Populism Fuels Love and Anger: The Impact of Message Features on Users’ Reactions on Facebook

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To increase the outreach of their messages, populists and nonpopulist political actors use populist communication strategies that stimulate users to interact with their messages on social media platforms. Yet, not much is known about the effect of such strategies on different types of user interactions of distinct valence. Applying a manual content analysis on posts of political parties and their top candidates (N = 1,540) during the German federal election campaign in 2017, we take Likes and Facebook Reactions (Angry and Love) into consideration. We find that exclusive populist message features (anti-elitism, excluding out-groups) and negative portrayals of political actors increase the number of Angry Reactions, whereas inclusive populism and the positive depiction of ordinary citizens lead to higher numbers of Love and simultaneously reduce the number Angry Reactions. The study thereby reflects the results of experimental research on the effects of populist communication. Against this backdrop, we argue that Love and Angry can be categorized as positive and negative one-click expressions of emotional states.

Keywords: populism, Facebook, reactions, emotions, content analysis

The Internet has significantly changed political communication processes in recent years. Because social media provides a feedback channel and enables new forms of interaction between politicians and citizens, it has become an important tool for political communication and is now an integral part of election campaigns (Magin, Podschuew, Haßler, & Russmann, 2016). Whereas political actors were largely dependent on mass media during the 20th century, political actors today can directly address potential voters or mobilize supporters and thereby bypass traditional journalistic selection processes (Chadwick, 2011). This makes social media attractive, especially for populist parties and politicians that can "uncontestedly articulate their ideology and spread their messages" (Engesser, Ernst, Esser, & Büchel, 2017, p. 1110) and establish a direct and more intimate connection to the "vox populi" via social media.
Because it relies on the feeling of the people’s community and appeals to citizens’ emotions, populism presumably fulfills the needs of social integration (Mudde, 2004). Therefore, it seems quite arguable that populist message features match social media users’ expectations and consequently fit in the “network media logic” that is guided by the principles of “individualization and attention-maximizing” (Klinger & Svensson, 2015, p. 1247). Moreover, populist message features induce emotional states (Wirz, 2018) that are important in the realm of political communication because they increase voters’ attention toward campaign messages and have mobilizing and persuading effects in campaign communication (Brader, 2005; Valentino, Brader, Groenendyk, Gregorowicz, & Hutchings, 2011). Particularly in social media, for political actors, the mobilizing effect of emotions is important because users’ interactions (e.g., Likes or Comments) enhance the outreach of their messages (Porten-Cheé, Haßler, Jost, Eilders, & Maurer, 2018).

Although the presence of populist message features in social media has received increasing attention in recent years (e.g., Engesser et al., 2017; Ernst, Blassnig, Engesser, Büchel, & Esser, 2019; Schmuck & Hameleers, 2019), only a few studies investigate how populist communication styles affect users’ interactions on Facebook (Blassnig, Ernst, Engesser, & Esser, 2019; Bobba, 2018; Heiss & Matthes, 2019; Mancosu, 2018).

Applying a manual content analysis of $N = 1,540$ Facebook posts of German parties and their top candidates during the election campaign for the German Bundestag in 2017, we examine the effect of populist message features, such as people centrism, anti-elitism, and the exclusion of out-groups (Jagers & Walgrave, 2007), and populist-related message features such as emotionalization and critical portrayals of politicians, on the number of Likes and on Angry and Love Reactions. Thus, we provide one of the first studies exploring how populist message features determine the volume of Facebook interactions of negative and positive valence. Further, the article addresses methodological issues; because we compare our findings with evidence stemming from experimental research, we can examine the validity of Facebook Reactions as users’ expressions with distinct valence. Moreover, we compare the effects of message features on Likes and Reactions and thus provide hints that might help to interpret existing studies using Likes as the dependent variable. In this way, we can deduce important implications for political communication.

**Populist Communication**

The core of populism is “the people,” understood as a monolithic and homogenous group whose welfare and interests are endangered and ignored by a culprit elite. Populists claim to be the only true representatives of the people’s will and therefore can be understood as “democratic extremism,” rejecting “all limitations on the expression of the general will” (Mudde, 2004, p. 561), such as the constitutional protection of minorities and many liberal democratic institutions, including courts and a free press. Populism can be combined with other (thin and full) ideologies such as nationalism, conservatism, liberalism, or socialism (Kaltwasser, 2012).

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1 To avoid confusion, we capitalize Reaction if it refers to the emoji-like popularity cues on Facebook.
In addition to the idea of populism as an ideology, populism can also be defined as a communication style that is observable in political party broadcasts (Jagers & Walgrave, 2007), parliamentary debates (Cranmer, 2011), press coverage (Müller et al., 2017), or social media communication of political actors (Engesser et al., 2017). Rather than covering all aspects of populism, statements can include single aspects of populist ideology. Although researchers use different typologies, the main features that shape populist communication are reference to “the people,” anti-elitism, and the exclusion of out-groups (e.g., de Vreese, Esser, Aalberg, Reinemann, & Stanyer, 2018; Jagers & Walgrave, 2007). Political actors can address the people according to nationality (e.g., “the Germans”) or class (e.g., “the hardworking people”) and stress the homogeneity of the people (Engesser et al., 2017; Jagers & Walgrave, 2007). Because reference to “the people” focuses on common characteristics and shared values without constructing any opponents, it primarily appeals to feelings of community and is therefore inclusive, at least for those who belong to the respective definition of the people (Hameleers, 2018). Because the focus on the people does not necessarily require any specification of political ideas, Jagers and Walgrave (2007) call it “empty populism.” This arbitrariness might be the reason that reference to the people has been found to be the most widespread populist feature (Cranmer, 2011).

