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Personality and susceptibility to political microtargeting: A comparison between a machine-learning and self-report approach

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ABSTRACT

Based on recent technological advances, campaigners and political actors can use psychographic-based political marketing. Yet, empirical evidence about its effectiveness is still very limited. Based on self-congruity theory, a pre-registered experiment (N = 280) investigated the persuasion effects of personality-congruent political microtargeting on the attitude toward the political party and voting intentions of citizens. More precisely, the focus was on the *thinking vs feeling* personality dimension (MBTI), and it was tested whether this personality "interacts" with exposure to a matching advertising appeal: *rational vs. emotional* political ad. To do so, two different methodological approaches were used: 1) a machine learning approach; 2) a self-report survey measure of personality. Results revealed significant "congruence effects" between personality and ad appeal, and showed that *perceived ad relevance* was serving as the underlying mechanism (mediator). However, these results were only found when the self-report measure of personality was used. When the algorithmic approach was used, no significant results were found. These findings feed into timely societal, methodological, and theoretical contributions.

1. Introduction

Over the past decades, political campaigns around the globe have massively employed digital technologies for mass persuasion. This era of "computational politics" is marked by using big data and sophisticated computational modeling to carry out opaque and supposedly effective political advertising campaigns (Kreiss, 2016; Tufekci, 2014). The strategies and tools of digital political marketing are complex and far-reaching, with many techniques operating under the radar of public awareness or accompanied by numerous misconceptions (Chester & Montgomery, 2017; Zarouali et al., 2021).This analytical approach allows to predict human characteristics and behavior to engage in psychographics-based political targeting (Krotzek, 2019; Zarouali et al., 2022). The topic of psychographic targeting and tailoring has stirred public debate in recent years because of its application in political persuasion (i.e., the Cambridge Analytica scandal), a practice of which the ethics are debatable (Ward, 2018). Besides Cambridge Analytica, psychographic classification and targeting is offered by companies such as Meltwater and IBM (Meltwater, 2019; IBM 2019), and can be employed on platforms such as Facebook and Instagram through the *custom audiences* targeting option.

The idea behind psychographic targeting is to build (data-driven) personality profiles of online users to show citizens political content that is in line with their personality; in turn, this should boost political persuasion effects. This technique could potentially influence voters in a manipulative and thus unfair way, which could damage electoral integrity (Susser et al., 2019). Unfair forms of political persuasion efforts deserve the highest scrutiny, and while past regulatory frameworks have been inadequate, the recent introduction of the Digital Services Act is an important step towards addressing concerns regarding transparency, accountability, and data protection on digital platforms (European Parliament, 2023).

An important source of digital footprints that has been used to predict consumers' personality is online *written text.* Based on Natural Language Processing (NLP) and the application of machine learning algorithms, it is possible to model latent psychological traits such as personality based on people's online text (Berger et al., 2020; Gjurković & Šnajder, 2018; Tufekci, 2014; Verhoeven & Daelemans, 2014). Studies found this type of personality profiling to be accurate in offering a window into people's personality (Park et al., 2015; Tskhay & Rule, 2014). As shown by Zarouali et al. (2022), a text-based personality prediction approach can be employed to craft tailored political ads,

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enhancing their impact on citizens' voting intentions and political attitudes. Similarly, Tappin et al. (2023) found that political microtargeting messages that were tailored toward people's demographic and psychological traits can be (substantially) more persuasive than other messaging strategies. Although personality-based targeting seems to be an effective technique, empirical evidence about its effectiveness is still very limited, especially in the political realm.

To fill this gap in extant literature, this pre-registered study builds upon Zarouali et al. (2022) and investigates the persuasion effects of personality-congruent political microtargeting on the party attitude and voting intention of citizens. More precisely, where Zarouali et al. (2022) focused on the Big Five personality trait extraversion, this study will focus on predicting the '*thinking vs. feeling*' personality dimension of the Myers-Briggs Type Indicator (MBTI; Myers & Myers, 2010; this dimension describes how people engage in decision-making), and test whether this personality type "interacts" with exposure to a *rational vs. emotional* political ad. This will be done by using two different methodological approaches: 1) a machine learning approach that allows to predict people's personality based on their written text on Twitter; 2) a self-report assessment of personality. Based on this (algorithmic inferred/self-reported) personality prediction, we will test the effects of political advertising that matches voters' personality traits. This provides novel insight into the effectiveness of psychographics in political campaigns; and should generate insights regarding the possibility of using digital trace data (i.e., Twitter text) to infer voter personality (by means of a direct comparison with the self-report measure). These findings will feed into timely societal, methodological, and theoretical contributions.

2. Literature review

2.1. Personality-congruent political microtargeting

Online digital traces offer political actors a innumerable pieces of information to persuade citizens by means of political microtargeting (PMT). PMT refers to the automated and specific alignment of political messages based on different parameters (e.g., age, gender, location, etc.), which enables the optimized delivery of these messages at predefined audiences. Most of the time, PMT focuses on sending out political ads that are in line with people's concerns around certain issues (*issue-congruent PMT*). However, based on recent technological advances, it is also possible to use psychometric data to trigger a whole range of emotional and subconscious responses (Chester & Montgomery, 2017; Zarouali & Schreuder, 2023). Psychometric profiling uses vast amounts of psychological data to create ads intended to have an increased impact on political opinions and voter preferences (Bashyakarla, 2019; Chester & Montgomery, 2017). This opens the door to unfair consumer tactics that exploit the "decision-making vulnerabilities and weaknesses" of online voters (Susser et al., 2019; Tufekci, 2014).

