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We Know your Personality! An Automated Personality Mining Approach on Twitter Data

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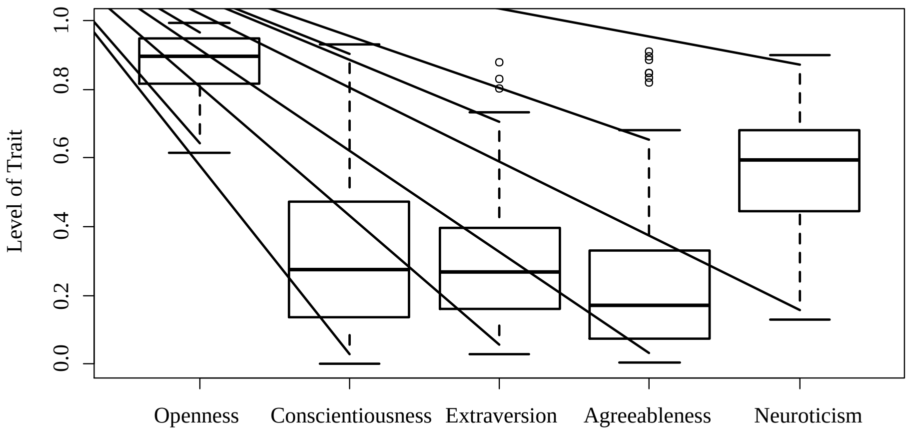

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Abstract

Twitter has become a globally relevant platform for political discussions. While social media analytics comprises various tools to identify important factors influencing political participation, the influence of personality traits in political discussions has only been investigated unsatisfactory. We begin to close this research gap by developing a framework to identify the prevailing "big five" personality traits of Twitter users. Our framework is based on hypotheses derived from political psychology. The application prototype then enables automated personality mining using IBM Watson Personality Insights. Our applicability check with UK-based Twitter users' data discussing the UK Brexit shows both practical applicability and interesting deviations from offline investigations for extraversion and neuroticism.

Keywords: Personality Mining, "Big Five" Personality Traits, Political Discussions, Twitter, UK Brexit

1 Introduction

In political discussions, Twitter has become a full-fledged multimedia platform in the last decade, enabling every user worldwide to easily publish ideas and thoughts in tweets and to exchange and interact with other people with practically no restrictions on reach and information growth (Oh and Kumar 2017; Gimpel et al. 2018; Yaqub et al. 2020). The behavior of expressing oneself politically is influenced by various factors. Especially in election campaigns, social media analytics tools have become widely used and powerful instruments for politicians and political parties to systematically gain insights into communication, popular topics and wording preferences to derive and adapt opinion forming strategies (Stieglitz and Dang-Xuan 2013; Nulty et al. 2016; Stieglitz et al. 2018). While personality traits have been a central component of various studies to analyze political behavior in offline contexts (Mondak and Halperin 2008; Hibbing et al. 2011; Cooper et al. 2013), the analysis of these traits of politically active social media users is unsatisfactory. Although researchers have examined the influence of various important factors, such as sociodemographic attributes like age, location and educational level, the behavior of people expressing their political opinions on social media cannot be explained satisfactory (Hoelig 2016). This indicates that other important factors also have an influence on the intention to express political opinions on social media, e.g., Twitter. Mondak et al. (2010) were able to identify the influence of personality traits on political orientation and how a person expresses him or herself on political opinions in offline discussions. Predicting personality traits by analyzing published Twitter tweets using automated personality mining has been successfully applied in other areas, e.g., recruiting (e.g., Hu et al. 2016) or health (e.g., Rüegger et al. 2016). Combining these research approaches and analyzing personality traits of users active in political discussions on Twitter can help to understand political opinion forming. Therefore, we focus on the following research question:

> **RQ 1:** How can personality traits be systematically analyzed for users expressing their political opinions on Twitter?
>
> **RQ 2:** How can the prevailing "big five" personality traits of UK-based Twitter users discussing the Brexit can be deduced?

We deduce twelve generally applicable hypotheses based on scientific findings of political psychology in offline discussions (first literature review). To test these hypotheses with Twitter tweets, first an automated personality mining framework is developed (second literature review). We discuss this framework to systematically examine personality traits of politically active Twitter users. To check its applicability, we test the hypotheses focusing on the most active UK-based Twitter users, who commented on the UK Brexit while answering RQ 2. Finally, we present limitations and conclusions.

2 Theoretical Background and Hypotheses

2.1 Political Behavior and Political Discussions on Twitter

Political behavior includes any action taken by people in their role as citizens, without coercion, to seek a political outcome (Houghton 2009; Van Deth 2014). Traditional forms of political participation include voting and engagement in a political party, but also actions aimed at raising awareness of specific problems, such as using demonstrations or petitions (Inglehart 1990; Van Deth 2014). For Internet-based political behavior, however, a distinction is made between the three forms of political behavior. While e-parties involve supporting a party by registering online as a member, e-target refers to online political activism in the form of signing online petitions (Gibson and Cantijoch 2013). E-expression, on the other hand, refers to the political behavior that takes place primarily in social media channels, in which users publicly express their political opinions through discussing positions and commenting on articles (Gibson and Cantijoch 2013; Rojas and Puig-i-Abril 2009). In particular Twitter can be highlighted as a platform for e-expression. The intention of Twitter is to encourage expressions of opinion, setting itself apart from other social media by enabling public, hashtag-based discussions where users who have not yet been in touch can exchange ideas and opinions (Schmidt 2014; Oh and Kumar 2017; Stolee and Caton 2018). By enabling users to retweet, use hashtags and address other users in a targeted manner, Twitter as a real-time information platform allows complex discussions in which a wide range of users can discuss issues (Oh and Kumar 2017). The social network allows its users to publicly post short text messages called tweets, which are limited to 280 characters. This limitation encourages users to focus on the most important information, which in turn promotes the rapid and unfiltered spread of concise information (Parmelee and Bichard 2012).

For political behavior, various researchers have investigated impact users on Twitter. Particular attention was paid to how the number of tweets related to a political hashtag is distributed among the contributing authors. By arranging the authors into three groups according to the number of posted tweets, various studies have shown that the most active users (MAU) are a small group, also called lead users (Bruns and Stieglitz 2014; Larsson and Moe 2014), that is publishing the majority of tweets. Further, several studies have shown that politically inclined Twitter users tend to take an ideologically extreme stance, which also contributes to the overall polarization of the discourse (Barberá 2015; Barberá and Rivero 2015; Jungherr 2016).

2.2 Personality and Political Psychology

In the field of political psychology, the scientific focus is on investigating complex psychological processes and backgrounds, by considering personality as one of the internal factors that shape political behavior (Cottam et al. 2010). One of the most important internal determinants of political behavior is individual political orientation, which serves the individual as a guideline for any political action (Cervone and Caprara 2000; Cottam et al. 2010). The personality of a person is seen as a stable inner factor, which is deeply anchored in the unconscious mind (Cottam et al. 2010; Gallego and Oberski 2012). In political psychology, personality is understood as a temporally stable accumulation of traits in the form of inclinations and behavioral patterns, which in turn is reflected in one’s political behavior, orientation, and action (Gallego and Oberski 2012).