Additionally, populist protagonists try to verbally exclude various out-groups and portray them as a danger to society. Anti-elitism blames the political sphere (e.g., parties or politicians), the media, or economic elites for acting against or at least ignoring the people’s welfare (vertical populism). As an alternative to shift the responsibility for problems to the elites, protagonists can also apply the exclusion of out-groups and contrast the homogenous people by stigmatizing other societal groups defined by ethnic, sexual, or cultural characteristics (horizontal populism) and framing them as a threat for the people’s culture or security (de Vreese et al., 2018; Jagers & Walgrave, 2007). Although these communication strategies can, but must not, make use of illiberal arguments, it is worth noting that the use of populist message features is not limited to parties labeled as populist; established parties also include populist message features in their communication repertoire (Cranmer, 2011).

In addition to the message features that are directly linked to the populist ideology, several populist-related message features are neither explicitly populist nor exclusively used by populist actors, but are often found to supplement populist communication (also referred to as “stylistic devices”; Ernst et al., 2019). Because populism is characterized by “the reliance on gut feelings rather than on rational facts” (Wirz, 2018, p. 1116), populist communication is often shaped by emotionalization. To trigger emotional responses, protagonists apply dramatized and emotional language or display their own emotions (Bos & Brants, 2014). Besides trying to appeal to citizens’ emotions, populists have a tendency to frame the condition of society in rather dark patterns. Protagonists focus on negative developments of societal issues and stress negative characteristics of political or societal actors (e.g., blame them for a lack of competence or integrity). Consequently, negative portrayal of political actors can be seen as another style element attached to populism (Alvares & Dahlgren, 2016; Ernst et al., 2019). Complementarily, populist communication aims at reducing the distance to the people. Therefore, it seems suitable for not only addressing the people as a homogenous group, but also for portraying citizens positively and depicting them and their actions in a favorable manner (Engesser et al., 2017). There should be no doubt that these populist-related features do not refer to populist ideology only. However, a study by Ernst and colleagues...
(2019) reveals that protagonists use these features in a manner similar to the strategies directly linked to populist ideology, especially on social media.

**User Interactions on Social Media**

Social media ended the age of one-sided mediated political top-down communication. As a result of its rise, candidates and parties can distribute their messages on platforms such as Facebook and Twitter and make their positions visible to the public. In turn, users of these platforms can interact with these messages by commenting, sharing, or clicking social buttons (e.g., Like). For citizens, this is an important opportunity to address political representatives, discuss political issues with others, or just articulate their opinions publicly.

For political actors, these interactions are important for at least two reasons. First, the algorithms of social network sites determine the reach of the messages, depending on a calculation of potential relevance for other users. Although the Facebook algorithm is a black box that is kept a well-guarded company secret, a document analysis of Facebook’s press releases shows that, among other indicators, the interaction rate of each message and the interaction rates of posts previously published by the profile are integral parts of the attributed relevance that determines the posts’ outreach (DeVito, 2017). Therefore, interactions are the currency in the network media logic (Klinger & Svensson, 2015). Second, social media offers political actors the opportunity to access followers’ reactions toward their messages—for example, by counting the number of interactions, also referred to as “popularity cues” (Porten-Cheé et al., 2018). Thus, politicians can learn which communication strategies or other message features fuel user interactions and then incorporate this knowledge into their future communication behavior.

**Facebook Popularity Cues as Dependent Variables**

Research on online user comments suggests that commenting is driven by expressive motives. Users pursue cognitive claims (e.g., promoting their experiences and contributing their views), but also cope with their emotions triggered by online content (e.g., expressing anger) when leaving comments below news articles or political messages of parties, candidates, or political institutions (Springer, Engelmann, & Pfaffinger, 2015). In addition to leaving comments, users can apply standardized forms of interactions on social media such as Facebook. The Like was the first social button, introduced as an alternative “way to let people know that you enjoy it without leaving a comment” (Facebook, 2018). This so-called click speech can be understood as a form of, or even a substitute for, online conversation (Pang et al., 2016).

Although applying Likes requires less cognitive effort, the motives of using standardized forms of interactions (such as Likes) seem to overlap with those of writing comments. Recent studies indicate that agreement with the posted content and the posters’ behavior (e.g., Hayes, Carr, & Wohn, 2016), as well as emotional attachment (Brandtzæg & Haugstveit, 2014), drives people to click the Like button. However, Gerlitz and Helmond (2013) stress the ambiguous use of the Like button that might also “express a variety of affective responses such as excitement, agreement, compassion, understanding, but also ironic and parodist liking” (p. 1358).
In 2016, Facebook announced that it had “developed ways [for users] to easily and quickly express how something [users] see in [their] News Feed makes [them] feel” (Facebook, 2016) and extended users’ post interaction options with the opportunity to react to posts with five emoji-like icons: Love, Haha, Wow, Sad, and Angry. By choosing a Reaction, users easily share their (emotional) response toward messages with others. A study by Larsson (2018) reveals that the introduction of Reactions led to a significant change in users’ interaction behavior; between January and May 2016, the share of Likes slightly decreased because users were able to assign Reactions on news posts. Since then, the use of Reactions has increased continually (Eberl et al., 2017).

