktivität und moderater Werte im Ranking; fehlende ganzheitliche Strategie o Amazon: sehr hohe Social Media Aktivität, positive Sentimentwerte, obwohl schlechte Werte im Ranking; sehr positive und überzeugende Posts mit Fakten täuschen über das schlechte Ranking hinweg
Publikationsort	Communications of the Association for Information Systems (Under Review)
Ranking VHB JQ 3	C
Autor(en) und Anteile	**Schmid, Isabel** **45%** Hammerl, Timo 45% Leist, Susanne 10%

Tabelle 8: Fact Sheet Beitrag 7

Social Media Communication about Sustainability: The Resonance of Users and its Implications

Abstract: *As sustainability is an important and publicly effective topic, companies can benefit from communicating their activities and efforts. Thereby companies can use different communication channels, one possibility is social media. But if and how social media can be used to be an effective way to communicate about sustainability issues is rather unclear. Therefore, we have analyzed 3.95 million tweets about #sustainability to identify relevant sustainability topics, users are talking about in social media, structured by the three dimensions: economy, environment, and social. Based on this, we further analyzed the reactions of users to these sustainability issues posted by companies. To assess this appropriately, we incorporated in our analysis three companies: Walmart, Target, and Amazon. Using a mixed-method approach, we compared the sentiment of Twitter users with an official ranking (The Newsweek) and the sustainability social media activities of these companies. Our results indicate that posting relevant topics, referring to objective facts and sources as well as establishing a holistic sustainability strategy are necessary to benefit from sustainability communication via social media. The results also have implications for the social media strategy.*

1 Introduction

Social media is a powerful mechanism for spreading any kind of messages as a company can reach and keep in touch with many stakeholders, can interact and connect with them, and can thus create a close stakeholder relationship (Williams et al. 2014, Manetti and Bellucci 2016). Experience has shown that it is not constructive to rely on trial and error in the dissemination of social media messages, but rather to pursue a social media strategy. This can improve the image and reputation of a company, especially when socially relevant and current topics are addressed. Nowadays, one of the most current and publicly effective topics, companies can benefit from communicating their activities and efforts to the public, is sustainability.

The deterioration of the natural environment and the related climate change is a predominant issue for society today as the earth´s warming will increase the risk of physical and economical hazards (Brundtland and Khalid 1987, McKinsey 2020). To avoid these fatal consequences, it is necessary to decarbonize both the daily lives of billions of people and the economy. So, as organizations are a main contributor to this challenge, they are also responsible for increasing their efforts in sustainability issues (Seidel et al. 2013). As a result, companies are no longer judged solely in terms of their financial but also in terms of their sustainability performances (Stohl et al. 2007, Stohl et al. 2017).

Sustainability is a guiding principle for the responsible use of resources (Brundtland and Khalid 1987). The aim is to ensure that needs are satisfied by preserving the natural regenerative capacity of the systems involved (especially living organisms and ecosystems). Thereby, there are three different ways of approaching sustainability, the so-called triple bottom line including the 1) economic, 2) environmental and 3) social dimension (Schaltegger and Burritt 2005, Ahmed and Sundaram 2007, Linnenluecke and Griffiths 2010, Williams et al. 2014, Tseng et al. 2019). Companies should therefore undertake efforts to meet the interests of internal and external stakeholders and thus focusing on sustainable economic growth, reducing the impacts of corporate activities on the environment and the diversity of social, cultural, and individual demands within a company (Schaltegger and Burritt 2005, Baumgartner and Ebner 2010).

Thereby, social media can be seen as a proponent of corporate sustainability as it provides extensive opportunities for sustainability communication (Lee et al. 2013, Stohl et al. 2017). Thus, the authentic stakeholder dialog focusing on sustainability can have positive organizational effects e.g., strengthening companies´ reputation and legitimacy (Etter 2014, Manetti and Bellucci 2016, Reilly and Larya 2018). However, these resulting outcomes and the stakeholders´ reactions are not always positive. Extensive and aggressive promotion of a company´s green advertising can evoke feelings of discomfort, disbelief, and skepticism (Minton et al. 2012, Lee et al. 2013). So, stakeholders assume that companies propagate self-serving ethical claims and want to "greenwash" themselves (Lee et al. 2013). Greenwashing means that a company deceives consumers regarding its sustainable practices or the environmental benefits of a product or a service (Gallicano 2011). Thus, people identify inconsistencies between companies´ actual sustainability activities and their communication about being green and sustainable. But often these critical greenwashing accusations are unjustified and false information is spread (Gallicano 2011). There are different reasons why green advertising and sustainability communication via social media is misunderstood as greenwashing. Companies for instance do not fully understand how they can integrate sustainability issues into their social media communications (Baumgartner and Ebner 2010, Jaques et al. 2019, Weder et al. 2021). Furthermore, reasons such as vague and poorly formulated messages, claims that are not correlated to sustainability and therefore irrelevant as well as messages with false labels, showing that the company does not conceive the issue and does not follow a concrete social media strategy, can lead to false accusations of greenwashing (Williams et al. 2014).

Although there are several benefits for companies to spread their sustainability issues via social media, it is these negative consequences that often unsettle companies. Therefore, they are often faced with the question of how to use social media and how to design the social media strategy in the most efficient way to provide value and mitigate any potential negative consequences in terms of authentic sustainability communication. Prior research has already discussed various aspects of this issue and ascertained that the negative consequences of sustainability communication via social media can be reduced when a company reveals its motives (Kim 2014) or by initiating a dialogue with customers and stakeholders as a way to receive input from each other (Araujo and Kollat 2018). Thus, to go into this dialogue and to avoid irrelevant and poorly formulated messages, it is useful for companies to know the topics that are currently relevant and interesting in social media in terms of sustainability. Prior research literature has already identified this as an important aspect for the sustainability communication via social media, but either include only too few posts in their analysis (Lodhia et al. 2020) or assess the content and issues of corporate sustainability communication based on the official sustainability reports (cf. Reilly and Hynan 2014). Further studies relate their results only to the merely quantitative number of tweets and followers (cf. Reilly and Larya 2018) or limit their content analysis on Facebook and Twitter accounts of companies (cf. Manetti et al. 2017) and therefore neglecting the perspective of the user. So, a lot of research has been undertaken in the field of sustainability communication via social media. But as this field of research is so broad and a huge amount of data is available, there are still many aspects and in particular the perspective of the user that has not been investigated sufficiently.

Consequently, with this paper at hand, we want to contribute to the further exploration of the research field by investigating how to communicate via social media about socially relevant topics such as sustainability effectively. Thus, we aim to contribute to the field of social media strategy and therefore highlighting starting points on how to engage with social media users regarding issues of social relevance. Therefore, we examine the social media communication of sustainability activities of companies and the reactions of users thereon to derive first insights for an effective sustainability communication and to include explicitly the user´s perspective in our analysis. To this end, we look at the Twitter posts of selected companies with #sustainability over a ten-year period and conducted both a frequency analysis of companies´ sustainability posts and a sentiment analysis of the users´ reactions as a basis for the evaluation of the posts. All in all, we examined 3.95 million tweets and thus performed a comprehensive analysis. Subsequently, we look at the ratings of the companies´ sustainability activities by means of an official ranking of "The Newsweek" and compared them with the users´ perceptions. Moreover, to gain more precise findings, we follow an inductive approach and so we decide to conduct our investigation by means of three selected companies. In the concluding discussion and in the outlook, we discuss the possibilities and limitations of generalizing the results. We incorporated in our analysis the three companies Walmart, Target and Amazon, as on the one hand the companies are comparable (all of them operate in the retail sector and have their headquarters in the U.S.) but on the other hand different posting behavior about sustainability issues of the companies can be observed. Thus, we aim to answer the following research questions:

> **RQ1:** What sentiment can be measured among users in response to sustainability topics of companies that are spread via social media?
>
> **RQ2:** How does this perception of the users correspond to the companies´ sustainability activities measured by an official ranking?

From answering the research questions, consequences for the social media strategy should be derived. The remainder of this paper is as follows: the next section provides a theoretical background by introducing important terms and definitions as well as related work regarding sustainability communication via social media. Next, the procedure of the research is described in the subsequent section. The section "Data analysis" shows the data tracking and collecting phase as well as the technical realization of the data analysis. We then present our results in the following section before we discuss them. Finally, the paper ends with concluding remarks, the contribution and an outlook for further research.

2 Theoretical Background

2.1 Terms and definitions

One of the most popular and commonly accepted definition of sustainability was introduced by the United Nations. They describe sustainability as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (p.8) (Brundtland and Khalid 1987). Thus, it is an ethical concept including combating poverty while defending the environment on a macro-level (Baumgartner and Ebner 2010). Nowadays, sustainability has become a buzzword employed by both individuals and companies to communicate a sense of caring about environmental issues (Minton et al. 2012). Companies aim to reduce environmental impacts and align their strategy to improve the quality of the environment (Tseng 2017).

Thus, corporate sustainability has its roots in the stakeholder theory, which highlights that a company should keep the interests of both stakeholder groups in mind: the primary stakeholders, who are fundamental for operations of the company (e.g., customers, employees) and secondary stakeholders, who affect the company´s operations indirectly (e.g., community and natural environment) (Du et al. 2016).

In this context, many scientific papers also use the term corporate social responsibility (CSR) as these two concepts (corporate sustainability and CSR) are closely related (Reilly and Larya 2018). CSR is defined as the commitment of companies to contribute to sustainable economic development by improving the lives of employees, their families, the local community, and society in ways that facilitate both business and sustainable development (Petkoski and Twose 2003, Reilly and Hynan 2014, Adi 2018, Reilly and Larya 2018). The idea behind this term is that companies have responsibilities beyond profit-making (Stohl et al. 2017). The focus of CSR (in contrast to sustainability) is more on the dialogue with their stakeholders about corporate activities regarding social, ethical, environmental, and economic issues (Fieseler et al. 2010, Bonsón and Ratkai 2013, Stohl et al. 2017). So, literature uses both terms to demonstrate the integration of sustainability issues into an organization´s culture, decision-making, strategy, and operations (Montiel 2008, Linnenluecke and Griffiths 2010, Reilly and Hynan 2014). This sustainable corporate behavior and its communication to primary external stakeholders can have beneficial effects regarding stakeholder relationships (Etter 2014).

Hence, the motivation for increasing attention to sustainability and its communication is multi-layered. By making internal processes sustainable, the expectations of external stakeholders, who became more knowledgeable and sensitive to sustainability initiatives, can be met (Reilly and Weirup 2012, Balasubramanian et al. 2020). This leads to a better external reputation that will help to build up a competitive advantage (Fieseler et al. 2010). But also, the internal stakeholders, e.g., the employees, and their social, cultural, and individual demands should be considered to ensure the existence and success of the company (Schaltegger and Burritt 2005, Fieseler et al. 2010).

Thereby, there are three different ways of approaching sustainability, the so-called triple bottom line including the economy, environment, and social dimensions (Schaltegger and Burritt 2005, Ahmed and Sundaram 2007, Linnenluecke and Griffiths 2010, Williams et al. 2014, Tseng 2017):

- **Economy**: This dimension is very generic, as it contains classic entrepreneurial and management tasks for achieving the best possible economic results (Schaltegger and Burritt 2005, Baumgartner and Ebner 2010). Aspects in the economical dimensions are e.g., innovation, technology, collaboration, and processes (Baumgartner and Ebner 2010).
- **Environment**: This dimension deals with the impacts of corporate activities on the environment. Environmental sustainability contains both the direct impact on the environment by e.g., resource use or emissions into the air and water and the indirect impact on biodiversity and environmental issues of the product over the life cycle (Schaltegger and Burritt 2005, Baumgartner and Ebner 2010).
- **Social**: This dimension contains aspects that are important in terms of the diversity of social, cultural, and individual social demands within a company (Schaltegger and Burritt 2005). It aims to positively affect all present and future relationships with internal and external stakeholders (Baumgartner and Ebner 2010). Internal

social aspects are e.g., human capital development, corporate governance, or health and safety whereas external social demands contain no corruption and cartel or ethical behavior and human rights.

2.2 Social media strategy for reputation building

Social media is generally 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 User Generated Content (UGC)’ (Kaplan and Haenlein 2010, p. 61). This has changed the traditional way of organizations interacting with people. Historically, the goal of engaging with people was achieved via unilateral communication channels from the organization to the people such as by radio, print or television. Even then, the goal of building a brand, image and reputation played a crucial role for organizations in order to succeed and keep up with the competition. Through the advent of the social media revolution this goal is still the same, however, pursuing it has changed drastically. The honeycomb framework of social media summarizes the changes in seven different social media functionality blocks such as identity, conversations, sharing, presence, relationships, reputation, and groups (Kietzmann et al. 2011). So, e.g., social media make it possible that users are able to communicate and interact with each other, and therefore also with companies, faster, more directly and more comprehensively (cf. conversations and sharing). Social media also allows new and direct relationships to be established and maintained in a network (cf. relationships), leading to greater trust and contiguousness between users and company (cf. reputation) (Kietzmann et al. 2011).

However, initiating social media campaigns is not a challenge for most companies but to combine social media with their marketing strategy to build long-term relationships with their customers (Li et al. 2021). Thus, social media appearance needs to be managed and planned accordingly for which a profound strategy is essential. A definition of social media strategy is provided by Ng and Wang (2013) stating that it is “a well - defined and tightly focused social media action plan, which has clear business objectives, specific policies, desired audience, desired resources and predefined metrics for measuring the social media impacts” (p.4). In current research literature different types of social media strategies can be distinguished: social commerce strategy, social content strategy, social monitoring strategy and social CRM strategy (Li, et al. 2021). Particularly the social media content strategy focuses on creating brand awareness as well as promising reputation for companies and refers to creating and disseminating educational and/or compelling content to rise and maintain customers (Pulizzi and Barrett 2009). According to the theory the content a company disseminates should be “relevant, useful, compelling and timely” (p.269) in order to encourage customer interactions and to initiate positive Word-of-Mouth (WoM) (Holliman and Rowley 2014). This strategy is divided into four categories: primary motivation, key activities, capabilities/ resources and major outcomes. The primary motivations for firms to focus on this strategy is to connect and collaborate with customers by conducting the key activities viral and influential marketing. The capabilities/ resources they use for creating the strategy is the marketing communication capability which includes the firm-initiated two-way communication by creating timely and valuable content based on customer needs. How popular and vital the content is, is dependent on the social message strategy, i.e. how the message is constructed (e.g. including brand names, functional and emotional appeals) (Li et al. 2021).