Literature on effects of psychometric political targeting is scarce. Some recent studies found that personality-congruent PMT generates a more positive feeling toward the political candidate (Krotzek, 2019), and influences voting intentions and attitudes towards the political party (Zarouali et al., 2022). However, more research can be found in the realm of consumer advertising. On the one hand, a number of studies found an increased ad effectiveness when ads where being matched to people's personality (e.g., Hirsh et al., 2012; Matz et al., 2017; Schreuder & Zarouali, 2023), whereas on the other hand, some scholars also found limited effects of personality-matched ads on intention to engage with the ad on social media, but not on purchase intentions, or attitudes toward the ad (e.g., Winter et al., 2021). The main theoretical framework that can explain the effectiveness of personality-congruent PMT is *self-congruity theory*. Self-congruity theory postulates that individuals prefer stimuli (e.g., ads) that are congruent with their own self-concept and psychological attributes (DeBono, 2006; Sirgy, 1982, 1985). In the field of consumer advertising research, self-congruity theory has been used to substantiate the idea that congruent ads (i.e., ads that contain text that is congruent with someone's personal goals, values, and personality) are more effective than incongruent ads due to an increase in personal relevance (e.g., Xue & Phelps, 2013). In other words, self-congruity theory suggests that a self-congruent message increases the perception of relevance of the message to the consumer (Dodoo, Wen, & Taylor, 2019; Heckler & Childers, 1992). In the area of *consumer* advertising, a wide body of research has already applied self-congruity theory in the context of "congruence effects" or "matching effects", providing preliminary evidence for the claim that advertisements are more effective when the content is tailored to people's personality (e.g., Hirsh et al., 2012; Matz et al., 2017; Zarouali & Schreuder, 2023). In the area of *political* advertising, there has been scant research and theoretical attention devoted to it (Zarouali et al., 2022).

Most of the studies on personality-congruent advertising studies have focused on the Big Five personality traits (Costa & McCrae, 1992), particularly on extraversion and openness (e.g., Matz et al., 2017; Moon, 2002). However, in this study, we will focus on the *thinking vs. feeling* personality dimension by adopting the MBTI-framework (Myers & Myers, 2010) to investigate the effectiveness of personality-congruent PMT on social media. This will be addressed in the next section.

2.2. MBTI: thinking vs feeling personality

The Myers-Briggs Type Indicator (Myers & Myers, 2010) provides a framework discussing people's psychological and behavioral preferences (Glaman et al., 1996). The MBTI model describes personality based on four dichotomous dimensions: *extraversion vs. introversion*, *sensing vs. intuition, judging vs. perceiving*, and *thinking vs. feeling*. Although people can exhibit features from both types of each dimension, they do tend to lean more toward one personality type. The MBTI has garnered significant attention and application across various academic disciplines, such as management and psychology, over the past decades. Despite its widespread usage, the MBTI has not been exempt from criticisms, particularly concerning its validity (Brown & Reilly, 2009). Nevertheless, multiple reasons can be articulated to support the suitability of the MBTI framework for this present research. First, several scholarly endeavors have underscored the instrument's validity (e.g., Carlson, 1989; Carlyn, 1977). Second, research has showed that MBTI dimensions have a clear overlap and convergence with the popular and widely used Big Five personality traits (the five factor NEO-PI) (Furnham, 1996; McCrae & Costa, 1989). Third, Celli and Lepri (2018) showed in their study that algorithms trained on MBTI-dimensions can have better performances than those trained on the Big Five (based on Twiter data). Given that the current study aims to automate personality predictions using Twitter text, the MBTI presents itself as a fruitful theoretical foundation for this. Fourth, in an empirical research context, Zarouali and Schreuder (2023) recently employed the MBTI framework in their study on targeted advertising, thereby demonstrating its suitability within an experimental communication design (similar to the present study).

In this study, the focus will be on a personality dimension that might be particularly interesting in the context of political microtargeting: the *thinking vs. feeling dimension*. This unique dimension of the MBTI describes how people process information and how they make decisions in their daily life (Sharp, 1987). More precisely, the MBTI (Myers & Myers, 2010) characterizes *thinkers* as being objective, making their decisions based on facts and figures, and following their mind instead of their heart in decision-making situations. On the other hand, *feelers* are described as being subjective, making decisions based on emotions, principles and values. Decision-making processes among feelers are predominantly ruled by heart instead of their mind. People's decision-making process is at the core of political and persuasive communication. Decision-making style has been shown to be a predicator of decision-making behavior (e.g., voting behavior) (2018), and a determinant factor in how the decision process unfolds (Chowdhury et al., 2009; Schwartz et al., 2002). So, understanding how people make decisions after being exposed to a political advertisement is inextricably linked to their own personal decision-making style. Therefore, this study will use the MBTI personality dimension *thinking vs feeling* (which refers to how people make decisions) as a framework in formulating hypotheses about when people will be persuaded by political microtargeting.

3. Hypotheses

3.1. Matching personality with PMT: rational vs. emotional appeal

Political microtargeting often uses appeals to influence the actions and choices of voters (Brader, 2006; Hegazy, 2016; Susser et al., 2019). There exists a long tradition in advertising to focus on cognition and affect, or in other words: *the rational vs. emotional appeal* (e.g., Albers--Miller & Stafford, 1999; Stafford & Day, 1995). An emotional appeal triggers emotions and feelings, such as fear, hope, empathy or guilt (Cutler & Javalgi, 1993), leveraging either positive or negative emotions in order to persuade people for a certain goal (e.g., voting) (De Pelsmacker, Geuens, & Van den Bergh, 2010). On the other hand, a rational appeal is often characterized by objectivity, and usually entails a straightforward presentation of factual and verifiable information that can serve as evaluative criteria (De Pelsmacker, Geuens, & Van den Bergh, 2010; Stafford & Day, 1995).

In this study, we expect the thinking vs. feeling personality dimension to be a viable and effective basis to target rational vs. emotional political advertising appeals. Thinking vs. feeling refers to how people process information and make decisions. It has been a long-standing idea that there should be a congruence between people's information processing style and attitudinal base on the one hand (cognitive – affective), and the predominance of certain appeals advertisements (rational – emotional) (Dastidar & Bhadra, 2017; Dube et al., 1996; Sojka & Giese, 1997). This can be explained by self-congruence theory (DeBono, 2006; Sirgy, 1982) that we have addressed above. In short, this theory posits that people prefer ads that are in line with their self-concept, and thus, are more likely to be persuaded by these self-relevant advertisements.