While the sentiments of Haha and Wow can be both positive or negative (e.g., ironic or sarcastic), the remaining three can be roughly separated into the expression of positive and negative emotions or affects: Love can be interpreted as a clearly positive emotional response toward a message, and Angry and Sad display negative emotions (see also the PANAS-X scales measuring emotions; Watson & Clark, 1994). In the study at hand, we focus on the Angry Reaction because anger is the more relevant emotion in the realm of political communication for several reasons: Literature suggests that anger especially increases people’s attention toward campaign messages and has a mobilizing and persuading effect on potential voters in campaign communication (Brader, 2005; Valentino et al., 2011). In contrast to anger, sadness does not lead to an enhanced arousal and therefore does not change the mode of information processing (Bodenhausen, Sheppard, & Kramer, 1994). Moreover, appraisal theory suggests that emotions are a result of an individual’s evaluation of events and their causes (Scherer, 2005). Accordingly, anger is likely to occur if an individual holds someone accountable for a negative situation that could have been avoided (e.g., Schemer, 2014). Because populism is largely based on blaming the elites or out-groups for social problems (Mudde, 2004), populist communication is likely to elicit anger toward these groups (Hameleers, Bos, & de Vreese, 2017). Finally, the selection of Like, Angry, and Love in our analysis is supported by their empirical relevance, given that they are found to be the most often used Reactions in the realm of political communication (Eberl et al., 2017).

Current Research on Popularity Cues

For communication researchers, the aggregated number of popularity cues provides an opportunity to access recipients’ responses toward political messages apart from classical experimental settings (Porten-Cheé et al., 2018). Therefore, various recent studies collect diverse message features via content analyses (independent variable) and model their effect on the number of likes or shares (dependent variable; e.g., Bene, 2017; Blassnig et al., 2019; Heiss, Schmuck, & Matthes, 2018; Staender, Ernst, & Steppat, 2019).

However, the interpretation of Reactions’ valence is difficult in some cases. The Wow Reaction refers to the expression of surprise. However, the emotional valence of surprise is ambiguous and depends on the motive (in)congruence of the new information (Reisenzein, Meyer, & Niepel, 2009). In the present context, a user might be (positively) surprised by an achievement in a bargaining process or be (negatively) astonished by a political failure. The ambiguity holds true as well for Haha, which might either indicate a benevolent evaluation (e.g., user laughs about a good joke) or point to a negative reaction (e.g., user sneers at politician’s failure). Thus, both Haha and Wow are excluded for the analyses of valence.
Studies explaining the effects of message features show that negativity in politicians’ status updates on Facebook seems to enhance the number of comments and shares (Bene, 2017; Heiss et al., 2018), and an emotional tone has a positive effect on the number of Likes (Heiss et al., 2018; Keller & Kleinen-von Königslöw, 2018). To date, only a few studies have attempted to assess the influence of populist message features on the number of interactions on Facebook. A study by Bobba (2018) reveals that Facebook messages from Italian politicians that contain exclusive populism receive more Likes compared with nonpopulist messages. On the contrary, Blassnig et al. (2019) find no indication of populism affecting the number of Likes, Shares, and Comments at the post level. However, their analysis reveals that posts of political actors who frequently use populist strategies on Facebook receive more interactions. Yet, the tendency to use populist features is a characteristic at the profile level, suggesting that posts of populists generally receive more interactions on Facebook.

Although these studies give great insights regarding the question of what drives user interaction, their results must be seen in light of some limitations. Only a few studies include profile characteristics in their analyses, and to date, only three studies statistically take into account that the posts are nested in the politicians’ Facebook pages (Eberl, Tolochko, Jost, Heidenreich, & Boomgaard, 2020; Heiss & Matthes, 2019; Heiss et al., 2018). Further, most existing studies have only used Likes, Shares, or Comments and therefore have only captured effects of unclear valence with the collected message features. The ambiguity of the Like is also reflected in the results of existing research. For instance, Heiss and colleagues (2018) find that negative and positive emotional Facebook posts enhance the number of Likes. Moreover, users’ competing motives for applying social buttons might blur the effects of some message features on the volume of Likes.

To date, only a few studies focus on distinct Reactions on Facebook. Eberl and colleagues find that negative sentiment of political posts is positively related to Angry Reactions, and positive sentiment increases the number of Love Reactions (Eberl et al., 2020). In the realm of populist communication, Mancosu (2018) finds that posts of populist parties in Italy receive more Angry Reactions if they apply a critical and emotionalized communication style. A study by Heiss and Matthes (2019) examines the effect of populist features on Angry Reactions, showing that anti-elitist and anti-immigrant messages enhance the number of Angry Reactions on posts of political actors in Germany and Austria. However, both studies examine the impact of negative populist message features on Angry Reactions. In consequence, a gap remains in the existing research regarding the influence of inclusive populism and the effect of populism on positive Reactions.

**Impact of Populist Message Features on Reactions and Likes**

Users’ interactions with posts on Facebook depend on message characteristics that function as independent variables in our analyses. In the following, we will illustrate the effects of populist message features and stylistic devices on emotional states that in turn might be reflected in Likes and Reactions to Facebook posts.