Although there are various paradigms in personality research that investigate interindividual differences while focusing on different aspects, political psychology mainly focuses on the trait paradigm. The trait paradigm is characterized by the assumption that individuals exhibit behavioral patterns that are influenced by deeply rooted psychological dispositions that remain stable over time (Cervone and Caprara 2000). However, the actual factors influencing behavior are not directly quantifiable, which is why empirical studies were conducted to classify behavioral differences on personality traits. In this regard, the personality trait paradigm follows the lexical hypothesis of Allport (1937) in which it is assumed that most striking and consistent differences between people are encoded in their use of words. The five personality factors of the trait paradigm, also known as the “big five” personality traits, are openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (John et al. 2008).

2.3 Personality Mining with Twitter Data

Social media users often reveal much about themselves by writing about their feelings and opinions (Carducci et al. 2018). Using natural language processing, it is possible to evaluate this large amount of data in the form of tweets in a meaningful way. This was done in various studies that have been proven to predict accurately personality traits based on tweets and could prove that social media profiles reflect the actual personality traits of a person as opposed to a distorted or idealized form (e.g., Arnoux et al. 2017; Azucar et al. 2018). In contrast to the traditional method using questionnaire-based self-report surveys, personality trait prediction based on tweets can be seen as a cost-effective and efficient alternative, in which significantly larger samples can be used and measurement errors can be minimized (Carducci et al. 2018, Park et al. 2015).

3 Research Hypotheses Development

To understand the reasons for the online commenting behavior of active users who participate in political discussions on Twitter, their personality traits can be investigated via personality mining. For this purpose, a structured literature search and literature analysis was first carried out with the aim of identifying the relationships between a person's personality traits, the tendency to actively participate in political discussions, and the frequency of involvement in the discussions. Additionally, the tendency to show an extreme ideological stance in the political spectrum, either left or right, depending on the level of traits was examined. Based on Webster and Watson (2002), a two-part literature review was carried out, comprising a literature search using search strings in the databases ScienceDirect, IEEE Xplore, SpringerLink, Wiley, AISeL, JSTOR, and Google Scholar. This was supplemented with a forward and backward search as well as a similarity search with the most valuable papers using Google Scholar. To identify the connection between personality traits, political orientation and participation in political discussions, an English and German full-text search of the seven databases was conducted using the search string (“Personality Traits”) AND (“Political Discussion” OR “E-Expression” OR “Political Participation” OR “Political Ideology” OR “Political Values” OR “Political Attitudes”). After all articles were examined for relevance by means of the title, 97 hits were found, which in turn was limited to 30 articles after closer abstract review. Using forward and backward search, 7 more articles were found, and using similarity search, 3 further relevant articles were discovered, so that a total of 40 relevant articles were identified, which were used for hypothesis generation in the following. Although reliable findings in research only originated from surveys targeting offline political behavior (e.g. Hibbing et al. 2011; Mondak and Halperin 2008; Fatke 2017; Gerber et al. 2010; de Neve 2015), they shall function as a base for formulating hypotheses about the users’ personality traits and their political commenting behavior on Twitter. From this, we developed the hypotheses listed below. Hypotheses H1a–H5a, H1b–H5b, H6, and H7 were formulated for the personality trait analysis of politically active users on Twitter. While H1a–H5a and H1b–H5b aim to actively participate in Twitter, H6, and H7 are concerned with the content of posted tweets regarding political orientation.

Individuals high in openness tend to be curious, perceptive and appreciative of novelty (John et al. 2008). Research has shown that this translates into their interest in the exchange of new political ideas and being politically informed. Therefore, these individuals tend to participate more frequently in political discussions in the offline world and thereby try to stay politically informed (Cooper et al. 2013; Hibbing et al. 2011; Gerber et al. 2011). Expecting similar results across users in the political discussions on Twitter, we deduce the following hypotheses:

H1a: Users in political discussions on Twitter will have a high level of openness.

H1b: Openness will be positively correlated to a user's comment frequency on Twitter.

Individuals high in conscientiousness tend to be organized, reliable, and diligent (Costa and McCrae 2008). Gerber et al. (2011) found that individuals high in conscientiousness tend to receive certain information about political topics passively rather than discuss them actively. However, regarding the number of political discussions, conscientiousness was positively related to encouraging more frequent discussions about regional political topics (Hibbing et al. 2011; Mondak and Halperin 2008). Transforming these findings to political debates on Twitter, we deduce the following:

H2a: Users in political discussions on Twitter will have a low level of conscientiousness.

H2b: Conscientiousness will be positively correlated to a user's comment frequency on Twitter.

Individuals with a high level of extraversion tend to be talkative, assertive and sociable (John et al. 2008). In this sense, extraverts gain satisfaction from interactions with other people and thus are more likely to express their ideas verbally (Costa and McCrae 2008). Studies have shown that these outgoing tendencies also transfer to the political realm with extraverted individuals engaging more frequently in political talk (Cooper et al. 2013; Hibbing et al. 2011). Moreover, research has indicated that people high in extraversion tend to have large discussion networks to interact with because of their sociable characteristics (Mondak et al. 2010). Based on the findings from the offline world and according to the positive relation between extraversion and the frequency of having political discussions, we deduce the following:

H3a: Users in political discussions on Twitter will have a high level of extraversion.

H3b: Extraversion will be positively correlated to a user's comment frequency on Twitter.

Individuals with high levels of agreeableness are considered trusting, modest, helpful, and empathic towards other people (John et al. 2008). Personality research has shown that these individuals show less political knowledge and a general lack of interest in politics (Mondak et al. 2010; Gerber et al. 2011). This general tendency to avoid political issues has been traced back to the inclination for harmony in individuals with high levels of agreeableness (Mondak and Halperin 2008). Politics is a highly opinionated field where people often tend to argue passionately over their positions, which puts off individuals high in agreeableness. However, a significant relationship between agreeableness and political talk offline has not been identified (Hibbing et al. 2011; Mondak and Halperin 2008). Thus, we deduce the same hypotheses in discussions on Twitter:

H4a: Users in political discussions on Twitter will have a low level of agreeableness.

H4b: Agreeableness will not be correlated to a user's comment frequency on Twitter.

Individuals high in neuroticism show inclinations for negative emotional states such as anxiety, nervousness, and sadness (John et al. 2008; Costa and McCrae 2008). In this regard, offline findings have revealed that neurotic individuals tend to avoid political discussions where they might be challenged in their views (Hibbing et al. 2011). However, no relation has been found between neuroticism and the frequency of engaging in political discussions (Hibbing et al. 2011; Mondak and Halperin 2008). Because Twitter is a highly public platform where many strong opinions are expressed in political discussions under a hashtag, we expect that the users will have a low level of neuroticism to prevent conflict with other views and thus contradictions in their own beliefs. Concerning the discussion frequency, no significant findings have been found in the literature, leading us to the following hypotheses:

H5a: Users in political discussions on Twitter will have a low level of neuroticism.