In line with this idea, Labarbera et al. (1998) adopted the MBTI model in the late nineties to argue that people with a thinking personality might favor arguments in advertisements, while people with a feeling personality type might prefer advertisements that express emotional appeals. This idea has been tested by Ruiz and Sicilia (2004), and they found that information vs. emotional advertising appeals that are matched with consumers' personality style (thinking vs. feeling) can generate more positive attitude toward the brand and increase purchase intentions. Therefore, we expect that the persuasive appeals in political ads might be more effective when the nature of the appeal (rational vs emotional) matches the MBTI personality type of the voter (thinking vs feeling personality). Effectiveness in this study will be measured based on two conventional dependent variables: attitude toward the political party and voting intention. Altogether, we formulate the following hypotheses:

H1a. People with a feeling-personality type will be more persuaded (DV's: party attitude and voting intention) by a political ad with an emotional appeal ad, compared to a political ad with a rational appeal.

H1b. People with a thinking-personality type will be more persuaded (DV's: party attitude and voting intention) by a political ad with a rational appeal, compared to a political ad with an emotional appeal.

3.2. Moderated mediation with ad relevance

Only a limited amount of studies have already investigated potential underlying mechanisms that can explain the effectiveness of matching PMT to a voters' personality traits (Krotzek, 2019; Zarouali et al., 2022). However, results from these studies are rather inconclusive, since the first study did not find significant results (mediators: *emotion, cognition and trust*), and the second study only focused on one mediator (mediator: *message elaboration*). In the field of consumer targeting and personalization, *perceived relevance* has been considered to be one of the most important mediators explaining the effectiveness of tailoring (Aguirre et al., 2015; Kalyanaraman & Sundar, 2006; Rimer & Kreuter, 2006; Vesanen, 2007). Ad relevance can be defined as the degree to which consumers perceive an advertisement to be related to their personal goals, values, and self-concept (Celsi & Olson, 1988). Advertising research has shown that perceived relevance plays an important positive mediating role in the effectiveness of personalized ads in terms of cognitive, affective and behavioral responses (e.g., De Keyzer et al., 2015; Dodoo et al., 2019; Kalyanaraman & Sundar, 2006; Tam & Ho, 2006). This can again be explained by the self-congruity theory (Sirgy, 1982). In a general way, perceived relevance reflects the extent to which the ad contributes to or presents a clear identification of the self-concept being communicated to the target audience (Fleck et al., 2012). This means that that the more congruent the consumers perceive the advertisement to their self-concept (e.g., personality trait), the more likely they are to evaluate the ad as relevant to them (Dodoo et al., 2019). In turn, messages that are targeted to be relevant to the self (-concept) lead to stronger persuasive effects (De Keyzer et al., 2015; Jung, 2017).

Based on this line of reasoning that mainly originates from the consumer communication literature, we expect similar effects for political communication. More precisely, we argue that a political ad based on a rational appeal to be congruent with people that have a thinking personality type, and vice versa with an emotional appeal and people with a feeling personality type; this congruence (or "match") will lead to an increase in perceived ad relevance, which in turn will generate an increase in political persuasion (see Fig. 1 for visual representation of this moderated mediation). In sum, we hypothesize:

H2. When a personality-based political ad is congruently matched with someone's personality, this will lead to an increase in ad relevance, which in turn has a positive impact on political persuasion (DV's: party attitude and voting intention) (moderated mediation).

3.3. Algorithm vs. self-report

As already addressed above, this study will focus on two different methodological approaches to measure the *thinking vs. feeling* personality: 1) a machine learning approach that allows to predict people's personality based on their written text on the social networking site Twitter; 2) a self-report assessment using a survey instrument to capture the MBTI personality types.

To perform the algorithmic personality prediction, we will use participants' *Twitter language*. Social media language and personality are closely related (Schwartz et al., 2013). The way we post things on social media reflects who we are, and how we present ourselves to other people (Berger et al., 2020). Scholars showed that personality can be accurately predicted based on text-based classifiers. A text-based classification algorithm refers to a machine learning technique that can automatically analyze written text and then assign a set of pre-defined categories to that text based on its content; for instance, categories regarding the

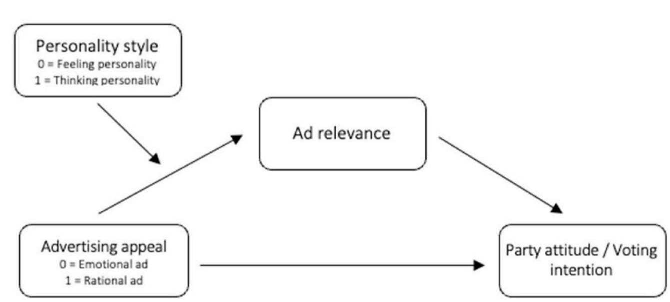

Fig. 1. Conceptual visualization of the moderated mediation model.

personality of an individual (e.g., introvert vs. extravert, feeling vs. thinking, etc.) (e.g., Berger et al., 2020; Park et al., 2015; Schwartz et al., 2013). Based on prior research, it was found that these types of algorithms can sometimes be as (or even more) accurate than humans in predicting these traits (Hinds & Joinson, 2019; Tskhay & Rule, 2014). Automated text-based personality classifiers have the advantage of scalability and enjoy a lesser risk of self-report bias because classifiers use (extant) text as input.

In extant literature on political microtargeting, these text-based personality classifiers have shown potential. Zarouali et al. (2022) used this type of algorithm to score people on introversion/extraversion and showed that people who saw a political ad congruent with their personality were more likely to be persuaded than those who saw an incongruent or neutral ad. However, despite the promise of automated text-based personality profiling, such classifiers received limited validation within communication research. Therefore, this study aims to compare the *thinking vs. feeling* self-report MBTI instrument (Jorgenson, 2015) with our automated text-based classifier. This means that we will collect from each participant text data (as input for the algorithmic MBTI-personality prediction) *and* the self-report MBTI data. This comparison will allow us to explore the results obtained based on these two methods with respect to their similarities and differences in a systemic way. This should lead to valuable methodological insights with regards to the promising nature of using algorithms (as compared to conventional self-report instruments) in (political) advertising research and political campaigns in general.

