Personality and Political Participation on Twitter:  
A Study of the E-expressive Mode
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1 Introduction

At the heart of democratic theory is participation; it is broadly considered a defining and essential element of the democratic citizenship (Verba and Nie, 1972; Dalton 2008). However, when our notion of democracy and citizenship changes, so does the idea of what constitutes political participation. Today, one could argue that the repertoire of political participatory acts has grown. Technological development has partly caused this expansion, offering new arenas to political participation, such as the Internet.

For years, political participation research has theorized about what factors affect political participation. Many social scientists study structural factors, for instance, socioeconomic status. But there are also those who focus on individual-level explanations. Scholars of Political Psychology often belong to the second group, exploring, e.g., personality as a factor using the Big Five Model.

The Big Five Model is a comprehensive classification scheme for personality traits. It is based on the assumption that our personalities have become encoded in our language. The model distinguishes five global factors, or trait domains, that are said to account for most variation in personality (Peabody and Goldberg, 1989; McCrae and Costa 2008). Personality research show that the trait domains relate differently to different forms of participation, e.g., some research finds that Extraversion is positively related to canvassing but that there is a negative association between Agreeableness and campaign-related activities (Mondak et al. 2010; Gerber et al. 2012).

Since the Internet was put into the public domain in the 1990s, online political participation of several kinds has become more and more common. With these emerging and increasingly important participatory forms, one may wonder: Does this change who participates in politics? When political participation sets on to a new arena, who follows? Although much has been done on the Big Five Model and political participation, there is considerably less research on the Big Five Model and online political participation. The merits of the research that does exist are indeed many. Yet, the field could gain from more empirical evidence. The first aim of my thesis is thus to provide more empirical results on the relationship between personality and online political participation.

Secondly, I use data from the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands)\(^1\). The LISS panel is one of the few databases to collect data on the Big Five Model. To the best of my knowledge, there is no study combining the datasets, and, using a

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\(^1\) (for more information, see LISS: https://www.lissdata.nl/about-panel and the Methodology section).
Dutch sample, my thesis may also add to the knowledge on cross-national variation of the relationship between personality and online political participation.

Last, but not the least, I employ a different operationalization. Gibson and Cantijoch reiterate Dalton’s claim that more and more people are turning away from official modes of participation in favor of more expressive ones. They also argue that, at the same time, technological change is transforming political participatory forms that we used to consider passive into more active forms. According to Gibson and Cantijoch, on the Internet, expressive activities become more collective, active, and networked (Gibson and Cantijoch 2013). For these reasons, I find it especially interesting to focus on expressive modes of online political participation. By zooming in on Twitter, a social network site that I argue emphasize expressive political participation, I explore how personality relates to expressive modes of online political participation in particular.

**Research question:**
How do the Big Five trait domains relate to political participation on Twitter?
2 Previous Research

2.1 Definitions of Political Participation

2.1.1 A Conceptual Expansion

Political participation has been a highly popular research subject among political scientists in the last 70 years or so. Perhaps the vast array of studies made on the topic also prove how difficult it is to define the concept. Some argue that this is because political participation is so inseparably linked to our notion of democracy and citizenship, two concepts whose meanings tend to shift across time and space.

For a long time, participation research was all about studying the electoral process, reflecting the stronghold representative democracy was in Western democracies. Electoral participation was seen as the citizen’s main road to political influence and political activity in-between elections as well as outside the polling stations was largely disregarded (Ekman and Amnå 2012; van Deth 2001). Then in the 1970s, things began to change. In their seminal book Participation in America, Sidney Verba and Norman H. Nie defined participation as “those activities by private citizens that are more or less directly aimed at influencing the governmental personnel and/or the actions that they take” (Verba and Nie 1972, p. 2). They thereby made the repertoire of political participatory acts more extensive and the arenas where such acts could take place more numerous. (Teorell, Torcal and Montero, 2007).

Although Verba and Nie expanded the concept of political participation, they still confined the definition to the governmental sphere. There was no room for, e.g., demonstrations or civil disobedience. In 1979, however, Samuel H. Barnes and Max Kaase with associates published a comparative study of political action in five Western democracies. The focus of the study was “unconventional” forms of political participation. The authors argued that changing values and outlooks had altered and would continue to alter the content of political participation (Budge 1981). Now political participation could include activities not only taking place in-between elections but also located outside the traditional government arenas such as strikes, protests, etc. (Conge 1988; Teorell, Torcal and Montero 2007; van Deth 2001).