H5b: Neuroticism will not be correlated to a user's comment frequency on Twitter.

To evaluate whether there is a link between user's personality traits and the political orientation he or she expresses in the respective tweets, a variety of papers were examined to formulate hypotheses H6 and H7. In this regard, openness and conscientiousness have been defined as the main personality traits for being left- or right-oriented (Fatke 2017).

Statistically significant results from previous papers have indicated that individuals with high scores in openness tend to be left-oriented (Cooper et al. 2013; Gerber et al. 2010; de Neve 2015; Fatke 2017). This means that they are committed to social and economic justice, support social change, and prefer an open society (Hirsh et al. 2010). This has become particularly evident in positive attitudes towards immigration, e.g., widening of the European Union (EU), diverse sexual orientation, and abortion (Nielsen 2016; Fatke 2017; Gerber et al. 2010). Accordingly, we deduce the following:

H6: Users expressing a left-oriented political position in their tweets will have a high level of openness.

The main personality trait found to be linked to an orientation on the right ideological spectrum is conscientiousness. Scientific findings have shown that people with high scores for conscientiousness tend to preserve the status quo and reject social change as well as cultural diversity (Hirsh et al. 2010; de Neve 2015; Fatke, 2017). As with openness, statistically significant tendencies were also all found across the above-mentioned specific attitudes but with a negative and opposing stance for individuals with a high level of conscientiousness (Fatke 2017; Gerber et al. 2010). In line with this rationale, we deduce the following hypothesis:

> **H7:** Users expressing a right-oriented political position in their tweets will have a high level of conscientiousness.

4 Methodology and Research Design

To be able to test the hypotheses, a second literature review was conducted to determine which methods of personality mining have already been applied in related fields and whether approaches have already been used to extract and analyze the personality traits of users in political discussions on Twitter. As a result, it can be stated that no approach has yet been taken to analyze users in political discussions on Twitter regarding their personality traits. To enhance this literature base with experiences from other personality mining applications, a further literature search in the seven databases mentioned above was carried out using the search string ("Personality Traits" AND "Social Media" AND "Mining"). Based on the title, 88 articles were selected, which were narrowed down to 16 articles after examining the abstracts. Using forward and backward search, 8 further articles and with similarity search 2 further relevant articles were selected, so that a total of 26 articles were considered as our basis for developing a framework. In the analysis of the existing literature, two main research areas could be identified. While several researchers have focused on the technical development and testing of algorithms to predict personality traits based on tweets (e.g. Azucar et al. 2018; Carducci et al. 2018), other researchers described the personality trait identification in practice-oriented applications such as recruiting (e.g. Hu et al. 2016), marketing topics (e.g. Tommasel et al. 2015) or mental health (e.g. Rüegger et al. 2016).

All these articles follow three general steps, which will be related to the political environment by adapting the analysis purpose step within the social media analytics framework in political context developed by Stieglitz and Dang-Xuang (2013). The framework starts with the purpose and scope definition before the data will be collected and preprocessed. This is followed by the extraction of personality traits from the collected tweets before statistical analyses are used to test the hypotheses. In addition to the procedure description, special attention will be paid to the use of appropriate tools to perform these steps. Representatively for automated personality mining tools, IBM Watson Personality Insights will serve as a core element to answer the hypotheses, since this tool has been used in a large part of the considered articles (e.g. Hu et al. 2016; ElSherief et al. 2018; Siemon et al. 2018; Gera and Kaur 2018) and is experiencing a high market penetration in research as well as in practice.