Even though the necessity of such a profound social media strategy especially the social media content strategy is well-founded in research literature (c.f. Kaul and Chaudhri 2011, Felix et al. 2016, Dolan et al. 2017), the study of such strategies in the context of rapidly changing societal issues (such as sustainability) using sound data analysis is becoming increasingly important and sparsely addressed in research, which is why it is important to further investigate the topic in detail.

2.3 Sustainability communication via social media

A company can use various communication channels to spread its sustainability performance to external stakeholders. This can take place on the one hand by employing traditional media such as paper-based report formats including annual reports, sustainability reports, or advertisements (Lodhia et al. 2020). This kind of communication offers the possibility to push messages and information from the company to the addressee. On the other hand, a company can also spread its sustainability issues and CSR agendas via contemporary media such as online disclosure or social media (Minton et al. 2012, Etter 2014, Manetti and Bellucci 2016). Thus, via social media e.g., a company can interact with external stakeholders actively as this communication channel provides a platform to enable dialogues in various ways: company to stakeholder, stakeholder to company, and stakeholder to stakeholder (Reilly and Larya 2018, Lodhia et al. 2020).

So, social media is an effective communication channel for reaching and keeping in contact with a large number of stakeholders at a very low-cost level (Minton et al. 2012, Manetti and Bellucci 2016). In terms of sustainability communication, social media such as Facebook or Twitter is often applied for green advertising (Minton et al. 2012). Employing the personal character of social media, which arises from the shared network and the connection between customer and company, credible marketing messages about sustainability can be spread effectively. In addition to that, there are further reasons to apply social media in terms of sustainability communication: social media is a highly accessible and scalable tool, that can be used to spread and distribute a huge quantity of information without any time and space limit (Sogari et al. 2017).

Hence, sustainability communication via social media can lead to a favorable awareness and thus a better reputation for companies that are active in terms of sustainability (Lee et al. 2013, Reilly and Larya 2018, Balasubramanian et al. 2020). Furthermore, prior investigations have shown that engagement and interaction in social media in terms of sustainability can result in establishing and maintaining a long-term relationship between a company and its external stakeholders (Etter 2014). This leads to beneficial outcomes for companies, such as trustworthiness and benevolence (Coyle et al. 2012, Etter 2014). So prior investigations essentially have shown that sustainability communication via social media is an important driver for consumer – company identification (Araujo and Kollat 2018). This demands transparency and accountability on the company´s part and active participation on the external´s part (Balasubramanian et al. 2020).

In addition to these potential factors, prior research literature has also explored other aspects of sustainability communication via social media. For example, Araujo and Kollat (2018) examine factors that stimulate the effectiveness of CSR communication on Twitter. By using automated content analysis, the authors investigate the influence of CSR communication. Content analysis is a prevalent method in this research area with either the aim of evaluating the scope of interaction between a company and its stakeholder within social media (Manetti and Bellucci 2016), or to examine the social and environmental disclosures (Lodhia et al. 2020). Another area of application is to assess the CSR-related contents of the 30 most central corporate accounts in a CSR Twitter network to derive different communication strategies for CSR communication in Twitter (Etter 2014). Deeper insights into the contents are rare, but (Vo et al. 2019) e.g., investigates how a company´s engagement in CSR influences WoM (negative or positive) during a service delay. Although these investigations engage intensely in content analysis an overview of main sustainability issues that are broached in social media is missing.

In addition to content analysis, prior investigations have also focused on the relationship between a company´s online appearance in terms of sustainability communication and their offline efforts measured by CSR ratings. Hence, Lee et al. (2013) found out that a higher CSR rating is a strong evidence for early online adoption, faster establishment of online presence (followers), higher responsiveness to the firm´s identity (replies and mentions), and stronger virality of the messages (retweets). Results from investigations of Reilly and Hynan (2014) and Balasubramabian et al. (2020) confirm these findings and emphasize that green companies report more sustainability information on social media platforms than non-green companies. But these papers are mainly based on quantitative results such as the number of followers, retweets, and mentions. But how customers react in terms of content or emotion to the social media presence of companies that exhibit high or low CSR ratings is disregarded so far.

3 Procedure of the Research

To make our findings and results comprehensible and to validate them, we followed a structured procedure of the research. Thus, to answer our research questions we have analyzed different data dimensions in terms of sustainability-related topics via advanced analysis procedures as well as an official sustainability ranking. In general, this means that we have combined qualitative and quantitative data and analyzed them to interpret these mixed methods against the background of sustainability communication via social media.

So, to put it into the context of our approach and to answer our proposed research questions, we rely our analyses on 3.95 Mio. Twitter data, focusing sustainability topics in terms of the three dimensions (environmental, economy, social) by using a multi-label classification in general, as well as filtering the dataset according to three U.S. retailers in particular: Amazon, Walmart, and Target. We have chosen these three companies, as on the one hand, the proposed companies should be comparable (all of them operate in the retail sector and have their headquarters in the U.S.) on the other hand we wanted to show differences between them. So particularly we considered different sources of data as well as analysis procedures to combine qualitative and quantitative data. To compare the companies` social media activities with official sustainability KPIs in terms of the above mentioned three dimensions, we drew upon an external sustainability ranking from The Newsweek (Newsweek 2020). This ranking, published by Newsweek, assesses America’s most responsible companies 2020 based on different KPIs derived from corporate annual reports, CSR reports, sustainability reports, and corporate citizenship reports (Newsweek 2020). Besides drawing upon the ranking, we quantified the social media activity level by using a frequency analysis. This way, we measure the quantity of sustainability-related posts, the companies have published via Twitter and determine the share of each dimension compared to the total of all sustainability-related tweets. By this quantification step of social media activities of the companies, we can discover if and how much each sustainability dimension is communicated via Twitter. Additionally, we also calculated the users´ sentiment about the sustainability activities of companies. By calculating these scores, we want to ascertain how the users react to the sustainability issues posted by companies on Twitter. Thus, we used VADER, a labeled dictionary adapted to the contextual characteristics of social media data. Hereby, VADER can combine the positive and negative inflections and generates a single sentiment score within the range of -1 to +1.

To apply the mixed method approach here, first, the data must be analyzed. Hence, for the process of the data analysis and to follow our research paradigm, we lean on the proposed social media analytics approach by (Stieglitz et al. 2014). The following passage describes the performed steps in more detail. This methodological approach which deals with the methods, processes, architecture, and technologies to transform raw social media data into meaningful and useful information for business operations, was established mainly to perform social media analysis in a structured way in the field of politics. However, it can be applied not only in the political context but also in the general area of information systems (Stieglitz et al. 2014). The major parts of the approach are delineated in the following Figure 1. An own representation based on the approach of (Stieglitz and Dang-Xuan 2013).

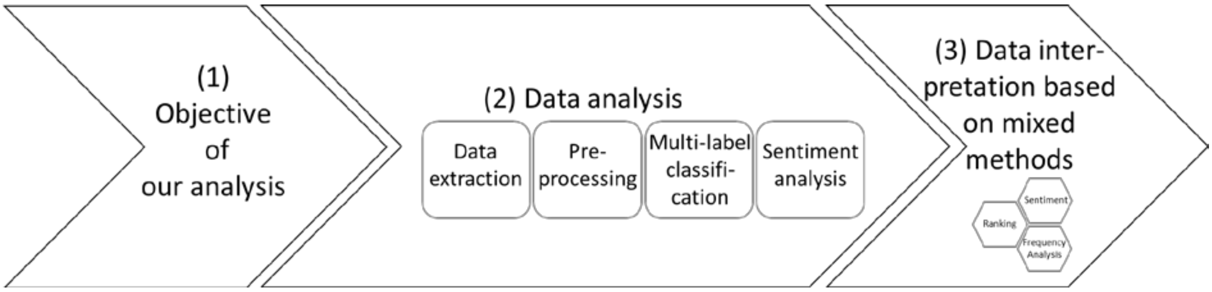

Figure 1: Social Media Analytics Approach (own representation based on (Stieglitz and Dang-Xuan 2013, Stieglitz et al. 2014))

Before we extracted the relevant data, we determined the objective of our analysis (step 1) and therefore of this paper. As stated above, we aim to identify the relevant topics posted about sustainability in social media structured by the three sustainability dimensions: economy, environment, and social. Based on this we further want to gain an insight into the reactions of users to these sustainability issues posted by companies and how communication via social media influences this (see section 1).

Thus, step 2 included the data analysis phases beginning with the definition of our tracking approach, which is hashtag-related (#sustainbility). For extracting the relevant data from the social media portal Twitter, we employed the so-called Twitter Intelligence Tool (TWINT) to also extract historical tweets. This was important since the official Twitter API only allows to extract streaming data but no historical tweets (see section 4.1 and 4.2). At large, we extracted both structured (number of retweets, comments, and likes) as well as unstructured (the content of posts) data from Twitter. Before we progressed to the selection of the analysis methods the data had to be prepared, i.e., pre-processed (see section 4.3). Next, we selected suitable analysis approaches regarding our research questions. This way, the pre-processed tweets were classified according to a multi-label classification approach based on the textual content of the tweets to have a solid baseline in terms of the three dimensions environment, economy, and social. After this, we applied a sentiment analysis on the classified tweets to determine the user's sentiment towards a specific sustainability topic. These two analysis methods will be described in more detail in subsequent sections (see sections 4.4 and 4.5).

In step 3 we analyzed the results of the methods and compared them with additional information to gain deeper insights. To address RQ2 in the most efficiently, besides analyzing the extracted and classified tweets via a sentiment analysis we drew upon an official sustainability ranking from The Newsweek as stated above. Via this ranking, an external assessment of sustainability efforts of the three investigated companies can be achieved. Additionally, we quantified the social media activity by using frequency analysis to assess companies' efforts in the communication of their sustainability activities. The analysis of the results of all these methods leads to further insights (see section 5) that are communicated and disclosed with this investigation.

4 Data Analysis

4.1 Extraction and Analysis Architecture

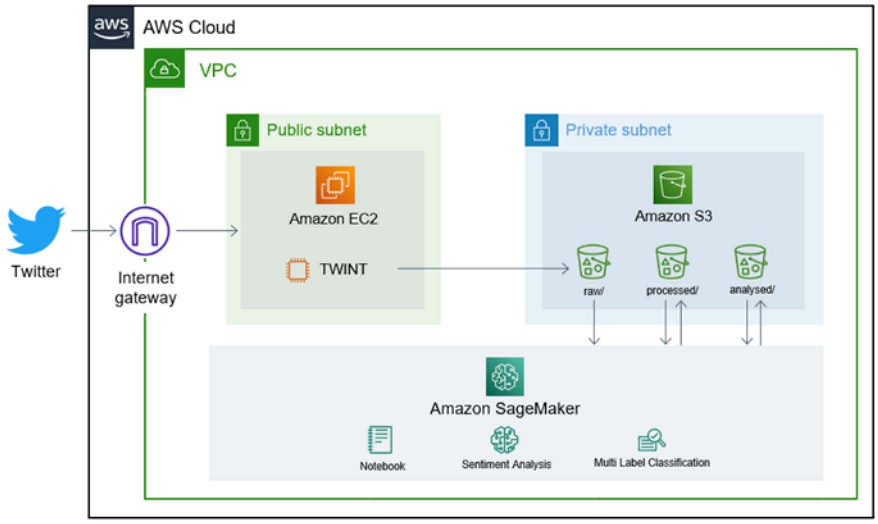

Figure 2: Extraction Architecture

Figure 2 describes the underlying architecture for the extraction and analysis of the Twitter data. Our model is built upon the AWS cloud computing services to facilitate our workflow due to several reasons: First, to provide high scalability, it was necessary to implement mechanisms for maximizing flexibility in terms of computing resources. Our goal was the extraction of historic tweets going back to the year 2010 until 2020. For this matter, we could not assess the number of extracted tweets and therefore the needed computing resources. Second, to keep computing times as low as possible implementing our architecture to cloud services seemed most promising in contrast to running the analysis on local machines, since AWS offers state-of-the-art horizontal scalability. As a first step, we set up an AWS Elastic Cloud Compute (EC2) instance to have scalable and fast computing resources at hand to extract the tweets. Additionally, for reasons of higher security we relied on a Virtual Private Cloud (VPC) environment which was also configurated via AWS. For the extraction process, we drew upon TWINT. The extraction itself was conducted via predefined search criteria, selected by the authors (an overview of all criteria is given in Table 1). The extracted tweets are initially saved to a Simple Storage Service (S3) bucket - called raw/ - for further processing. In the AWS context, an

S3 provides a highly scalable storage solution to storage and retrieve any sort of data. After this, we created an additional bucket for the manual classification process to label the tweets according to the three dimensions (environment, economy, and social). This step is important since it is needed to train the machine learning classifier for the automated classification of the entire dataset (for details see section 4.4). After the raw data was cleaned and processed according to predefined rules (see section 4.3), the tweets were saved to the /processed bucket which was the foundation of the conducted data mining methods. In this matter, the proposed architecture serves as a basis for conducting the multi-label classification approach as well as the sentiment analysis to answer the research question as defined in section 1.

4.2 Data Extraction

Table 1: Search conditions

Timeframe	2010 – 2020
Social Media Platform	Twitter
Extraction Tool	TWINT
Search Terms	#sustainability
No. of extracted Tweets	~ 3.95 Mio.