When the interest in deliberative and direct democracy grew stronger, the focus of some political participation shifted. Although previous definitions had not required political participation to occur in the government sphere, they were still aimed at those who occupied it. With the emerging forms of political participation, it became more common to target actors outside of the government sphere, e.g., organizations, companies. Therefore, definitions that regarded political
participation only to be directed towards politicians or elected public officials did no longer suffice. In 1998, Henry E. Brady defined political participation as “action by ordinary citizens directed toward influencing some political outcomes”. With this definition and the likes of it, political participation could be seen as occurring outside of the government sphere and also be directed towards non-political figures. What matters here is that the participants aim for their actions to have political consequences.

In the early 1990s, the Internet was put into the public domain. As computers became a standard piece of property and access to the Internet widespread, political participation found its way onto the new arena. When online political participation rose in importance, academia became interested in understanding the "true nature" of online political participation and how to best define and classify political activity in cyberspace. Is it a different mode from offline participation, and what sub-modes constitutes it?

2.1.2 Online Political Participation: A Distinct Set of Modes?

Today, there are still mixed opinions on this matter. Some research suggests online and offline participation should be regarded as different modes, often referring to the so-called mobilization hypothesis (see, e.g., Oser 2013). According to the mobilization hypothesis, online political participation should be regarded as a distinct mode or set of modes because it mobilizes different socio-demographic groups. Others instead focus on the makeup of the participatory acts. In the article “Beyond the Online/ Offline Divide: How Youth's Online and Offline Civic Activities Converge” (2011), Hirzalla and van Zoonen, e.g., claim that we ascribe too much importance to the matter of place. Hirzalla and van Zoonen are skeptical of treating online activity as one or one set of variables and offline as a different. Such a theoretical separation is solely built on the idea of spatial division and does not take into regard the nature of the activities themselves. Their results suggest that political participation among youth is relatively dependent on mode but rather independent of place. (Hirzalla and van Zoonen 2011).

Nevertheless, in my opinion, the article “Conceptualizing and measuring participation in the age of the Internet: Is online political engagement really different to offline?” (2013) by Gibson and Cantijoch stands out. Gibson and Cantijoch study the underlying structure of online political participation and how it relates to offline political participation. They conduct a confirmatory factor analysis using survey data from the U.K. General Election of 2010 and discern four modes which they call e-party, e-targeted, e-expressive, and e-news. E-party describes the mode that relates primarily to electoral campaigns and party activity such as registering as a member of a party, supporting a party on a party’s website, or accessing party tools. E-targeted includes more “traditional” online political activities, such as contacting a government official, signing a petition, donating money to a party, or a political cause. E-news refers to reading online newspapers,
blogs, watching video clips online, etc., anything that includes political news and can be consumed through online news sources. Finally, e-expressive captures modes that relate to discussion or expression of political content and takes place mainly on social media, where e-expressive activities such as posting, forward, or embedding political messages or engaging in discussion in the comments. (Gibson and Cantijoch 2013; Russo and Amnå 2016)

Gibson and Cantijoch find that all the sub-modes replicate or correspond to sub-modes of offline political participation. However, only some modes merge across spheres. For example, when it comes to more active or targeted types of activity, such as contacting a politician or signing a petition, people tend to use online and offline modes alternately and interchangeably. However, medium matters more for activities that fall under e-news and e-expressive because online they are taking on a more active, collective and networked quality than offline. Gibson and Cantijoch write: “Posting one’s opinion to a blog or a social network site arguably makes a more immediate and potentially influential public statement than wearing a lapel badge. For news consumption, the greater opportunities available in the online sphere for individuals to seek out sources and share them with others may also be leading to an “upgrading” of this mode of engagement into a more active participatory form.” (Gibson and Canitjoch 2013, p. 714). In other words, the birth of social media may be encouraging more active forms of political activity to emerge from formerly considered passive ones. That means that although sub-modes online often mirror those offline, a few are actually being transformed due to medium. Thus, Gibson and Cantijoch argue, what makes online political engagement to some degree different from offline is this particular transformation of the modes e-expressive and e-news. (Gibson and Canitjoch 2013)

I find Gibson and Cantijoch’s arguments convincing, and therefore, adopt their view of online political participation being a different mode and make it a departure point for this thesis. Gibson and Cantijoch’s framework also captures shifts in democratic ideals and participatory modes with, e.g., modes such as e-expressive. Furthermore, it sheds new light on how technological change might intensify political influence, with the “upgrading” of e-expressive and e-news. I also find their taxonomy appealing and decide to use it. The peculiarity of expressive activities online, perhaps becoming more active, collective, and networked in quality, makes e-expressive and e-news especially interesting modes to study. For reasons that will become clear later, I will choose to study online e-expressive only. Focusing on the e-expressive mode, however, requires a more inclusive definition of political participation. Brady’s definition fits: e-e-expressive can occur in-between elections, outside the traditional government sphere, includes unconventional forms of political participation, and is not only directed towards politicians or public officials but rather aimed at influencing political outcomes.
2.2 Political Participation in Political Psychology

