Sustainability Awareness and Smart Meter Privacy Concerns: The cases of US and Germany

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Abstract

We investigate public awareness about sustainability, e-mobility and smart meters in Germany and the US, two countries leading the e-mobility development, but with different sustainability policies. By applying sentiment analysis and Natural Language Processing on tweets from the two countries over the last decade (2010 to end of 2019), we found that the sustainability awareness in Germany is higher than the US. We see that the US is at an earlier sustainability maturity state, creating fertile grounds for establishing sustainability policies on time to shape public opinion. Furthermore, we find that after the introduction of the Sustainable Development Goals (SDGs) in 2015, the overall awareness in both countries has increased, showing the potential of such policies. In addition, in contrast to expectations, we see that the smart meter privacy concerns have recently started to deteriorate, possibly as a result of governmental efforts to educate the public about smart meter technology. Finally, we see that the German public tweets more positively about e-mobility, compared to the US, whereas the content of e-mobility discussions differs: Germany is more concerned about e-mobility adoption, whereas the US is more focused on battery efficiency and other technological developments associated with e-mobility.

Keywords: *public awareness, sustainability, electric mobility, smart meter privacy, natural language processing, sentiment analysis*

1. Introduction

Global warming, caused by CO_2 emissions, is one of the major challenges humankind is currently facing (Watson et al., 2010; Ritchie & Roser, 2019). To limit such extreme climate change effects, United Nations (UN) members have committed to global warming limits as part of the Paris Agreement in 2016 (United Nations, 2015). In their efforts to meet the UN targets, governments strive to raise public awareness about climate change. However, this effort to mobilize industries and the public toward more sustainable behaviors - also known as “sustainability transition” - is challenging (EEA, 2019). First, there is significant resistance to change from traditional industries that refuse to change their business operation models to more sustainable practices (Markard et al., 2020). Second, there are niche technologies, such as electric vehicles, that require explicit stimulation by policymakers to be massively accepted (Kanger et al., 2020). Without stimulation measures the transition results might get stagnated. And third, consumers are not convinced to change some of their possibly excessive consumption patterns or switch to more sustainable behaviors (Markard et al., 2020).

Electric mobility (e-mobility) is key in this sustainability transition, as it reduces CO_2 emissions and air pollution (United Nations Environment Programme, 2020). With the help of various public awareness initiatives, citizens start recognizing the vital link between e-mobility and sustainability.[1] However, despite the popularity of e-mobility, in Europe, the most common transportation mode is the traditional car. In 2017, road transport accounted for 72% of Europe's greenhouse gas emissions from transport (EEA, 2018), while "the market-share of hybrid electric vehicles (HEV) in the EU was 3% in 2018" (Campestrini & Mock, 2019). The reasons for such low market shares are the numerous challenges the e-mobility industry is facing. First, the charging infrastructure is costly and requires careful analysis about its placement within cities (Yi & Bauer, 2016; Zhang et al., 2020). Furthermore, the cost allocation of such infrastructure is another major point in the e-mobility debate (Peterson & Michalek, 2013; Nicholas, 2019). In addition, the battery size, which needs to be sufficiently large for commuters to satisfy their driving needs, but at the same time sufficiently light for the vehicle to be able to move well, is another major challenge for e-mobility.[2]

The e-mobility adoption is further damaged by the lack of public trust in smart meters (IBM, 2020), which are necessary for the charging of electric vehicles (EVs). While smart meters have been proven useful for households because of their ability to reduce energy bills (Mogles et al., 2017), at the same time, there are important challenges the smart meter industry is facing toward large-scale rollouts. First, the distributed nature of smart metering systems (remote monitoring S/W, advanced H/W, etc.) makes their implementation costly for the industry as well as the consumers (Al-Waisi & Agyeman, 2018). Second, and most important, the installation of smart meters raises data privacy concerns (Asghar et al., 2017). Hackers can exploit the detailed user profiles recorded by smart meters and invade individual privacy (Asghar et al., 2017). For example, detailed monitoring of electricity consumption would reveal sensitive information about

[1] https://sdgaccountability.org/working-with-informal-processes/raising-awareness-through-public-outreach-campaigns/
[2] https://cordis.europa.eu/article/id/124006-electric-mobility-opportunities-and-challenges

a person's sleeping patterns, work schedules, long absences, etc. (Odendahl, 2019). Third, smart meter data can help "infer religious practices", [3] e.g., Ramadan, or carry the risk of "profiling and mass surveillance".[3] For example, "law enforcement agencies, tax authorities, insurance companies, landlords, employers, and other third parties may also be interested in accessing personal energy consumption information". [3] As a result, users are concerned that installing smart meters will be costly, and their data might be used abusively against them.

However, for a large-scale EV rollout, smart meters are necessary. Therefore, governments and energy policymakers struggle on two fronts: that of encouraging the installation of smart meters and that of incentivizing large-scale EV adoption. Nevertheless, there seems to be a conflict between being sustainable in terms of adopting EVs and disclosing personal information. Especially because of this conflict, Germany hesitated, in the past, to rollout smart meters nationally; instead, the country formulated specific privacy standards and regulations to create public trust (Kieserling, 2020). Despite such efforts, the share of smart meters in Germany accounted for only 5% in 2015, which is by far the lowest compared to other countries (CBI, 2016). As of January 31st, 2020, Germany has officially started the rollout of smart meters. This forced rollout raises many privacy questions in the minds of the public (Kieserling, 2020) and it is likely not to yield the desired results if not accepted by the citizens (Lewandowsky et al., 2013). Therefore, it is important to sense the public opinion about it. As such concerns might indirectly affect the sentiment towards e-mobility as well, it is important to study the public sentiment toward smart metering together with the public opinion about e-mobility itself (Langer et al., 2013).

In order to understand the public opinion better, social media are key, as people take a public stand about political or social topics on platforms (Borch et al., 2020) such as Twitter (Geetha et al., 2018). Benefiting from this vast opinion availability on Twitter, we analyze the evolution of public sentiment about sustainability, e-mobility, and smart metering privacy over a decade (2010-end of 2019). We select as our case studies Germany and the US, two countries leading the e-mobility development, but with different policies and e-mobility adoption maturity.

To date, scarce research has investigated together the sentiment about sustainability, e-mobility and smart meter privacy concerns expressed on microblogs. These themes taken together have important implications because, for example, while the majority of Germans accept e-mobility (Electric Mobility in Germany, 2019), they seem very cautious about trusting smart meters, which ultimately inhibits the EV adoption (Meyer, 2019). Hence, understanding e-mobility awareness

[3] https://edps.europa.eu/data-protection/our-work/publications/techdispatch/techdispatch-2-smart-meters-smart-homes_en

in combination with smart meter privacy concerns is imperative to foster e-mobility adoption and ultimately, for governments to reach their climate goals. We address this void by exploring how *public awareness about sustainability and e-mobility as well as consumer sentiment toward smart meter privacy evolve over time* in the US and Germany. Specifically, the objectives of this study are:

- To examine the public awareness about sustainability in Germany and the US
- To examine how the introduction of the Sustainable Development Goals (SDGs) might have played a role in changing this awareness
- To examine the public awareness about e-mobility in Germany and the US
- To understand the sentiment about smart meters in Germany and the US
- To explore the most important smart-meter and sustainability-related concerns in Germany and the US

Our findings contribute to the sentiment analysis literature about sustainability, electromobility and smart meters. Academic literature has examined public opinions about climate change (An et al., 2014, Pearce et al., 2014, Cody et al., 2015, Kirilenko et al., 2015, Abbar et al., 2016, Fownes et al., 2018, Reyes-Menendez et al,, 2018, Loureiro & Alló, 2020), e-mobility customer needs (Kühl et al., 2019, Kinra et al., 2020), or sustainability (Ilieva & McPhearson, 2018, Merle et al., 2019, Pilař et al., 2019) separately, using Twitter data; however, there is scarce work examining the public opinion about smart meter privacy, or more importantly combining this opinion with the opinion and sentiment about e-mobility and sustainability. Furthermore, our study is one of the first to analyze over the last decade (2010-end of 2019) the cases of US and Germany; two countries with different sustainability and e-mobility maturity (Buehler et al., 2011). Thus, our work contributes, as well, to the literature about exploring possible effects of different governmental approaches on sustainability. Traditionally, literature about those topics is mostly survey- or interview-based (Parkinson et al., 2013, Nakamura, 2018, Ernst & Shamon, 2020, Sareen, 2020), whereas we show that by mining large volumes of social media data, value-adding insights of a larger scale, as well as evolving opinions can be extracted. We are also able to provide a more informed picture of society's awareness, as in surveys individuals tend to overreport their opinion due to social desirability bias (OECD Development Communication Network, 2017).

From a policy point of view, this paper's findings can help policymakers make more informed choices when designing policies about e-mobility (Burnstein, 2003). Within the last decade, policymakers have established regulations that focus on encouraging consumers to reduce their

CO_2 emissions (Wigder, 2018), via, for example, the promotion of EVs. In this effort, they strive to improve the charging infrastructure which is found to be a major pain-point in consumer adoption (Lieven, 2015, Pevec et al., 2018). Therefore, together with sensing the public sentiment, policymakers using our findings can understand the reasons that inhibit e-mobility adoption and modify policies accordingly. The same can happen with smart meter adoption, overcoming crucial privacy concerns. Furthermore, our findings could be useful for energy utilities who are responsible for offering secure services to their customers. Our findings can help providers, first, understand their customer pain-points, second, improve their service, and finally, incentivize the adoption of smart meters further by establishing trust. Moreover, governmental entities could use our findings to understand the citizen reaction towards new legislations about electromobility, sustainability and smart meters. With such real-time approaches, governmental entities can observe citizen reactions and act quickly, engaging the public more closely.

2. Literature Review

To set the stage, we first, examine the role of user-generated content and natural language processing in capturing public opinions. Second, we examine the public sustainability perception and e-mobility awareness over the last decade. Third, the consumer perceptions about smart meters are explained.

2.1 Microblogging, Big Data and Natural Language Processing

Micro-blogs are defined as smaller versions of traditional weblogs with social networking features (Barnes & Böhringer, 2011). With this even faster and easier mode of communication, users are able to broadcast opinions, news or experiences publicly (Nardi et al., 2004). Microblogging did not only lead to generation of large volumes of data (big data), but also to the emergence of electronic word of mouth (eWOM). WOM is defined as the exchange of information between users, leading to behavioral changes towards certain products and services (Katz & Lazarsfeld, 1955). Hence, analyzing microblogging data has become attractive for researchers who desire to measure public opinions and facilitate more informed decision-making, replacing traditional surveys (Dahal et al., 2019). Microblogging and text-mining have been used to analyze data in various contexts, for example, climate change (An et al., 2014, Pearce et al., 2014, Cody et al., 2015, Kirilenko et al., 2015, Abbar et al., 2016, Fownes et al., 2018, Reyes-Menendez et al,, 2018, Loureiro & Alló, 2020), e-mobility customer needs (Kühl et al., 2019, Kinra et al., 2020), sustainability (Ilieva & McPhearson, 2018, Merle et al., 2019, Pilař et al., 2019), as well consumer perceptions, consumer engagement, consumer product reviews (Bian et al., 2016; Dahal et al., 2019; Hanson et al., 2018; Wang et al., 2019). In this paper, we benefit from the vast volumes of microblogging data to derive more insights about the trade-off between promoting sustainability and concerns about privacy.

To process these large volumes of data, we employ Natural Language Processing, and specifically, topic modeling and sentiment analysis. Topic modeling describes a class of machine learning algorithms that discover hidden semantic structures and human interpretable topics over a collection of documents (Ottesen et al., 2017). Specifically, we use Latent Dirichlet Allocation (LDA), an unsupervised generative Bayesian mixture model able to infer latent coherent themes, called *topics*, from large textual datasets (Blei et al., 2003; Ottesen et al., 2017). LDA is considered the state-of-the-art method when it comes to topic modeling because of its ability to summarize large volumes of textual data into comprehensive themes. An advantage of these themes is that they can be relatively easily interpreted by humans. LDA has been used to analyze container shipping's industry reports with regards to their sustainability objectives (Zhou et al., 2021), to track trends in sustainability research (Lee et al., 2021) as well as trends in e-mobility research in China (Jia & Wu, 2018).[4]

In addition, we use sentiment analysis, which aims to understand the sentiment of textual data. We employed the algorithm "**V**alence **A**ware **D**ictionary and s**E**ntiment **R**easoner" (VADER), which is specifically designed for sentiment analysis on social media, taking into account informal writing styles, multiple punctuation marks, emoticons and acronyms (Hutto & Gilbert, 2014). VADER is commonly used for short informal text mainly posted online and has been employed to analyze the sentiment in online reviews (Chaithra, 2019; Olagunju et al., 2020), customer responses (Borg & Boldt, 2020), teaching evaluations (Newman & Joyner, 2018), bitcoin tweets (Pano & Kashef, 2020), as well as the sentiment of different news articles and their impact on stock prices (Schmidt, 2019).