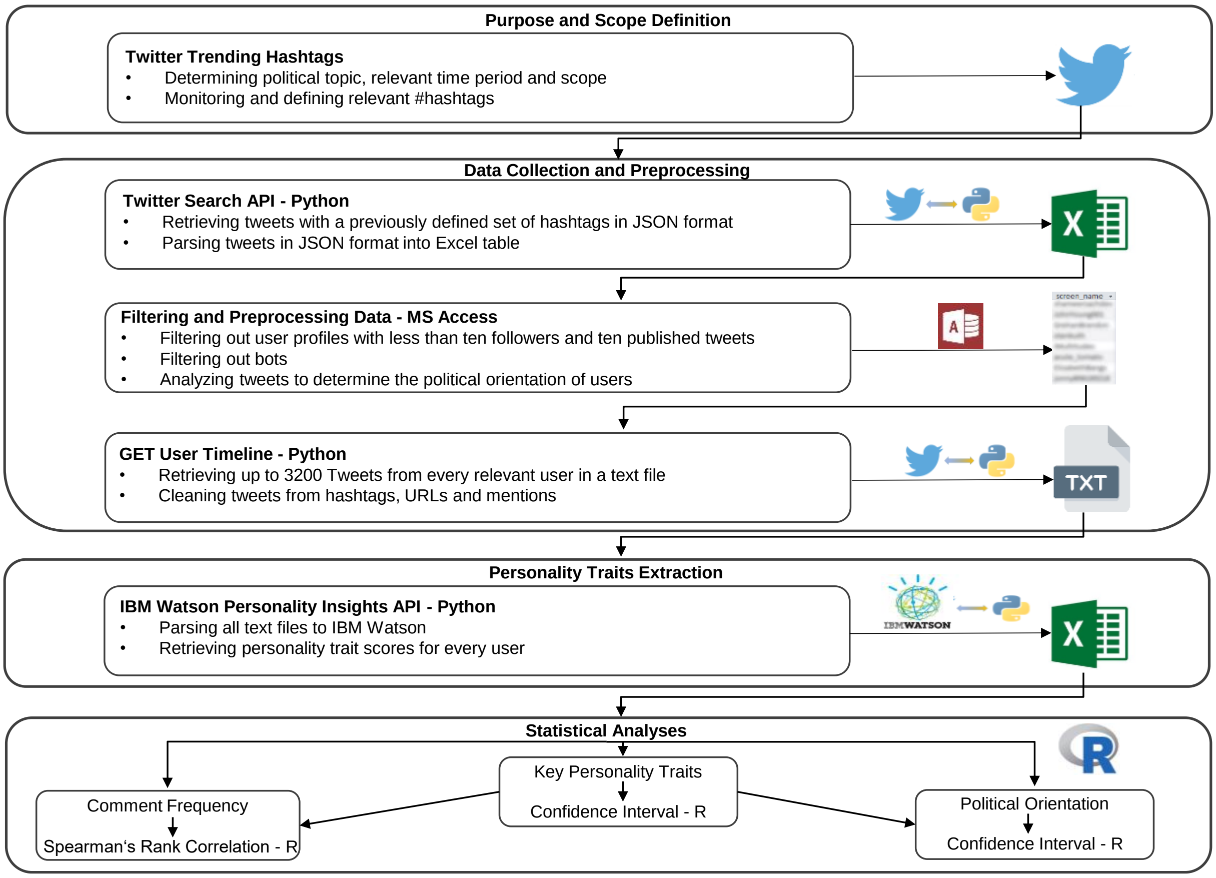

Figure 1. Personality Mining Framework for Political Discussions

Purpose and Scope Definition

To test the hypotheses by means of users participating in political discussions on Twitter, the scope of the study must first be determined before the database for a political discussion can be collected from Twitter. Stieglitz et al. (2018) described the identification of relevant topics, events and trends as a major challenge in social media analytics due to the huge and dynamically growing amount of data. This also includes the identification of hashtags, which are created and modified by Twitter users on a situational basis (Stieglitz et al. 2014). For this purpose, the first step is to define a political topic and the related hashtags that are widely used in a political discussion. These keywords representing a policy topic must be carefully and systematically selected to achieve a high degree of data completeness (Stieglitz and Dang-Xuan 2013). To identify most popular hashtags, Nulty et al. (2016) inserted the social network visualization software Gephi for generating a country-by-hashtag matrix based on published tweets regarding the European Parliament elections. Another option to identify widely used hashtags in real time is to apply twitter trending tools such as trendmaps[5] and trends24[6].

[5] https://www.trendsmap.com/

[6] https://trends24.in/

Data Collection and Preprocessing

Twitter data is publicly accessible via application programming interfaces (API), for which the Twitter Search API and the Twitter Streaming API can be used (Gimpel et al. 2018; Recuero et al. 2019). The Twitter Search API allows the extraction of historical data in the form of certain tweets from a time period using a programming language such as Python while the Twitter Streaming API delivers tweets in real-time (Stieglitz et al. 2018). Tweets are delivered by the Twitter API in JavaScript Object Notation (JSON) format with additional metadata besides plain text. Metadata needed for the further proceeding are the tweet ID, username, user ID, timestamp and localization, as well as the type of tweet (e.g. original tweet or retweet). Retweets published without additional textual information have to be filtered out in order to include only users who have participated in the debate with an original tweet. To simplify data processing, tweets with the metadata previously defined as relevant, can be collected into an Excel spreadsheet using an additional Python code.

After collecting the tweets related to a political debate, filtering and pre-processing procedure follows to prepare the data for the subsequent stages. First, all collected tweets are grouped by the user ID ("screen_name"), and the number of published tweets related to the political topic is counted. To obtain meaningful user profiles, Tommasel et al. (2015) included only user profiles with at least ten followers and ten published tweets, which can also be adopted as a rule for political discussions, since personality mining requires a minimum of 600 words to determine personality traits. Location information can also be used to limit the data set to certain countries, although it must be noted that this information is given voluntarily and cannot be checked for correctness (Yaqub et al. 2020).

To test the hypotheses concerning the personality traits of politically involved users on Twitter, twitterbots ("bots") must be filtered out. Veale et al. (2015) defined twitterbots as autonomous software systems that are designed to automatically publish content in the form of tweets with their own design and composition and without manual intervention. Bots are highly sophisticated systems that mimic human behavior, which is why various studies are concerned with identifying these accounts as accurately as possible (e.g. Gurajala et al. 2016; Onuchowska and Berndt 2019). Using bot detection techniques described in previous articles (e.g. Wright and Anise 2018; Gilani et al. 2o19; Yaqub et al. 2020), the "source" and "creation_time" columns are used for filtering. While Gilani et al. (2019) found that 91.77% of identified human Twitter accounts tweet from a standard web or mobile client, such as "Twitter for Android", or "Twitter Web Client", all other sources such as "Cheap Bots, Done Quick!", or "JimRoyleBot", must be filtered out. Wright and Anise (2018) observed that bots often tweet at regular intervals and at specific times. Therefore, the time intervals between the individual tweets of a user should be calculated using the column ("created_at"). If an account has short time intervals or repeated time intervals between tweets, it is likely that this account is a bot and must be filtered out (Yaqub et al. 2020). However, even after applying the described filters, no absolute certainty for a clean dataset can

be given, because not all bots have to twitter in periodic time intervals, and there are likely also bots that twitter from a regular web or mobile client (Onuchowska and Berndt 2019). Even using machine learning methods, it is still a highly complex process to filter out these bot accounts effectively (Gilani et al. 2019).
To test hypotheses H6 and H7, in which the political orientation of users and their personality trait scores are examined, left-oriented and right-oriented users must previously be identified what can be performed based on two different approaches. There is the possibility to draw on existing text mining approaches, such as using the SentiWordNet lexicon for opinion mining (e.g. Le et al. 2017) or the Python library TextBlob, which provides an API for natural language processing (NLP) (e.g. Yaqub et al. 2020). For an accurate sentiment analysis, various researchers (e.g. Oh and Kumar 2017; Belcastro et al. 2019), however, follow the approach to develop a domain-specific affection lexicon which then serves as the basis for the development of an algorithm. Nulty et al. (2016) used an elastic net regularized regression model for measuring the EU position out of a published hashtag on twitter and combined it with expert judgements. Pak and Paroubek (2010) developed a four-step approach to identify frequent words and word pairs, based on which an assessment of political orientation can be given. Therefore, all elements in the tweets that do not provide any value in terms of the analysis need to be filtered out. This includes special characters, URLs, mentions, hashtags and non-alphanumeric characters (Pak and Paroubek 2010; Oh and Kumar 2017). This is followed by tokenization using e.g. the library TweetNLP, in which each tweet is split by spaces into individual tokens (Ramachandran and Parvathi 2019; Le et al. 2017). The tokens need to be cleaned up with respect to stop words which are frequently used but do not provide any value for analysis, for which the NLTK Python library can be used (Oh and Kumar 2017). The cleaned tokens form the basis for the mathematical calculation of the most frequently used words and word pairs using the bigram function from the NLTK library. The most frequently used word pairs can then be used to determine political orientation in a manual way. For automatically classifying tweets, the Naive Bayes machine learning algorithm is widely used in sentiment analysis for tweets (Oh and Kumar 2017; Ramachandran and Parvanthi 2019).
To calculate the personality traits of the identified Twitter users quite reliably, IBM Watson[7] needs at least 600 words per user. Using the timeline function of the Twitter API[8], the last 3200 original tweets from each account are captured, which in turn must be cleaned from mentions, hashtags, and URLs.

Personality Traits Extraction

To identify the personality traits of Twitter users, personality mining systems are widely used that automatically derive the personality traits of an individual from text, such as emails or tweets, by applying linguistic analysis and personality models (Siemon et al.