To gather relevant social media posts regarding sustainability, the authors found it most suitable to draw upon Twitter due to several reasons. First, with 359 million active monthly users[1], this platform provides a huge set of potential data. Furthermore, because of its open character, worldwide tweets can be viewed as well as extracted. Additionally, Twitter allows the implicit categorization of tweets via the use of hashtags. In this matter, the authors decided to use the hashtag #sustainability to filter for relevant tweets. Since the topic of sustainability experiences a hype towards online communications in recent years, the authors found it most promising to set the timeframe for the data extraction to ten years from 2010 – 2020 to consider an extensive viewpoint. This can also be substantiated with the fact, that Twitter had its breakthrough as a viral short messaging service around 2010 and is growing its monthly user base ever since[2]. For the technical side (as described in Section 4.1) we drew upon the tool TWINT to also extract historical tweets. This was important since the official Twitter API only lets you extract streaming data but no historical tweets. With the above-explained search criteria and the underlying architecture, the extraction of tweets leads to a total of ~ 3.95 million (raw) sustainability tweets for further processing. Table 1 provides an overview of the explained and selected search criteria.

[1] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/ (retrieved on: 09/06/21)

[2] https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/ (retrieved on: 09/06/21)

4.3 Pre-Processing

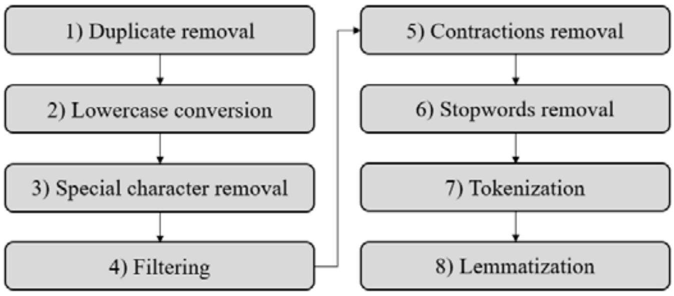

Figure 3: Pre-processing steps

As an initial step for the multi-label classification as well as the sentiment analysis the extracted tweets were pre-processed to eliminate any incomplete, noisy, and inconsistent data. By doing so, the procedure involved the following steps (see Figure 3 for visualization) to prepare the dataset for further data mining techniques: 1) The removal of duplicates resulted in a reduction of the initial 3.95 million tweets to 3.36 million tweets for further consideration. Next, we transformed the text to 2) lowercase since it tends to improve the classification success in terms of accuracy (Uysal and Gunal 2014). After this, we 3) removed special characters such as mentions ("@"), hashtags (#), URLs since these characters do not contain any sentiment in textual data or contribute to the classification in any way. Also, retweets (abbreviated with "\RT") were removed in this step, since retweeting is the process of sharing another user's post. In terms of dealing with special characters, it is important to mention, that we explicitly did not remove emojis from the tweets since our used sentiment analysis tool VADER can deal with those special characters and therefore additional sentiment can be gathered from the emojis. This is a huge advantage of VADER since the majority of social media posts tend to be informal and therefore might contain a variety of emojis expressing and substantiating the underlying opinion of the users.

In the next step of pre-processing, we conducted some 4) filtering of the tweets. On the one hand, we searched for words containing more than three consecutive letters and reduced these. This can be explained by the fact that people often express their excitement towards a specific topic by repeating letters (e.g., "aweeeeeesome", "nooooooo way"). However, by leaving such words in their initial form, they might not be considered for the conducted sentiment analysis, since VADER does not know how to deal with it. As such, the sentence "This is awesome" was analyzed as a positive post (compound: 0.6588), whereas the similar sentence „This is aweeeeesome" is considered as a neutral post (compound: 0.0), even though this sentence tends to contain more excitement than the other. Additionally, we also set the minimum word count of tweets to five for being considered for sentiment analysis. This can be substantiated with the fact that this number is seen as most promising for containing potential sentiment in the eyes of the authors since sustainability tends to be a topic of interest where users have a sophisticated opinion much rather than only expressing their feelings such as "I like", "this is bulls****", etc. By considering these two steps for filtering the tweets were reduced to a total of 2.85 million tweets for the classification and sentiment analysis approach. In step 5) we removed contractions, such as isn't to is not. Next, common 6) stopwords in the English language were removed. We did this by using and updating the Natural language toolkit (NLTK) in Python. Step 7) deals with the tokenization of sentences. In particular, we used the white space tokenization technique for splitting sentences into tokens whenever whitespace is encountered. As a final step for the pre-processing, we conducted the text normalization technique 8) lemmatization on the tweets, to reduce different words to the same core root. Our choice of lemmatization in contrast to stemming is substantiated with the fact that lemmatization considers a language full vocabulary to apply to the analysis of a word's and also determines a given words part of speech by looking at the surrounding text.

4.4 A Multi-label Classification Approach

In accordance with our aim of our research was the classification of the extracted tweets in environment, economy, and social categories. To achieve this, we drew upon (Tsoumakas and Katakis 2007) who provide an overview of different classification approaches. The authors differentiate between single-label classification which can further be divided into binary and multi-class classification on the one hand and multi-label classification on the other hand. First, a binary classification approach was considered but not seen as suitable for the obvious fact that more than two categories are being analyzed. Additionally, the multi-class classification approach was examined, which at first seemed promising since it deals with multiple classes or categories. However, this approach is mutually exclusive in terms of the single categories, meaning that a tweet could either be environment, economy, or social. Since a tweet in the context of sustainability can contain text potentially fitting two or all three of the above-defined categories, the category allocation cannot be seen as mutually exclusive per se. Therefore, by using a multi-class classification approach some context for further analysis might come shorthanded. Ultimately, a classification approach is needed that deals with multiple category allocation. Taking the above-mentioned shortcomings into account, the authors have chosen a multi-label classification approach to allocate multiple categories to the tweets simultaneously. As (Tai and Lin 2012) state, multi-label classification problems naturally arise in text mining domains, where a document or text is associated with more than one category. Some examples falling in this categorization approach in terms of processing of textual data are news article classification, product reviews, and obviously, social media posts. In this matter, multi-label classification is often considered as a generalization of the traditional multi-class classification approach.

To train and test the different classification algorithms, a partial dataset of the extracted tweets was classified manually according to the three categories (environment, economy, social). This process was conducted by four researchers individually to minimize potential subjectivity and in case of disagreements, discussions were held until a consensus was reached on the specific tweet category. In this matter, a total of approximately 3.000 tweets was analyzed and afterward split into a training and test dataset with a ratio of 90/10.

Before continuing with the description of the selected multi-label classification algorithms, it is important to explain the used evaluation metrics for assessing the classification accuracy. Using the conventional metrics for single-label classification problems (binary, or multi-class) such as accuracy, F-measure, area under the ROC curve (AUC), might come shorthanded since each example can be associated with multiple labels simultaneously (Zhang and Zhou 2013). Therefore, a number of different evaluation metrics are proposed in literature that specifically deal with the evaluation of multi-label classification approaches. Zhang and Zhou (2013) provide an extensive overview and taxonomy by categorizing them into two groups being example-based

(Schapire and Singer 2000, Godbole and Sarawagi 2004, Ghamrawi and McCallum 2005) and label-based metrics (Tsoumakas and Katakis 2007). For the research at hand, we drew up-on a metric from the example-based category, that is the subset accuracy. This metric "evaluates the fraction of correctly classified examples, i.e., the predicted label set is identical to the ground-truth label set. Intuitively, subset accuracy can be regarded as a multi-label counterpart of the traditional accuracy metric […]" (Zhang and Zhou 2013). Fortunately, there is a function in the Python scikit-learn library that implements this metric, called accuracy_score. Having an appropriate accuracy metric at hand, we started to select and evaluate potential classification algorithms and adapted them to the context of our research. The algorithms selected and trained were: Naive Bayes Classifier, LinearSVC, Logistic Regression, OneVsRest, ClassifierChains, and Label Powerset. Out of these six algorithms, Logistic Regression performed best with an accuracy of 0.7 for the economy dimension, 0.7231 for the environment dimension, and 0.8846 for the social dimension. With this, we laid the foundation for the application of the Logistic Regression algorithms on 2.85 million sustainability tweets.

4.5 Sentiment Analysis

One key aspect of this research paper is the analysis of the underlying sentiment in terms of sustainability towards specific companies. In this matter, sentiment analysis, a subarea in the field of natural language processing and highly dynamic research field, deals with the analysis of people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions (Liu 2012, Yue et al. 2019, Capatina et al. 2020). To achieve this, we needed a comprehensive approach dealing with the special and yet very informal character of social media posts, since such text is known for containing slang, abbreviations (e.g., LOL) as well as specific pictograms expressing emotions (called *emojis*). A promising tool that was specially built for the analysis of social media texts and therefore dealing with the above-mentioned text characteristics, is VADER (*V*alence *A*ware *D*ictionary for s*E*ntiment *R*easoning). The authors and creators of VADER (Gilbert and Hutto 2014) used a combination of qualitative and quantitative methods to produce as well as empirically validate a gold-standard sentiment lexicon that is especially attuned to microblog-like contexts. One major finding is that VADER outperforms human raters in terms of classification accuracy at correctly determining the sentiment of tweets into positive, neutral, or negative classes. Having this major benefit at hand, we used VADER by implementing it into your Python script via the *vaderSentiment* library. As a next step, we calculated the according sentiment of each tweet and saved it to specific numeric attributes. These attributes are "Positive", "Negative", "Neutral", and "Compound". As the first three are self-explanatory, the fourth attribute, the Compound score, is computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive)[3].

[3] https://github.com/cjhutto/vaderSentiment#readme (retrieved on 09/06/21)

5 Results

5.1 Topics about sustainability

As a first step towards gaining an understanding of the most relevant and popular topics in terms of the three sustainability dimensions, we used the trained Linear Regression algorithm for the multi-label classification of the ~ 2.85 million sustainability tweets to classify the extracted Twitter posts to the corresponding dimensions. By doing so, this resulted in a distribution as shown in Figure 4, whereby the focus is clearly on the environmental dimension since it outweighs the other two by far. However, this result is not seen as too surprising, since in general, the broad opinion in terms of sustainability is linked to environmental aspects. This is also emphasized by the fact that news and articles are reporting more and more about topics such as CO2 emissions, climate change, etc. On the other side, the least number of tweets could be allocated to the social dimensions. One possible reason for this could be the fact that even though social aspects such as human rights, ethnical factors, and others are without a doubt highly relevant in today's society and also communicated and discussed frequently, however, these topics might not be associated with sustainability by the broad public just yet.

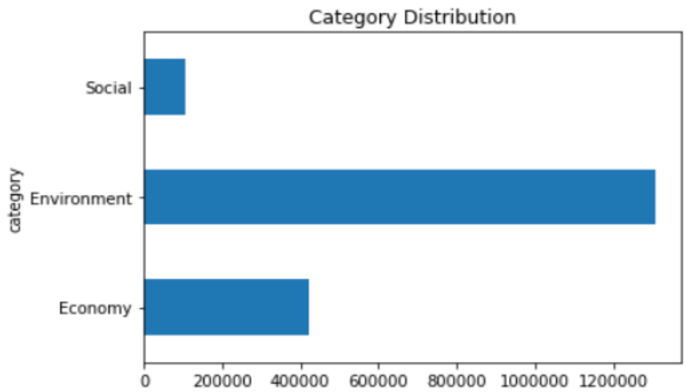

Figure 4: Tweets dimension distribution

By looking at Figure 4 it can be noticed that not all 2.85 million tweets could have been classified to the corresponding dimensions. This is due to the fact that Twitter tends to be very informal in terms of what is posted with a hashtag. Therefore, we are aware that the topic of sustainability is very large and heterogenous so an allocation of a tweet with a very specific topic to the three dimensions might simply not be suitable (e.g., the user @AHeikkinenPhD tweeted about marketing on 2019-03-05 with the post: "*Still time to register for #RBRS2019. Seminar is free of charge and open for all interested. Registration open until March 6. #CSR #vastuullisuus #Sustainability*"). However, we are concentrating explicitly on the three dimensions and therefore cannot cover the entire scope of any potential topic area.

The application of a multi-label classification approach was the first step towards generating a common understanding in terms of deriving popular and relevant topics from the three dimensions. In the next step, we used so-called wordclouds for the visualization of these topics. In this matter, a wordcloud is a technique for visualizing frequent words in a text where the size of the words represents their frequency. By doing so, we made use of an available python package called *wordcloud* that made it possible for us, to run a term frequency analysis right out of the box. To better narrow the focus, we have set a limit of the top 50 words of the three dimensions.

Figure 5 illustrates the wordclouds for the three dimensions of all sustainability tweets. The larger a word is displayed, the more often it occurs in the context of the respective dimension. Likewise, the color of the words does not matter in terms of frequency or relevance. Rather, it is only used as a differentiation facilitator for the wordclouds.

Concerning the economy wordcloud, it can be stated that there is not one topic that has significant relevance over the others. Rather, there are several topics in this context that can be considered more or less equally relevant. To better understand the context, we have selected one tweet per topic as an example and attached it here. As such, the Twitter user @NkirotePatricia tweeted on 2020-10-12 16:00:26: *"Social sustainability within the supply chain must be protected. Economic Sustainability cannot be achieved at the expense of Social sustainability. Such unethical concerns can only be picked if there is a robust Supply Chain Risk assessment model in place."* Interestingly, this example shows the need for a multi-label approach in practice (the foundations are explained in section 4.4), since the post can be classified in the context of economy as well as social. As a second highly relevant topic the area of *innovation* was identified via the wordcloud. In this regard @weconnectdata tweeted on 2020-01-27 09:10:05: *"Studies show that 67% of corporate executives think collaboration with a broader sustainable #innovation ecosystem is imperative for successful delivery of their #sustainability strategies."*

Figure 5: Wordclouds of the three dimensions

In the next step, we take a closer look at the environment dimension where *climate change*, *renewable energy*, and the buzzword *green* stand out. This also does not come by surprise since these three topics are clearly related to environmental aspects and are ever-growing in popularity. More concretely, @Eco_Meego posted on 2020-10-19 12:46:27: *"In the United States, people dump around 40% of the total food produced in waste. Restaurants contribute a total of 4 to 10 percent of this figure. #ecofriendly*

#sustainability #zerowaste #climatechange #globalwarming." regarding the climate change topic. Further, @GreenSparkNRG tweeted about renewable energy on 2019-09-27 20:12:01: *"Google has announced the largest renewable energy purchase in history! Totaling 1,600 megawatts, we are excited to see many of these large corporations taking steps toward greener operations. #solar #sustainability"*. Dealing with the third topic *green* was a bit cumbersome since the algorithm for the wordcloud combined many other words to the topic of *green* (e.g., green csr, green eco, green building, green energy, etc.). Nonetheless, to put the context into perspective, the user @_smartcity_ tweeted on 2020-06-10 21:00:12: *"More than 200 central bankers, G20 finance ministers and top academics decided that much of the trillions of dollars of spending tied to coronavirus relief programs should go toward green technology. But which technology? #hydrogen #sustainability"*.