2.2 Environmental and Sustainability Awareness

Survey-based opinion research finds that societal awareness and concerns about climate change differ among countries (Fagan & Huang, 2019; T. M. Lee et al., 2015). In 2018[5], the majority of individuals surveyed worldwide (68%) classified global climate change as a major threat. Nonetheless, differences among countries exist, e.g., 90% of Greek indicate high concerns,

[4] There are numerous applications of LDA pertaining to topics outside of the scope of this work. In the interest of space, we have omitted references to such applications.
[5] https://www.pewresearch.org/fact-tank/2019/04/18/a-look-at-how-people-around-the-world-view-climate-change/

compared to 59% of Americans expressing the same level of concern. On the other end, almost a quarter of Americans (23%) see global climate change as a minor threat (Fagan & Huang, 2019).

Similarly, sustainability is frequently investigated. A crucial sustainability milestone was the adoption of the 17 SDGs in 2015 (United Nations Sustainable Development, 2020). As of then, UN countries worked heavily toward meeting these goals. In 2019, Germany had an SDG index score of 81.1 and was ranked 6^{th} among all 160 participating countries, whereas the US had a score of 74.5, ranked 35^{th} (Sachs et al., 2019).[6] In addition, literature has shown Germans tend to be worried about climate change, whereas Americans see climate change as a medium threat (Fagan & Huang, 2019; T. M. Lee et al., 2015; Leiserowitz et al., 2015; Timperley, 2017). Thus, we hypothesize that:

***H1**: Public awareness about sustainability differs among the US and Germany.*

Public awareness about sustainability, via the proxy of CO_2-based technologies that aim to reduce carbon footprint, has been examined in Germany during 2017 via a survey distributed to 509 individuals (Arning et al., 2019). In a similar vein, survey-based research has been used to understand sustainability attitudes as expressed by Germans with respect to meat consumption (Cordts et al., 2014). At a broader scale, a pan-EU survey has been launched to explore the public awareness about anthropogenic effects on marine environments (Gelcich et al., 2014). Our work extends these results by exploring this awareness over a larger time interval (10 years) and by having access to a larger data sample.

Similar surveys have been launched to examine climate change awareness in the USA or worldwide (Fagan & Huang, 2019; Hamilton, 2016; T. M. Lee et al., 2015; Leiserowitz et al., 2015; Timperley, 2017). In contrast to this literature that examines public awareness about climate change mostly using surveys or experiments, we provide a more holistic view, analyzing tweets about sustainability during a decade (2010-end of 2019). In this way, we overcome the limited volume constraint of experiments, and the limitation of not stating one's true awareness in surveys due to social desirability bias (OECD Development Communication Network, 2017). Our results, examining the difference in country awareness, could give local authorities and federal governments an overview of society´s perception about sustainability. This can help engage with citizens and "mobilize them into action" (OECD Development Communication Network, 2017). Further, our results shed light on two different societies and can offer valuable

[6] The SDG index indicates the country's equally-weighted average for their performance of all 17 goals.

insights about setting policies in countries with comparable to the US or Germany societal characteristics.

Finally, major events are expected to change sustainability awareness, hence, we examine the impact of the introduction of the SDGs in 2015 on public awareness. While the introduction of the SDGs was expected to raise awareness about sustainability, to date very few evidence exist about its actual effect. Hence, we hypothesize:

***H2**: Public awareness about sustainability increases after the introduction of the SDGs in 2015.*

2.3 Electric Mobility Awareness

EVs have received a lot of attention from car manufacturers as well as governments (Ba et al., 2013; Cornet et al., 2019). EV sales grew throughout the last years; however contrary to expectations, EVs represent only a fraction in the overall car market (Hertzke et al., 2019). Researchers try to explain this adoption gap by studying people's sustainability awareness and general sentiment toward e-mobility. Research has found higher EV adoption rates among individuals with high sustainability awareness (Egbue & Long, 2012). Furthermore, scholars find that consumer awareness about sustainability affects the EV purchasing intentions (Carley et al., 2013; Lane & Potter, 2007; Rezvani et al., 2015; Skippon & Garwood, 2011; Steinhilber et al., 2013). However, there are environmental studies and surveys that find consumers questioning the positive impact of EVs on the environment (Caperello & Kurani, 2012; Egbue & Long, 2012; Moons & de Pelsmacker, 2012).

At a macro-level, recent studies have analyzed the adoption of EVs in countries such as Germany, France, Norway, or the US mainly based on factual figures about each country´s EV stock (Künle & Minke, 2020; Slowik & Lutsey, 2018). More relevant to our work, field studies (Franke et al., 2012) and survey-based experiments (Plötz et al., 2014) have also been launched in Germany to understand customer e-mobility acceptance. Overall, to date, most literature addresses the public sentiment about e-mobility using a single point in time and relatively small samples, whereas we analyze the over-time public opinion, potentially affected by the advancements in technology. As people are rather resistant to change (Duff, 2003), awareness and adoption may need time. Therefore, we pose the hypothesis:

***H3**: Public awareness about electric mobility has increased over the last decade in both the US and Germany.*

2.4 Smart Metering

Smart meters are devices that report electricity usage in real-time (McDaniel & McLaughlin, 2009; Wolsink, 2012). In the EU, all member-states must replace 80% of traditional electricity meters with smart meters, mainly due to inaccuracies coming from the former (Directive 2009/28/EC of the European Parliament and of the Council, 2009). The smart-meter rollout in Europe advances faster in some countries than others (Alejandro et al., 2014). In the UK, 15.97 million smart meters had been installed in the first quarter of 2019, which is 6.9% more than in the previous quarter (GOV UK, 2019). Even though Germany has committed to a nationwide rollout, when it comes to the actual adoption of smart meters, Germans are very skeptical (Han & Ang, 2018). Survey responses highlight that the public is still concerned due to privacy breaches and, therefore, only a minority install smart meters in their homes (Alejandro et al., 2014; Han & Ang, 2018; Zhou & Brown, 2017). Nonetheless, research shows that there is high satisfaction among users once installed smart meters and that 80% use energy more efficiently, enjoying energy bill savings (GOV, 2018). In North America, it is expected that until 2024 the adoption of smart meters will reach 81%.[7] North America has been the leader when it comes to smart grid technology adoption. However, similarly to Germany, some states express skepticisms towards the technology. Hence, overall, the opinions in Germany and the US are equally skeptical when it comes to smart metering adoption.

Even though smart metering offers consumer benefits such as energy savings resulting in cost savings (Del Rio et al., 2020), there are multiple consumer concerns related to privacy and security, that must be addressed (McDaniel & McLaughlin, 2009, Balta-Ozkan et al., 2013). These concerns stem mainly from the fact that smart meters are a common target for hackers. Software interference attacks range from simple power thefts and falsified bills to fires and explosions (Wilson, 2019). Next to security breaches, smart meters inevitably imply customer privacy issues (Langer et al., 2013; McDaniel & McLaughlin, 2009). Detailed consumer profiles are created with the help of high frequency readings. These profiles reveal detailed information about individual energy consumption and general behavior patterns that can be easily misused by hackers (Langer et al., 2013). Thus, users worry about their privacy when it comes to adopting smart meters (Alejandro et al., 2014; Han & Ang, 2018; Zhou & Brown, 2017).

However, literature has shown that technology concerns reduce when more knowledge about the technology is publicized, e.g., via successful use-cases (Beaulieu et al., 2016) and when individuals become more tech-savvy (Chawla et al, 2020). As a result, one can expect that these

[7] https://www.smart-energy.com/industry-sectors/smart-meters/smart-meter-penetration-in-north-america-will-reach-81-by-2024/

concerns weaken over time, as governments publicize more information about the -still novel- smart metering technology. Therefore, we hypothesize:

H4: *The public sentiment towards smart meters improves positively over time.*

Prior work has attempted to examine the consumer sentiment about smart meters in countries spanning from Poland (Chawla et al, 2020) and the Netherlands to the UK (Milchram et al., 2018) and Australia (Riesz, 2013). Specifically for the USA, semi-structured interviews and a survey administered to 129 participants (Krishnamurti et al., 2012) were used. Along similar lines, psychological perspectives have been used to understand the consumer sentiment via data obtained by US energy utilities (Karlin, 2012). At a higher level, smart meter concerns and their relation to consumer adoption have been examined under the prism of US and Canadian organizations' opinions (Hess, 2014). As a result, while there is some evidence about the sentiment toward smart meters in the US and Germany, we are lacking systematic understanding of its evolution as well as the major dimensions that form it. Thus, in addition to longitudinal sentiment analysis, we perform in-depth text analysis to derive information about the pain-points that inhibit the smart meter adoption. This evidence will help us analyze and explain more accurately the previous quantitative findings.

Finally, prior work in countries such as the UK or Spain has shown that there are country differences in topics of discussion when tweeting about climate change (Loureiro & Alló, 2020). Therefore, we hypothesize:

H5*: Topic tweet discussion differs in Germany and the US.*

3. Methodology

To derive results about US and Germany, we use microblogging data from Twitter during 2010-end of 2019. Specifically, we use text analytics on Twitter data to:

- Identify possible changes in tweeting behavior about sustainability, e-mobility, and smart meters, over time and across the two countries
- Identify whether certain topics are dominant in either Germany or the US
- Identify whether topics can be associated with a positive or negative sentiment and how this sentiment about topics might have changed over time

Figure 1 shows an overview of our text-mining methodology. In the following sub-sections, we present the details of the main steps in Figure 1 and in Appendix C we present details about all steps of our methodology.

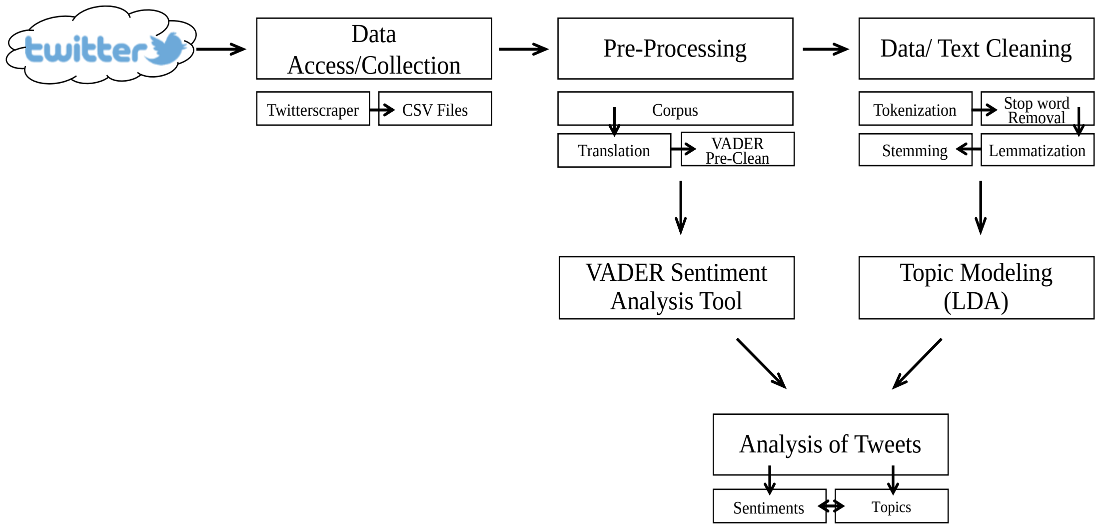


Figure 1: Methodology Overview

3.1 Data Description

Twitter is one of the most used social networking and microblogging platforms,[8] where users publish real-time messages of maximum 140 characters, called tweets (*Twitter Dev.*, 2020). Tweets express opinions and feelings with specific vocabulary, slang, acronyms and emoticons which generate highly unstructured data (Agarwal et al., 2011). One specific feature is the use of hashtags: the use of a hash mark (#) followed by certain words or abbreviations serving as indicators for the content of a tweet (Ottesen et al., 2017).

We collected tweets about "sustainability", "e-mobility" and "smart metering & privacy", in Germany and US, posted from January 1st 2010 until December 31st 2019. Our dataset includes 9,975 users who tweeted 43,750 times about "sustainability", "e-mobility" and "smart metering & privacy". Out of these 43,750 tweets, 25,259 and 18,491 were generated in Germany and the US, respectively. To select the tweets relevant to our analysis, we used the hashtags #sustainability, #electricmobility, #smartmeter and variants of them. Together with each tweet, we derived tweet-specific information such as username, country, timestamp, and others as shown in Table 1. Details about our data collection are presented in Appendix C.