[7]https://cloud.ibm.com/docs/services/personality–insights?topic=personality–insights–input&locale=en#sufficientGuidelines
[8]https://developer.twitter.com/en/docs/tweets/timelines/api–reference/get–statuses–user_timeline

2018). Our literature review revealed that researchers (e.g. Siemon et al. 2018; ElSherief et al. 2018; Tommasel et al. 2015) predominantly have extracted personality traits based on the pre-engineered IBM Watson Personality Insights algorithm, rather than by building and training their own algorithm. IBM Watson offers the Personality Insights service API to calculate personality traits from tweets and other digital communication sources (Hu et al. 2016). The service is based on an algorithm that uses an open vocabulary approach to derive the intrinsic personality traits of individuals. For each personality trait, the service provides normalized scores from 0 to 1 based on the textual input. These normalized scores represent the percentile ranking of the author's trait level compared to the sample population. IBM[9] defines every score above 0.75 as a readily discernible trait and thus it can be considered as a high level. For scores above 0.5, the trait is expressed higher than average in the respective individual and therefore can be considered medium-high. IBM makes the same declarations for the definition of low trait levels in the opposite direction. All text files extracted with the Twitter timeline function will be calculated by the IBM Watson Personality Insights Service, which then provides the personality trait scores for each individual user.

Statistical Analyses

To test the theoretical assumptions against a collected set of empirical data and to confirm or reject the formulated hypotheses, a tripartite analysis is appropriate, as shown in Fig. 1. While the first analysis section aims to determine the personality traits of Twitter users who participate in political discussions, the second part focuses on the relationship between the comment frequency of these most active Twitter users and their personality traits. The third part concentrates on the political orientation of users and needs to be examined in terms of their level of openness and conscientiousness. Before the inferential statistical analyses can be carried out, the data must first be summarized and analyzed in a descriptive statistical manner to determine whether an approximate normal distribution exists (Mishra et al. 2019). Since many statistical methods assume a normal distribution, it is essential to verify this assumption of an approximate normal distribution before proceeding with relevant statistical methods and, if necessary, to consider using a non-parametric statistical method (Razali and Wah 2011). To test the normality assumption, two approaches are commonly used: performing a normality test or executing boxplots (Ahad et al. 2011; Razali and Wah 2011). The Shapiro-Wilk test is considered to be the most meaningful and sensitive normality test for violation of the normal distribution (Razali and Wah, 2011; Ahad et al. 2011). However, the Shapiro-Wilk test is very sensitive to large sample data, such as large amounts of Twitter data, which is why any marginal deviation from normality can be significant (Ruxton et al. 2015). For large sample sizes, the depiction of data in the form of boxplots is suitable for testing the normality assumption (Razali and Wah 2011).

[9] https://cloud.ibm.com/docs/personality–insights?topic=personality–insights–agreeableness

If a perfectly normal distribution of the data is given, the data is symmetrical around the median, which is in the middle of the box. Deviations from a normal distribution can be observed in the boxplot by observing longer whiskers in the positive direction or in the negative direction (Lane 2013). Using nonparametric methods on data that is normally distributed is accompanied by minimal loss of performance, while conversely, when normality has been violated, the performance gains from these tests are highly significant. Since a violation of the normality assumption does not distort the result of nonparametric statistical analyses as much as in cases where parametric methods are applied to the data, nonparametric methods are seen as a more robust analytical approach (Kitchen 2009), which is why nonparametric statistical analyses are described below. As Stieglitz et al. (2018) recommend the programming language R to quickly run analyses while processing large datasets, the required statistical analyses and visualizations can be carried out in R Studio using the packages bootES, plotrix and Hmisc.

Confidence intervals need to be calculated for each personality trait to determine the traits scores of the politically active users and to confirm or reject hypotheses H1a–H5a. Depending on where the boundaries of the confidence intervals are localized, statistical statements can be made with a certain probability of error as to whether the true value for the respective personality trait in the form of the mean value of all the users considered, lies in the low, medium or high range. For the calculation of nonparametric confidence intervals, the bootES package in R can be used, which offers Bootstrapping methods to determine the parameters of the confidence intervals based on 2000 resamples (Kirby and Gerlanc 2013).

H1b–H5b investigate the relationships between individual personality traits and the comment frequencies of the politically active Twitter users. Spearman's correlation method can be used for this purpose, if the sample contains a high number of outliers leading to deviation from normality. The Spearman rank correlation coefficient is calculated by fractional ranking and has the advantage that this nonparametric measure is relatively robust for heavy-tailed distributions having outliers (de Winter et al. 2016; Schober et al. 2018). Before the calculations, a scatterplot matrix of the independent variables (personality trait scores) and dependent variable (comment frequency) should be generated and examined to ensure that the variables are not related in a quadratic or higher relationship. Otherwise, this can lead to a distortion of the Spearman rank correlation results (Schober et al. 2018).

The third part of the analysis focuses on hypotheses 6 and 7, with the aim of determining whether there are strong expressions of openness and conscientiousness among Twitter users who reveal politically extreme positions in their tweets. For this purpose, a previously defined number of right-oriented and left-oriented numbers of users needs to be identified among the total sample, using manual or automated coding, before calculating the respective confidence intervals of the mean values using the bootES package.

5 Discussion, Implications, Recommendations and Further Research

Increasingly numbers of people are becoming involved in political discussions in social networks. Twitter is seen as a central space for free political expression. With the formulation of the hypotheses, the findings from political personality research in the offline sphere were rendered verifiable for the social network Twitter. By applying the personality mining framework, see Fig. 1, developed to test the hypotheses, it is now possible to determine the expression of personality traits of active Twitter users in various political discussions. From a practical perspective, it serves as a guideline for a systematic analysis. By using algorithm-based personality mining services, such as IBM Watson Personality Insights, to calculate these personality traits, it is possible to process huge amounts of data, making this approach in terms of quantity, costs and time superior to traditional questionnaire-based personality research. Since users are not aware of the analysis of their tweets, a self-reporting bias can further be avoided, which is often observed in survey-based studies (Ebstrup et al. 2011).

The developed framework as well as the hypotheses focus on the consideration of a political topic. It is exciting to compare the results of the hypotheses between different political events, debates and groups. On the one hand, the personality traits of users in different discussions can be compared and on the other hand, it allows the investigation of which political topics users with certain personality traits are more interested in. To enable this comparison, ANOVA tests can be used to identify personality trait differences between user groups. By focusing on sub-groups within a political issue on Twitter, the 1/9/90 sub-grouping of Bruns and Stieglitz (2014), who distinguished Twitter users based on their number of tweets into the three groups highly active, active and less active, can be suitable. Beyond that, it is advisable to use multivariate statistical methods, such as regression analysis, to assess correlations between personality traits and political tweet behavior, including control variables such as age, gender, educational level, and origin. Even though some Twitter users provide information on age, gender, and location in their profile, the validity of this information is difficult to verify, and the full details of all users are difficult to obtain.