In sum, we will first test the correlation between the self-report and the automated personality classification. Second, we will examine the extent to which there are differences in results (in the testing of H1a-H1b and H2) when we compare the automated classifier with the self-report. This leads to the following research questions:

RQ1. Is there a significant agreement between the algorithmic classifier and the self-reported measure?

RQ2. Are there differences in the results related to H1a-H1b & H2 when comparing the algorithmic classifier vs. self-reported measure?

4. Methods

4.1. Design & sample

This study used a 2x2 between-subjects factorial design, with *type of advertisement* (rational vs emotional appeal) and *type of personality* (thinking vs feeling personality) as factors. In pior literature (see Zarouali et al., 2022), it has been argued that effect sizes for these type of "personality matching effects" tend to be small to moderate. Based on this knowledge, we conducted an a-priori power analysis with G*Power (Faul et al., 2007), with a significance level of $\alpha = 0.05$, an effect size of $d = 0.35$, and a statistical power of $(1-\beta) = 0.80$. This analysis suggested a total sample size of 259 participants.

This experiment was preregistered via the OSF framework. The preregistration is accessible via this link[1]. Participants were recruited by a Dutch research company specialized in recruitment for academic purposes. Data collection took place in June–July 2021. We requested the panel company to recruit Dutch citizens who met the following criteria: they should be evenly distributed by gender, possess an education level representative of the Netherlands, be aged between 25 and 40 years, be familiar with Twitter, and have a centrist political orientation (see below for more information about the measures used). The sample consisted of 376 participants who completed the survey. After removing participants who did not follow instructions correctly (e.g., people who refused to write tweets, people who wrote the same text in all six tweets, people who wrote nonsense such as "blablabla", etc.), the sample consisted of 280 participants. In total, 63.44 % of the sample was female. Regarding education, 4.64 % was low educated, 36.43 had a moderate education, and 58.93 % had a high education. We aimed for a younger and higher educated sample because of two reasons: i) the algorithmic prediction of personality was based on Twitter text, so we needed participants that were active on this platform, which are typically younger and higher educated people (Blank, 2017; Mellon & Prosser, 2017); ii) younger and higher educated people increased the likelihood that the advertisement that we used in this study (i.e., a political ad about the problems that first-time buyers experience on the housing market because of skyrocketing prices) would resonate with the audience. The mean age in the sample was 32.48 ($SD = 4.29$; min = 25, max = 40). Similar to the approach of Zarouali et al. (2022), we aimed for a sample that positioned themselves in the political center, because this study adopts an ad promoting a centrist party, which are most likely targeting people in the center of the political spectrum (i.e., targeting the "persuadables", which are more likely to be influenced by a centrist party). This mirrors the strategy of real political advertisers, who usually target people who are perceived to be open to the specific political message, rather than targeting a broad heterogeneous group of people (e.g., Dobber et al., 2017).

When it comes to political orientation, participants saw a screening question that asked for their left-right political orientation on a scale from 1 to 11. The participants who scored 4, 5, 6, 7 or 8 were selected ($M = 6.15$; $SD = 1.35$). Moreover, because the study asked participants to write tweets, only participants who were familiar with Twitter were selected in the sample. This was measured with the following question on a 5-point scale: *To what extent are you familiar with Twitter*? Participants who scored 3 or higher were selected ($M = 4.07$, $SD = .78$).

4.2. Procedure

After answering demographic questions, all participants were asked to write six tweets about current topics in June–July 2021 (i.e., UEFA European football championship, Eurovision Song Festival, the current political coalition formation in the Netherlands, the COVID-19 pandemic, summer vacation plans, their opinion about the last television show they watched). This number (six tweets) was chosen because a recent study by Zarouali et al. (2022) showed that it is possible to predict respondents' personality with roughly 100 words based on a personality profiling algorithm. With six tweets, we managed to get around 100 words per participants. The text in these tweets served as input for this study's algorithmic classifier to predict personality (see *Type of personality* paragraph below). However, as this study aims to compare the algorithmic classifier with the MBTI self-report instrument (Myers & Myers, 2010), all participants were also asked to fill in the MBTI-items. This MBTI inventory was presented after participants wrote their tweets. After the MBTI-questions, participants were exposure to the experimental stimulus (emotional appeal ad or rational appeal ad). The stimulus was displayed as an individual screenshot, consistent with the presentation found in the Appendix. It is important to note that participants accessed the study exclusively via desktop (to avoid device effects). Stimulus exposure was followed by the dependant variables, the mediator variable, the realism check and the suspicion probe. After finishing the experiment, participants were debriefed.

This experimental protocol has been approved by the ethical review board of our institution (ethical review board number: 2021-PC-13732).

5. Independent variables

5.1. Type of advertisement (rational versus emotional)

The advertisement promoted a Dutch center-progressive party (D66) on Facebook. The ad focused on a salient issue in the Netherlands: the shortage of available and affordable houses. According to recent polls in the Netherlands, the housing market was by far the most important issue

[1] https://osf.io/me2tn/

for younger people (between 18 and 34 years old) (Harmsen, 2022). The image that we used in the ad was held constant in both conditions, but the text differed. In the rational appeal condition, the text read: *The tightness experienced by first-time buyers in the housing market is due to a shortage of affordable housing. So it is logical to build 1 million homes over the next decade to solve this problem.* In contrast, the emotional appeal condition read: *First-time homebuyers are groaning from the tightness they are experiencing in the unfair and deeply frustrating housing market. We are alleviating their suffering by building 1 million homes for them over the next decade*. See Appendix for both ads. Both ads were pre-tested based on a convenience sample ($N = 20$). The pretest showed that the thinking ad was indeed perceived significantly more appealing to cognition ($M = 5.55$, $SD = 0.89$) rather than emotions ($M = 2.55$, $SD = 1.19$) ($t(19) = -8.27$, $p < .001$). The emotional ad was perceived to be significantly more appealing to emotions ($M = 6.20$, $SD = 1.01$) than cognitions ($M = 2.50$, $SD = 0.83$) ($t(19) = 11.38$, $p < .001$).