**Populist features:** Recent studies reveal the effects of populist message features. For instance, anti-immigrant and anti-elitist messages can negatively influence attitudes toward attacked groups (Hameleers
et al., 2017; Schmuck & Matthes, 2015). Moreover, exclusive populist messages have the potential to elicit negative emotions such as anger and fear (Wirz, 2018), which is reflected by an increased number of Angry Reactions to political posts on Facebook (Heiss & Matthes, 2019). In contrast, an inclusive populist style (reference to the people) elicits more positive emotions, such as hope and pride (Wirz, 2018). Consequently, we assume:

**H1.1:** Anti-elitism and exclusion of out-groups increase the number of Angry Reactions.

**H1.2:** References to the people increase the number of Love Reactions.

Because emotional states might also trigger users’ involvement and, therefore, their general willingness to interact with posts, both exclusive and inclusive populist message features should have a positive effect on the number of Likes. Contrary to this assumption, research reveals that only excluding other groups (but neither anti-elitism nor inclusive populism) has an effect on the likability of political Facebook posts (Bobba, 2018) or finds no effect of populism (Blassnig et al., 2019). Against the backdrop of ambiguous findings, we pose this open research question:

**RQ1:** How do inclusive and exclusive populist message features affect the number of Likes?

**Emotionalization:** According to the appraisal theory, emotional messages can produce affective reactions similar to the displayed emotions. For instance, people may feel anger when politicians express their anger about an opponent (Schemer, 2014). Positive and negative emotional arousal enhances attention and cognitive capacity; therefore, it is positively linked to engagement with political messages and campaigns (Brader, 2005). Studies show that politicians’ Facebook messages receive more Likes, Shares, and comments when they contain emotional language (Bene, 2017; Heiss et al., 2018). In line with these findings, we assume:

**H2:** Emotionality increases the number of both Angry (H2.1) and Love (H2.2) Reactions as well as the number of Likes (H2.3).

**Valence:** Further, we aim to analyze how the positive and negative evaluations of actors affect the Reactions on Facebook. Research on political campaigns has shown that negativity in ads fuels interest in campaigns (Brader, 2005), and negative (campaign) messages lead to negative emotional states (Chang, 2001). In contrast, positive content can evoke positive emotional states (Schemer, 2014; Scherer, 2005). Consequently, we assume:

**H3.1:** Negative portrayals of political actors increase the number of Angry Reactions.

**H3.2:** Positive portrayals of ordinary citizens increase the number of Love Reactions.

Research on the effects of posts’ valence on the number of Likes is ambiguous; some studies find negative and positive effects (Heiss et al., 2018), solely negative effects (Bobba, 2018), or no effect of messages’ valence (Bene, 2017) on the number of Likes. Thus, we ask:
RQ2: How do both negative portrayals of political actors and positive portrayals of citizens affect the number of Likes?

Method

To test our hypotheses and answer our research questions, we implemented a manual quantitative content analysis of Facebook posts from all parties and top candidates represented in the 19th German Bundestag. The conservative Christian Democratic Party (CDU) and the Bavarian Christian Social Union (CSU) constituted the government in a coalition with the Social Democratic Party (SPD). The Leftist Party (Die Linke) and the Green Party (Bündnis 90 – die Grünen) formed the opposition. The Liberal Democratic Party (FDP) and the right-wing populist Alternative for Germany (AfD) were not represented in the parliament before the election. According to the data of the Chapel Hill Expert Flash Survey (Polk et al., 2017), the Leftist Party and the AfD make more use of anti-elite and anti-establishment rhetoric than any other German party (Bene, 2017). Both can thus be counted as populist parties. Whereas the CDU/CSU, FDP, and the SPD nominated only one top candidate each, the Green, Leftist, and AfD had two top candidates. Thus, we analyzed 17 profiles in total. We collected all 1,540 Facebook posts that were published on the Facebook profiles of parties and candidates during the month before the election (August 25, 2017, to September 24, 2017). The posts were collected via the Facebook API using the software Facepager (Keyling & Jünger, 2019) immediately after election day. The data also include information on the post type (i.e., status update with text, picture, or video). The interactions were collected in January 2018. The number of followers was collected for each profile via the platform Pluragraph.de (the number accessed at the beginning of the analyzed period). The coding was performed by 42 students who were recruited at a content analysis seminar. All coders were intensively trained. The training process included jointly coding in class and individual coding at home, followed by a mutual comparison in the course. After several reliability tests and refinements of the codebook, all coders coded a subsample of 25 posts each with the final categories to assess the reliability of the manually coded variables.

Independent variables: We conducted a manual quantitative content analysis to examine the posts’ characteristics. First, we collected the presence of inclusive and exclusive populist features, namely reference to the people ($\alpha_k = .83$), and anti-elitism and the exclusion of out-groups ($\alpha_k = .65$).  

Reference to the people was coded if politicians addressed “the people” as a monolithic mass with common characteristics and homogenous interests, ethnic identity, or values (e.g., by using such as “the Germans,” “the ordinary citizens,” “the hardworking people”). Anti-elitism was coded when functional elites or institutions (e.g., “the established parties,” “the economic leaders,” “the media”) were portrayed as corrupt or ignorant regarding concerns of the people. Exclusion of out-groups was coded when protagonists stressed the contrast between the people and out-groups by referring to social, ethnic, or sexual differences (e.g.,

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3 Because the growth of new Reactions is typically saturated within few days (Jost, Mangold, & Jürgens, 2019), it is very likely that the number of Reactions did not change after the collection of the Reactions.