At first sight, it looked as if the topic of *jobs* does also have significant relevance for the social dimension since it is displayed multiple times in the wordcloud. However, by analyzing the tweets in more detail we concluded that this topic is very biased by a lot of job offerings via Twitter in the era of sustainability and does therefore not provide any value to the social dimension of sustainability, since it can be seen as a unilateral marketing purpose. In this regard, the prominent word *getalljobs* from the wordcloud also is associated with job postings and does therefore not play a significant role in terms of social responsibility since we want to analyze and cluster highly discussed topics and not emphasize marketing efforts. However, we do not want to exclude the possibility that the job category does contain certain relevant posts in terms of the social dimension. By considering the above-mentioned arguments it becomes evident, that the social dimension of sustainability is far more heterogeneous than the other two dimensions. Interestingly, buzzwords such as human rights or working conditions are not seen as a relevant topic (or are at least not tweeted about) via the Twitter audience. In this matter, we took a closer look at the areas of *education* and *fashion* for the social dimension. At this point, we would like to address the fact again that of the three sustainability dimensions, the social dimension was by far the one with the least number of extracted tweets (see Figure 4). However, we explicitly do not argue that this dimension is less relevant than the other ones in terms of the total number of published tweets. More, it can be stated that this dimension is more heterogeneous than initially assumed and topics in this area are not yet clearly linked to the domain of sustainability. As such, @alademartha tweeted on 2020-01-25 00:34:59 about the topic of education: *"Education is the key to unlock a sustainable future in Africa and the world. Happy #educationday #SDGs #Sustainability #AfricaCodeWeek @sap4good @google @unesco @TeachersNg @mywitin #GirlsinICT"*. Further, in terms of fashion @ResponsibleFur reported on 2020-03-17 09:54:07: *"Whether it is for food or for #fashion, we need to stop keeping animals in such a sordid way. The #COVID2019 is not here for nothing. We need to reset the system. What are we waiting? #fur #intensivefarming #sustainability"*.

5.2 Users' perceptions of sustainability issues

After we have identified the most popular sustainability topics on Twitter via the use of wordclouds, we further proceed with gaining insights into the reactions of users to sustainability topics posted by the three selected companies: Amazon, Walmart, and Target. To answer our research questions, we drew upon three different data dimensions (see section 3): the Newsweek ranking to assess the level of sustainability activity measured by an official ranking, the social media activity level to detect of and how the sustainability issues are spread on Twitter and the sentiment to ascertain how the users react to the sustainability issues posted by companies on Twitter (see Table 2).

Table 2: Results of the analyses

Company	Ranking				Social Media Activity				Sentiment			
	OS	**Env.**	**Eco.**	**So.**	**∑**	**Env.**	**Eco.**	**So.**	**OS**	**Env.**	**Eco.**	**So.**
Amazon	60.1	48.8	73.5	57.9	1233	390 31,63 %	500 40,55 %	343 27,82 %	0.293	0.287	0.286	0.289
Walmart	69.4	57.6	75.9	74.8	5739	1479 25,77 %	2121 36,96 %	2139 37,27 %	0.158	0.144	0.184	0.195
Target	82.9	73.8	87.0	88.1	1045	259 24,78 %	473 45,26 %	313 29,35 %	0.328	0.284	0.404	0.169

Before comparing the results of the three different analysis methods with each other we consider them individually, starting with the ranking (see Table 2). First, we provide brief background information on how the ranking came about. The creation of the Newsweek ranking was based on a 4-phase process starting with composing top 2000 public companies by revenue with headquarters in the U.S. After that in a pre-screening phase it was analyzed, whether the company has published a CSR report, sustainability report, corporate citizenship report or anything similar. Furthermore, it was ensured that the companies´ activities did not concentrate on defense or that they were not involved in major lawsuits or scandals. This was followed by a detailed analysis including a survey of U.S. citizens and research of KPIs. The survey was conducted among 6,500 U.S. citizens via an online access panel. The survey asked the participants how the company´s CSR activities are perceived regarding their general perception and their perception in the three dimensions environment, social, and economy. Afterward, data from CSR reports (or similar) were disclosed and the KPIs were calculated. Various KPIs were consulted to evaluate the individual dimensions. Thus, in the environment dimension, aspects such as waste, emissions, water, or energy use were appraised. The economy dimension compasses two main aspects, disclosure, and transparency (e.g., the scope of CSR report, CSR-section on the website, compliance/ anti-corruption guideline) as well as economic performance (e.g., financial stability, innovation capacity). The third dimension, the social dimension, includes the leadership diversity (e.g., the share of women in board of directors), employees (e.g., average training hours) and philanthropy, and engagement (e.g., human rights policy, examples of social projects in CSR report) (Newsweek 2020). The research data was thereby binary or numerical. The respective scores of the three dimensions were then calculated using a weighting: 70% KPIs and 30% survey. This has resulted in an overall score for each of the companies. Each of these scores are rated between 0 and 100. The higher the score is, the better the companies perform in social responsibility matters in the U.S. The 300 companies with the best scores are included in the Newsweek ranking (Newsweek 2020).

Amazon ranked 300th in the Newsweek Ranking with an overall score of 60.1, the lowest of all companies surveyed. Thus, according to this ranking Amazon is the worst-performing company across all three dimensions. Looking at these three dimensions individually, it can be stated that Amazon scores particularly poorly in the environment dimension with a value of 48.8. This means that aspects such as waste, water, or carbon intensity as well as statements about reduction of energy use have not proven well. The same result can be observed in the social dimension social. Specifically, in this dimension, Amazon´s score (57.9) is by far lower than that of the two other companies Walmart (74.8) and Target (88.1). KPIs such as the share of women and minorities in the board of directors or the average training hours per employee were assessed here and best rated for the retailer Target. Closely related to this is the third dimension "economy" which takes KPIs such as the scope of the CSR report or the financial stability (Piotroski F-Score test) into account. With regards to this dimension, the differences between the companies are not as huge as for the other ones. Nevertheless, Target performs best here with a value of 87.0 again. With an overall score of 82.9, Target ranks 21st in the overall ranking of Newsweek´s "America´s Most Responsible Companies 2020". Particularly in the retail sector (and thus also here in the comparison to the other two retailers), Target has taken the first place. Especially in the environment dimension, Target (73.8) leaves the other two companies far behind (Walmart: 57.6 and Amazon: 48.8). Walmart´s average ranking in the environment dimension is evident in the overall score. The retailer´s overall score of 69.4 means a rank of 168 of the 300 considered companies in the Newsweek Ranking and is therefore in the midfield of the 300 companies.

In addition to the ranking, we also examined the social media activity in terms of sustainability communication for the three retailers. The conducted frequency analysis here refers to the total number of tweets posted by the companies about sustainability issues. The comparison of the companies´ overall scores indicates that Walmart has posted most about sustainability with 5739 tweets in total. This high level of activity is also reflected in the three dimensions. Thus, Walmart is most active in the environment (1479), the economy (2121), and in the social (2139) dimension in contrast to Amazon or Target. Amazon, however, posts slightly more about environmental (390), economic (500), and social (343) issues than Target with an overall score of 1045 posts. Considering Target, the least addressed dimension is the environment dimension (259), closely followed by the social (313) and economy dimension (473). Overall, it can also be stated here that the topic of sustainability is not very actively shared by the companies via social media, as even the company with the most written posts cannot be seen as highly active with 5739 posts over a period of 10 years. The last analysis method that we have examined is the sentiment. Again, we distinguish between the overall score and the scores for the individual dimensions. The company that has received the most positive feedback from Twitter users is Target, with an overall sentiment value of 0.328. The dimension with the most positive response here is the dimension "economy" (0.404), followed by "environment" (0.284) and "social" (0.169). In the last dimension, however, Target exhibited the worst sentiment score compared to the other two retailers, especially compared to Amazon (0.289). For Amazon, the sentiment values hardly differ across the three dimensions and thus the dimension "economy" featured a value of 0.286 and "environment" a value of 0.287. Particularly in these two dimensions, the reactions of the users are not as positive as for the other two companies. Walmart scores in relation to environmental aspects a value of 0.144 and in relation to economic aspects a value of 0.184. Thus, these worse scores in the individual dimensions are also reflected in the overall score (0.158).

Now that we have focused on the values separately, we compare them to each other. A cursory glance at Table 2 reveals that the values of the individual analysis methods depict a heterogeneous picture. This means that a high ranking does not automatically mean a high activity level or a very positive sentiment. Thus, the overall score shows for Amazon that it exhibits the worst ranking result (60.1) of the three retailers. This means that according to the Newsweek, the social responsibility performance of Amazon is poorly developed. However, Amazon appears relatively active on the social media platform Twitter and posted 1233 posts about sustainability. Also, the overall resonance about the sustainability activities is on average positive (0.293). The users react to the sustainability issues of Amazon with a more positive sentiment than on sustainability issues of Walmart. Although Walmart reached a higher ranking (69.4) and therefore performed better in social responsibility matters, they hit a comparatively negative response (0.158) to their high social media efforts (5739) especially in contrast to the other two companies. Target is least active in disseminating sustainability content via social media here. The retailer posted only 1045 posts about sustainable issues. These relatively few posts are met with a positive response (0.328). Target also performs best in the overall ranking here. To gain a better insight into the results and to make them more comprehensible, we have transferred the data into radar charts (see Figure 6).

Interesting insights can also be observed when examining the individual dimensions (economy, environment, and social). Walmart for instance is ranked relatively good with a score of 57.6 and also communicates that with 1479 posts actively. But the users do not react very positively (0.144) to environmental posts. The opposite can be detected at Amazon: this retailer exhibits a relatively bad ranking, does not communicate very much about it, and gets a positive response anyway. This trend can also be perceived in the social dimension: although this aspect is the worst rated in the official ranking, the users´ perceptions here are very positive (especially compared to the other companies). Different to Target, whose score (88.1) is very high but receives a comparatively bad resonance in the social dimension. However, Target faces better results within the economy dimension. Here they perceive the most positive values of the user´s sentiment for their active (social media) behavior represented by the Newsweek ranking and the number of tweets. Target and Walmart exhibit similar scores in the Newsweek ranking, Walmart communicates in social media much more strongly about this issue but receives worse results within the sentiment analysis compared to the other two companies.

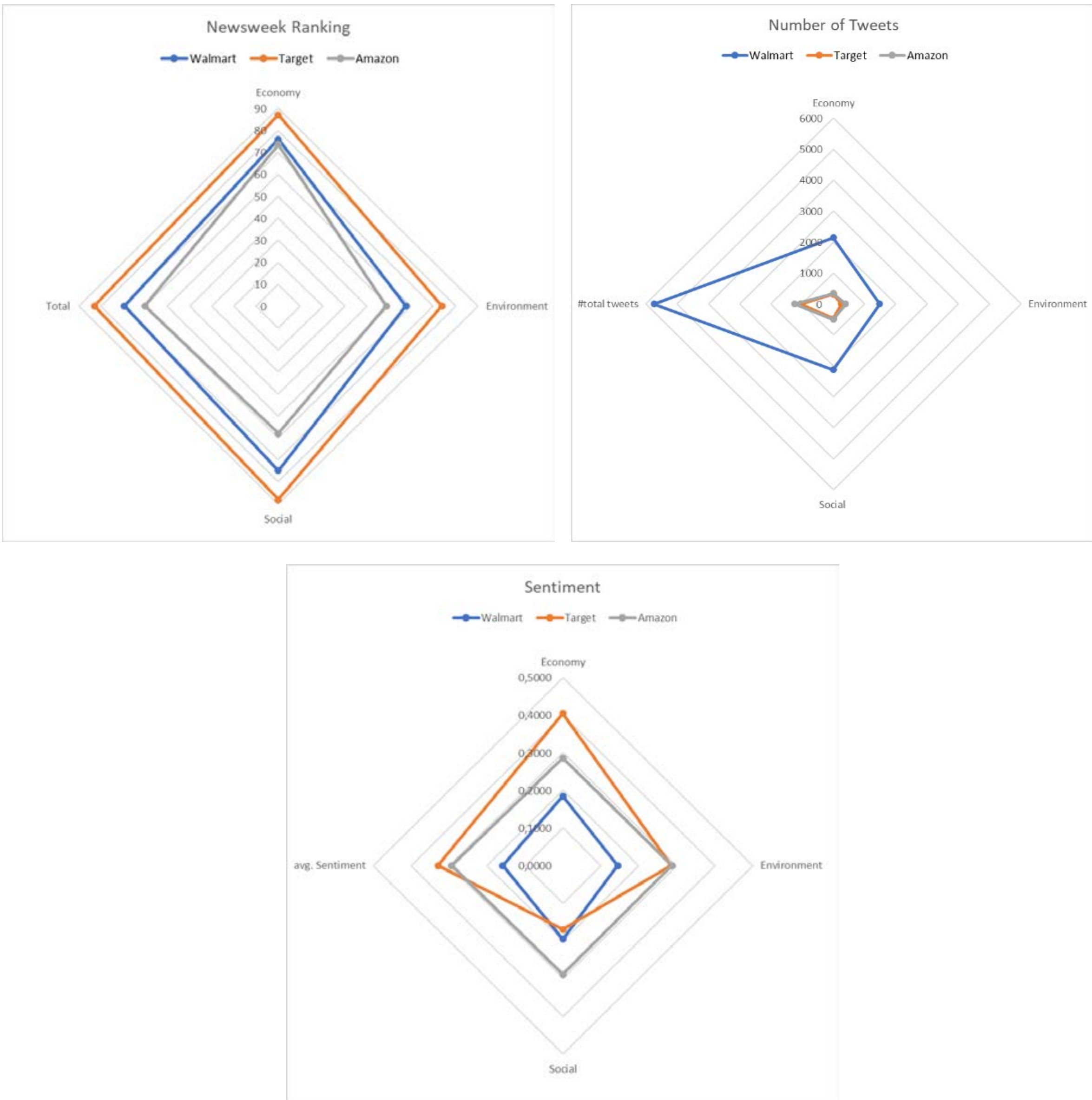

Figure 6. Radar charts

6 Discussion

Our investigation has contributed to identify the topics that are spread about sustainability via Twitter (see RQ1). With the help of the multi-label classification approach, we structured the results and classified them regarding the triple-bottom line including the dimensions of sustainability: economy, environment, and social. The analysis of the most important topics has shown which topics have been relevant in social media in the last 10 years and can thus be used by companies to formulate appropriate posts with a meaningful label. As the majority of the 2.85 million analyzed posts are written by individual users expressing their personal opinions about sustainability, companies can use this knowledge by aligning themselves with the needs of these external stakeholders. Further reasons that were identified in the current research literature that led to misconceptions between user and company such as vague and poorly formulated messages or claims that are not correlated to sustainability showing that the company does not conceive the issue (Williams et al. 2014) can thus be counteracted.