[8] At the end of 2019, Twitter's global reach amounted around 152 million active Twitter users, of which in April 2020 64.2 million users were in the US and 6.1 million in Germany (Clement, 2020).

Table 1: Tweet-specific information collected. Adapted from (Twitter Developer, 2020).

Name	Description	Abbreviation
User ID	integer representation of the unique identifier for the user	User_id
Tweet ID	integer representation of the unique identifier for the tweet	tweet_id
Username	user who posted the tweet	username
Tweet Text	text content/body of tweet	text
Date	timestamp when the tweet was created, EU time, YYYY-MM-DD	timestamp
Hashtags	key word/phrases following a hashtag (#) sign used in Tweet Text	hashtags
Likes	number of times a tweet was liked by another user	likes
Replies	number of times a tweet has been replied to by another user	replies
Retweets	number of times a tweet was retweeted by another user	retweets
Link/URLs	URL used within the tweet (e.g picture URL, Facebook/Instagram post	links
Country	country where tweet was posted from (US or Germany)	country

Note. Items that have been removed: has_media, img_urls, is_replied, is_reply_to, parent_tweet_id, reply_to_user, screen_name, text_html, timestamp_epochs, tweet_url, video_url

3.2 Sentiment Analysis

To measure the sentiment of each tweet, we employed the algorithm "**V**alence **A**ware **D**ictionary and s**E**ntiment **R**easoner" (VADER), which is specifically designed for sentiment analysis on Twitter (Hutto & Gilbert, 2014). It examines the lexical features of a tweet and calculates a sentiment score based on syntactic and grammatical cues, taking word-order relationships into account. One advantage of our algorithm is that it accounts for contrastive conjunctions and negations, which most other methods do not (Agarwal et al., 2011; Hutto & Gilbert, 2014). Overall, VADER calculates a positive, negative, neutral, and compound sentiment. Positive, negative, and neutral scores range from 0 to 1 and represent the proportions of a tweet falling in each category, hence the strength of the categorization. The compound score represents the summation of the scores of each word in the tweet, normalized to be between -1 (most extreme negative) and +1 (most extreme positive).[9] Table 3 shows one exemplary tweet, that was categorized as "positive". The details about our sentiment analysis implementation are presented in Appendix C.

Table 3: Exemplary Sentiment Calculation

Username	Original Tweet	Semi-Cleaned Tweet for VADER	Sentiment	Compound	Pos	Neg	Neu	Cleaned Tweet
KayHerget 🌍	Good news for #ElectricMobility: @BoschGlobal develops a new #cloudbased service that helps batteries maintain performance for longer. Mobility Services Provider @DidiChuxing is the first company to use our new battery services. #BoschCS via @Forbes https://www.forbes.com/sites/edgarsten/2019/07/09/a-cloud-based-ev-battery-management-service-launched/?ss=logistics-transport#696d0d434d3c	Good news for #ElectricMobility: develops a new #cloudbased service that helps batteries maintain performance for longer. Mobility Services Provider is the first company to use our new battery services. #BoschCS via	Positive	0.681	0.211	0	0.789	good, news, emob, develop, new, cloudba, servic, help, batteri, maintain, perform, longer, mobil, servic, provid, first, compani, use, new, batteri, servic, bosch, via

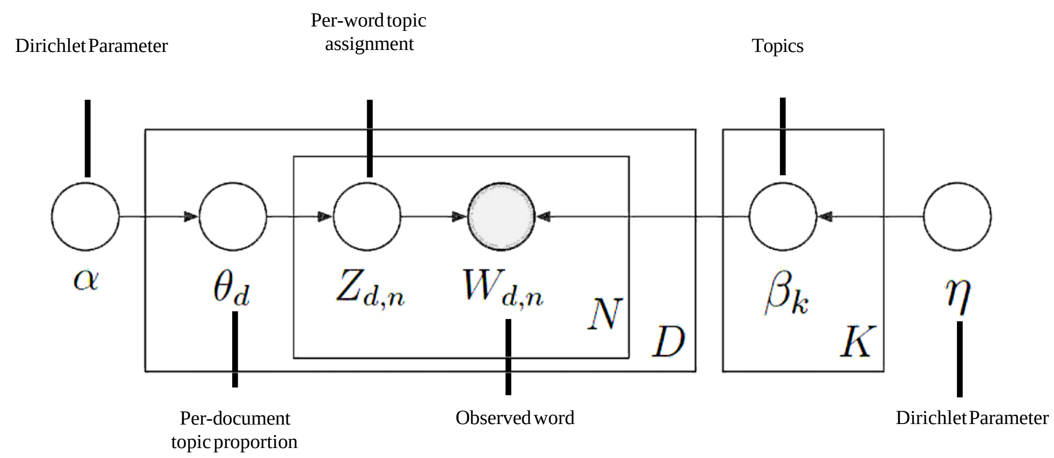
[9] https://github.com/cjhutto/vaderSentiment

3.3 Topic Modeling

To examine the public discussions at each point in time in each country, we use natural language processing and specifically LDA (Blei et al., 2003). LDA is an unsupervised generative Bayesian mixture model which combines knowledge from linguistics and, using probabilistic reasoning, derives human interpretable topics from large volumes of textual data. (Blei et al., 2003; Ottesen et al., 2017).

LDA assumes a generative process in every text (Figure 2). In other words, it assumes that a textual dataset ("corpus") is comprised by distributions of discussion themes, known as *topics*. In general, documents are comprised by multiple topics. Each topic is essentially a group of words associated with a theme or statistically, a distribution of terms in a fixed vocabulary (β). First, topics are chosen for sampling β. For each document *D*, a distribution over topics is derived (Θd). Then for each word in each document *N*, the distribution over terms associated with the topic (*z*) and the word from the corresponding distribution over terms is chosen (*w*). The parameters α and η represent hyperparameters for the LDA distributions calculating the per-document topic vectors (Θ) and the topic vectors (β) (Blei et al., 2003). Generally, LDA receives as inputs textual data, and using posterior knowledge, derives "hidden" topics of discussion coming from this data. The human decision-maker must decide about the number of topics to be uncovered. We present the details regarding topic number selection in Appendix C.

Figure 2 Generative Process (LDA). Adapted from Blei et al. (2003)



In addition, each topic has a set of prominent words which characterize it. These prominent words capture the essence of each topic and can be used by the human decision-makers to name (or "label") the topics. To label the topics, we used the most representative tweets (tweets with the highest probability of belonging in a topic) in combination with the most prominent words per topic. Specific results about the topic labelling process are presented in Appendix A.

4. Results and Discussion

Our focus is sustainability, e-mobility and smart metering public awareness. As proxies for public awareness, we use *the frequency* and *sentiment of tweeting*. The tweet frequency per country indicates the intensity of discussions, whereas the sentiment is a more explicit expression of opinions. The tweet sentiment is commonly used as proxy for public awareness (O'Connor et al., 2010). We add the frequency of tweeting as a second indicator, as individuals who tweet more about a theme tend to be more aware. Lastly, for each theme (sustainability, e-mobility and smart metering) we use topic modeling to get more in-depth insights about discussions and potential pain-points. The latter serves as qualitative confirmation of the indications provided by the tweet sentiment and frequency. Furthermore, this topic analysis offers further understanding about each country's reactions to policies. Figure 3 presents a schematic overview of the result derivation process.

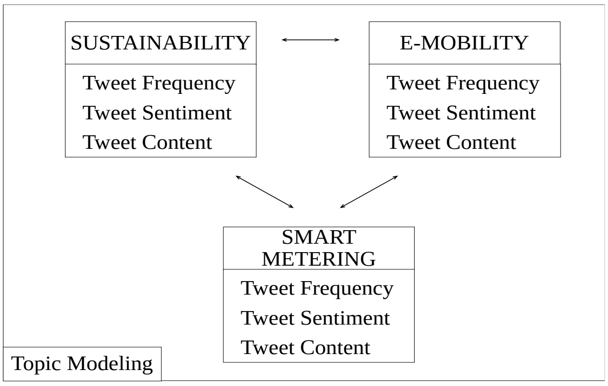


Figure 3: Result Derivation Process

Note. To derive results for each theme (sustainability, e-mobility, and smart metering) we analyze the tweet frequencies, tweet sentiments as well as tweet contents for each country.

4.1. Sustainability

First, we examine the difference in sustainability awareness in US and Germany, considering all sustainability-related tweets. Overall, 5,227 tweets are classified as "sustainability" tweets (selected based on containing words such as "sustainability", "sustain", "environment" etc.) with only 12% of these tweets generated in the US. This is an early indicator that Germany is more advanced with regards to recognizing sustainability as a major societal challenge, whereas US is at an earlier stage.

Throughout the timeframe 2010-end of 2019, the tweet frequency (country tweet count per year divided by the total tweet count per year) increased (Figure 4, left). In 2010 (frequency 1%) and 2013 (frequency 5%) there is no significant difference in sustainability tweet frequency between US and Germany, whereas in the rest of the years this frequency shows differences. In 2019, there is a substantial increase in sustainability tweet frequency in Germany; almost 50% of all sustainability tweets was generated in 2019. In this year, the sustainability tweet frequency in Germany is 57%, whereas in the US is 18%. This could be because 2019 is known as "the E-Mobility year in Germany"; many well-established car manufacturers and start-ups launched new EVs during 2019 (BMWi3, VW, Sonomotors, e.Go etc.).

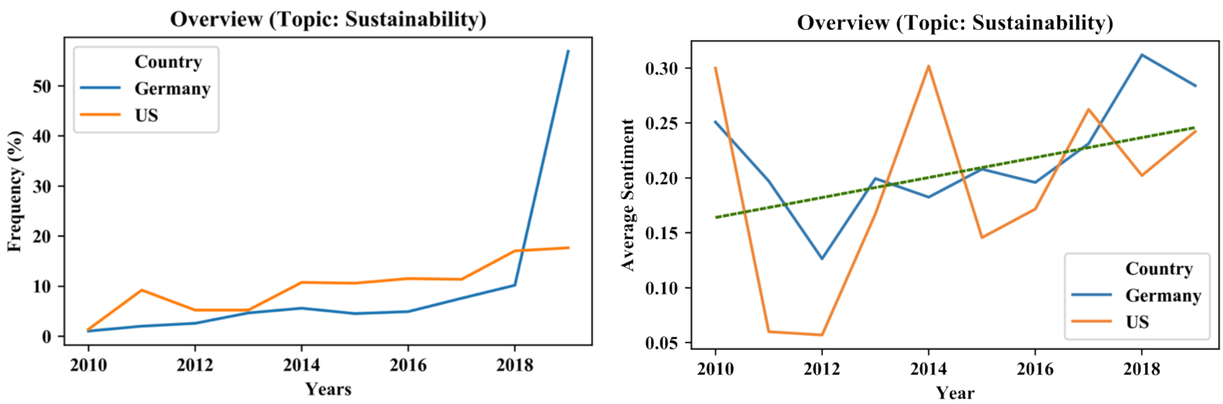


Figure 4: Tweet Frequency & Average Tweet Sentiment over Time (Sustainability)

The tweeting sentiment reveals major differences across the two countries (Figure 4, right). Fluctuations are observed in US tweets during the ten years, while the German tweet sentiment fluctuates less as of 2013 with a mean value of around 0.2. The high fluctuations in the US could reflect indecisiveness in the US public about currently established policies (Simpson, 2017). In addition, it could indicate that the US is at an earlier stage in the sustainability adoption process. In such earlier stages, it is more logical to have fluctuation in public opinions, as opposed to more mature sustainability adoption stages where the public opinion does not fluctuate as much. Overall, there is a positive trend in both countries showing that citizens tweet more positively about sustainability over the years.

Next, we analyze the sentiment scores of positive, negative, and neutral tweets (Table 4). We observe that the negative sentiment in German tweets about sustainability (0.351) is significantly higher than the negative sentiment (0.297) in US tweets (p=0.029), while the neutral sentiment is slightly lower in Germany than in the US (p=0.088) (Table 4). Finally, there are no significant differences in the positive tweets. As a result of Figure 4 and Table 4, hypothesis (***H1***) stating that there is a difference in public awareness about sustainability between the US and Germany can be accepted.

Table 4: Tweet Sentiment (Sustainability)

Tweet Sentiment	Germany	US	t-stat.	Sig.
negative	0.351	0.297	2.213	0.029**
neutral	0.999	1.000	1.707	0.088*
positive	0.532	0.513	-1.226	0.221

Note. T-statistics are based on a t-test for the difference in average tweet sentiment of countries; *p<0.1; **p<0.05; ***p<0.01

Furthermore, from a policy point of view, it is interesting to examine whether the public awareness about sustainability increases after the introduction of the SDGs in September 2015 (***H2***). Behavior changes do not become visible immediately as several environmental, personal, and social factors can affect the speed of behavioral change (Central Office of Information, 2009; Clements & Zarkowska, 2000). Hence, we investigate whether public awareness increased as of 2016, leaving some time for such behavioral change to manifest itself.