The personality mining framework, see Fig. 1, can be adapted not only to analyze active Twitter users discussing a political topic, but also to analyze followers of political parties or of politicians according to their dominant personality traits. A comparison between survey-based results and the results of tweet-based personality mining is also exciting. Bakker et al. (2020) found out in a cross-national survey-based study that there is a strong correlation between a low level of agreeableness and the support of populist left and right parties. Analyzing the followers of these parties can shed light on whether similar personality trait tendencies can also be found on Twitter. To verify this, Twitter profiles can be analyzed using the presented approach, before comparing the findings with questionnaire-based results from offline world. Subject of research can also be personality trait analysis of upcoming echo chambers in political discourses. Polarization and extremism can arise when users are surrounded by others who share the same facts, sources and opinions and no longer hear the arguments of the opposition (Garimella et al. 2018). It is particularly relevant to investigate whether the people within echo chambers have similar personality traits and whether these traits differ on various political topics. In addition to its potentials for research, a practical application of this framework can be achieved by political stakeholders in order to adjust their messages on Twitter, such as appeals for voter mobilization shortly before elections, to the personality traits of their voters. Social media analytics, which is widely used by political institutions to identify political opinion leaders as well as to uncover popular topics and voters' preferred linguistic features (Stieglitz and Dang-Xuan 2013; Nulty et al. 2016; Le et al. 2017; Stieglitz et al. 2018), can be expanded through personality mining. Gerber et al. (2013), for example, observed that people with higher values for the personality trait openness react particularly strongly to election calls highlighting social responsibility and the importance of the vote. In contrast, persons with high scores for agreeableness, for example, tend to be very inhibited by negative political statements, while highly extraverted persons respond very positively (Weinschenk and Panagopoulos 2014).

6 Applicability Check: The UK Brexit Case

Obviously, our deduced twelve hypotheses cannot be tested in general. Long-term research is necessary to further test, discuss, adapt and expand these hypotheses. To test these hypotheses in a first illustrative use case using the personality mining framework, see Fig. 1, for political discussions described above, we conducted an applicability check based on the Brexit. In June 2016, the population of the United Kingdom (UK) voted to leave the EU after 44 years of membership (Garretsen et al. 2018). The British referendum on EU membership, known as Brexit, split the nation into two opposing camps, Eurosceptic people voting "Leave" and EU supporters voting for "Remain" (Hobolt 2016; Becker et al. 2017; Grčar et al. 2017). Various studies have analyzed the influence of socio-economic factors, such as educational status and demography (e.g., Hobolt 2016; Becker et al. 2017), personality trait scores (Peshkopia et al. 2019) and the connection between geographically different personality traits and Brexit behavior (Garretsen et al. 2018), to gain an understanding of voting behavior. Grčar et al. (2017) discovered an imbalance between Leave and Remain tweets by investigating political tweets about the Brexit referendum from Twitter users. The study showed that there were very active and organized Leave campaigns, which published a large proportion of Brexit tweets, while the Remain community was much larger in terms of users but published far fewer tweets in total (Grčar et al. 2017). After a lengthy period of uncertainty and several postponements of the Brexit agreement, the withdrawal was realized on 31st of January 2020. Accordingly, from the 29th of January until the 2nd of February, the Brexit discussion

was one of the most polarizing topics on Twitter, with various trending hashtags covering the withdrawal of the UK from the EU. From this period, the personality traits of the MAU, also called lead users, who published tweets most frequently under the most trending hashtags, were analyzed regarding the formulated hypotheses. Accordingly, the procedure was to collect tweets with those hashtags, identify the users who commented most frequently on this topic, collect the tweets from their timelines and then extract their personality traits for the subsequent analysis, as shown in Fig. 1. Therefore, 60,729 English tweets with the hashtags #brexitday, #brexit, #brexiteve and #brexitreality, published between the 29th of January 2020 and the 2nd of February 2020 were captured using the Twitter Search API. This was followed by filtering and preprocessing by excluding all tweets from users who had not specified the UK as their location in their profile and filtering out bots, resulting in a subset of 18,329 tweets.
To ensure the ability to identify those users who are politically very active, we excluded all accounts that published less than three Brexit-related tweets during the observed time frame. By assigning these tweets to their authors, the 800 MAU, posting between three and forty tweets were identified. In order to test H6 and H7, 150 pro Brexit and 150 contra Brexit users were identified from these 800 users by analyzing 3,546 tweets in terms of the most frequently used words (Fig. 2) and word pairs (Fig. 3) that indicate a pro or contra Brexit opinion.

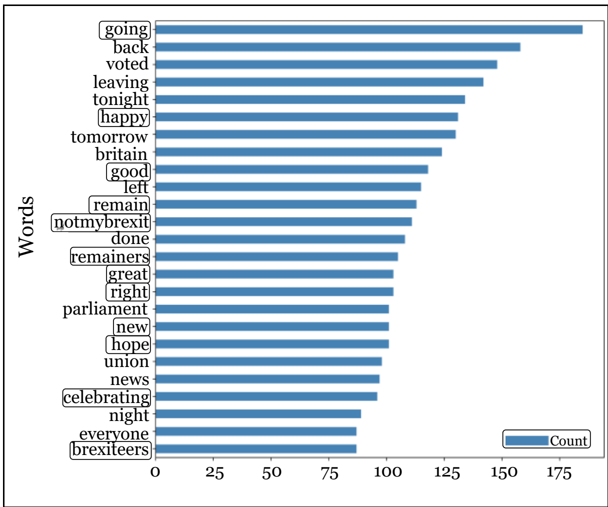

Figure 2. Visualization of the Most Used Words

Figure 3. Visualization of the Most Used Word Pairs

Individual text files containing up to 3,200 tweets were extracted for each of these 800 users using the Twitter timeline function. The files were passed on to the IBM Watson Personality Insights service to retrieve personality trait scores for all 800 MAU. To test our theoretical assumptions against the collected empirical data and to confirm or reject our formulated hypotheses, we used the tripartite analysis, as shown in Fig. 1. While the first analysis section aimed to determine the personality traits of the very active users on Twitter who participate in political discussions, the second part focused on the relationship between the comment frequency of these MAU and their personality traits. The third part focused on the political orientation of the MAU, for which 150 pro and 150 contra Brexit users, identified by manual coding, were examined for their level of openness and conscientiousness. The required statistical analyses were carried out in R Studio, using the packages bootES, plotrix and Hmisc. Tab. 1 provides an overview of the descriptive data for the collected personality trait scores. The numerical representations of the Shapiro-Wilk test (see Tab. 1) and the results of the boxplots (see Tab. 1) show that a deviation from the normal distribution exists. Non-parametric methods for inferential statistics were therefore applied in the forthcoming deliberations.