Furthermore, the frequency distribution of the three dimensions has shown that especially the dimension “environment” is prevailing in Twitter. At the same time, the results of the three companies have indicated that according to the Newsweek ranking, the retailers do not prioritize this dimension in their sustainability activities. The ranking scores for all three companies are worse in this dimension. However, knowing that Twitter users pay particular attention to environmental issues, there is a considerable need for action in this dimension. Focusing on topics such as climate change or renewable energies is more important than ever since the Friday´s for Future movement set the climate crises on a worldwide agenda. Especially younger generations are claiming that companies should focus on green and sustainable values.

We further analyzed our data to gain an insight into the users´ reactions to sustainability issues posted by companies, thus we have covered RQ1. We further wanted to ascertain whether social media is a suitable communication channel for companies to disseminate sustainability issues. A clear and stringent statement cannot be made here. Our results reveal that especially Walmart´s communication strategy is not very successful. As mentioned in section 5 the users´ reactions are only weakly positive towards the sustainability efforts of Walmart although their overall ranking score is 69.4 and although they communicate a lot via social media. It makes the impression that Walmart does not have a holistic sustainability strategy. Indeed, on the one hand, they are quite active in the different sustainability dimensions but on the other hand, there are also elementary things that are not constantly applied, especially in the offline areas. We have found some examples as we have taken a closer look at the posts about Walmart. E.g., users criticize Walmart for dumping too much food (especially fruits and vegetables) even though it is still good. Other examples include the fact that the leadership did not speak out in favor of sustainability at the world economic forum in Davos or that Walmart tries to score points with green advertising but appears to not implement it holistically in their retail stores (“@Walmart your sustainability #earthday commercial was touching, but I got a free recycle bag from @target”). Another reason for negative comments prevailing in the Twitter data is also a report that was spread within the network. This report entitled “10 Ways Walmart fails on Sustainability” and the authors state that Walmart disregards the huge problems with its business model that harm the environment, undermine healthy food choices, and compound poverty. Due to the network nature of Twitter, this article has spread quickly and widely. Through these examples, it seems that Walmart's strategy is not entirely coherent. If sustainability is advocated, then this must be implemented and lived throughout the entire company and across all hierarchical levels. It is therefore advisable to push for a holistic strategy within the meaning of sustainability, which also includes a change in the corporate culture if necessary.

Target, however, applies another strategy: they hardly communicate about sustainability via social media. When they post something, they disseminate facts, e.g., their five years sustainability plan, a Greenpeace rating with Target ranging as most sustainable seafood retailer, or other reports about sustainability commitments underpinned with significant numbers. Users rated this as positive and also highlighted other online efforts regarding sustainability such as the TargetChat about sustainability with management attendance. Thus (re)posting facts and objective reports on sustainability activities can lead to positive feedback.

Amazon follows a different path and focuses on the positive and convincing communication of its sustainability activities. Although the company exhibits bad values in the Newsweek Ranking, which is an indicator for disregarding sustainability efforts, Amazon got good responses from users regarding the sentiment analysis. Based on our data it seems that the company therefore adopts a responsible image on Twitter without a sufficient basis. This is particularly surprising in the case of the social dimension. Amazon exhibits a score of 57.9 in the Newsweek ranking. KPIs such as the share of women and minorities in the board of directors (leadership diversity) or the handling with employees are evaluated here. Apparently, Amazon performs poorly here. Nevertheless, the sentiment score was the most positive (0.289) in this dimension compared to the others. Amazon manages to spread good vibes by posting merely convincing messages. Thus, they distract from their deficits within the sustainability area. Additionally, this can be seen in the environmental dimension when Amazon promote e.g., on Twitter that it considers including “Hydrogen as a green shipping option”. With this post, Amazon is positively highlighting that they care about the environment. So, a quick Twitter reader should be conveyed that an environmental orientation is taking place at Amazon. In fact, however, due to the very vague wording, no conclusions can be drawn about the actual sustainability activities of the company. This vagueness in the sustainability Twitter posts is an indicator that Amazon is engaging in some degree of greenwashing (Williams et al. 2014). But also, the fact of “No-proof” within the social dimension (see above) means sustainability claims that cannot be substantiated by easily accessible information or by a reliable third-party certification is another indicator for greenwashing according to Williams et al. (2014). So, greenwashing via social media can be achieved quite successfully by implementing a sophisticated communication strategy.

Hence, our results show that only communicating about sustainability issues via social media is not immediately successful when spreading sustainability issues. In fact, as mentioned in the theoretical background (see Section 2.2.), social media communication must follow a strategy to be successful and to build a long-term relationship between the customer and the company (Li et al. 2021). Our in-depth analysis of the company's sustainability communication on social media and the derived results also enabled us to find starting points for the social media (sustainability) strategy (Li et al. 2021, Ng and Wang 2013, Pulizzi and Barrett 2009). Results from Walmart, for example, show that the manager´s misconduct and the practice of food dumping is not in line with Walmart’s social media sustainability content strategy. These inconsistencies between the company’s overall direction and social media content strategy are negatively perceived by social media users. A company’s holistic focus on the topic of sustainability is therefore indispensable, and a social media content strategy should be included in the company’s overall strategy. Consequently, the social media content strategy should be expanded with a frame of reference such as sustainability; external influencing factors should also be considered here. This means the social media content strategy focusing on sustainability should be embedded within the overall strategic orientation of the company.

Furthermore, the results of the users’ sentiment values about the sustainability communication of Target and Amazon provide an indication that a multidimensional social message strategy (Li et al. 2021) can generate positive WoM resulting in a relationship between the customer and the company. Target uses the social media message strategy, of sharing high-quality content on Twitter at low frequency, which has generated very positive user reactions (0.328). Thus, for example, Target reposts current sustainability reports from independent third parties and therefore follows parts of the strategy about the content being relevant, useful and timely (Pulizzi and Barrett 2009). However, a comparison of Target’s sentiment values for the environmental and social dimensions with those of Amazon, shows that the factor of compelling content, may be decisive for the more positive sentiment values Amazon achieved for these two dimensions. Thus, we can conclude from our results that storytelling and being compelling in combination with using well-presented facts (i.e., relevant, useful, compelling and timely content) (Li et al. 2021, Pulizzi and Barrett 2009) is a promising way to generate positive WoM (Holliman and Rowley 2014) in terms of environmental and social sustainability. Amazon complies with this strategy and can therefore also compensate for its poor ranking values (in fact a lack of an overall sustainability strategy). With its social media content strategy, Amazon also follows aspects that are crucial in relationship management theory for building a long-term relationship (Sweetser 2010). A closer look at Amazon’s sustainability posts and social media activities shows that the company focuses on factors such as positivity and openness. It is above all the cheerful and direct communication that leads us to conclude that the company has anchored these factors in their social media strategy. Especially with very sensitive topics such as environmental and social sustainability, building a relationship between the company and its customers with the aim of generating trust is very important for establishing brand awareness and achieving the status of a trusted sustainable brand (Li et al. 2021, Sweetser, 2010). The combination of positivity and openness in the social media sustainability strategy can obviously outweigh other factors (e.g., following a holistic strategy) and still lead to a positive response and relationship. Future research could address this point and further focus on the connection between social media content strategy theory and relationship management theory in terms of sustainability and how the combination of these theories impacts users’ sentiment values.

On the whole, it is important in terms of the social media sustainability strategy to be aligned with the overall strategy and to personalize content through storytelling to build a relationship with customers. This is especially true considering how bad news about companies and the suspicion of greenwashing spreads much faster on social media than offline and must therefore be avoided. However, there are also companies that use sustainability communication via social media so successfully that they can distract attention from their weak points and even improve their image as a result. Nevertheless, Amazon is also rumored to have used fake accounts claiming to be Amazon workers and praising their working conditions on Twitter (Timmler 2018, BBC 2021).

7 Conclusion and Outlook

The paper at hand provides detailed insights in the social media communication of sustainability in terms of classification and sentiment analysis for the ever-increasing importance and relevance of sustainability for society and organizations. Therefore, over 3.95 million Twitter posts related to the topic of sustainability were extracted in the timeframe from 2010 to 2020. First, we introduced and highlighted the three main sustainability dimensions which are economy, environment, and social. Having identified these dimensions for the purpose of a text classification approach, we manually classified a subset of the Twitter data to create a training set for machine learning algorithms in terms of an automated text classification. After pre-processing the 3.95 million tweets were reduced to 2.85 million. We found that Linear Regression performed best compared to other tested approaches and therefore applied this trained algorithm to the 2.85 million sustainability tweets. We visualized our findings via wordclouds and we identified the most discussed topics for each of the three dimensions. Further, to also get deeper insights in terms of organization's sustainability efforts and communications via social media, we picked three large retail companies to analyze and compare their official sustainability scores based on Newsweek's ranking for America's most responsible companies (Newsweek 2020) with the sentiment derived from their sustainability Twitter posts as well as with the quantitative number of published sustainability tweets. This comparison revealed a very heterogeneous picture meaning that being high ranked in official sustainability ratings does not necessarily relate to a very positive sentiment neither to high activity levels on Twitter.

This paper provides starting points for contributing to theory and practice alike. As a contribution to social media strategy in terms of sustainability, the company-related results show that a company's social media content strategy should be aligned with the company's overall strategy. Consequentially, when creating a social media content strategy, external and internal factors that directly influence the corporate strategy and thus also indirectly influence the social media strategy must be considered. In addition, the results show how important it is for companies to use storytelling and build a long-term relationship with customers by spreading positivity and openness while communicating sustainability via social media. This seems to be the most promising way to generate positive WoM and thus stand out as a sustainable company on social media. As a contribution to practice, the results show the main topics about sustainability that are spread and discussed via Twitter. These results can be used to identify areas that companies are not currently paying attention to, such as the environmental dimension. Focusing on these topics and promoting them on social media can enable companies to be perceived as more sustainable brands. Moreover, companies can deliver on our contributions to social media strategy by, for example, considering their overall strategy or integrating storytelling into sustainability communication. As a final insight, the paper shows that sustainability communication via social media can also help some companies improve their image by distracting from their weak points. If a long-term relationship based on trust exists between the customer and the company, negative news about the company is not immediately questioned. Thus, companies can also use Twitter to successfully achieve the goal of greenwashing.

However, the paper at hand does not come without limitations: First, even though we evaluated a total of six common algorithms for text classification, we are aware of the fact that there are still others as well. The scope of this paper, however, does not lay on an in-depth analysis and comparison of all possible text classification approaches, rather, it is on the analysis and practical insights from the sustainability tweets. Second, we did not analyze other social media platforms such as Facebook or Instagram to get the most holistic view. However, since we were able to extract almost four million tweets, we consider this as a representative basis to validate our results.

In the future, we aim to further train the used algorithms to get even better classification results which might also lead to a more homogeneous view on the social dimension of sustainability tweets. Additionally, an extension of our approach to also compare other branches than the retail industry is considered. This way, we are also aiming to containerize our data analysis approach for making it available to the public, so that it can be adapted and used in any possible way and therefore provide value not only for the research community but also to organizations to better understand their image and reputation in terms of sustainability towards the general public.

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3. Schlussbetrachtung und Fazit

Dieses Kapitel ist zunächst ein Resümee der Forschungsergebnisse der Dissertation. In Abschnitt 3.2 wird dann der Beitrag der Dissertation für Wissenschaft und Praxis nochmals zusammenfassenden verdeutlicht. Eine kritische Würdigung sowie ein Ausblick, (Abschnitt 3.3) schließen die Arbeit ab.

3.1 Zusammenfassung der Forschungsergebnisse

Das erste Themengebiet der Dissertation umfasst die Analyse von Nutzertypen in Social Media Networks. Die dabei adressierten Forschungslücken zeigen vor allem auf, dass diejenigen Nutzer, die für Unternehmen besonders wertvoll sind, nur rudimentär beschrieben und charakterisiert wurden. Einflussreiche Nutzer können in verschiedener Art und Weise zum Erfolg von Social Media Networks beitragen. Dafür müssen sie aber unterschieden und charakterisiert werden (Zielstellung 1). Der **erste Beitrag** der Dissertation setzt bei dieser Zielstellung an und fasst mit Hilfe eines strukturierten Literature Reviews den aktuellen Stand der Forschung zusammen. Insgesamt 52 relevante Publikationen wurden identifiziert und nach den Ansätzen von Nickerson et al. (2013) und Mayring (2014) klassifiziert, indem ein Framework mit den beiden Dimensionen „Attribute eines einflussreichen Nutzers“ und „Nutzertypen“ erstellt wurde (**Forschungsfrage 1**). Durch die Systematisierung der verschiedenen Charakteristika der einzelnen Nutzertypen wurde eine Grundlage für die **Forschungsfrage 2** geschaffen, die verschiedenen Merkmale von einflussreichen Nutzern in einem Social Media Network thematisiert und danach fragt, wie diese von anderen Nutzergruppen abgegrenzt werden können. Darüber hinaus wurde der Charakterisierungs- und Identifizierungsprozess mit Hilfe eines morphologischen Kastens spezifiziert. Dieser morphologische Kasten ermöglicht die Differenzierung nach verschiedenen einflussreichen Nutzertypen, was durch eine beispielhafte Anwendung zwei verschiedener Nutzertypen, des Influencer und des Lead User, gezeigt werden konnte.