4 The Krippendorff reliability score is below the critical value. However, variables with a skewed distribution are more likely to fail because of the great sensitivity of chance-corrected coefficients (Lacy, Watson, Riffe, & Lovejoy, 2015). The pairwise agreements of anti-elitism (.80) and exclusion of out-groups (.82) seem adequate.
"the feminists," “the immigrants”) that are often depicted as abnormal or deviant. Similar to the people, elites and out-groups must have been portrayed in a generalized manner without individual features and were only coded when the statement portrayed those groups as antagonists of the people.

Regarding the populist-related message features, we collected the posts’ emotionality on a 5-point scale ranging from 1 (detached) to 5 (emotional; \( \alpha = .65 \)) and recoded the variable dichotomously (values above 3 were counted).\(^5\) Emotionality includes the use of rhetorical devices (e.g., polarization, hyperboles, and interjections), crisis rhetoric, or the explicit verbal display of subjective experiences and emotional states of both positive and negative valence (Bos & Brants, 2014). Moreover, we collected up to three actors in each post (\( \alpha = .82 \)). An actor was coded if an object was not solely mentioned, but was portrayed as actively acting. The evaluations of actors were collected on a 5-point scale ranging from -2 (negative) to 2 (positive; \( \alpha = .69 \)) and finally dichotomized (values lower than 0 = negative; values higher than 0 = positive). In our analyses, we concentrate on the negative evaluation of individual political actors (e.g., Angela Merkel, ministers), parties, and institutions (e.g., CDU, “the Bundestag”). In contrast to anti-elitism, in this case, the tone concerning individual political actors who were not portrayed as part of a homogenous mass was coded. We further coded whether the post evaluated ordinary citizens. In contrast to reference to the people, the variable covers citizens who were described as individuals or a clearly distinguishable group of citizens without necessarily stressing homogeneity of the people or being described as a counterpart of the elites (e.g., workers of a specific company or industry/sector). Positive portrayal of citizens was coded when the value of evaluation was higher than zero.

**Control variables:** At the profile level, the number of followers determined the number of users who were initially shown a post. Consequently, the more followers a profile had, the more users potentially distributed the profile’s posts. Therefore, we controlled for the number of followers in our regression models. Additionally, we controlled for differences between party (collective actor) and candidate (individual) profiles (Heiss et al., 2018).

Furthermore, political parties have different followers who potentially interact with their messages. The majority of users follow candidates and parties on Facebook and other social media platforms only when these actors represent their own political positions (Macafee, 2013). Survey data indicate that supporters of the German right-wing populist AfD and voters of the Leftist Party tend to see their own future and societal developments more pessimistically (Brenke & Kritikos, 2017). The negative attitudes and dissatisfaction of populist party supporters are reflected in the Reactions on Facebook (Eberl et al., 2017). To avoid the confounding of the message features and the followers’ predispositions, we controlled for both populist parties.

Regarding the controls at the post level, research indicates that specific issues elicit more emotions than others (Schemer, 2014). This holds true for immigration, which was one of the most prevalent issues in public discourse during the election in 2017 and described as being part of (right-wing) populist strategy. Therefore, we coded up to three issues per post (\( \alpha = .80 \)) and implemented the immigration issue as a

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\(^5\) Because emotionality is a latent construct, the reliability seems acceptable. The pairwise agreement of dichotomously coded emotionality (.89) seems adequate.
control variable in our regression models. Further, research has shown that multimedia features potentially increase the number of user interactions (Heiss et al., 2018). Thus, we controlled for the presence of pictures and videos. Table 1 shows the relative usage of different message features grouped by party.

Table 1. Relative Frequencies of Message Features by Party.

<table>
<thead>
<tr>
<th>Message Features</th>
<th>Party (in %)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CDU</td>
<td>CSU</td>
</tr>
<tr>
<td>Reference to the people</td>
<td>25</td>
<td>15</td>
</tr>
<tr>
<td>Anti-elitism</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Exclusion of out-groups</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Emotionality</td>
<td>34</td>
<td>27</td>
</tr>
<tr>
<td>Political actors (neg)</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Citizens (pos)</td>
<td>&lt;1</td>
<td>1</td>
</tr>
</tbody>
</table>


Results

Descriptive Analysis

Our descriptive results show that reference to the people is the most prevalent populist message feature, while criticizing the elites is especially popular among the populist Leftist Party and the right-wing populist AfD, but also used by the moderate-left SPD and the Greens in roughly every 10th post. In contrast, the exclusion of out-groups plays a minor role in political actors’ communication on Facebook; the AfD is the only party that noticeably stresses the antagonism of the people and other social groups. The most widespread stylistic device is emotionalization, followed by the negative portrayal of political actors, most often used by populists but also by the Greens and the SPD, while the positive portrayals of citizens play a minor role.

Further, we found Like to be the most prevalent form of interaction ($M = 2,726.24; SD = 4,610.94$), followed by Love ($M = 142.98; SD = 321.24$), and Angry ($M = 87.26; SD = 319.04$, see Figure 1).
To assess the influence of message features statistically adequately, we applied multilevel regression models, allowing varying intercepts for each profile (Hox, 2010). In doing so, we statistically considered that the differences in profile characteristics randomly affected the volume of Likes and Love and Angry Reactions. Because of the right-skewed distribution of analyzed count data, we used negative binomial models, correcting for skew (Lawless, 1987). We ran separate models for the number of Likes, Love, and Angry. The regression models showed significant influences of populist message features (see Figure 2 and Table 2).