Table 5: Public Awareness Before and After 2016 (Sustainability)

	Public Awareness	2010-2015	2016-2019	t-stat.	Sig.
Total	Tweet Frequency	5.2%	17.2%	-1.729	0.091*
	Tweet Sentiment	0.183	0.237	-7.058	1.91E-12***
Germany	Tweet Frequency	3.4%	19.9%	-1.329	0.138
	Tweet Sentiment	0.194	0.256	-6.208	5.84E-10***
US	Tweet Frequency	7.1%	14.4%	-3.199	0.007***
	Tweet Sentiment	0.172	0.220	-2.014	0.044**

Note. T-statistics are based on a t-test for the difference in average tweet frequency & average tweet sentiment before and after 2016. Before accounts for the years 2010-2015, while after includes the years 2016 – end of 2019 ; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

We find an increase of 17.2% in the sustainability tweet frequency after the introduction of SDGs (Table 5, p = 0.091), in the pooled data (US and Germany). More importantly, the sentiment has increased significantly from 0.183 to 0.237 (Table 5, p = 1.91E-12). Furthermore, examining the two countries separately, we find significant changes in public awareness. In the US, both tweet frequency and tweet sentiment increased significantly (p <0.001). In Germany, the tweet sentiment changed significantly from 0.194 to 0.256 (p = 5.84E-10). This could mean that the introduction of SDGs affected public opinion globally, as well as in each country separately. Thus, hypothesis ***H2*** is accepted. This first exploratory evidence can open interesting paths for further investigation.

4.2 Electric Mobility

Next, we test whether the public awareness about e-mobility has increased in Germany and the US over the last decade (***H3***). All tweets related to e-mobility[10] are 19,092, of which 9,930 and 9,162 were generated in Germany and the US, respectively, within the ten years.

First, we examine the tweet frequency in the US and Germany (Figure 5). We find an increase in both countries' tweet frequency, which means that both the US and Germany are becoming gradually more interested in e-mobility. In the pooled sample, this upward relationship can be described by the best-fit linear function: *frequency* = 0.057+0.008**time*. In both countries, we observe that after 2016 the tweet frequency about e-mobility follows a more pronounced upward trend. This could result from the introduction of SDGs late in 2015, which increased awareness about e-mobility in US and Germany. Over the years, there is no significant difference across the two countries, except for 2019, when the two frequencies differ by 7.6%. Similarly to before, this could be explained by the fact that 2019 is known as "the E-Mobility year in Germany".

[10] Tweets are classified as electric mobility tweets when they contain words or variation of terms such as "electric mobility", "e-mobility", "ev", etc.

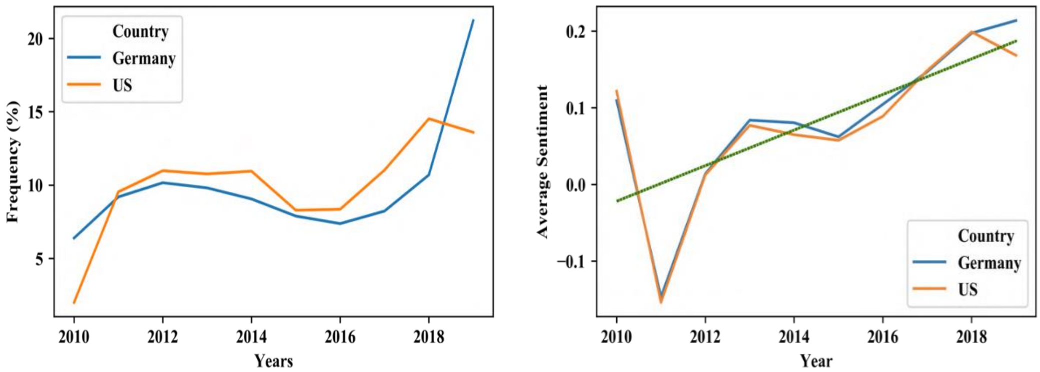


Figure 5: Tweet Frequency & Average Tweet Sentiment over Time (E-Mobility)

The average sentiment per year in each country reveals that in 2011 the sentiment direction changes to negative (approx. -0.15) in both countries. This could be an indirect effect of the fact that the International Agency for Research in Cancer (IARC) "classified radiofrequency electromagnetic fields as possibly carcinogenic to humans (Group 2B)" (IARC, 2011), in May 2011. This frequency is broadcast by smart meters indicating that they can increase cancer risk (CDPHE, 2012). As smart meters are required for EV adoption, we expect this negative announcement to have affected the sentiment about e-mobility. Overall, the average sentiment is very similar in both countries showing an upward trend (*sentiment*=-0.045+0.023**time)*, only with a difference of around 0.046 in 2019 (Figure 5).

Investigating the distribution of sentiment for each country, we see that the positive tone of German tweets about e-mobility (0.478) is significantly higher than the US (0.454) tweets (Table 6, p=0.000). This shows that Germany is more mature in terms of e-mobility adoption, possibly as a result of intense governmental efforts and automotive industry ventures.

Table 6: Tweet Sentiment (E-Mobility)

Tweet Sentiment	Germany	US	t-stat.	Sig.
negative	0.283	0.275	1.640	0.101
neutral	0.999	1.000	1.706	0.088*
positive	0.478	0.454	-3.530	0.000***

Note. T-statistics are based on a t-test for the difference in average tweet sentiment of countries; *p<0.1; **p<0.05; ***p<0.01

In order to test ***H3***, besides the frequency and sentiment trends over the years, we also examine the differences in the e-mobility topics in the US and Germany (Figure 6). In the positive tweet segment, both countries tweet about battery charging and stations, whereas notably a greater focus is put on sustainability and environmental impacts in Germany. In the negative segment, again we see similarities in the discussed topics, with prominent ones being the engine features of EVs, as well as associated job opportunities. This shows that both countries evolve in similar ways when it comes to e-mobility discussions.

To probe deeper into each country's electromobility adoption state, in Germany in 2010, we see a fairly positive tweeting behavior about e-mobility (Figure 7). This could be the result of many development projects, research, testing plans and reports published during this year. Hence, one could argue that Germany was in the early stages of e-mobility adoption, in which people express their enthusiasm and excitement for the future. This assumption is verified by the German National Platform for Electric Mobility (NPE) stating that the years 2010-2014 can be categorized as the pre-market phase for e-mobility, marked by R&D, projects, investments/funding and testing (NPE, 2012).

In the US, we see an increase in electromobility tweet frequency over the years, indicating a growing awareness. Delving deeper into the content of these tweets, we find that the US focuses on batteries, energy, and efficiency; hence, performance indicators instead of sustainability indicators. This difference in tweeting behavior indicates that the US is still growing in terms of technological e-mobility advancements, whereas Germany, which already has mature technology knowledge, focuses more on the social acceptance of EVs. In addition, most technology firms (start-ups and multinationals) are based in the US (Cornet et al., 2019; Möller et al., 2019), which could explain the focus on performance rather than acceptance of EVs. Overall, hypothesis ***H3*** can be accepted.

Figure 6: Most Frequent Words per Country & Sentiment (E-Mobility)

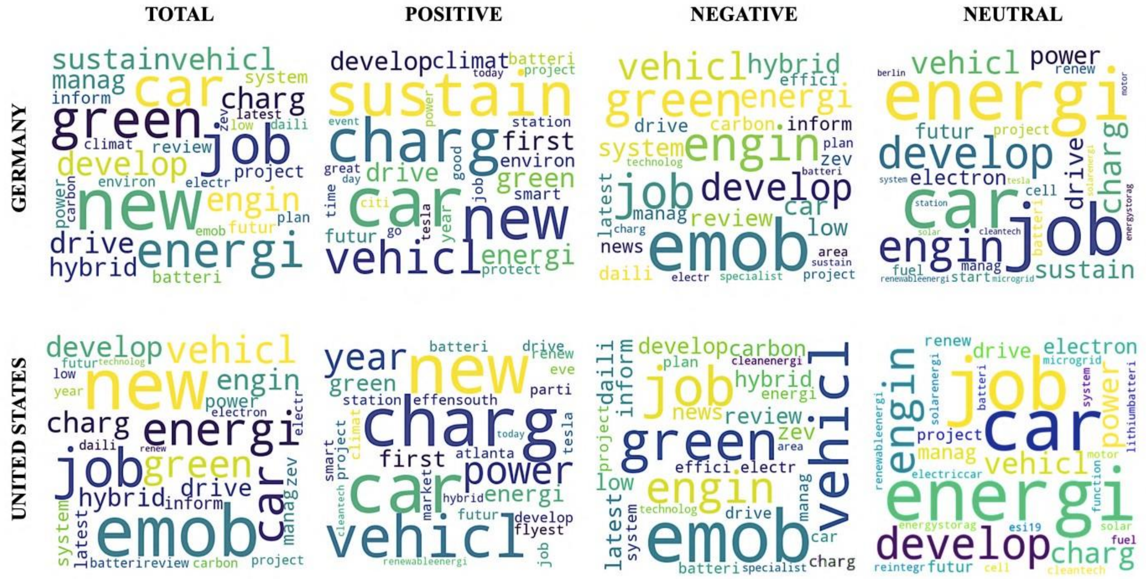
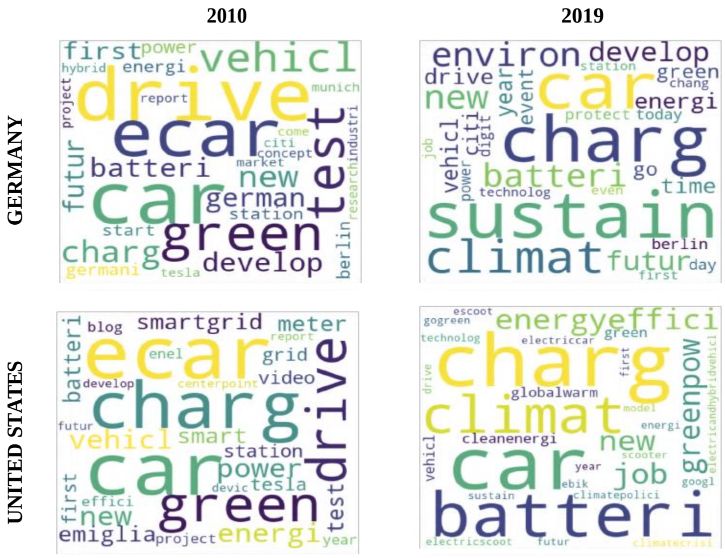


Figure 7: Most Frequent Words per Country & Year (E-Mobility)



4.3 Smart Meter Privacy Concerns

Next, we examine the tweets related to smart meters and privacy. Overall, 5,500 tweets belong in this category, of which 3,081 and 2,419 tweets were generated in Germany and the US, respectively.[11] With regards to the tweet frequency over the years, both countries

[11] As relevant tweets we selected those containing terms such as "smart metering", both "smart metering" and "privacy" or variations of them.

follow a similar trend (Figure 8). Only in 2019, the tweet count increases by 15% in Germany; possibly because 2019 was a milestone year for Germany with regards to e-mobility as well as sustainability-related events (e.g., “Urban Mobility Day”, “E-Mobility parade”, “IAA2019”, “Berlin E-Prix”, “RM Summit 2019”).

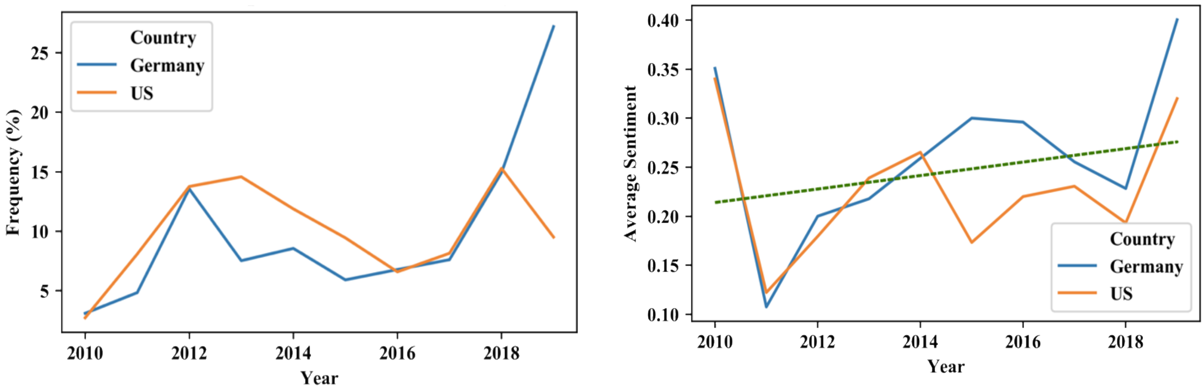


Figure 8: Tweet Frequency & Average Tweet Sentiment over Time (Smart Metering)

The average tweet sentiment about smart metering exhibits a positive trend overall (*sentiment*=0.227+0.009**time*), with both countries expressing a similar average sentiment over the years (Figure 8, right). Similarly to the e-mobility tweets, the sentiment score dropped substantially in 2011, validating the negative attitude of Germany and the US toward smart meters. As before this could be due to the International Agency for Research in Cancer (IARC) announcement in May 2011. The content of negative tweets in 2011 strengthens this reasoning (prominent word “cancer”).