Um als Unternehmen allerdings von einem einflussreichen Nutzer profitieren zu können, ist vor allem die (automatisierte) Identifikation dieser Nutzer ein entscheidender Punkt. Die zuvor beschriebenen Charakteristika müssen also mit Hilfe von verschiedenen Methoden zur Analyse von strukturierten und unstrukturierten Social Media Daten umgesetzt werden (Zielstellung 2). In der vorhandenen Literatur gibt es viele verschiedene Ansätze zur Identifizierung von Lead User. Diese Untersuchungen sind aber in ihrer Aussagekraft limitiert, da sie sich entweder auf nur wenige Lead User Merkmale konzentrieren (Martínez-Torres, 2014), eine sehr geringe Datenmenge einbeziehen (Hau and Kang, 2016) oder sich deren gewählter Ansatz auf die Selbsteinschätzung der Nutzer stützten (Hienerth and Lettl, 2017). Dieses Problem wird durch die enorme Anzahl an Online Community Daten verschärft, was die Identifizierung von Lead User noch schwieriger, kostspieliger und zeitaufwändiger macht. Hier setzt **der zweite Beitrag** (**Forschungsfrage 2, 3 und 4**) an, in dem eine automatisierte und – nach Aussage des befragten Experten – effektive Methode zur Identifikation von Lead User vorgestellt wurde. Basierend auf der aktuellen Forschungsliteratur wurde ein Tool entwickelt und implementiert, das einerseits alle für einen Lead User relevanten Charakteristika berücksichtigt und andererseits die Tatsache miteinbezieht, dass Lead User in verschiedenen Phasen des Innovationsprozesses eingesetzt werden können. Um die Validität und den Mehrwert des Artefakts zu demonstrieren, wurde das Tool auf 11.481 Beiträge von 945 Nutzern eines Online Forums für Kiteboarding angewendet. Nach der Identifizierung der Lead User wurden die Ergebnisse durch Befragungen der jeweiligen Lead User sowie eines Experten evaluiert und bestätigt. Um besonders **Forschungsfrage 4** gerecht zu werden, wurden in diesem Artikel vor allem die verschiedenen Beiträge für die Praxis sowie für die Forschung (Kernel Theorien: Innovations- und Lead User Theorie; Design Theorie: Ableitung von Design Prinzipien) herausgearbeitet.

Neben der Identifizierung der einflussreichen Nutzer im Zuge des OSN lässt sich diese Art von Nutzern auch im Bereich ESN identifizieren. Auch hier gibt es in der aktuellen Forschungsliteratur nur unzureichende Ansätze, die wertstiftende Nutzer zu identifizieren versuchen. Die initiale Literaturrecherche **im dritten Beitrag** hat einen Überblick über bestehende Charakteristika von wertstiftenden Nutzern ermöglicht und zusätzlich die Erkenntnis geliefert, dass ein wertstiftender Nutzer vor dem Hintergrund einer bestimmten Zielstellung definiert werden muss (**Forschungsfrage 3**). Die Merkmale eines wertstiftenden Nutzers als Ergebnisse der Literaturrecherche, wurden mit Hilfe der Dimensionen: Netzwerkstruktur, Nachrichteninhalt, Verhalten und Social Media Affinität strukturiert. Dadurch wurde ein umfassender Überblick über die Definition und die Charakterisierung von wertstiftenden Nutzern erarbeitet. Basierend darauf folgte im Zuge der Single Case Study eine Untersuchung der Anwendbarkeit der Dimensionen und Ziele, indem verschiedene wertstiftende Nutzer in einem realen ESN Datensatz eines Partnerunternehmens identifiziert wurden. Durch zusätzlich durchgeführte Interviews mit Entscheidungsträgern des Unternehmens konnten weitere Anforderungen an einen wertstiftenden Nutzer identifiziert werden. Infolgedessen wurden auch weitere

Analysearten wie die Emotionsanalyse und die Themenanalyse miteinbezogen. Die Interviews dienten dazu, die Ergebnisse zusätzlich abzusichern und zu bestätigen. Zusammengefasst haben die Ergebnisse der Untersuchung gezeigt, dass das Einbeziehen von Zielen und weiteren Analysemethoden ein wichtiger Schritt ist, um wertstiftende Nutzer zu identifizieren und aus Unternehmenssicht effektiv einzusetzen.

Neben der Analyse von Nutzern in Social Media Networks wurden im Zuge der Dissertation auch Beiträge vorgestellt, die vor allem die Analyse von Social Media Network Daten fokussieren. Durch die große Anzahl an Social Media Daten ist es fast unmöglich diese manuell zu analysieren. Automatisierte Techniken sind dadurch unverzichtbar. Um beispielsweise Kundenwünsche aus den Daten zu extrahieren, hat sich die Methode des Topic Modelling als geeignet erwiesen. Diese kann die in den Dokumenten enthaltenen Themen automatisiert extrahieren (z. B. Eickhoff und Neuss, 2017; Vayansky und Kumar, 2020). In der aktuellen Forschungsliteratur sowie in der Praxis lässt sich dabei auch beobachten, dass insbesondere für marketingspezifische Anwendungen die Technik LDA verwendet wurde. Da aber LDA nicht alle Anforderungen an Topic Modelling Techniken (wie z.B. das Abbilden von Hierarchien) hinsichtlich der Einsatzgebiete Inhaltsextraktion, Trend Analyse und Inhaltsstrukturierung erfüllen kann, müssen andere Topic Modelling Techniken herangezogen werden. Um Handlungsempfehlungen hinsichtlich deren Einsatz abgeben zu können, wurde **im vierten Beitrag** ein Vergleich zwischen verschiedenen Topic Modelling Techniken angestellt. Zunächst wurden für die identifizierten Anwendungsfälle Anforderungen identifiziert und Metriken (Log-Likelihood, Coherence, Build Time, Word und Topic Intrusion) zur Bewertung der Topic Modelling Techniken erhoben (**Forschungsfrage 5**). So wurden die Techniken LDA, DMR und PAM an einem realen Datensatz angewendet, evaluiert und miteinander verglichen. Die Ergebnisse, die zur Beantwortung der **Forschungsfrage 6** der Dissertation herangezogen werden können, haben gezeigt, dass bei der Themenextraktion DMR verwendet werden sollte, wenn eine große Anzahl an extrahierten Themen gefordert ist. Bei nur geringer Anzahl an extrahierten Themen, wenn die resultierenden Themen also eher abstrakter sein, führt LDA laut den Ergebnissen zu besseren Ergebnissen. Hinsichtlich des zweiten Anwendungsfalls der Trend Analyse hat sich DMR als geeignete Topic Modelling Technik herausgestellt, da es die sinnvollsten und aussagekräftigsten Themen identifiziert und gleichzeitig schnell Ergebnisse liefert. Zudem kann DMR externe Parameter wie zum Beispiel Zeit oder Geolokationen berücksichtigen. Hinsichtlich des dritten

Anwendungsfalls – Inhaltsstrukturierung – muss die Topic Modelling Technik vor allem in der Lage sein, Beziehungen und Zusammenhänge zwischen den Techniken zu identifizieren, was PAM, am besten kann. Solche Empfehlungen dahingehend, welche Topic Modelling Technik für welches Einsatzszenario eingesetzt werden soll, können in Zukunft sowohl von der Wissenschaft als auch in der Praxis verwendet werden.

Da aber nicht nur die Auswahl der geeigneten Topic Modelling Technik eine Herausforderung darstellt, sondern auch ihre praktische Anwendung, wurde in der **Veröffentlichung 5** ein Topic Modelling Tool (MANTRA) erstellt, das für die Trendanalyse eingesetzt werden kann. Mit Hilfe des Design Science Ansatzes wurde das Social Media Analyse Tool MANTRA erarbeitet, indem Anforderungen an das Artefakt aus der Forschungsliteratur hinsichtlich der Anwendungsfälle (a) Produktentwicklung, (b) Kundenverhaltensanalyse und (c) Markt-/Markenbeobachtung identifiziert und technisch realisiert wurden (**Forschungsfrage 7**). Dadurch, dass einer der drei Anwendungsfälle, nämlich Produktentwicklung, auf einen realen Social Media Datensatz (~1,03 Millionen Yelp-Bewertungen) angewandt wurde, konnte gezeigt werden, dass das entwickelte Tool in der Lage ist, unter Berücksichtigung aller dafür wichtigen Anforderungen, relevante Trends zu identifizieren. Insbesondere wird durch die Ergebnisse auch deutlich, wie wichtig es ist, externe Parameter, wie z.B. Geolokationen, in die Trenduntersuchung einzubeziehen. Je nach Standort waren die identifizierten Trends mit divergierenden Sentimentwerten konnotiert. Durch die strukturierte Entwicklung des Softwareartefakts und die daraus erzielten Ergebnisse konnten wir Beiträge für die Praxis (z.B. automatisierte Identifikation der VoC zur Anpassung der Produkte an die Vorstellungen der Kunden) und für die IS-Forschung (Design Theorie und Kernel Theorien) ableiten. Eine Erweiterung des Trendanalyse Tools MANTRA stellt die **Veröffentlichung 6** dar, die zusätzlich bei der Trendanalyse hinsichtlich der Produktentwicklung die aspekt-basierte Sentimentanalyse berücksichtigt. Diese Analysetechnik hat sich als effektiver Ansatz erwiesen, wenn es darum geht, Trends von Produkten und deren Eigenschaften nachzuvollziehen und zu untersuchen. Auf der Grundlage von in der Literatur identifizierten Anforderungen an den Anwendungsfall Produktentwicklung wurde erneut ein Artefakt, wieder mit Hilfe des Design Science Ansatzes, erstellt (**Forschungsfrage 8**). Auch hier wurde das automatisierte Trend Analyse Tool auf einen realen Social Media Datensatz angewendet (37.638 Yelp Bewertungen). Damit konnte gezeigt werden, dass das Tool in der Lage ist, feingranulare Produkttrends zu identifizieren. Zudem hat das reale Beispiel gezeigt, dass es vor allem bei Trends wichtig ist, dass das Tool, Trend Themen sowohl ohne Vorwissen als auch mit bestehendem Vorwissen identifizieren kann. Zudem ist das Berücksichtigen von externen Parametern elementar, um Unterschiede im Sentiment zwischen verschiedenen Geolokationen herauszustellen. Auch die Darstellung von Hierarchien und Zusammenhängen zwischen den einzelnen Trends führt zu genaueren und aussagekräftigeren Ergebnissen hinsichtlich der Verbesserung von Produkteigenschaften.

Dass die Analyse von Sentimentwerten aber nicht nur im Zuge der Produktentwicklung hilfreich sein kann, zeigt **Veröffentlichung 7**, die die Zielstellung verfolgt, durch die Analyse von Nutzerdaten, Gestaltungsansätze für die Social Media Strategie bei gesellschaftlich relevanten Themen (wie z.B. Nachhaltigkeit) abzuleiten. Um dieser Zielstellung gerecht zu werden, wurden 3,95 Millionen Tweets zum Thema Nachhaltigkeit analysiert, um zunächst relevante Nachhaltigkeitsthemen, welche Nutzer in Social Media diskutieren, zu identifizieren. Diese wurden dabei in die drei Dimensionen der Nachhaltigkeit Wirtschaft, Umwelt und Soziales klassifiziert. Eine Häufigkeitsanalyse hat ergeben, dass das Thema Umwelt von den Nutzern in Twitter am häufigsten angesprochen wird. Themen, die dabei besonders relevant sind, sind z.B. der Klimawandel oder erneuerbare Energien. Auch die wichtigsten Themen der anderen beiden Dimensionen wurden mit Hilfe von Wordclouds visualisiert. Basierend auf diesen Ergebnissen wurden bei drei Handelsunternehmen (Amazon, Walmart und Target) Posts mit Nachhaltigkeitsthemen identifiziert und die Reaktionen der Nutzer darauf mit Hilfe der Sentimentanalyse untersucht (**Forschungsfrage 9**). Diese Stimmung der Twitter-Nutzer wurde im Zuge der Untersuchung mit den Nachhaltigkeitsaktivitäten der Unternehmen in Social Media (Häufigkeitsanalyse) und einem Ranking (The Newsweek) verglichen, um tiefere Einblicke hinsichtlich der Nachhaltigkeitskommunikation via Social Media zu erhalten. Die Ergebnisse, die zur Beantwortung der **Forschungsfrage 10** herangezogen werden können, zeigen ein sehr heterogenes Bild, was bedeutet, dass ein gutes Rankingergebnis nicht unbedingt mit einem sehr positiven Sentiment oder einem hohen Aktivitätsniveau auf Twitter einhergehen muss. Vielmehr haben die Ergebnisse gezeigt, dass das Veröffentlichen von Fakten und das Verweisen auf externe Berichte über die Nachhaltigkeitsstrategie von Unternehmen ein möglicher Weg sein kann, um positive Reaktionen zu erhalten. Eine zusätzliche Alternative kann das sog. story-telling sein. Ergebnisse für Amazon haben beispielsweise gezeigt, dass eine positive und überzeugende Sprache bei der Verbreitung von Nachhaltigkeitsthemen zu positiven Reaktionen und somit auch zum Aufbau einer nachhaltigen Beziehung zwischen

Unternehmen und Kunden führen kann. Darüber hinaus ist das Etablieren einer ganzheitlichen Nachhaltigkeitsstrategie, an der sich auch die Social Media Inhaltsstrategie ausrichten sollte, elementar, um von der Nachhaltigkeitskommunikation in den sozialen Medien zu profitieren.

3.2 Beitrag für Wissenschaft und Praxis

Von den Forschungsergebnissen der vorliegenden Dissertation lassen sich sowohl Beiträge für die Wissenschaft als auch für die Praxis ableiten.