As we hypothesized (H1.1), exclusive populism increased the number of Angry Reactions. Posts that included anti-elitism (indicence rate ratio [IRR] = 1.66) received 66% more Angry Reactions than posts that did not criticize the elite. The effects of excluding out-groups—almost exclusively used by the AfD—(IRR = 2.45) were even more pronounced; if political actors stressed the deviance of ethnic or social minorities and portrayed them negatively, the posts received 145% more Angry Reactions. Because both exclusionary populist features enhanced the number of Angry Reactions, H1.1 was supported.
In contrast, inclusive populism (H1.2) had a positive effect on the number of Love Reactions (IRR = 1.22). Referencing the people and their common characteristics and norms led to 22% more Love Reactions. Thus, H1.2 was supported. Moreover, the use of inclusive populism even seemed to reduce negative emotional responses, given that the number of Angry Reactions (IRR = 0.87) shrank by 13%. Further, we were interested in the effect of populist features on the number of Likes (RQ1). The regression model revealed that only anti-elitism (IRR = 1.12) had a marginal effect, enhancing the number of Likes by 12%. Our findings suggest that excluding neither dangerous others nor reference to the people affects the number of Likes.

Figure 2. Fixed effects of message features on Reactions and Likes. Incidence rate ratios depicted with 95% confidence intervals. Models include control variables (Table 2).
<table>
<thead>
<tr>
<th>Predictors</th>
<th>Likes IRR</th>
<th>Likes CI</th>
<th>Love IRR</th>
<th>Love CI</th>
<th>Angry IRR</th>
<th>Angry CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile Level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual</td>
<td>0.67</td>
<td>0.27 – 1.69</td>
<td>0.53</td>
<td>0.20 – 1.43</td>
<td>0.46</td>
<td>0.19 – 1.19</td>
</tr>
<tr>
<td>No. of followers (log)</td>
<td><strong>1.68</strong></td>
<td><strong>1.18 – 2.41</strong></td>
<td><strong>2.05</strong>*</td>
<td><strong>1.39 – 3.02</strong></td>
<td><strong>2.00</strong>*</td>
<td><strong>1.41 – 2.86</strong></td>
</tr>
<tr>
<td>Leftist</td>
<td>1.85</td>
<td>0.56 – 6.08</td>
<td>2.54</td>
<td>0.70 – 9.19</td>
<td>1.51</td>
<td>0.49 – 5.22</td>
</tr>
<tr>
<td>AfD</td>
<td>† 2.89*</td>
<td>0.88 – 9.47</td>
<td><strong>4.46</strong></td>
<td>1.24 – 16.09</td>
<td><strong>6.99</strong></td>
<td><strong>2.31 – 24.39</strong></td>
</tr>
<tr>
<td>Postlevel</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Picture</td>
<td><strong>1.51</strong>*</td>
<td><strong>1.34 – 1.71</strong></td>
<td><strong>1.45</strong>*</td>
<td><strong>1.27 – 1.65</strong></td>
<td>1.00</td>
<td>0.87 – 1.15</td>
</tr>
<tr>
<td>Video</td>
<td><strong>1.23</strong></td>
<td><strong>1.09 – 1.40</strong></td>
<td><strong>1.88</strong>*</td>
<td><strong>1.65 – 2.14</strong></td>
<td>1.00</td>
<td>0.87 – 1.15</td>
</tr>
<tr>
<td>Immigration</td>
<td>1.18*</td>
<td><strong>1.02 – 1.36</strong></td>
<td><strong>0.79</strong></td>
<td><strong>0.68 – 0.92</strong></td>
<td><strong>2.20</strong>*</td>
<td><strong>1.86 – 2.60</strong></td>
</tr>
<tr>
<td>Reference to the people</td>
<td>1.10</td>
<td><strong>0.97 – 1.23</strong></td>
<td><strong>1.22</strong></td>
<td><strong>1.08 – 1.37</strong></td>
<td><strong>0.87</strong></td>
<td><strong>0.77 – 0.99</strong></td>
</tr>
<tr>
<td>Anti-elitism</td>
<td><strong>1.12</strong> †</td>
<td><strong>1.00 – 1.26</strong></td>
<td>0.93</td>
<td><strong>0.82 – 1.05</strong></td>
<td><strong>1.66</strong>*</td>
<td><strong>1.47 – 1.87</strong></td>
</tr>
<tr>
<td>Exclusion of out-groups</td>
<td>1.12</td>
<td>0.87 – 1.44</td>
<td>0.87</td>
<td>0.66 – 1.14</td>
<td><strong>2.45</strong>*</td>
<td><strong>1.85 – 3.23</strong></td>
</tr>
<tr>
<td>Emotionality</td>
<td><strong>1.11</strong></td>
<td><strong>1.03 – 1.20</strong></td>
<td><strong>0.84</strong>*</td>
<td><strong>0.77 – 0.91</strong></td>
<td><strong>1.38</strong>*</td>
<td><strong>1.27 – 1.51</strong></td>
</tr>
<tr>
<td>Pol actors (neg)</td>
<td><strong>1.21</strong>*</td>
<td><strong>1.08 – 1.36</strong></td>
<td>1.03</td>
<td>0.91 – 1.16</td>
<td><strong>2.34</strong>*</td>
<td><strong>2.08 – 2.63</strong></td>
</tr>
<tr>
<td>Citizens (pos)</td>
<td>1.29*</td>
<td><strong>1.04 – 1.59</strong></td>
<td><strong>1.59</strong>*</td>
<td><strong>1.28 – 1.98</strong></td>
<td><strong>0.60</strong>*</td>
<td><strong>0.47 – 0.75</strong></td>
</tr>
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<td>Random effects</td>
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</tr>
<tr>
<td>$\sigma^2$ Profile</td>
<td>0.41</td>
<td>0.41</td>
<td>0.43</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_{00}$ Profile</td>
<td>0.84</td>
<td>0.98</td>
<td>0.83</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICC Profile</td>
<td>0.67</td>
<td>0.70</td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Groups/Obs.</td>
<td><strong>17/1,540</strong></td>
<td>17/1,540</td>
<td><strong>17/1,540</strong></td>
<td>17/1,540</td>
<td>17/1,540</td>
<td>17/1,540</td>
</tr>
<tr>
<td>AIC</td>
<td>26,120.718</td>
<td>17,168.754</td>
<td>15,392.050</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. N = 1,540 posts; negative binomial regression models with fixed-effect estimation (varying intercepts for profiles); IRR = incidence rate ratios; values > 1 indicate positive influence; predictors were dichotomous, 1 indicating presence.