5.2. Type of personality (thinking vs feeling): self-report measure

Participants were classified on the thinking versus feeling personality dimension of the Myers-Briggs Type Indicator by means of the Open Extended Jungian Type Scale (Jorgenson, 2015). The measurement contains eight pairs of personality descriptions (i.e., items) connected by a five-point scale. For example: *follows the heart* vs *follows the mind*, or *strives for the respect of others* vs *strives for the love of others*. Based on the scorings, we conclude that 49.3% of the participants had a predominant feeling personality, 50.7% of the participants had a more thinking personality.

5.3. Type of personality (thinking vs feeling): algorithmic classifier

Next to the MBTI self-report items, this study employed an automated personality classifier that used their written tweets as input (see *Procedure* paragraph above). Based on these tweets, predictions of the thinking vs. feeling personality types of the participants were made using an algorithm that was developed for this study. The algorithm utilized a machine-learning (ML) model that was trained on correlates between linguistic cues and MBTI personality traits to predict the thinking vs. feeling dimension of participants as outcome variable. To assess linguistic cues in both the tweets written by participants and the text used to train the ML model, the LIWC2015 classification algorithm (Pennebaker et al., 2015) was used. The LIWC2015 is a Natural Language Processing (NLP) tool that outputs the percentage of words in a given text that fall into categories of the *Linguistic Inquiry and Word Count* (LIWC) dictionary (Pennebaker et al., 2003): a collection of over 80 linguistic (e.g. first person singular pronouns), psychological (e.g. positive emotions) and topical (e.g. money, religion) classifications for words. In exant literature, many studies found that personality traits were significantly correlated with the LIWC categories (e.g., Lee et al., 2007; Mairesse et al., 2007; Yarkoni, 2010).

The regression-based ML model was trained to predict the thinking vs. feeling dimension as a dichotomous outcome variable (0 = feeling, 1 = thinking), using the LIWC categories as input. Linear regression can successfully assign class labels based on a threshold value on fitted values (in this case 0.5). Both linear and logistic regression models were tested, but since the goal of the model was predictive accuracy and the linear model consistently outperformed the logistic model, the former was selected for this study.

The final dataset that was used to train the model contained MBTI categories of 21747 individuals and their written texts, with an average word count of 2286. The texts in the dataset originated from multiple online sources: tweets that were scraped from Twitter based on the Twisty corpus ($N = 807$, mean $WC = 22223$, Verhoeven, Daelemans & Plank; 2014), posts from users active in the r/MBTI subreddit that were scraped from Reddit ($N = 12265$, mean WC = 1690), and a dataset found on Kaggle, consisting of texts from users of the online forum PersonalityCafe ($N = 8675$, mean $WC = 1273$). We then proceeded to clean the text. Since the LIWC2015 dictionary does not allow for the analysis of symbols, the text was cleaned by removing emoticons, pictographs and other symbols (e.g., Chinese characters) in addition to hashtags, mentions and links. After this, the LIWC categories were extracted using the LIWC2015 dictionary.

The thinking vs. feeling variable was extracted from the MBTI categories, revealing a distribution of 47,6% thinkers and 52,4% feelers in the sample. To determine the accuracy of the model, the dataset was split into a train-dataset ($N = 17\,397$), and a test-dataset ($N = 4349$). A regression ML model was then trained on the train-dataset and applied to the test-dataset, predicting the thinking vs. feeling dimension with an accuracy of 72.5%. The ROC curve had an AUC value of 0.72, which is within an acceptable range. The model was then trained with the complete dataset, to be applied to the tweets collected for the experimental study.

Before cleaning and applying the LIWC2015 algorithm to the texts written by the participants of the study, the tweets were manually examined. Duplicate text and/or random characters (e.g., "asdfe") were removed from the tweets of 41 participants, and 8 participants were removed from the dataset due to unusable tweets. The average word count in the final dataset was 179 words. This number of words is sufficient, since the study by Zarouali et al. (2022) showed that it is possible to predict personality with 100 words or less. The ML model was then applied to the dataset, predicting a distribution of 57.6% feelers and 42.4% thinkers. The (Python) scripts used for this algorithmic approach can be found in the OSF pre-registration page[1].

6. Dependent variables

6.1. Voting intention

Participants' intention to vote for the party that sponsored the advertisement was measured using a single-scale item from Zarouali et al. (2022): *how likely is it that you will vote for D66 in the future?* This item was presented on a 7-point Likert scale, with answer options ranging from *very unlikely* to *very likely* ($M = 3.41$, $SD = 1.82$).

6.2. Attitude toward the political party

Following Seltzer & Zhang (2010), this study used two items to measure participants' attitude toward the party. Participants scored the political party D66 on a 7-point bipolar scale with the items *negative/-positive* and *dislike/like* ($M = 3.78$, $SD = 1.68$, Cronbach's alpha = .97).

6.3. **Ad relevance**

This variable is considered as a mediator and was measured using three items from Williams and Drolet (2005): *The ad was meaningful to me; the ad was important to me; the ad was relevant to me*. These three items were presented on a 7-point Likert scale with answer options ranging from *strongly disagree* to *strongly agree*. The items were averaged to form a scale ($M = 3.80$, $SD = 1.66$) with a Cronbach's alpha of .93.

7. Results

7.1. Randomization check

When we used the algorithmic approach to measure participants personality, we found a good distribution of participants across the different conditions: condition 1 (thinking personality – emotional ad; $n = 62$), condition 2 (thinking personality – rational ad; $n = 56$), condition 3 (feeling personality – emotional ad; $n = 77$), condition 4 (feeling personality; rational ad; $n = 85$). In addition, we conducted a between-condition randomization check at the outset of the analyses. This showed that the conditions did not differ with respect to age, $F(3, 276)$

= 1.05, p = .37, gender, $\chi^2(3) = 2.55$, p = .47, education, $\chi^2(6) = 6.25$, p = .40, and political orientation, $F(3, 276) = 0.51$, p = .68. When we used the self-report assessment to classify people's personality, we also found an even distribution across contitions: condition 1 (thinking personality – emotional ad; n = 71), condition 2 (thinking personality – rational ad; n = 71), condition 3 (feeling personality – emotional ad; n = 68), condition 4 (feeling personality; rational ad; n = 70). Furthermore, the randomization check revealed that there were no significant different between the conditions in terms of age, $F(3, 276) = 0.66$, p = .58) gender, $\chi^2(3) = 4.71$, p = .20, education, $\chi^2(6) = 5.65$, p = .46 and political orientation, $F(3, 276) = 0.93$, p = .43.