	Min	**Max**	**Median**	**Mean**	**1st Quartal**	**3rd Quartal**	**Std. Dev.**	**Shapiro Wilk**
Openness	0.0575	0.9991	0.8633	0.8003	0.7339	0.9343	0.1789	2.2e-16
Conscientiousness	0.0013	0.9708	0.3098	0.3517	0.1713	0.5119	0.3395	2.2e-12
Extraversion	0.0092	0.9594	0.2766	0.3087	0.1642	0.4111	0.1916	2.2e-16
Agreeableness	0.0009	0.9992	0.1527	0.2291	0.0676	0.3044	0.2258	2.2e-16
Neuroticism	0.0495	0.9999	0.5867	0.5718	0.4501	0.6970	0.1789	0.01269

Note: N=800

Table 1. Descriptive Statistics for the Personality Traits of Most Active Users

Confidence intervals were calculated for each personality trait to determine the key personality traits of the MAU in a political discussion and to confirm or reject hypotheses H1a–H5a. Depending on where the boundaries of the confidence intervals are placed, statistical statements can be made with a certain probability of error as to whether the true value for the respective personality trait in the form of the mean value of all users considered lies in the low, medium or high range. For the calculation of the confidence intervals, the Bootstrapping method in the form of bootES package in R was used, which calculated the parameters that were used as a basis for the calculation of the confidence intervals, without assuming a normal distribution, by resampling over 2000 resamples (Kirby and Gerlanc 2013).

In H1a, a high value of openness was assumed among the MAU, which was confirmed by the 99% CI [0.781, 0.817] for the mean value of openness within the considered group. Thus, the lower CI bound is above 0.75 which is defined by IBM as a high trait expression, and the hypothesis **H1a is supported**. In H2a it was assumed that the conscientiousness of MAU within the Brexit discussion on Twitter will be low, as studies have shown that people with a high level of conscientiousness behave passively in political discussions and tend to consume rather than actively interact with others (Gerber et al. 2011). Contrary to this assumption, the value of conscientiousness is at a medium-low level, with 99% CI [0.328, 0.373], which is why hypothesis **H2a is not supported**, even if the extent is still relatively low. In H3a it was hypothesized that users who participate extensively in political discussions on Twitter have a high degree of extraversion. Hypothesis **H3a is not supported** because the 99% CI [0.292, 0.327] shows that the 800 users considered have a medium-low level of extraversion. In H4a it was assumed that the users considered had a low degree of agreeableness, because people with a high degree of agreeableness tend to avoid political discussions in order not to endanger a harmonious coexistence. Hypothesis **H4a is supported** with a CI of 99% [0.21, 0.249] because the true mean value is below 0.25, which is a weak trait expression. In hypothesis H5a, it was assumed that neuroticism will have a low level among MAU in political discussions on Twitter, because people with high levels of neuroticism are more likely to stay away from polarizing discussions as a protective instinct against emotional experiences. In contrast to this assumption, the neuroticism expression is in a medium-high range, with a 99% CI [0.557, 0.588], so hypothesis **H5a is not supported**.

H1b–H5b investigate the relationship between individual personality traits and the comment frequency of the 800 MAU. Spearman's correlation method was used for this purpose, since the sample contained outliers without a normal distribution. As a basis for these calculations, a scatterplot matrix was first generated from the comment frequency and the characteristics of the personality traits. The calculated scatterplot results show that there is no quadratic or higher relationship between the variables, so the Spearman rank correlation is suitable.

	O	C	E	A	N	Comments
Openness	1.00	0.03*	0,09*	-0.26*	-0.39*	0.11*
Conscientiousness		1.00	0.33*	0.28*	-0.33*	0.07*
Extraversion			1.00	0.32*	-0.14*	0.12*
Agreeableness				1.00	0.14*	-0.02
Neuroticism					1.00	-0.04
Comments						1.00

Note: N=800; Number of comments variable (scale 3-40); *p<0.05

Table 2. Correlation Matrix for the Big Five Personality Traits and Comment Frequency

The correlation matrix in Tab. 2 shows the correlation between the personality traits and the comment frequencies of the 800 users considered, with the comment column being the most noteworthy. As suspected in H1b, a statistically significant positive correlation between openness and the frequency of comments of the users considered was discovered, thus, hypothesis **H1b is supported**, despite the weakness of the correlation. **H2b is supported** because, as expected, there is a statistically significant positive correlation between conscientiousness and the comment frequency. Hypothesis **H3b is also supported** by detecting a statistically significant correlation between extraversion and comment frequency on Twitter, even if this correlation is weak. **H4b is supported**, as no statistically significant correlation between agreeableness and comment frequency could be detected. **H5b is supported**, as there was no significant correlation ($p < 0.05$) between neuroticism and the comment frequency of the 800 lead users. In summary, even if a statistically significant correlation between personality traits and comment frequencies could be identified, these values can be classified as quite weak.

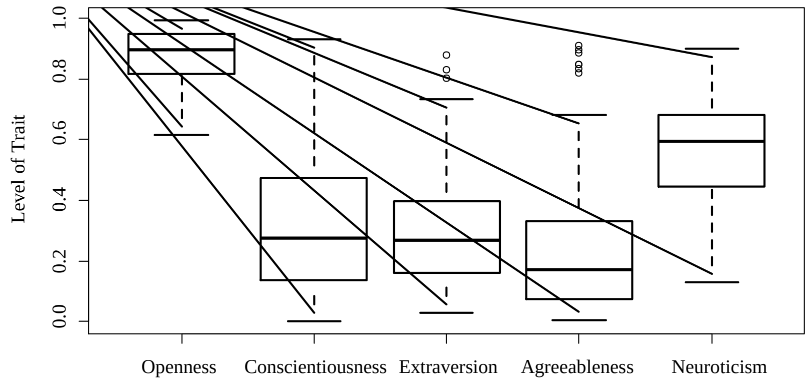

Figure 4. Boxplots of Contra Brexit Users

The third part of our analysis focuses on hypotheses H6 and H7 with the aim of determining whether there are strong expressions of openness and conscientiousness among lead users who reveal politically extreme positions in their tweets. For this purpose, 150 pro and 150 contra Brexit followers were identified among the 800 users considered, using manual coding, before calculating the confidence intervals of the mean values using the bootES package (see Figure 4 and Figure 5).

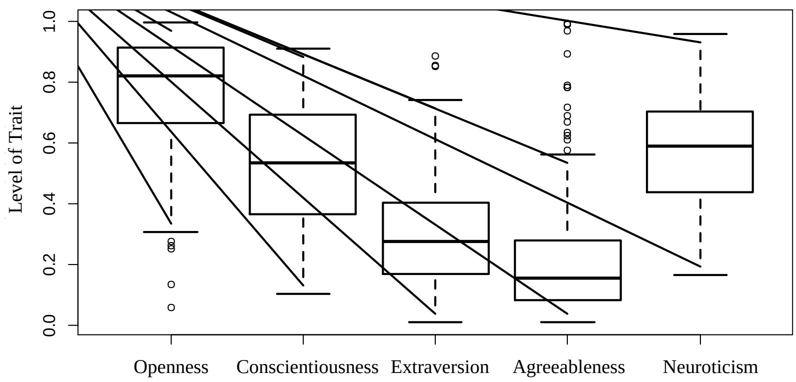

Figure 5. Boxplots of Pro Brexit Users

Based on scientific studies (e.g., de Neve 2015; Fatke 2017), which have established that persons who are left-oriented in their political opinion have high values of openness, it was assumed in H6 that persons who refuse to leave the EU have a high degree of openness. Hypothesis **H6 is supported** with a 99% CI [0.853, 0.892], in that the lower limit is seen above the value of 0.75. However, it must be considered that the results of the total group with 800 users also show a high value of openness, with 99% CI [0.781, 0.817], although not as high as in the contra Brexit group. H7, on the other hand, deals with the assumption that Twitter users who are pro Brexit in their tweets show a high level of conscientiousness. The analysis of the 99% CI [0.491, 0.576] shows that the hypothesis **H7 is not supported** as the 150 pro Brexit users show a medium-low level of conscientiousness. However, compared to the 99% CI [0.328, 0.373] with all 800 users, the pro Brexit users showed a significantly higher level of conscientiousness than the total group.