†p < .1. *p < .05. **p < .01. ***p < .001.
Besides the populist features, we investigated the effects of populist-related message features. We expected emotionality to have a positive effect on both positive and negative Reactions (H2.1 and H2.2). The regression models revealed that emotionality enhanced the volume of Angry Reactions (IRR = 1.38) by 38% compared with posts with a more detached tonality, showing support for H2.1. Contrary to our assumptions, emotionality had a moderate but negative influence on Love Reactions (IRR = 0.84) and decreased the volume of Love Reactions by 16%. Consequently, H2.2 was not supported. We further assumed a positive effect of emotionalization on the number of Likes (H2.3), which was confirmed by our data; posts that contained emotional language (IRR = 1.11) received 11% more Likes compared with posts with a detached tone. Thus, H2.3 was supported.

Moreover, the models showed the significant influences of both positive and negative actors’ evaluation. The negative portrayal (H3.1) of political actors (IRR = 2.34) increased the number of Angry Reactions by 134%, showing support for H3.1, whereas the positive evaluation of citizens (IRR = 1.59) increased the number of Love Reactions by 59%. Consequently, H3.2 was supported. Further, the positive portrayal of ordinary citizens simultaneously decreased the number of Angry Reactions (IRR = 0.60) by 40%. Moreover, we found both negative and positive evaluations of actors to have an impact on the number of Likes (RQ2); when political actors portrayed their colleagues negatively (IRR = 1.21), the number of Likes increased by 21%. At the same time, posts that portrayed citizens positively (IRR = 1.29) received 29% more Likes compared with posts without positive portrayals.

In addition to the effects of populist and populist-related message features, we found influences of additional variables that might improve the understanding of how interaction in the realm of political communication on Facebook is constituted. At the profile level, regression models revealed that posts stemming from the AfD and its candidates received more Reactions compared with profiles of other parties. This held true for both Love (IRR = 4.25) and Angry (IRR = 6.99) Reactions. On the post level, we found a remarkable influence of the immigration topic. When political actors wrote about immigration, the number of Love Reactions (IRR = 0.78) decreased, while posts about this topic doubled the number of Angry Reactions (IRR = 1.99) and increased the number of Likes (IRR = 1.18) by 18%.

**Discussion**

In our analysis, we find evidence for the influence of populist message features on the number of Likes and Reactions that a post receives; users respond with the Love Reaction when politicians and parties apply inclusive populist styles (i.e., reference to the people), but react with anger to exclusive populism (i.e., anti-elitism and exclusion of out-groups). Therefore, our study is in line with findings from experimental research on the effects of populist communication (Wirz, 2018). We also find effects of populist-related message features on Reactions and Likes, indicating that emotionality has a positive effect on the total number of Angry Reactions and Likes, but, contrary to our assumptions, a negative effect of emotionalization on Love Reactions. Whereas the former is in line with the findings of Bene (2017), who only found negative emotional tone to increase the number of interactions, the latter seems to be less conclusive. We can only
speculate that the Love-decreasing effect of emotionalization might be due to the fact that it is quite more often combined with negative issues and evaluations.\(^6\)

With respect to the valence of the actor’s evaluation, we find that portraying political actors negatively leads to more Angry Reactions. This seems to reflect negative emotional states, such as anger, when people are confronted with negative information, which is also found in studies using experimental designs (Chang, 2001). On the contrary, when portraying citizens in a positive light, users are more willing to apply Love Reactions and less likely to respond with Angry Reactions to politicians’ Facebook posts.