Regarding the sentiment, in Germany the average positive sentiment is higher than in the US (Table 7, p=0.092); hence, we could deduct that despite the concerns, Germans tweet more positively about smart metering. The latter could be another indicator of a more mature adoption stage, where after having expressed critical concerns, the public starts to accept the new technology.

Table 7: Tweet Sentiment (Smart Metering)

Tweet Sentiment	Germany	US	t-stat.	Sig.
negative	0.378	0.357	1.217	0.224
neutral	1.000	1.000	-	-
positive	0.559	0.544	-1.683	0.092^{*}

Note. T-statistics are based on a t-test for the difference in average tweet sentiment in countries; *p<0.1;**p<0.05; ***p<0.01

In this context, we also investigate the actual content of the tweets in both countries over the years (Figure 9, Figure 10). While we see the word privacy having a prominent position in 2010 and 2011, in 2019 privacy does not appear as an important discussion topic. The latter possibly indicates that the German audience has matured with regards to smart metering adoption or governmental actions about privacy succeeded. In the US, we observe in 2011 prominent discussions about the security of smart metering, whereas in 2019 the discussion about smart meters mainly revolves around their connection to EVs and smart grid technologies, such as blockchain.

As a result of the positive slope (0.009) in the sentiment trend over time and the qualitative confirmation from the topic modeling, hypothesis ***H4*** can be accepted.

Figure 9: Most Frequent Words per Sentiment & Year in Germany (Smart Metering)

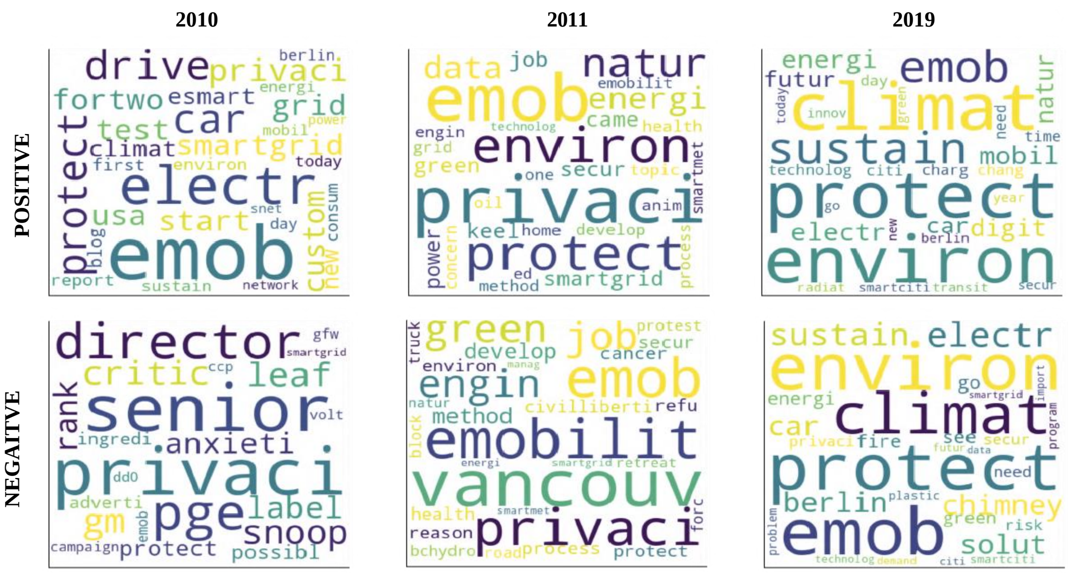
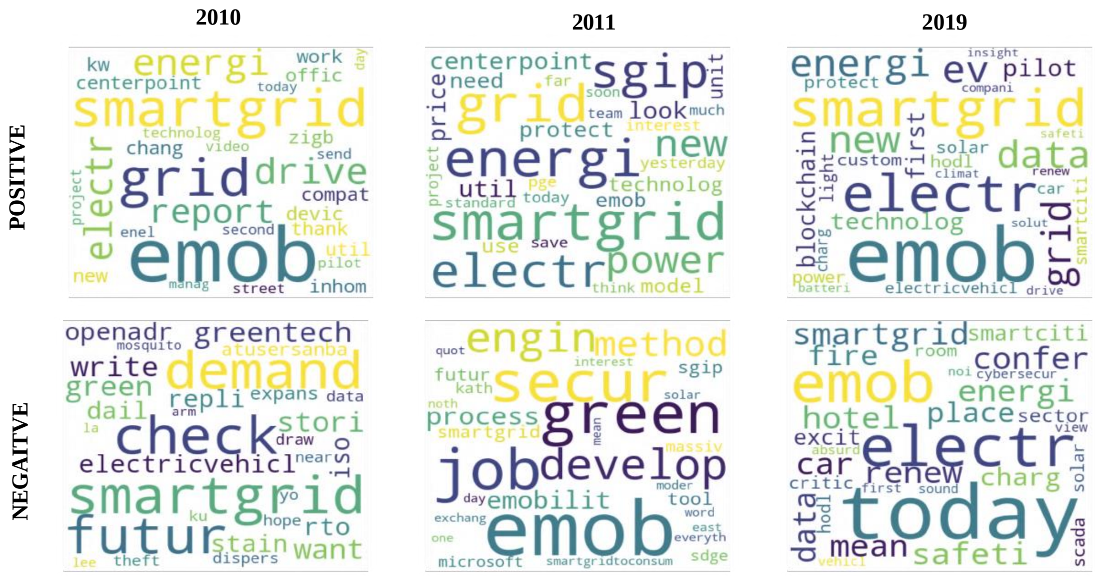


Figure 10: Most Frequent Words per Sentiment & Year in the US (Smart Metering)



4.4 Overall Tweeting behavior in Germany and US

Next, we examine whether tweet behavior differs across Germany and the US (***H5***). Using LDA, as described in Section 3, we elicited 7 topics from the pooled data (US and Germany). After we labeled the topics (as described in Appendix C), each tweet was classified to a topic. Next, we measured the frequency of tweets belonging to each topic, for US and Germany (Figure 11). For example, German tweets deal considerably more (14% compared to 9% in American tweets) with the topic "EV Charging (stations, infrastructure, meters)" while a high number of American tweets fall under the topic "Specialists/Experts in E-Mobility Industry" (25%).

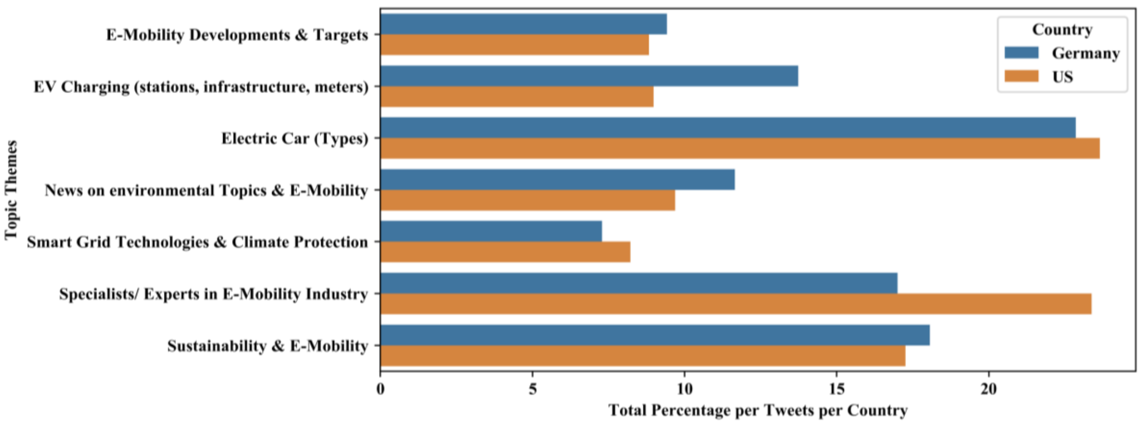
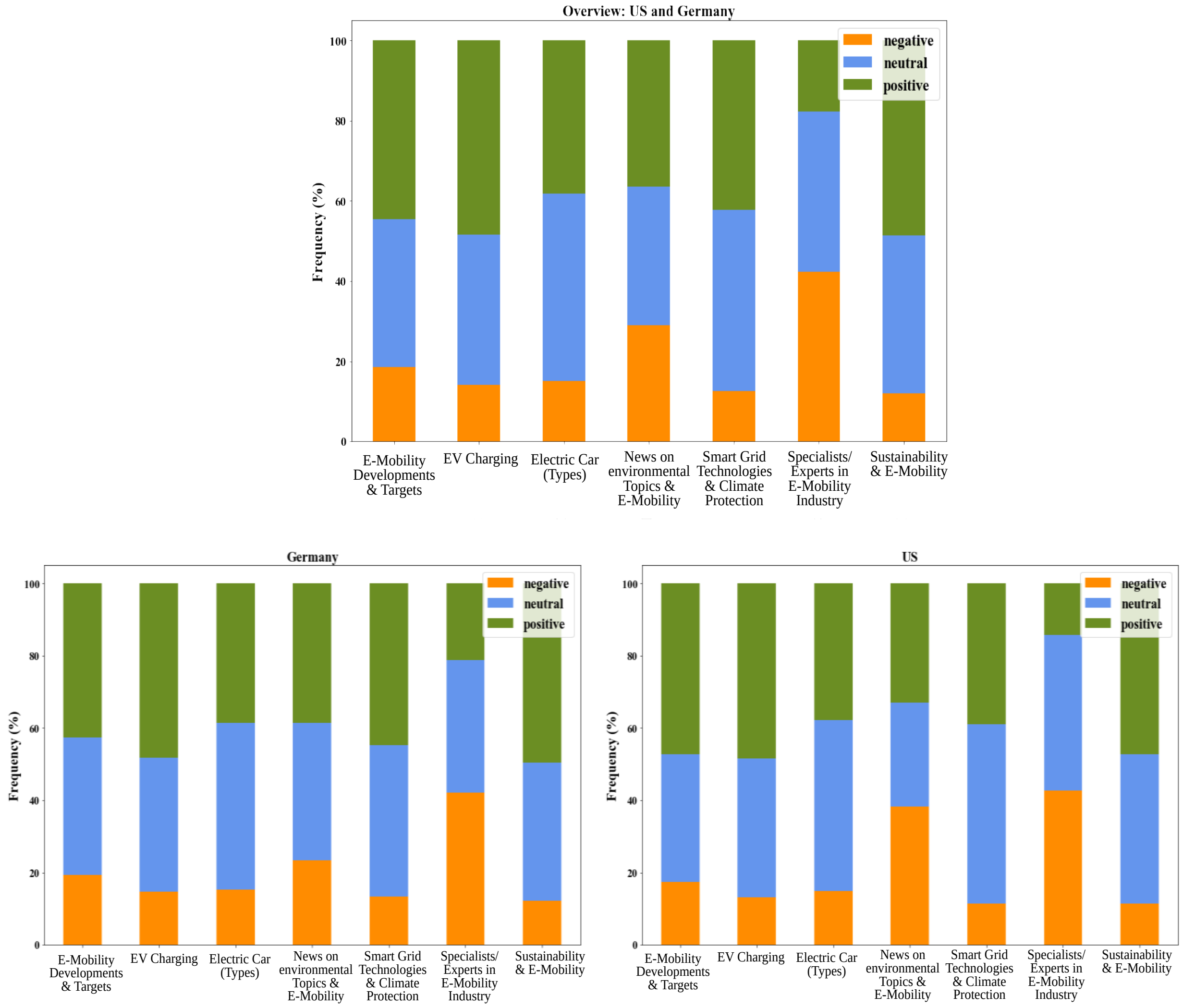


Figure 11: Topic Prominence in the US and Germany

The overall sentiment among all topics is mostly positive or neutral; however, notably, within the “Specialists/Experts in E-Mobility Industry” segment, about 40% of tweets are negatively connotated (Figure 12). Similarly, within the “News on environmental Topics & E-Mobility” fragment 30% are negative tweets. On a country level, comparable sentiment trends are observed for American and German tweets (Figure 12, lower panels). Further results about the sentiment across topics over time are presented in Appendix B.