6.1 Brexit Discussion

Our results and discussion show that participation in political debates on Twitter seems to be unbalanced from the personality perspective. People with certain personality traits expressed their opinions and thoughts more often than others. This is problematic in that certain political views dominate on Twitter, resulting in an asymmetrical opinion landscape.

Of the twelve hypotheses tested concerning personality trait expression among the Twitter users active in the Brexit discourse, eight hypotheses were supported. Two others are not supported but exhibited only minor deviations from the assumed personality trait scores (H2a and H7). The personality traits extraversion (H3a) and neuroticism (H5a), however, differed the most from identified personality structures within offline political discussions and had no support at all. In contrast to the findings from the offline discussions, where individuals who tend to be outgoing, sociable and talkative dominate political discussions, a medium-low level of extraversion was discovered among the 800 MAU in the political Brexit discussion. This may be explained by the fact that people tend to feel more secure in a protected environment where they can share their thoughts about political views in a relatively anonymous way using pseudonyms, as Twitter permits. Our observations are consistent with the findings of Hughes et al. (2012), who found that introverted people who are more averse to face-to-face discussion are more likely to use Twitter. This can indicate that, depending on the degree of their extraversion, people exchange their political views through different channels of communication. When policymakers evaluate Twitter data, the results may differ from previous procedures because, among other factors, introverts were represented more strongly and extraverts less strongly than in other communication channels.

Contrary to the findings from the offline political field in which people tend to have a very low level of neuroticism, we observed that, among the Brexit Twitter users we examined, this trait is medium-high pronounced. This finding also fits with the option of anonymity on Twitter. People who tend to be emotionally unstable and vulnerable publish their political thoughts without showing their face and name, while discussions in offline talk shows and panels make it more difficult to avoid confrontation and personal attacks. Regardless of this political context, people with high neuroticism tend to use social media to compensate for feelings of loneliness (Ryan and Xenos 2011; Correa et al. 2010; Hughes et al. 2012).

As Aidt and Rauh discovered a causality between the core personality traits and party preferences concerning Brexit, we were also able to show that right- and left-oriented people have different personality traits. Aidt and Rauh further demonstrated that that personality traits influence whether people feel close to a party at all, which is particularly important in the UK, as many citizens do not have a strong party identification. If these findings were transferred to the analysis of Twitter data, this would indicate that it ought to be possible to use automated personality mining for

election campaigns, to find out whether a person feels close to a party or whether he or she is without a strong party identification and should be addressed specifically, similar to the Cambridge Analytics exploitation scandal within 2016 US selections (Krotzek 2019).
Our results show that some people were over-represented in the Brexit debate, while others avoided using this channel to express their opinions. It can be stated that the previously developed procedure framework is suitable for identifying the personality traits of politically active Twitter users.

7 Limitations and Outlook

As with every research, our article carries several limitations. By extracting 60,729 English tweets over a period of four days and taking a closer look at 800 users, we only analyzed a small sample of all twitter users. It should be considered that when performing research based on Twitter users, the findings obtained are not representative of the total population in a country and should therefore not be confused with conclusions about general trends in society. There are some limitations concerning the Twitter Search API and IBM Watson. Twitter only provides a selection of tweets to the specified search criteria according to relevance but without specifying their filtering criteria[10]. To analyze the personality traits of users discussing about Brexit, we inserted IBM Watson Personality Insights. The technical processes and the steps behind the trait calculation are a black box, as IBM sells the service to its customers. Despite this, automated personality mining is a cheaper and faster method of determining personality scores than questionnaire-based surveys, which is why this article can be seen as an application study and guide for the future use of automated personality mining in research. Despite our limitations discussed above, our research makes several illustrative contributions to analyze personality profiles of people engaging in political and social discussions on Twitter.
Our results provide a first approach to the personality traits of Twitter users in political discussions. Our evaluation of the Brexit use case reveals the tendency that in political discussions, online and offline, different personality traits partly dominate. Especially more neurotic and introverted individuals participated in online discussions on Twitter, in contrary to offline political discussions. However, to obtain valid correlations, further analyses must be carried out comparing personality traits in different political discussions on Twitter using more advanced statistical methods, such as one-way ANOVA. In recent years, right-wing populists have become more popular in various countries of the European Union, such as Hungary and Germany (Cervone & Caprara, 2000). The question arises whether UK can be seen as an outsider when it comes to this differentiation between left-oriented and right-oriented concerning personality traits. Future research should therefore focus on other political events, such as national

[10] https://developer.twitter.com/en/docs/twitter-api/v1/tweets/search/api-reference/get-search-tweets

elections, and consider if the hypotheses derived in Section 3 are supported. We focused entirely on the expression of personality traits in the political environment on Twitter. However, the decision to actively participate in political discussions on Twitter is also influenced by other important factors, such as age as well as educational, social and cultural background. Therefore, these factors can be included to assess the influence of personality traits on commentator behavior with the consideration of these control variables. However, this faces the challenge that such information is difficult to extract and validate from Twitter profiles. Despite our limitations discussed above, our research makes several illustrative contributions to analyze personality profiles of people engaging in political discussions on Twitter.

8 Conclusions

We developed a personality mining framework to investigate the personality trait profiles of Twitter users engaging in political discussions. By applying this framework to UK Brexit discussions on Twitter, we showed how this framework can be adapted to gain deeper insights into the personality profiles of politically active users on Twitter by analyzing a series of hypotheses. The social network Twitter has grown to become a central platform where users around the world can exchange and discuss political opinions in real time with minimal effort and virtually no restrictions on reach. Although various researchers have investigated the connection between personality traits and political behavior by conducting survey-based studies, no particular attention has so far been given exclusively to the expression of political opinions in the social network Twitter. By combining scientific findings from the field of political psychology and personality mining methods, our aim was to show how the personality profiles of politically active users on Twitter can be analyzed.

To contribute to the understanding of political discussions on Twitter, we developed twelve hypotheses regarding the personality traits of Twitter users engaged in political discussions. During an applicability check we tested the previously developed procedure framework, on 800 UK-based Twitter users who were the most active participants in political discussions about Brexit in a four-day timeframe around the withdrawal date. Around the withdrawal date, we discovered that Twitter users politically involved in Brexit discussions, e.g., have a higher degree of neuroticism than in political offline discussions, which could be attributed to their anonymity on Twitter.

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