7.2. Realism and suspicion check

The realism check (measured on a 7-point Likert scale) revealed that participants evaluate both the experimental protocol (M = 4.34, SD = 1.69) and the advertisements as moderately realistic (M = 4.00, SD = 1.75). In addition, we analyzed all the answers participants gave on the (open-ended) suspicion probe, and we conclude that no one was aware of the true purpose of the study.

7.3. Moderation effects

To test the interaction in H1a & H1b, we relied on analyses of variance (Type III) in SPSS with personality type and ad type as factors, and party attitude and voting intention as dependent variables. We ran these analyses twice, first with the algorithmic assessed personality type, followed by the self-reported personality type.

Based on the algorithmic approach, the two-way interaction was not found to be significant for attitude toward the political party, $F(1, 276) = 0.43$ p = .51, ηp = 0.00, nor voting intention, $F(1, 278) = 0.68$, p = .41, ηp = 0.00. This means that the congruence hypotheses between personality and advertising appeal was not supported based on algorithmic-predicted personality as a factor. However, when we ran the exact same analyses with the self-reported personality assessment, different results were obtained. With the self-report measure, we found a significant interaction effect between personality and ad appeal for both party attitude, $F(1, 276) = 4.97$, p = .03, ηp = 0.02, and voting intention, $F(1, 276) = 4.75$, p = .03 ηp = 0.02. The nature of this significant interaction was further analyzed with simple main effects, which allows us to determine the effects of one independent variable at different levels of the other independent variable (see Fig. 2 for a visualization of this interaction).

These analyses revealed that people with a feeling personality had a more favorable attitude toward the political party after being exposed to the emotional ad (M = 3.76) compared to the rational ad (M = 3.17), $F(1, 276) = 4.40$, p = .04, ηp = 0.02. The same results were found for the dependent variable voting intention: for people with a feeling personality, exposure to an emotional ad (M = 3.46) led to higher voting intention than a rational ad (M = 2.69), $F(1, 276) = 6.49$, p = .01, ηp = 0.02. Thus, H1a can be supported only based on the self-report assessment of personality (and not with the algorithmic method of personality prediction).

For people with a thinking personality score, we did not find a significant difference in party attitude after exposure to either a rational ad (M = 4.23) or an emotional ad (M = 3.94), $F(1, 276) = 1.10$ p = 30, ηp = 0.00. The same non-significant pattern was found for the dependent variable voting intention: there was no difference between exposing thinking-style people to a rational ad (M = 3.82) vs. an emotional ad (M = 3.66), $F(1, 276) = 0.27$, p = 60, ηp = 0.00. Thus, H1b can be rejected.

7.4. Moderated mediation effects

To test H2 (see Fig. 1), we used PROCESS to estimate conditional indirect effects (Model 7 – BC 95% confidence intervals) (Hayes, 2013). When using the algorithmic approach to classify people's personality, we could not establish a significant moderated mediation relationship for the DV's attitude toward the political party (b = −.26, S.E. = 0.22; BC 95% CI [-0.682 to 0.176]) and voting intention (b = −0.27, S.E. = 0.23; BC 95% CI [-0.745 to 0.169]). Thus, the moderated mediation hypotheses could not be supported based on the algorithmic method.

However, similar to the previous analyses, we did find significant effects when using the self-reported personality classification instead. The PROCESS-output can be found in Table 1. More precisely, with attitude toward the party as a dependent variable, results yielded a significant index of a moderated mediation model (b = 0.46, SE = 0.22; BC 95% CI [0.029–0.892]). A closer inspection at the conditional indirect effects revealed interesting findings. On the one hand, participants with a feeling personality generated more favorable party attitude *only* when they were being exposed to a political ad with an emotional appeal, via ad relevance as a mediator (b = 0.31, SE = 0.14; BC 95% CI [0.033–0.596]). On the other hand, participants with a thinking personality did generate higher attitude toward the political party via ad relevance as a mediator *only* in the condition when they saw a rational ad (b = 0.31, SE = 0.14). When participants with an emotional personality where exposed to a rational ad, no significant effect was found on increasing party attitude via ad relevance (b = 0.29, SE = 0.12). The same results were found when voting intention was used as a dependent variable. Participants with a feeling personality had a significant higher voting intention (via ad relevance) only when there were exposed to an ad with an emotion appeal (b = 0.36, SE = 0.14); participants with a thinking personality had an increased voting intention *only* after exposure to a rational ad (b = 0.32, SE = 0.15). So based on these results, we can conform H2 based on the self-report assessment (but not based on the algorithmic prediction).

7.5. Self-report vs algorithmic approach

To assess the level of agreement between the self-report measure of personality and the algorithmic classifier (RQ1), we used a

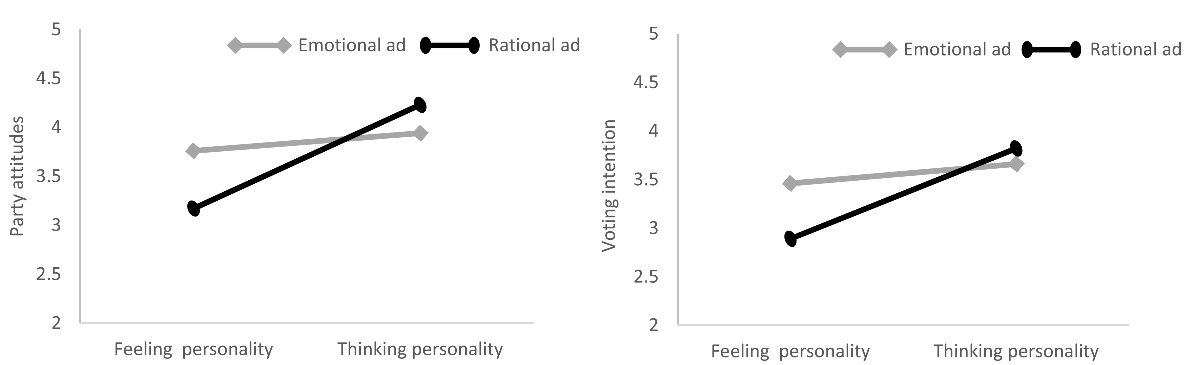

Fig. 2. Visualization of the interaction effects.