Zunächst trägt die Dissertation durch die initiale strukturierte Aufarbeitung der aktuellen Forschungsliteratur hinsichtlich der einflussreichen Nutzer in Social Media Networks zur Wissenschaft bei. Durch das daraus resultierende Framework konnte zum einen ein Überblick über das Themengebiet geschaffen werden. Zum anderen konnte durch die Klassifikation der relevanten Literatur eine Möglichkeit geschaffen werden, bestehende Forschungslücken aufzudecken. Zudem wurde so deutlich, dass es in der aktuellen Forschungsliteratur viele verschiedene Terminologien wie z.B. Hub, Influencer, Key User etc. gibt, die den einflussreichen Nutzern zugeordnet werden können. Da eine klare Definition und eine Abgrenzung der Begriffe voneinander bislang fehlte und einige Untersuchungen die Begriffe sogar synonym verwenden (z.B. Galeotti und Goyal, 2009), wurde durch den ersten Forschungsbeitrag („*Influential Users in Social Media Networks: A Literature Review*") ein erster Schritt in Richtung standardisierter Definition der verschiedenen Nutzertypen und deren klarer Charakterisierung unternommen.

Ein besonderes Augenmerk legt die Dissertation v.a. auf einen Nutzertyp, der im Hinblick auf Innovationen wertstiftend ist, den Lead User. Damit trägt die Dissertation im Rahmen der Untersuchung 2 („*Automated identification of different lead users regarding the innovation process*") zu den zugrundeliegenden Kernel Theorien (Lead User Theorie, Innovationstheorie) bei. Mit Hilfe der Untersuchung wurde zunächst gezeigt, dass es sinnvoll ist, Lead User nach den unterschiedlichen Phasen des Innovationsprozesses aufgrund ihrer unterschiedlichen Kompetenzen, Charakteristika und Anwendungsbereiche zu unterscheiden. Unsere Ergebnisse haben gezeigt, dass eine getrennte Betrachtung eine gezielte Identifikation ermöglicht und dadurch Lead User zielgerichteter eingesetzt werden können. Dadurch wurde eine neue Dimension in die Lead User Theorie nach Von Hippel (1986) eingeführt, nämlich, dass ein Lead User vor dem Hintergrund seines Zwecks definiert werden soll. Definition und Charakterisierung eines Lead Users sollen sich also nicht nur auf die Merkmale, sondern auch auf den

Zweck seiner Nutzung konzentrieren. Des Weiteren tragen die Ergebnisse der Untersuchung dazu bei, dass der 4-Schritte Prozess von Von Hippel (1986) bez. der Nutzung eines Lead User flexibler gestaltet werden kann und einfacher nutzbar ist. So ist der initiale Schritt, nämlich die Identifikation der Trends, nicht mehr als obligatorische Prämisse für den zweiten Schritt anzusehen. Der vorgestellte Ansatz vereint nun beide Schritte. Des Weiteren bietet der entwickelte Ansatz die Möglichkeit, mehrere Trends und die dazugehörigen Lead User gleichzeitig zu identifizieren. Drittens hat die Forschungsarbeit einen Beitrag zur automatisierten Identifikation von Lead User geleistet, indem für jedes, in der Literatur identifiziertes Charakteristikum eine technische Umsetzung gefunden wurde. Zukünftige Forschungsarbeiten können von der nunmehr automatisierten Identifikation der Lead User Charakteristika profitieren, indem eine umfassende, feingranulare und zielgerichtete Identifikation von Lead User ermöglicht wird. Zielgerichtet auch vor dem Hintergrund, dass der Ansatz es zulässt, Gewichte für jedes Charakteristikum einzustellen und damit den in den verschiedenen Phasen des Innovationsprozesses unterschiedlichen Anforderungen an einen Lead User gerecht zu werden. Damit trägt die Dissertation auch zur Innovationstheorie bei. Durch die Integration eines Lead Users in die unterschiedlichen Phasen des Innovationsprozesses – z.B. in das Stage Gate Modell – wird der strikte Ablauf von „stages“ und „gates“ aufgebrochen, indem die externe Sichtweise stetig miteinbezogen wird. Dadurch wird ein agiler und zielorientierter Ansatz im Rahmen des Innovationsprozesses geschaffen und es kann so genauer auf die Wünsche der Kunden eingegangen werden.

Neben dem Beitrag zu den Kernel Theorien lässt sich auch ein solcher zur Design Theorie ableiten. Durch die Erstellung von Design Prinzipien konnte ein Beitrag zur „Nascent design theory“ (Gregor and Hevner, 2013) geleistet werden. Durch die praktische Umsetzung bei der Entwicklung des Artefakts sowie der anschließenden Demonstration und Evaluation konnte eine implizite empirische Fundierung der Design Prinzipien erreicht werden (Heinrich and Schwabe, 2014). Durch die Berücksichtigung z.B. des Design Prinzips 3. Kontextabhängige Anpassungsfähigkeit wird die Bedeutung des Kontexts, in dem ein Nutzer-Identifikationstool erstellt wird, hervorgehoben. Da sich der Kontext direkt auf Definition und Umsetzung der Anforderungen an ein solches auswirkt, wird die Ausrichtung auf den Kontext auch bei der Erstellung von anderen (Identifikations-)Tools zu zielgerichteteren Ergebnissen führen.

Auch in Bezug auf den wertstiftenden Nutzer im Bereich ESN kann die Dissertation mit der Veröffentlichung 3 („*Identifying Value-adding Users in Enterprise Social*

Networks“) einen Beitrag zur Wissenschaft leisten, weil ein umfassender Überblick über das Forschungsgebiet aufgezeigt wurde. Dabei wurden sowohl die unterschiedlichen Ziele, für die ein wertstiftender Nutzer eingesetzt werden kann, als auch, die in der Literatur existierenden, Charakteristika berücksichtigt. Zudem wird ein Beitrag zum Verständnis der Wertgenerierung innerhalb eines ESN geleistet. Dass Nutzer auf unterschiedliche Art und Weise (z.B. durch Wissensgenerierung oder durch Echtzeit Feedback) zum Wert eines ESN beitragen können, wird in der aktuellen Forschungsliteratur bisher kaum berücksichtigt. Durch den Fokus auf wertstiftende Nutzer und deren Einfluss auf das Netzwerk konnte so ein wesentlicher Beitrag zur Wissenschaft geleistet werden.

Neben den Ergebnissen der Dissertation im Bereich der Analyse von Nutzertypen in Social Media Networks, lassen sich auch für den zweiten Teil der Dissertation – die Analyse der Daten in Social Media Networks – theoretische Beiträge ableiten. Vor allem hinsichtlich des Topic Modelling geht die Dissertation über das bisher Bekannte hinaus. Die verschiedenen Topic Modelling Techniken LDA, DMR und PAM wurden im Rahmen der Veröffentlichung 4 („*COMPARISON OF TOPIC MODELLING TECHNIQUES IN MARKETING – RESULTS FROM AN ANALYSIS OF DISTINCTIVE USE CASES*“) mit Hilfe eines realen Datensatzes hinsichtlich fünf verschiedener Evaluationsmetriken miteinander verglichen mit der Absicht Stärken (z. B. kann DMR bevorzugt für die Trendanalyse in Betracht gezogen werden) und Schwächen (z. B. ist PAM aufgrund des hohen Zeitaufwands und der mangelnden Fähigkeit zur Kontextualisierung von Themen nicht für die Trendanalyse geeignet) der Ansätze aufzudecken, was sowohl für Forschende als auch für Praktiker wertvoll ist. Dieser Vergleich basiert auf dem GQM Ansatz, der ein systematisches Forschungsvorgehen darstellt und somit reproduzierbare Ergebnisse ermöglicht. Zudem konnten Potenziale für weitere Verbesserungen (z.B. Berücksichtigung einer schnelleren Erstellungszeit für PAM bei $k > 50$) entwickelt werden. Im Zuge der Untersuchungen zum Thema Topic Modelling wurde außerdem näher auf die Trendanalyse und die in der Literatur zu findenden Anforderungen eingegangen (siehe Beitrag 5 „*MANTRA – A Topic Modeling-Based Tool to Support Trend Analysis on Social Media*“). So entstand ein Überblick über den aktuellen Stand der Forschung über das Thema Trendanalyse auf Basis von Topic Modelling im Marketing. Des Weiteren bereichert die Untersuchung die Social Media Theorie, indem gezielte Datenanalysemethoden bei der Konzeption und Entwicklung eines automatisierten Trendanalysetools kombiniert und auf die Anforderungen der

Anwendungsfälle konkret angepasst wurden. Da die Social Media Theorie in der praktischen Anwendung bei der automatisierten Analyse von Social Media Inhalten immer noch vor großen Herausforderungen steht, konnte mit Hilfe der Untersuchung erste Ansatzpunkte dahingehend aufgezeigt werden, wie z.B. Anforderungen in der Trendanalyse technisch konkret umgesetzt werden können. Darüber hinaus bringen die Ergebnisse Erkenntnisse zur Erweiterung der Innovationstheorie. Auch mit Hilfe von MANTRA kann die strikte Reihenfolge von „stages“ and „gates“ des Stage Gate Modells aufgebrochen werden, indem die externe Sichtweise miteinbezogen wird. Dadurch wird ein agiler und zielorientierter Ansatz im Rahmen des Innovationsprozesses geschaffen und es kann so genauer auf die Wünsche der Kunden eingegangen werden.

Zusätzlich zu den Beiträgen der Kernel Theorien, leistet MANTRA sowie das Trendanalysetool mit aspektbasierter Sentimentanalyse einen Beitrag zu der Design Theorie (siehe Beitrag 6 „*Supporting Product Development by a Trend Analysis Tool applying Aspect-based Sentiment Detection*“). Bei der Gestaltung der beiden Trend Analyse Tools wurden Design Prinzipien abgeleitet, die zum einen die literaturbasierten Anforderungen und zum anderen die Kernel Theorien als Ausgangspunkt der Überlegung haben. Durch deren Umsetzungen bei der jeweiligen Entwicklung der Artefakte und der anschließenden Demonstration wurde eine implizite empirische Fundierung der Design Prinzipien erreicht. Die aufgestellten Design Prinzipien erfassen designbezogenes Wissen und können daher die Entwicklung neuer Artefakte unterstützen. Bei der Gestaltung weiterer (Trendanalyse-)Tools in verwandten Bereichen können die Design Prinzipien übertragen und auch angewandt werden, da sie allgemein formuliert sind (siehe Beitrag 5 und 6).

Auch im Beitrag 7 („*Social Media Communication about Sustainability: the Resonance of Users and its Implications*“) der sich mit der Analyse von Social Media Textdaten zum Thema Nachhaltigkeit beschäftigt, kann ein Beitrag für die Theorie abgeleitet werden. Dieser Beitrag bezieht sich insbesondere auf die Social Media Inhaltsstrategie. Zunächst haben die erzielten Ergebnisse gezeigt, dass die Social Media Inhaltsstrategie einen Bezugsrahmen bzw. externe Einflussfaktoren miteinbeziehen sollte. Das heißt, die Social Media Inhaltsstrategie muss in die gesamte strategische Ausrichtung des Unternehmens eingebettet werden. Ein weiterer Aspekt, der sich aus den Ergebnissen für die Forschung ergibt, ist der Beitrag zur Social Media Nachrichtenstrategie (als Teil der Social Media Inhaltsstrategie) und deren Ausrichtung auf das Thema Nachhaltigkeit. Unsere Ergebnisse haben in diesem Zusammenhang gezeigt, dass eine mehrdimensionale

Strategie notwendig ist, um positive Reaktionen bei den Nutzern hervorzurufen und eine langfristige Beziehung zwischen Nutzer und Unternehmen zu etablieren. Vor allem die Kombination aus überzeugenden Marketingposts, die Elemente des story-telling beinhalten, und gut präsentierten Fakten (d.h. relevante, nützliche, überzeugende und themenaktuelle Inhalte) ist ein vielversprechender Weg, positives WoM im Sinne der Nachhaltigkeit zu generieren. Hierbei ist es zudem wichtig, eine langfristige Beziehung aufzubauen, mit dem Ziel, Vertrauen zu schaffen und ein nachhaltiges Markenbewusstsein beim Kunden zu verankern. Eine enge Verbindung zur Beziehungsmanagement-Theorie lässt sich dabei erkennen und weitere Gestaltungsmöglichkeiten in diesem Bereich können in zukünftigen Forschungsarbeiten aufgegriffen und vertieft werden.

Zusammenfassend lässt sich festhalten, dass die vorliegende Dissertation einen wesentlichen theoretischen Beitrag zu verschiedenen Kernel Theorien leistet. Theorien wie z. B. die Social Media Theorie, mit Schwerpunkten auf der Lead User Theorie und der Theorie zur Social Media Inhaltstrategie, oder die Innovationstheorie wurden durch die verschiedenen Beiträge ausführlich behandelt und mit Hilfe der erzielten Ergebnisse in Teilen weiterentwickelt. Zudem wurden auch in drei Veröffentlichungen Design Prinzipien strukturiert erstellt und somit ein Beitrag zur Design Theorie geleistet.

Zusätzlich zu den theoretischen Beiträgen, die die Dissertation beinhaltet, lassen sich auch Ergebnisse für die Praxis ableiten. So können Praktiker im Bereich der Analyse von Nutzern von den vorgestellten Ergebnissen dahinhingehend profitieren, dass sie von den Fähigkeiten der verschiedenen einflussreichen Nutzertypen Gebrauch machen, wenn das Unternehmen sie an unterschiedlichen Stellen der Wertschöpfungskette einbindet (**Beitrag 1**). Durch die ausführliche Beschreibung und Unterscheidung ihrer Charakteristika können die jeweiligen Nutzertypen identifiziert und zielgerichtet eingesetzt werden. Dies wurde vor allem durch die beispielhafte Identifikation eines Lead User, der im Zuge des Innovationsprozesses und der Identifikation eines Influencer, welcher für die Verbreitung der Marketingbotschaft eingesetzt werden kann, deutlich. Ein Unternehmen kann somit durch verschiedene Nutzertypen in unterschiedlicher Weise profitieren.