2.2.1 The Big Five Framework

A fundamental idea in trait psychology is that people can be described based on their patterns of thoughts, emotions, and actions and that individual-level variation in traits can be empirically assessed (McCrae and Costa 2008). For years, scholars devoted much time to studying specific traits. But the field was missing a comprehensive classification scheme, one that strove to account for an individual’s entire personality, and, at the same time, would be widely accepted and easily applied (Goldberg 1993; John et al. 2008). In the 1980s, however, things began to happen. Researchers picked up on earlier lexical studies, conducted by e.g., Allport and Odbert, and Catell (see e.g. Allport and Odbert 1936; Catell 1943). Out of a diverse body of research on personality-descriptive terms, the Big Five Model developed, and during the last three decades, it has become a well-known and appreciated framework (Goldberg 1992; Goldberg 1993; John et al. 2008; Mondak et al. 2010).

The Big Five Model is a framework that distinguishes five global and universal factors that are believed to account for most variation in personality, relying on the assumption that human personality has become encoded in our language (Peabody and Goldberg, 1989; McCrae and Costa 2008). The five factors are thus best understood as “trait domains”, each containing multiple subsidiary traits (Mondak et al. 2010, p. 86). So far, there is no consensus on which trait falls under what domain. Consequently, many versions of the Big Five Model exist, and various measurements have hitherto been proposed (John et al. 2008; Mondak et al. 2010). Therefore, how researchers define each trait domain differ slightly, depending on their preferred framework. The datasets I work with utilize the 50-item IPIP representation of the Goldberg (1992) markers for the Big-Five factor structure (Personality LISS Core Study Codebook 2013). Hence, I have consciously let Goldberg’s definitions guide me, but I have also used John et al.’s text “Paradigm Shift to Integrative Big Five Trait Taxonomy” (2008) since it gives a very encompassing description of the trait domains. What follows is a brief description of the Big Five.

**Agreeableness**

*Agreeableness* describes an individual’s “prosocial and communal orientation towards others” (John et al. 2008, p. 120). According to Goldberg, people high in Agreeableness are highly associated with, e.g., cooperation, amiability, empathy, and leniency but tend to score low on belligerence, rudeness, “overcriticalness”, and “bossiness” (Goldberg 1990). In the IPIP framework, a positively keyed example of how to measure Agreeableness is by making respondents assess how well the statements “Am interested in other people” or “Sympathize with others’
feelings” fit their personality. Two negatively keyed examples are the statements “Insult people” and “Feel little concern for others” (IPIP website 2019).

**Conscientiousness**

Conscientiousness implies to what extent it comes naturally to a person to comply with societal rules and norms, how easily one can control impulses, and to what degree an individual possesses the determination associated with completing tasks and working towards long-term goals (John et al. 2008). When it comes to Conscientiousness, Goldberg finds that individuals high in this trait domain are highly associated with, e.g., organization, efficiency, dependability and precision. Disorganization, negligence, inconsistency and forgetfulness are some factors that characterize people low in Conscientiousness (Goldberg 1990). To measure Conscientiousness, the IPIP Framework uses positively keyed statements such as “Get chores done right away” and “Am exacting in my work” and negatively keyed statements like “Make a mess of things” and “Often forget to put back things in their proper place” (IPIP Website 2019).

**Emotional Stability**

Emotional Stability describes to what extent a person experiences general ease and satisfaction as well as the volatility of his or her temperament (John et al. 2008). According to Goldberg, people high in Emotional Stability are generally characterized as placid and independent, while those who score low are often described as insecure, fearing, instable, envious, and emotional (Goldberg 1990). In the IPIP framework, a positively keyed example of how to measure Emotional Stability is by making respondents assess how well the statements “Seldom feel blue” and “Am relaxed most of the time” fit their personality. Two negatively keyed examples are the statements “Worry about things” and “Change my mood a lot” (IPIP Website 2019).

**Extraversion**

The trait dimension Extraversion is said to describe the level of energy and positivity with which a person engages in social and material life (John et al. 2008). Goldberg’s studies show that individuals high in Extraversion are associated with spiritedness, gregariousness, playfulness, and expressiveness but on the contrary, tend not to be associated with, e.g., aloofness, silence, reservation and shyness (Goldberg 1990). To measure Extraversion, the IPIP Framework makes use of positively keyed statements such as “Am the life of the party” and “Start conversations” and negatively keyed statements like “Keep in the background” and “Am quiet around strangers” (IPIP Website 2019).