Examining whether topic tweet behavior differs in Germany and the US, we observe only slight differences (Figure 11 and Figure 12). As a result, hypothesis ***H5*** is not supported.

Figure 12: Tweet Sentiment per Topic (Overall, Germany and US)



5. Conclusions and Policy Implications

We explored differences in sustainability, e-mobility and smart metering awareness in Germany and the US, two countries leading the EV development. Our study is one of first to comparatively analyze these two countries with very different approaches to policy formulations, governmental actions, and societal thinking. Furthermore, in contrast to prior work that examines certain points in time, we conduct longitudinal analyses, investigating public perceptions during the last decade. The latter allows us to derive deeper insights about the effects of policies and the evolution of public perception in both countries. Specifically, by applying sentiment analysis and Natural Language Processing on tweets from the two countries during 2010-end of 2019, we find that during the last decade, the sustainability, e-mobility and smart metering awareness have increased in both countries. This is an encouraging finding for sustainability policy, as it confirms that, at a higher level, policy efforts to raise awareness have succeeded. More interestingly, we see that the introduction of the Sustainable Development Goals (SDGs) had a positive effect in raising awareness. This is one the first large-scale evidence about the actual impact of the SDGs. In addition, regarding smart-meter-related concerns, we find that Germany is more interested in the connection of smart meters to sustainability, whereas the US is mostly interested in the connection of smart meters to e-mobility. Also, we find that privacy concerns start to deteriorate in Germany, possibly signaling that the policies in place are succeeding in reassuring the public. Finally, we explore the most important general concerns in Germany and the US. We see that both US and German citizens are interested in EV developments, however, in Germany the concerns about EV charging infrastructure are much higher. This finding is interesting considering that the driving distances in the US are on average higher than in Germany, hence one would expect US citizens to be more concerned about the charging infrastructure availability. In contrast, in the US we see a much higher interest in EV specialists and the EV industry as a whole. This is another unexpected finding considering the longstanding automotive industry presence in Germany. However, policymakers need to consider the strong presence of e-mobility companies such as Tesla in the US.

Our results can contribute to better decision making by showing that initiatives such as the SDGs, or privacy-related policies can help increase awareness and create positive public sentiment. Furthermore, considering that public perception affects the adoption of new technologies (e.g., smart meters or EVs), policymakers can conduct similar analyses after the introduction of new technologies or sustainability initiatives. In this way, policymakers (such as local or federal governments) can understand potential issues with newly-introduced policies, quickly. For example, if such an analysis was conducted in May 2011 right after the IARC´s announcement about smart meters and potential cancer association, policymakers would be able to quickly intervene and via proper communication channels change this negative sentiment about smart meters.

Also, our results help sense public opinions about sustainability-related policies. For example, the public perception about topics such as smart meters is vital for massive roll-outs. In Germany, despite the growing positive sentiment, there is a lot of reluctance to adopt them. Similarly, in the US there are many states that support "smart meter opt-out policies". Hence, governments need to sense the public opinion and take measures to address public concerns. While the measures taken by policymakers to address such concerns vary per country, it would be beneficial to mention that in the "social-media era" we are living in, influencing key nodes of social networks ("influencers") would be effective in changing the public opinion. For example, once the negative sentiment about smart meters is spotted in the data-driven analysis, the most influential users can be identified and approached. Such approaches can possibly change their opinion, and they in turn, will be able to diffuse this change to the rest of the network that is influenced by them.

Below, we present specific implications for the three dimensions of our analysis: sustainability, e-mobility and smart metering,

5.1 Sustainability Implications

At a country level, our results show that only 12% of the sustainability tweets were generated in the US, and the remainder in Germany. This could signal that the US is at an earlier maturity state with regards to sustainability; hence, it provides fertile grounds for developing successful policies on time to shape the public opinion. A society at an earlier adoption stage might be more open to new policies, as there is no established public opinion. This finding is also confirmed by the high fluctuations in the US tweet sentiment across the years. This volatile trend could reflect an indecisiveness in the US public about currently established policies, pointing again to an earlier sustainability adoption stage. Our findings are supported by US public surveys which find that only 22% of the adults feel that climate change is affecting a lot their local communities.[12] From a policy point of view, this implies that a careful policy design is required in order to advance the sustainability maturity of the US society.

In Germany, on the other hand, we see more shaped public opinion about sustainability, something which is directly related with the extensive policy efforts to promote sustainability. A striking increase in public awareness about sustainability in Germany is observed in 2019. This could be because 2019 is known as "the E-Mobility year in Germany"; many well-established car manufacturers and start-ups launched new EVs during this year (i.e., BMWi3, VW, Sonomotors, e.Go etc.). Furthermore, the negative sentiment about sustainability in Germany is significantly higher compared to the US. This shows that in a society with already shaped public opinion, criticisms are more likely to emerge (as the public has a more complete opinion). As a result, more intense policy efforts are required, for example launching new technologies that address user criticisms. These findings are supported by EU surveys which showed that Germans consider climate change the most serious problem and they think their politicians are not doing enough to address it.[13] From a policy point of view, it is clear that in Germany the sustainability efforts need to be intensified via providing incentives for adopting e-mobility, incentivize recycling, etc.

Taken together, our results show clear differences in sustainability awareness in Germany and the US, highlighting pain-points for policymakers, and most importantly, creating policy opportunities in societies with a growing interest in sustainability, such as the US. The differences in sustainability awareness in these two countries are affecting their neighbors. Mainly in the case of Germany, we see neighboring countries such as the Netherlands following a similar sustainability awareness path, considering sustainability the most serious problem to be addressed.[13] Austria on the other hand, does not consider climate change as important and only 15% of its population (well below the European average) is concerned about it.[13] Therefore, the influence of Germany, as a more sustainability-mature country could lead to an increase in sustainability awareness. However, this will require proper policy design as the Austrian public seems to be at an earlier maturity stage when it comes to sustainability. On the other hand, in contrast to the US that shows relatively low awareness

[12] https://www.pewresearch.org/science/2019/11/25/u-s-public-views-on-climate-and-energy/
[13] https://europa.eu/eurobarometer/surveys/detail/2273

about sustainability, in many Asian countries such as China and Japan the public opinion starts becoming much more supportive of climate change initiatives.[14,15] The latter could possibly put pressure on the US public to align with the international developments. It is interesting to mention that despite the low sustainability awareness, the US has a lot of technological advancements with respect to sustainability, such as battery technology and e-mobility companies (e.g., Tesla). Therefore, such advancements might indirectly incentivize the Asian countries to compete, considering that their citizens are more open to sustainability initiatives, and this can be an advantage in the sustainability race.

5.2 Electric Mobility Implications

A similar pattern to sustainability is observed in e-mobility tweeting behavior. This could mean that societies have recognized the essential role of e-mobility towards a more sustainable future. First, we find a very sharp increase in tweeting about e-mobility in 2019 in Germany, most likely a result of the “the E-Mobility year in Germany”. Further, examining the content of German tweets in 2019, we see massive tweeting about e-mobility, charging, etc. in a more positive tone than in the US. A cause for this positivity could be that during this year, not only new EVs were launched but also several events took place in Germany, e.g., “Urban Mobility Day”, “E-Mobility parade”, “IAA2019”, “Berlin E-Prix”, “RM Summit 2019”. This is an interesting finding suggesting that events targeting to raise awareness can be a powerful tool for policymakers. Indeed, factual data state that in 2020 Germany recorded the highest number of EV sales.[16] Similarly, our less positive but gradually improving findings about e-mobility in the US are supported by surveys launched in the US public.[17]

In both US and Germany, we observe an over-time increase in e-mobility awareness, however, there are distinct per-country differences. The US discussions focus on batteries, energy, and efficiency; hence, performance indicators instead of sustainability indicators. This could signal that the US is still growing in terms of technological e-mobility advancements. This is supported by a recent US survey which recognizes the early adoption stage of EVs in the US; however, it shows that 39% of the US adults are likely to buy an EV

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[14] https://unfccc.int/sites/default/files/resource/Press%20Release%20-%202.pdf
[15] https://www.oecd-ilibrary.org/sites/4cf50c3b-en/index.html?itemId=/content/component/4cf50c3b-en
[16] https://energypost.eu/e-mobility-in-germany-a-record-year-but-still-way-off-target/
[17] https://www.pewresearch.org/fact-tank/2021/06/03/electric-vehicles-get-mixed-reception-from-american-consumers/

in the future.[17] In contrast, Germany already has a more mature technology knowledge base; hence, German tweets focus more on the social acceptance of EVs. In addition, most tech firms (start-ups and multinationals) are based in the US (Cornet et al., 2019; Möller et al., 2019), which could explain the focus on performance rather than acceptance of EVs.

The current US policy has recognized these deficiencies and is trying to increase access to e-mobility via financial incentives to low-income buyers or expanding car-sharing services.[18] To make such policies more effective, relevant decision-makers can leverage the tech know-how and affinity with disruptive e-mobility technologies in the US. In addition, the negative US tweets about e-mobility reveal concerns about battery technology and its performance. Hence, policymakers can emphasize technology solutions or battery-related information, in order to increase e-mobility awareness and adoption. The current policy in Germany is mainly focusing on several financial incentives or tax rebates to prospective EV buyers.[19] However, there are limited attempts to address social acceptance issues which appear as prominent in the negative e-mobility tweets. Hence, one point for policy design would be to address social issues around e-mobility as well as charging infrastructure availability, which seems to be a major concern in Germany.

5.3 Smart Metering Implications

The smart-meter-related results show that society became more aware of smart meters throughout the last decade. Between 2010 and 2012, there were critical discussions about smart meters. The overall increase in conversations from 2010 to 2019 and the steep increase in Germany as of 2017 is most likely because Germany announced to replace 80% of all traditional electric meters with smart meters (Directive 2009/28/EC of the European Parliament and of the Council, 2009). This shows that "forced" adjustments place a topic at the center of the public conversation, and indirectly raise public awareness.

In addition, we found that the public sentiment toward smart meters increased over time. In contrast to existing literature that presents severe user skepticism toward smart meters (Alejandro et al., 2014; Han & Ang, 2018; Zhou & Brown, 2017), we find an upward trend in the over-time sentiment. This is an interesting finding, showing that despite the overall

[18] https://theicct.org/sites/default/files/publications/Expanding-access-electric-mobility_ICCT-Briefing_06122017_vF.pdf
[19] https://www.bmwi.de/Redaktion/EN/Artikel/Industry/regulatory-environment-and-incentives-for-using-electric-vehicles.html

skepticism, there are certain actions that can improve the public sentiment. For example, it is proven that once a smart meter is installed, users were very satisfied (GOV, 2018). Therefore, positive word-of-mouth from these users can influence the public sentiment. Furthermore, more tech-savvy individuals tend to be more open toward smart meters (Chawla et al, 2020), therefore, educating the public about new technologies can have a positive impact on adoption. Finally, when more knowledge about the technology is publicized, individuals tend to become more open to adopting (Beaulieu et al., 2016). Therefore, all these three drivers can be leveraged when designing public policy about smart meter adoption.

Especially, in Germany, while in 2011 the general privacy issues were concerning the public, in 2019 privacy does not appear as an important discussion topic. The latter possibly indicates that the German audience has matured with regards to smart metering adoption. Similarly, in the US, we observe in 2011 intense presence of security concerns, whereas in 2019 the public is more focused on the connection of smart meters to EVs and smart grid technologies, such as blockchain. Our results find support from recent factual data about smart meter installation in the US, which show a slow but steady increase in the numbers of smart meters.[20]

From a policy point of view, Germany has imposed a forced roll-out irrespective of public opinion. This strategy seems to be effective, as the sentiment toward smart meters started becoming more positive at the end of 2019. However, German policymakers, in their effort to address important privacy concerns expressed by citizens (as we also found in the tweets about smart meters), paused this roll-out in March 2021.[21] This pause was a result of a dispute between smart meter companies and the government, because of the high security standards set for smart meter production.[22] This immediate reaction by the German government shows that consumer privacy is very important and could serve as a reassurance that could increase future adoption. In the US on the other hand, there are “opt-out” policies in some states[23] which allow users to opt-out from installing smart meters. Therefore, in the US policymakers must put significant effort to reduce these opt-out behaviors in their quest

[20] https://www.ferc.gov/sites/default/files/2020-05/DR-AM-Report2018.pdf
[21] https://www.welt.de/regionales/nrw/article227716907/OVG-stoppt-Einbaupflicht-von-intelligenten-Stromzaehlern.html
[22] Data security standards set for smart meters are higher than for online banking. https://www.bmwi.de/Redaktion/DE/Textsammlungen/Energie/smart-meter.html
[23] https://www.ncsl.org/research/energy/smart-meter-opt-out-policies.aspx

to incentivize smart meter adoption. Identifying consumer concerns that lead to such opt-out behaviors can help policymakers form more targeted policies, like the German policies addressing privacy concerns.