Durch den **Beitrag 2** wurde einer dieser Nutzertypen – der Lead User – und sein Einsatzgebiet im Innovationsprozess eines Unternehmens genauer beleuchtet und Aspekte für einen praktischen Beitrag aufgezeigt. Unternehmen, die verschiedene Lead User für unterschiedliche Phasen im Innovationsprozess identifizieren wollen, können von dem dargestellten modularen und umfassenden Artefakt, also dem erarbeiteten automatisierten Lead User Identifikationstool, profitieren. Unternehmen sind dadurch in der Lage, große Mengen an Social Media Daten zu analysieren. Somit befähigen sie sich, entsprechende Lead User unter Berücksichtigung ihrer unternehmensspezifischen Gegebenheiten, automatisiert zu identifizieren. So können Unternehmen den Identifizierungsprozess an ihre eigenen Bedürfnisse anpassen, indem sie (1) ihren unternehmensspezifischen Datensatz hochladen, (2) alle oder lediglich ausgewählte Charakteristika miteinbeziehen und (3) diese entweder mit Hilfe der voreingestellten Gewichtung (ausschlaggebend für die Unterscheidung der zwei Phasen im Innovationsprozess) unterschiedlich stark bewerten oder diese Gewichte individualisiert einstellen. Die Gewichtung des jeweiligen Charakteristikums wird also bereits zu Beginn des Analyseprozesses festgelegt. Der Identifikationsprozess kann somit auf Nutzer ausgerichtet werden, die entweder einzelne Kriterien oder eine Kombination von Kriterien dominieren. Damit wurde ein umfassender, flexibler und ressourcensparender Ansatz zur Lead User Identifikation (laut Forschungsliteratur der schwierigste und zeitaufwändigste Aspekt innerhalb der Lead User Methode) geschaffen, der auf nachvollziehbaren Merkmalen basiert und von Unternehmen leicht angewendet werden kann.

Nicht nur im Zuge des OSN kann ein Unternehmen von bestimmten Nutzertypen profitieren, sondern auch hinsichtlich des ESN. So kann ein wertstiftender Nutzer im Unternehmen zur Wissensverbreitung, zur Lebhaftigkeit des Netzwerkes oder zur Aufdeckung von Schwachpunkten beitragen, indem er/sie Echtzeit Feedback gibt. Durch die Untersuchung in **Beitrag 3** wurde aufgezeigt, dass mit Hilfe der Kombination der relevanten Dimensionen solche wertstiftenden Nutzer zielgerichtet identifiziert werden können. Zusätzlich wurden Ansatzpunkte formuliert, die verdeutlichen, wie Mitarbeitende motiviert werden können, aktiv zur Wissensverbreitung oder zur Lebhaftigkeit des Netzwerkes beizutragen, wodurch das gesamte Netzwerk profitiert.

Neben der praktischen Relevanz der Beiträge hinsichtlich der Analyse von Nutzern lässt sich auch über den zweiten Themenbereich, die Analyse von Social Media Daten, ein Mehrwert für die Praxis ableiten. Zunächst bietet die vorliegende Dissertation eine tragfähige Grundlage für die Entscheidungsfindung hinsichtlich der passenden Topic Modelling Technik. Das bedeutet, Entscheidungsträger im Bereich Marketing können ihr konkretes Anliegen in eines der drei Anwendungsgebiete einordnen und daraus eine Empfehlung für die Auswahl einer geeigneten Technik ableiten. Darüber hinaus bieten die beiden auf Topic Modelling basierenden Tools, das Trend Analyse Tool (MANTRA) sowie das Trend Analyse Tool mit aspekt-basierter Sentimentanalyse zur Produktverbesserung, erheblichen Mehrwert für die Praxis (**Beitrag 4** und **Beitrag 5**). MANTRA kann im Gegensatz zu bestehenden Tools externe Parameter, die für die Anwendungsfälle Produktentwicklung, Kundenverhaltensanalyse und Marktbeobachtung elementar sind, flexibel integrieren. Dadurch können Analysen von Unternehmen zielgerichtet unter Berücksichtigung von Zeit und Geolokationen durchgeführt werden. Zudem muss ein Unternehmen keine Vorkenntnisse über einen bestimmten Trend haben, da das Setzen von Startwörtern bei MANTRA nicht zwingend erforderlich ist (anders als bei vorherrschenden Social Listening Tools). Ein weiterer Vorteil des Tools für ein Unternehmen besteht darin, dass es die VoC auf Basis von Social Media Daten identifizieren kann. Des Weiteren kann jedes Unternehmen die Trend Analyse an seine individuellen Gegebenheiten anpassen, da verschiedene Machine-Learning-Ansätze kombiniert wurden und das Tool modular aufgebaut ist. Diese positiven Aspekte lassen sich auch bei dem weiteren Trendanalyse Tool erkennen, das zusätzlich die aspekt-basierte Sentimentanalyse integriert. Vor allem große Unternehmen, mit mehreren Niederlassungen an verschiedenen Orten, können zusätzlich davon profitieren, dass feingranulare Schwankungen des Sentiments für bestimmte Zeiträume und Geolokationen dargestellt werden können. Standortspezifische Stimmungsänderungen können so aufgezeigt werden und eine zielgerichtete Reaktion von Seiten des Unternehmens ist möglich.

Der Beitrag der Dissertation hinsichtlich der **Veröffentlichung 7**, liefert Ansatzpunkte zur praktischen Ausgestaltung der Social Media Kommunikation von Nachhaltigkeitsthemen. Zum einen hat die Untersuchung in diesem Zusammenhang gezeigt, welche Themen bez. Nachhaltigkeit in Twitter derzeit aktuell sind. Dies kann genutzt werden, um Bereiche zu identifizieren (wie z.B. die Dimension Umwelt), die von Unternehmen bisher zu wenig berücksichtigt wurden, obwohl sie vermehrt in Social Media diskutiert wurde. Zum anderen zeigen die Ergebnisse, dass eine ganzheitliche Strategie in Bezug auf Nachhaltigkeit (online und offline) notwendig ist, um als Unternehmen glaubwürdig zu sein, da primär fakten- und quellenbasierte Beiträge dazu beitragen, eine positive Stimmung zu erzeugen. Abschließend ist die Arbeit zur Erkenntnis gelangt, dass die Nachhaltigkeitskommunikation über soziale Medien für Unternehmen ein guter Weg sein kann, ihr Image zu verbessern, indem sie damit von ihren Schwachstellen ablenken. So kann Twitter beispielsweise auch für Unternehmen mit dem Ziel des Greenwashings erfolgreich eingesetzt werden.

Zusammenfassend bietet die vorliegende Dissertation durch die Charakterisierung und zielgerichteten Identifikation einflussreicher Nutzer Unternehmen die Möglichkeit diese wertvollen Nutzertypen im Rahmen der unternehmenseigenen Wertschöpfungskette effektiv einzusetzen und dadurch auf verschiedene Art und Weise zu profitieren. Darüber hinaus werden auch diverse Softwaretools vorgestellt, die zur automatisierten Informationsextraktion aus Social Network Daten von Unternehmen genutzt werden können.

Insgesamt können also durch die Forschungsergebnisse, die in dieser Dissertation vorgestellt wurden, sowohl Wissenschaft als auch Praxis profitieren.

3.3 Kritische Würdigung und Ausblick auf weitere Forschungsfelder

Die in der Dissertation vorgestellten Forschungsergebnisse sollen im Folgenden kritisch eingeschätzt werden. Die sich daraus ergebenen weiteren Forschungsfelder werden aufgezeigt.

Die Limitation, die sich aus dem **Beitrag 1** (Abschnitt 2.1) ergibt, liegt in der Tatsache begründet, dass ein Literature Review, gemäß seiner Natur, nur eine Momentaufnahme von Untersuchungen darstellt. Das bedeutet, es ist es möglich, dass, obwohl eine umfangreiche Literatursuche durchgeführt wurde, nicht alle für das Thema relevanten Forschungsartikel identifiziert wurden. Weitere Literatur könnte die Ergebnistabelle verändern, Forschungslücken sähen ggf. anders aus. Eine weitere Limitation des Artikels ist die fehlende empirische Validierung der Ergebnisse. Basierend auf der vorliegenden Untersuchung wäre es sinnvoll, in zukünftigen Forschungsarbeiten zu untersuchen, ob die Zuordnung der verschiedenen Nutzertypen zu den jeweiligen Stufen der Wertschöpfungskette empirisch stichhaltig und haltbar ist oder nicht. Zudem könnten weitere Konzepte, wie z.B. die soziale Homophilie, die bei der Untersuchung des Einflusses eine Rolle spielt, den ein einflussreicher Nutzer auf andere ausübt, berücksichtigen.

Im **Beitrag 2** (siehe Abschnitt 2.2) kann festgestellt werden, dass es Charakteristika von Lead User in der Forschungsliteratur gibt, die im Zuge der Untersuchung nicht gefunden und damit nicht berücksichtigt wurden. Zudem ist es möglich, dass es weitere

Untersuchungen gibt, die die Charakteristika hinsichtlich einer bestimmten Phase des Innovationsprozesses miteinbeziehen, welche vernachlässigt wurden, wodurch eine Verschiebung der Gewichte möglich ist. Durch den modularen Aufbau des präsentierten Artefakts ist ein individuelles Einstellen der Gewichte aber nicht ausgeschlossen, das heißt eine dynamische Anpassung an veränderte Umstände – sei es von Seiten der Literatur oder von Seiten des Unternehmens – ist jederzeit möglich. Auch im Hinblick auf nicht identische Gegebenheiten in anderen Unternehmen könnte der vorgestellte Ansatz weiterentwickelt bzw. neu evaluiert werden. Eine Evaluation unserer Ergebnisse mit anderen Kooperationspartnern könnte so zur Neueinschätzung von Vollständigkeit und Nützlichkeit unseres Ansatzes führen. Zudem haben die Interviews im Zuge der Evaluation gezeigt, dass die Frage, ab wann ein Lead User als erfahren angesehen werden kann, noch nicht final beantwortet ist.

Auch der **dritte**, in der Dissertation behandelte Beitrag (Abschnitt 2.3), weist Limitationen auf. In der beschriebenen Fallstudie hat sich die Untersuchung auf solche Ziele eines wertstiftenden Nutzers beschränkt, die auf das betreffende Unternehmen abgestimmt waren. In anderen Unternehmenszusammenhängen müssen möglicherweise andere Ziele und Werte festgelegt werden. Deshalb sollte eine weitere Untersuchung mit einem größeren Datensatz durchgeführt werden. So kann analysiert werden, ob der vorgestellte Ansatz in einem großen Netzwerk haltbar ist oder welche Auswirkung die Veränderung der Größe des Netzwerks auf die wertstiftenden Nutzer und ihre Merkmale hat. Es könnte vor allem untersucht werden, ob aufgrund von weiteren Zielsetzungen mehr wertstiftende Nutzer identifiziert werden können und ob sich weitere Merkmale ableiten lassen.

Des Weiteren ließen sich in der **vierten Studie** (Abschnitt 2.4) folgende Limitationen feststellen: Die Anzahl an Forschungsarbeiten, die wir bei der Identifizierung der Anwendungsfälle und der damit verbundenen Anforderungen an das Topic Modelling im Marketing einbezogen haben, ist begrenzt. Das heißt, es ist durchaus möglich, dass es weitere zentrale Anforderungen gibt, die in dem vorgestellten Ansatz nicht miteinbezogen wurden. Zudem wurde die Auswahl der zu vergleichenden Topic Modelling Techniken auf drei (LDA, DMR und PAM) beschränkt. Obwohl damit die von Liu et al. (2016) vorgeschlagenen Erweiterungen weitgehend berücksichtigt werden konnten, könnten zukünftige Forschungsarbeiten für jede etwaige Erweiterung zusätzliche Topic Modelling Techniken einbeziehen und damit die von uns gegebenen Empfehlungen weiter schärfen.

Da Aufbau und Analyse der Daten in **Untersuchung 5 und 6** (Abschnitt 2.5 und 2.6) recht ähnlich sind, werden Limitationen hier zusammengefasst dargestellt: Wie schon bei den vorherigen Untersuchungen ist es auch hier möglich, dass weitere Anforderungen oder Anwendungsfälle, in denen die Trend Analyse (inkl. aspekt-basierter Sentimentanalyse) Verwendung findet, nicht berücksichtigt wurden. Es ist denkbar, dass sich daraus weitere Design Prinzipien für die Entwicklung der Trend Analysetools ergeben. Da beide Untersuchungen sich auf Anwendungsfälle im Bereich Marketing konzentrieren, könnten sich weitere Forschungsarbeiten anderen Unternehmensbereichen widmen und dafür spezifische Anwendungsfälle identifizieren. Zudem würden die beiden Forschungsarbeiten von einer ausgedehnten Evaluation profitieren. Eine langfristige Evaluation der vorgestellten Ergebnisse mit Hilfe von mehreren Kooperationspartnern könnte dazu beitragen, dass die Analysequalität, die Benutzerfreundlichkeit und somit das gesamte Artefakt verbessert werden.

Hinsichtlich des **Beitrags 7** (Abschnitt 2.7) lassen sich folgende Einschränkungen feststellen: Im Zuge der Analyse haben wir sechs gängige Algorithmen zur Textklassifikation miteinander verglichen und den Algorithmus verwendet, der in diesem Vergleich am besten abgeschnitten hat. Da es allerdings noch viele weitere Algorithmen zur Textklassifikation gibt, ist es durchaus möglich, dass ein anderer Algorithmus zu noch besseren Ergebnissen führt. Zudem ist unsere Analyse auf die Social Media Plattform Twitter beschränkt. Weitere Plattformen, wie z.B. Facebook, Instagram oder LinkedIn, wurden hier nicht berücksichtigt. Da sich die Kommunikation zwischen Kunden und Unternehmen plattformspezifisch verändern kann bzw. diese dann daran angepasst werden muss, ist es durchaus möglich, dass die Schwerpunkte unserer Ergebnisse eine Ergänzung erfahren werden. Da wir jedoch fast vier Millionen Tweets extrahieren und analysieren konnten, betrachten wir unsere Auswahl als eine repräsentative Grundlage für die Validierung der Ergebnisse. Zukünftige Forschungsarbeiten könnten diesen Punkt aufgreifen und sich mit der Untersuchung der Social Media Inhaltsstrategie mit Fokus auf das Thema Nachhaltigkeit auf anderen Plattformen beschäftigen.

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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