Table 1
OLS-regression coefficients for the moderated mediation model (with the self-report classification).

	Model 1		Model 2			
	Ad relevance		DV: Party attitude		DV: Vote intention	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Constant	3.74***	0.20	1.87***	0.23	1.48***	0.25
Ad condition (0 = emotional ad, 1 = rational ad)	−0.28	0.28	−0.23	0.17	−0.39*	0.19
Personality (0 = feeling, 1 = thinking)	−0.03	0.28	–	–	–	–
Ad cond * Personality	0.86*	0.39	–	–	–	–
Ad relevance	–	–	0.53***	0.05	0.56***	0.06
	$R^2 = 0.03$		$R^2 = 0.28$		$R^2 = 0.27$	
	$F(3,276) = 3.15$*		$F(2,277) = 54.12$***		$F(2,277) = 50.78$***	
			ModMed index: b = 0.46, SE = .22; BC 95% CI [.029–.892]		*ModMed index: b* = .31, SE = .14; BC 95% CI [.033–.596]	

*p < .05; **p < .01; ***p < .001.

crosstabulation approach to investigate the relationship between these two nominals (dichotomous) variables. To quantify the level of agreement between these two methods, Cohen's Kappa statistic was computed, resulting in a value of $\kappa = 0.26$ ($p < .001$). Based on the conventional benchmarks established by Landis & Koch (1977), this positive Kappa value suggests a "fair agreement" beyond what might occur by chance, emphasizing a slight alignment between the self-reported measure and the algorithm's classifications. This statistically significant agreement between the algorithmic classifier and the self-reported measure provides an answer to RQ1. With regards to RQ2, the analyses earlier already showed that the hypotheses could only be supported when the self-report method was used. Thus, the answer would be: yes, there are clear differences in the results related to H1a-H1b & H2 when comparing the algorithmic classifier with the self-reported personality. The implications of this finding will be further discussed in the general discussion below.

8. General discussion

In this study, we set out to address three important questions: i) is personality-based political microtargeting effective in influencing citizens attitude toward the political party and voting intentions? ii) can digital trace data (i.e., text data) and machine learning techniques be used in the context of personality-based political microtargeting? and ii) how does this differ from a self-report approach? As such, the results of this study add valuable contributions to the literature in three different ways.

First, this study showed the extent to which personality-based persuasion efforts can be successful when based on the *thinking versus feeling* MBTI personality dimension (Myers & Myers, 2010), and the extent to which *ad relevance* serves as a mediator (important note: this only holds for personality classifications that were made based on self-report measure; this will be addressed in the next paragraph). More precisely this study finds that the thinking versus feeling personality dimension is a somewhat promising characterization for political persuasion efforts. In line with self-congruity theory (Sirgy, 1982), citizens might be more affected by an emotional political ad (vs rational) that is congruent with their feeling personality (vs thinking), and ad relevance serves as a mediator that explain this increased effectiveness of certain ad types among certain personalities. Although these "congruence effects" (i.e., the "match-up" hypothesis) have received considerable scholarly attention in the area of consumer advertising, scientific evidence in the field of political communication is still very limited and in need of a wider body of research and knowledge (see Zarouali et al., 2022). Therefore, this study adds valuable insights to the literature of political advertising by showing a previously unexplored congruence-effect between people's feeling personality style on the one hand (a personality style that has received little academic attention, although it represents an important dimension in how people make decisions), and the presence of emotional appeals in political advertisements (see Dastidar & Bhadra, 2017; Dube et al., 1996; Sojka & Giese, 1997).

In addition, this study also found that perceived relevance operates as the underlying mechanism (or mediator) in this congruence effect. It has been a long-standing idea within consumer advertising research that information that is perceived as personally relevant has a higher chance of being persuasive (Aguirre et al., 2015; Jung, 2017; Kalyanaraman & Sundar, 2006; Rimer & Kreuter, 2006). However, in political communication, perceived relevance is less explored as a construct, raising important questions about its exact role and effect. This study shows that personality-congruent political communication on social media can indeed be effective and persuasive when they are perceived by people as more personally relevant.

Second, we found that algorithmic classifiers based on Twitter text are relatively straightforward and easy to use to predict people's personality traits. By "easy to use", we highlight the procedural and methodological simplicity of using an algorithm for personality prediction purposes, rather than its accuracy within this specific study. Because indeed, it is worth noting that the algorithmic approach in this study did not lead to results that support our hypotheses. Nonetheless, we believe that with more extensive training data, such text classification algorithms can serve as valuable tools for modeling personality traits. Particularly in the realm of political campaigners, who typically have access to larger datasets, our findings underscore that Natural Language Processing and machine learning algorithms could potentially be used as a tool to model latent psychological traits such as personality (Berger et al., 2020; Hinds & Joinson, 2019; Park et al., 2015). With these larger amounts of data, algorithmic predictions generally become more accurate, and thus, potentially more effective in persuading voters. Our study distinctly advances the work initiated by Zarouali et al. (2022), who showed the potential of personality-classifying algorithms in bolstering political persuasion. A significant difference in our research approach lies in our algorithmic methodology. While Zarouali et al. (2022) used an algorithm sourced from an AI-technology firm (i.e., Textgain), we undertook the rigorous task of developing our own algorithm tailored to predict personality, granting us a more comprehensive insight into its training, nuances, and functioning. In addition, this personality classifier exhibited a significant fair agreement with the self-reported personality measure, underscoring its potential validity and utility in the field. This more detailed grasp of the algorithm's intricacies, coupled with its fair agreement with traditional self-reporting methods, underscores the value and unique contribution of our research approach in the broader academic discourse.