5.4 Limitations and Future work

This study has a set of limitations that open pathways for future work. First, the results are focused Germany and the US, and due to this specificity, they might not necessarily be generalizable to other countries. Nevertheless, for countries culturally close or with similar developments, the results could be transferable. Second, only hashtags were used to collect the data of interest. Future research might see value in tweet contents that did not use any hashtags and are, hence, disregarded in this research. Third, some tweets, especially retweets might be indecipherable due to missing context of the original tweets which do not become visible when scraping. Therefore, a more accurate look at the context of the tweets could lead to more informed findings.

6. References

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7. Appendices

Appendix A - Topic Labeling

We labeled the topics based on the most salient terms and the content of tweets with the highest probability of belonging to the topic (some examples are presented in Table A2). Figure A1 shows the most prominent keywords of each topic.

To demonstrate our topic labelling process, let us take the example of topic No. 6 “EV Charging (stations, infrastructure, meters)”. Combining the tweets in Table A2, the most salient terms in Table A1 and the word cloud of this topic (Figure A1), we see that charging is the most important term, combining this with other salient terms, we label it as “EV Charging (stations, infrastructure, meters)”. The same process is followed for the rest of the topics.

Table A1: Most Salient Terms for Each Topic

topic_theme	Smart Grid Technologies & Climate Protection	Sustainability & E-Mobility	Electric Car (Types)	Specialists/ Experts in E-Mobility Industry
Word 0	smartgrid	emob	emob	emob
Word 1	technolog	work	electr	job
Word 2	emob	futur	car	green
Word 3	power	fuel	engin	energi
Word 4	smartmet	natur	drive	renew
Word 5	effici	new	hybrid	manag
Word 6	climat	smartciti	mobil	plan
Word 7	protect	great	vehicl	batteri
Word 8	use	day	want	world
Word 9	bmw	tesla	privaci	electricvehicl
Word 10	compani	cell	smart	product
Word 11	traffic	mobil	germani	specialist
Word 12	digit	design	come	better
Word 13	open	ecar	new	construct
Word 14	electron	look	present	expert

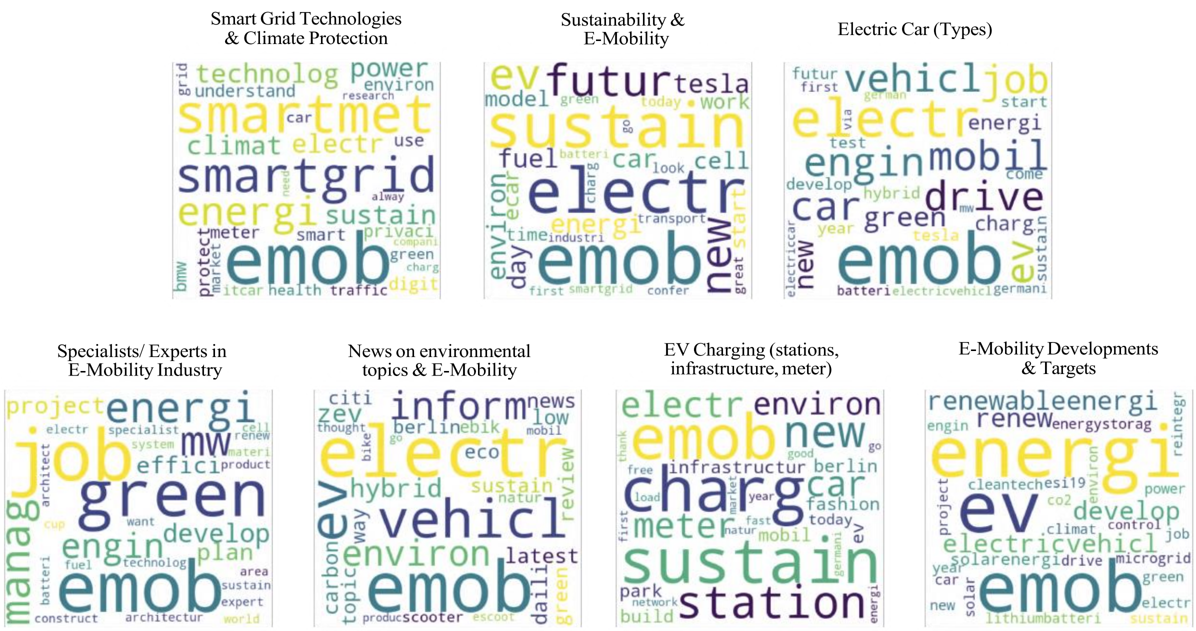
topic_theme	News on environmental Topics & E-Mobility	EV Charging (stations, infrastructure, meters)	E-Mobility Developments & Targets
Word 0	environ	sustain	develop
Word 1	emob	charg	emob
Word 2	vehicl	new	project
Word 3	eco	meter	innov
Word 4	news	emob	renewableenergi
Word 5	inform	build	solar
Word 6	latest	station	review
Word 7	carbon	center	year
Word 8	daili	ecofriendli	energystorag
Word 9	zev	infrastructur	process
Word 10	low	fashion	busi
Word 11	berlin	today	solarenergi
Word 12	secur	produc	co2
Word 13	citi	berlin	invest
Word 14	way	park	control

Table A2: Most Representative Tweets for Topic 6: "EV Charging (stations, infrastructure, meters)"

Most representative tweets belonging to "EV Charging (stations, infrastructure, meters)"

1	Today, the first charging points of e-laad.nl have successfully migrated to the new Logic CiMS platform. #EV #emobility #CiMS
2	#emobility:"We must not build charging stations in public places in #Wien" http://diepresse.com/home/leben/mensch/4764711/Leben-in-der-Zukunft
3	@ePionier 22kW is available via @ladenetz 43kW-AC, #CCS + #CHAdeMO via RFID from Total Operator 24h/7T From July14! #emobility
4	The new fast charging station #emobility is here! Thank you @Swiss_eMobility, paytec, @Alpiq, @EVTECfastcharge http://bit.ly/1Fy8Wxv
5	#EV-Charging #electromobility Now first stations in #Hamburg with charging forecasts and #TimeTravel @moovility_depic.twitter.com/TaNPEp0fw3
6	The @RenaultZoe will be equipped with #CCS-Charging capabilities by 2019. http://ow.ly/BQqr30794Bg #EVcharging #EV #emobility
7	Commissioning of the first Parkpod in #Karlsruhe on 18.02.2010 with Mayor Mergen nhttp://tinyurl.com/yhm3e5r-n-Electromobility

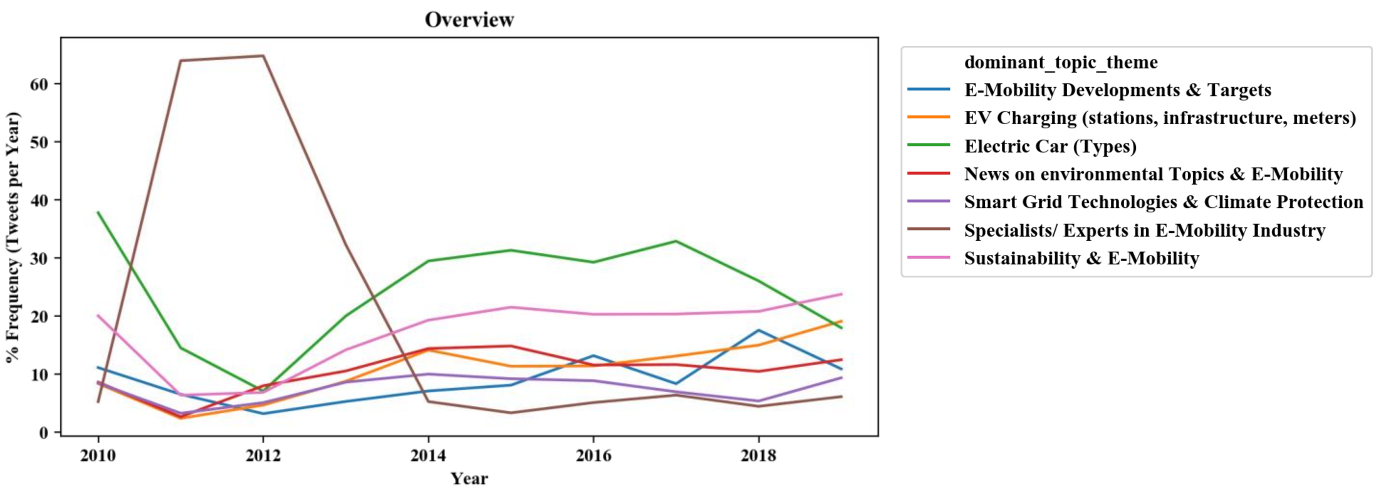
Figure A1: Most Frequent Words per Topic



Appendix B - Topic Modeling Additional Results

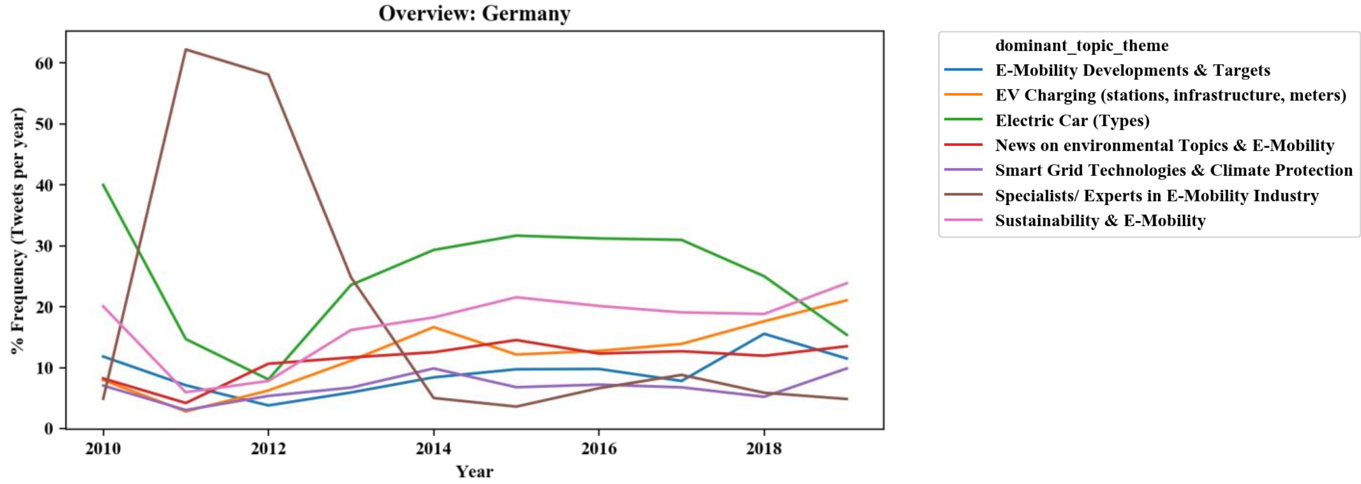
The frequency of tweets within each topic increases steadily, only for topic "Specialists/Experts in E-Mobility Industry", almost all tweets were posted in the years 2011 and 2012 (Figure B1). Similar trends are seen from a country perspective (Figure B2). One difference can be observed in the topic "News on environmental Topics & E-Mobility" as the frequency fluctuates in the years 2015 until 2019 more in the US. For example, a quarter of all tweets belonging to this topic were generated in 2018, while only 8% were generated in 2019 and 2017. In 2013, most tweets posted in each year could be categorized as "Electric Car (Types)". As of 2019, however, most tweets fall under the "Sustainability & E-Mobility" topic, followed by "EV-Charging (stations, infrastructure, meters)". When looking at the average sentiment score per topic (Figure B3) in each year, the sentiment fluctuates for almost all topics. In general, the topic "News on environmental Topics & E-Mobility" was most negatively tweeted about in both countries. Overall, there is an increase in positive sentiment for all topics over the years.

Figure B1: Tweet Frequencies Over Years per Total Tweets in Each Year



Note. The yearly frequency scores are calculated with the number of tweets in a topic in a year divided by the total number of tweets belonging to one topic.