Beyond the effects of populist and populist-related message features, the results suggest that differences between the parties determine a large number of reactions, indicating that followers of AfD profiles are more willing to interact with status updates. Thus, it seems plausible that AfD supporters are more likely to interact with posts of their party and their top candidates because they are disappointed by the traditional mass media. Additionally, there are hints that these Reactions are actively forced by the party itself as it activates partisans to react to its posts, which in turn increases the reach within the network (Serrano, Shahrezaye, Papakyriakopoulos, & Hegelich, 2019). Fostering such inauthentic user behavior as a strategic and—in a democratic sense—unethical alignment to the digital environment is a result of the “disruptive and transformative effect[s]” (Kitchin, 2017, p. 26) of algorithms in the realm of political communication. Additionally, the algorithmic message distribution itself might also have an effect on the number of user interactions. They determine the visibility of posts because of their influence on the attribution of relevance, thereby affecting the number of possible interactions; consequently, they might blur the effects of message features. However, we can only speculate the degree to which the algorithm influences the number of interactions, given that it is kept secret and is hardly observable for researchers (Kitchin, 2017). Moreover, we do not have information on which posts were sponsored by the political actors we focused on. Future studies might use Facebook’s newly developed Ad Archive to gather data, analyzing the effect of message features in combination with sponsorship on the number of Likes and Reactions.

In addition to these platform-specific issues, some other limitations should be taken into account when interpreting the study’s results or conducting further research: We cannot rule out that, in some cases, partisans from opposite political camps are reacting to posts on Facebook. Although there are good reasons to assume that most Reactions stem from profiles’ followers (Macafee, 2013), supporters of political opponents might interact with parties’ and candidates’ posts and especially use negative Reactions to show their disagreement.

Finally, more research is needed to identify the objects that users refer to when they assign Reactions or Likes. For instance, when a post contains anti-elitism, users might feel anger toward the political elite or toward the politician because he or she used a populist strategy; both will increase the number of Angry Reactions. The problems of opposing motives and reference points for Reactions can only be investigated in further studies focusing on Facebook users and their motives for applying Reactions.

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\(^6\) To prove this alternative assumption, we ran additional regression models, including interactions of emotionalization and other message features, but we could not find any significant effect.
Conclusion

Despite these limitations, our study opens methodological perspectives and holds substantive implications for political communication on Facebook and its research. We find populist message features to have an impact on Likes and both types of Reactions, suggesting that populism enhances the relevance of messages on Facebook and affects the valence of users’ responses. The results of our study reveal similarities to those that stem from experimental research concerning the effects of inclusive and exclusive populism (Wirz, 2018), message valence, or emotionalization (Brader, 2005; Chang, 2001).

Therefore, the study demonstrates that the combination of content analyses and Reactions has the potential to reveal the effects of various message features on positive and negative emotional states represented by Reactions. Our results show opposing effects of message features on both types of Reactions in most cases. The features that have a positive effect on one type of Reaction have a significant negative effect on the other type of Reaction (see Figure 2), suggesting “hydraulic patterns.” Therefore, Love and Angry can be convincingly categorized as positive and respective negative one-click expressions of emotional states. On the contrary, we find Likes to be induced by message features of both positive and negative valence, strengthening the assumption of the ambiguous meaning of Likes (Gerlitz & Helmond, 2013).

Moreover, message features with opposing effects on Angry and Love (i.e., reference to the people and negative evaluation of political actors) have no effect on the number of Likes, suggesting that the effects of message features might be blurred by the ambivalent use. Conclusively, in contrast to studies applying Likes only, Love and Angry Reactions might be interpreted more straightforwardly as user expressions of negative and positive emotional states related to the stimuli. Therefore, using these Reactions as dependent variables in combination with content analysis complements the “classical” (i.e., experimental) setting of research on media effects by providing a nonreactive setting; in this setting, the number of potential independent variables is only restricted by their natural occurrence instead of being limited by the number of experimental groups. Researchers who are interested in the aggregated effects of both communicator and message characteristics on emotional responses (at least of party supporters) might especially apply such designs in the future.

In addition to the methodological perspectives, the results have implications that might be interesting for both communication theorists and political practitioners. For instance, supporters of the right-wing AfD tend to interact more often with the posts of the party and its candidates. In combination with their large number of followers, this gives them essential advantages when it comes to algorithmic reach within the network. Therefore, Facebook seems to be an ideal channel for addressing voters who are unsatisfied with the traditional mass media (Arzheimer, 2015).

Our results further suggest that the use of certain populist message features and stylistic devices has the potential to enhance or reduce users’ willingness to assign different types of Reactions that are likely to represent different emotional responses to posts’ content. Emotions have the potential to both persuade and mobilize voters (Brader, 2005). The mobilizing effect especially holds true for negative but not for positive emotional states (Valentino et al., 2011). Thus, it seems quite arguable that political parties use specific message features to trigger negative emotional states to mobilize their followers and incorporate these strategies into their communication behavior. Such alignments are not exclusively possible in social
media; however, the observation of users’ Reactions makes it easier for politicians to approximate the impact of their messages, detect successful strategies, and align their future communication strategies.

As our data reveal, especially exclusive populist message features and the negative depiction of political actors enhance the number of Angry Reactions. Because political actors also monitor the Reactions to their posts, it seems possible that they will use these features more often in their future communication. Because anti-elitism and the negative portrayal of political actors might enhance dissatisfaction and distrust with the political system (Hameleers & Schmuck, 2017), excluding dangerous others leads to negative attitudes toward social minorities (Schmuck & Matthes, 2015). This goes beyond the expression of anger on Facebook—but such strategic alignments are problematic and should be kept under scrutiny.

References


Macafee, T. (2013). Some of these things are not like the others: Examining motivations and political predispositions among political Facebook activity. *Computers in Human Behavior, 29*(6), 2766–2775. doi:10.1016/j.chb.2013.07.019