Third, despite observing a significant agreement, we also found substantial differences between the algorithmic classifier and the self-report measure. As previously noted, we found no significant effects in testing our hypotheses when the machine learning approach was used, whereas hypotheses were supported when using the self-report measure. Methodologically, this appears to indicate the self-report measure's superior performance over the algorithmic classifier, particularly with a limited number of data points per participant (i.e., low amount of text data per participant). With a larger text data sample, outcomes might vary. Yet, our research underscores that the *gold-standard method* for acquiring personality assessments in political advertising research remains the collection of questionnaires directly filled out by participants (see Hinds & Joinson, 2019). Nonetheless, our work offers a valuable and transparent contribution for researchers keen on exploring personality measurements rooted in the promising methodology of analyzing (social media) text. We have documented our methodology and made it publicly available on OSF[1].

The underwhelming performance of this study's automated personality classifier also suggests that, while the threat of automated personality classification is real (see Zarouali et al., 2022), the scalability of the technique might not be easily achieved. Annotated training datasets are sparse, which makes it challenging to improve performance of the *thinking vs. feeling* classifier. While *NLP* techniques develop quickly, getting a well-performing personality classifier still requires a lot of (hard-to-get) training data. From a societal perspective the sub-optimal scalability of existing classifiers on the one hand suggests that the large-scale use of text-based personality classifiers might not be happening soon. On the other hand, the persuasive power of personality-based targeting (which we found based on the self-report results) suggests that investing in training a well-performing classifier could be worthwhile for political actors. However, using text that people have left behind at some point on Twitter (or other social media) to influence them in the future, without those people knowing that they are being shown political ads based on their past social media behavior can be considered manipulative (Susser et al., 2019). Recent work on *inoculation* against personality-based microtargeting (Lorenz-Spreen et al., 2021) does show some promise in decreasing the information asymmetry between advertiser and citizen by improving people's capabilities of recognizing personality-based advertising (and its persuasive intent). Building upon Lorenz-Spreen et al. (2021) who found that prompting individuals to reflect about their personality (e.g., thinking vs. feeling, or introvert vs. extravert) boosts their ability to recognize microtargeted advertising more accurately, our study offers a distinct contribution. Specifically, our methodology uncovers the nuanced ways in which advertisers can use past online data (in this context, written text on social media) to build targeted personality profiles. By detailing these mechanisms, we aimed to clarify how past actions can be repurposed into predictive personality models by advertisers. Consequently, prompting users to reflect about these processes offers them a clearer window into how they may be influenced in advertising campaigns. This awareness forms a critical step towards equipping users to 'inoculate' (McGuire, 1961) themselves or activate their 'persuasion knowledge' (Friestad & Wright, 1994). In theory, an informed individual is better positioned to resist subsequent microtargeted persuasive efforts. However, for these countermeasures to be truly impactful on a broad scale, they must be integrated into a comprehensive policy approach that addresses the unfair facets of political advertising.

While this study contributes to our understanding of the effects of personality-based targeting and of the potential of automated personality classification, there are notable limitations. First, participants were forced to write tweets while they normally might not be inclined to do so. Or they would be more likely to write about different issues. So future research might consider using a similar methodological setup, but instead, use participants' real tweets as input data. This can be done, for instance, with a data donation approach where you can ask people to download their data from online platforms (e.g., all their tweets, posts, etc.), and subsequently voluntarily donate their data (Boeschoten et al., 2022).

Second, it is important to acknowledge the main limitations of the dictionary-based LIWC approach used in this study. Although LIWC analysis has shown to be very useful for examining a number of psychological characteristics, it still examines word usage only, and thus, is not being able to take into account both the context that words are placed in and the different meanings they might hold (in different situations) (Biggiogera et al., 2021; Hirsh & Peterson, 2009). In addition, LIWC's analytic power highly depends on the accuracy and comprehensiveness of the dictionary they are based upon, thus following a "closed" approach to text analytics (Schwartz et al., 2013). Therefore, we encourage advertising scholars to also explore different (more advanced) machine learning models for the purpose of personality detection (for an overview, see Mehta et al., 2020).

Third, it is also important to highlight the criticism from the academic community concerning MBTI. Stein and Swan (2019) argued that the MBTI falls short on rigorous theoretical criteria in that it: (1) lacks agreement with known facts and data, (2) possesses internal contradictions (internal consistency problems), and (3) lacks testability (the ability to generate empirical predictions). Based on these arguments, the authors concluded that despite its popularity, the MBTI might not be a suitable framework for understanding personality. Although some of the main criticisms regarding MBTI have already been addressed (e.g., Kerwin, 2018; The Myers-Briggs Company, 2018), we still believe that the critique is something that needs to be acknowledge and taken into account in future research endeavors.

Fourth, our sampling strategy also merits some comments. That is, our narrow sample (younger, and higher-educated people, who are familiar with Twitter) also limits the generalizability of the findings. Future research could focus on a different societal segment to increase our knowledge about this important and timely topic. Furthermore, we narrowed down our scope to people with centrist political views for reasons of feasibility. A broader sample would require a more sophisticated design with different ads from different political advertisers/ parties, which would make the comparability between groups more complex. Additionally, we build upon the work of Zarouali et al. (2022) who previously concentrated on samples from both left and right-leaning orientations, demonstrating the potential impact of personality-congruent microtargeting among these groups as well.

Fifth, we could not measure party preferences and topic interest because this might have impacted the (unbiased) measurement of our dependent variables. In this regard, Vecchione et al. (2011) showed that the personality traits openness and conscientiousness might correlate with party preferences, and thus might serve as a confounder. However, since our participants were successfully randomized across conditions (with political orientation being evenly balanced across these conditions) we are confident that the potential confounding impact is minimal.

In conclusion, we believe this study adds relevant insights to the political microtargeting literature. First, based on the self-congruity theory, this study showed a significant congruence effect between personality and ad appeal, and revealed that perceived ad relevance was serving as the underlying mechanism. Second, this research also compared a self-report and machine learning approach to personality-based political microtargeting, and found important differences between the two methods, which lead to timely methodological contributions.

CRediT authorship contribution statement

Brahim Zarouali: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. **Tom Dobber:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. **Jurrian Schreuder:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2023.108024.

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