Figure B2: Tweet Frequencies Over Years per Total Tweets in Each Year, Germany and US



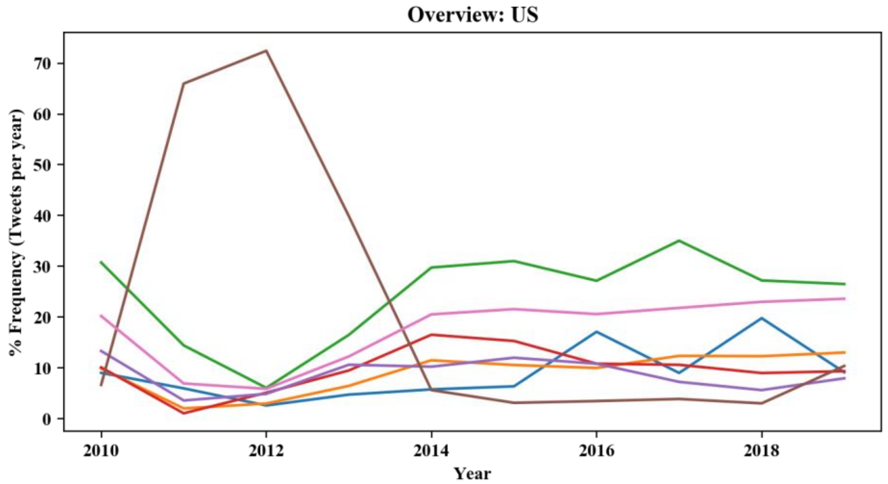
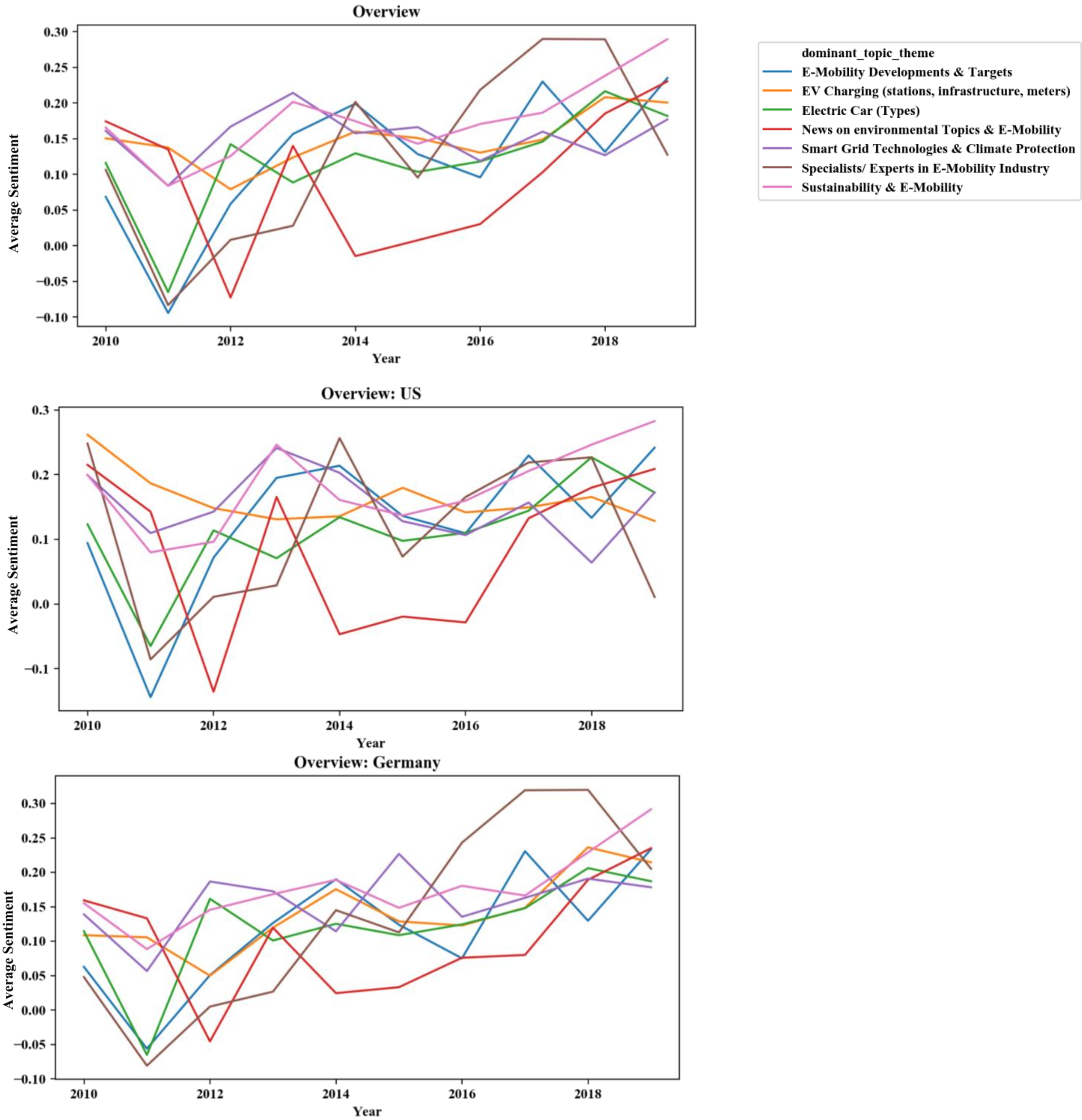


Figure B3: Average Tweet Sentiment per Year



Note. The figures depict the yearly average tweet sentiment scores per topic.

Appendix C – Methodology Details

Data Collection

To collect our 43,750 tweets, we used the programming language Python. Specifically, we scraped our tweets of interest from Twitter using the Python Package "twitterscraper".[24] This package allows for scraping tweets in a long time-horizon; hence, we were able to scrape tweets for the decade 2010 to the end of 2019. The package is linked to the Twitter Advanced Search filtering for specific hashtags and location. Therefore, we were able to access tweets for the locations of Germany and the US. Furthermore, we selected the relevant hashtags in order to account for variations in hashtag usage and language differences (e.g., #emobility and #electricmobility; #sustainability and #nachhaltigkeit). We repeated the same process for sustainability, e-mobility, and smart meters. For Germany, we used hashtags both in English and in German.

Pre-Processing

Text from social media and microblogging platforms is highly unstructured (Agarwal et al., 2011), hence, first, we cleaned the unstructured data from noise. Next, we translated the non-English tweets using the Google Translate API and afterwards, a bilingual German and English individual manually checked the translations to ensure correctness. As a last pre-processing step, specific tweet or text components, such as URLs, User IDs, numbers, "RT" standing for retweets and "@" followed by user mentions, were removed. In Table C1, we present descriptive statistics of the 43,750 tweets in our dataset. We see that the number of likes as well as the number of retweets span from 0 to higher than 2,300, whereas the hashtags vary from 1 to 29.

Table C1: Descriptive Statistics of Tweets

n = 43,750	**Likes per tweet**	**Replies per tweet**	**Retweets per tweet**	**Hashtags per tweet**
Max	2,474	407	2,363	29
Mean	1.88	0.15	0.87	4
Min	0	0	0	1

[24] https://pypi.org/project/twitterscraper/0.2.7/

Note. From total number of 43,750 tweets (after cleaning), numbers are extracted on an individual level meaning that, the maximum number of likes a tweet received accounted 2,474.

Sentiment Analysis - VADER

VADER considers lexical topographies of a document and calculates a score based on syntactic and grammatical cues taking word-order relationships into account (Dahal et al., 2019). Specifically, it is a rule-based sentiment analysis algorithm that has become popular in Twitter sentiment analysis due to its ability to understand informal writing styles and syntax usually used in social media. Evaluating the sentiment in each tweet is not trivial, as tweets might include both positive and negative or neutral sentiments. For this reason, for each tweet, VADER gives four polarity scores - positive, negative, neutral, and compound sentiment scores. The three former scores range from zero to one representing the strength of the positive, negative, or neutral categorization of a tweet, whereas the latter is normalized ranging from -1 to 1. The latter is the normalized sum of all ratings of all tweets (Hutto & Gilbert, 2014); hence we use it to express the overall sentiment of each tweet.

VADER is remarkably accurate in assessing the sentiment of sentences as it uses a *sentiment lexicon* evaluated by many human subjects (Hutto & Gilbert, 2014). That is, the actual sentiment of each word as well as conjunction included in the lexicon has been evaluated by numerous human subjects. In this way, VADER is pre-trained to understand sentiments of sentences in a similar way the human subjects would understand. In simulation experiments with other state-of-the-art sentiment analysis algorithms, VADER had the highest accuracy with respect to identifying the sentiment of Tweets (F1 classification score 0.96) (Hutto & Gilbert, 2014).

Data Cleaning for Topic Modeling

Before moving to topic modeling, we further cleaned the textual data contained in the tweets. First, we *tokenized* the tweets in order to break sentences into a list of words using regular expressions (RegEx), then, we *removed stopwords* as these words usually have very low predictive power and *lemmatized* the words in order to bring words to their roots or stems (Kolchyna et al., 2015; Vu et al., 2015). Finally, we checked our dataset for other noisy words that could distort its results. Such sources of noise are usually words shorter than two characters.[25]

Topic Selection for Topic Modeling

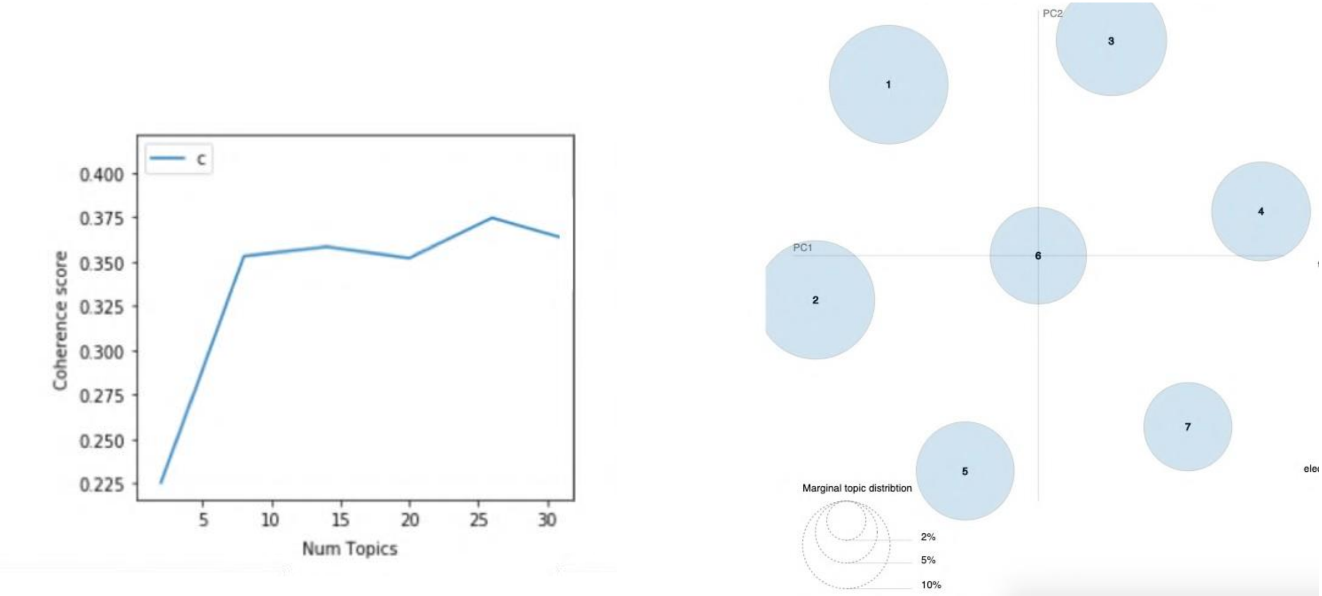
LDA's performance is dependent on the number of topics *k* inferred from the textual data. As LDA is an unsupervised method, researchers cannot know ex-ante how many topics exist in each dataset. Therefore, the optimal number of *k* topics is estimated based on a topic coherence score (Blei et al., 2003). Topic coherence indicates the semantic similarity between the words in a topic. To measure coherence, we employ the coherence score presented by Röder et al. (2015), which is found to be one of the best-performing metrics and is the combination of a cosine measure and a Boolean sliding window (Röder et al., 2015).

The number *k* of topics comes with trade-offs, as a large number *k* of topics may segment the data too much, whereas a smaller number of *k* topics might generalize topics in a way that accurate claims cannot be made. Therefore, typically, researchers choose the number of topics that ensures high coherence, without compromising their ability to make topic-specific claims. In our dataset, we observe that the coherence does not improve significantly after selecting seven topics Figure C1. Therefore, we select *k*=7 as optimal number of topics.

[25] Two-character words that are of interest for our analysis, such as "EV" were not removed.

Figure C1

Topic Coherence Scores & Topic Distances



Note. The figure on the left shows different number of topics with their respective topic coherence scores calculated based on c_v measures. The biggest marginal gain can be seen with seven topics. The right figure displays intertopic distances for the seven topics. It can be seen the topics are non-overlapping.