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2 Some scholars use the trait dimension Neuroticism instead, an inverted measure of Extraversion. See e.g. Russo and Amnå.
Openness to Experience

Openness to Experience\(^3\) (from this point referred to only as Openness) implies a person’s mental and experimental life (John et al. 2008, p. 120). Goldberg finds that people who score high in this particular trait dimension are often associated with intellectuality, depth, insight, and intelligence but not with, e.g., shallowness, unimaginativeness, imperceptiveness, or stupidity (Goldberg 1990). For this trait dimension, the IPIP Framework uses statements such as “Am quick to understand things” and “Have a rich vocabulary” (positively keyed) as well as “Have difficulty understanding abstract ideas” and “Do not have a good imagination” (negatively keyed) (IPIP Website 2019).

2.2.2 The Big Five Applied on Political Participation

Because the Big Five Model has proved stable and replicable, it has gained scholars’ attention from all kinds of fields. The result is that today, there exists a large body of research that focuses on the application of the Big Five Model to explain many forms of behavior. Political participation is no exception. What follows is a review of previous research on the Big Five Model and political participation.

Extraversion is the trait dimension that yields the most consistent findings. Although not always reaching significance, Extraversion appears to be associated with higher levels of participation when it does (Gerber et al. 2011b). Some argue that what drives Extraverts to political participation is the need for social interaction and attention. Consequently, individuals high in Extraversion might prefer activities that stimulate them socially. Mondak et al. (2010), e.g., find that when you break down political participation into sub-activities, there is no longer a statistically positive association between Extraversion and less social political activities. However, the positive association remains between the trait dimension and activities such as canvassing, attending meetings, etc. Hence, whether the form of participation includes a social element or not might be what determines if there is a significant relationship. (Mondak et al. 2010).

Some research also suggests that the sociability of the Extraverts makes them less bothered by heterogeneity, discussion, and disagreement in their network (Mondak et al. 2010; Gerber et al. 2012). Furthermore, Extraversion appears to influence political interest and political efficacy positively, two things that may affect the participatory level (Gerber et al. 2011c; Gallego and Oberski 2012; Vecchione and Caprara 2009).

\(^3\) The IPIP framework uses the term Intellect but these two words refer to the same trait domain. I use Openness because I find it describes the trait domain better and my impression is that it is used more often.
Second to Extraversion, Openness is the trait dimension that yields the most consistent findings in previous research. Generally, the results point towards a positive association between Openness and political participation. For example, Mondak et al.’s results show that there is a strong positive association between Openness and political participation of all forms, from voting to attending public meetings and political rallies to donating money to a political cause and displaying political yard signs. They believe this is because individuals who are high on Openness tend to be positive towards new experiences and thus embrace political forms that are new to them. (Mondak et al. 2010).

Mondak et al. also argue that people high in Openness are to a more considerable degree exposed to information of all sorts, which gives them a higher sense of political efficacy. A higher sense of political efficacy could, in turn, make it easier for them to participate politically. Vecchione and Caprara also find a positive association between the trait dimension and political efficacy. High levels of Openness mean people have a genuine curiosity towards the outside world and an eagerness to learn new things. This might make them want to keep up with current events and cultivate their intellectuality in a way that make them feel more as politically able citizens. (Mondak et al. 2010; Vecchione and Caprara 2009).

When it comes to Agreeableness, the results from previous research are more mixed. For instance, Mondak et al. (2010) find no significant direct effects of Agreeableness on any of the participatory acts and what is more, both negative and positive estimates. Mondak and Halperin also find positive and negative associations (Mondak and Halperin 2008). Gerber et al. make the argument that individuals high on Agreeableness can very well be drawn to political participation but just not activities that involve contention. They, therefore, expect Agreeableness to be positively associated with, e.g. voting but not with, e.g. attending a rally. Moreover, supporting this hypothesis, they do find a negative, significant (in some cases just so) association between with Agreeableness and campaign-related activities. However, the results when it comes to electoral turnout are mixed and repeatedly insignificant across samples (Gerber et al. 2012).

It is also difficult to discern any consistent pattern of the trait dimension Conscientiousness. Some studies suggest there is a positive association between Conscientiousness and certain political activities, such as contacting officials or media, but a negative association with others, e.g., attending a rally. Other studies show a consistent negative association between the trait dimension and different participation variables (Ha et al. 2013; Mondak and Halperin 2008; Gerber et al. 2011b; Mondak 2010). Mondak et al. (2010) test whether the participation level of the Conscientious is dependent upon their perception of duty. They expect and find that Conscientious people primarily participate in politics if they believe it is their civic duty. E.g., Mondak et al. observe a negative relationship between Conscientiousness and campaign activity. However, when they introduce an interaction between Conscientiousness and the perceived importance of campaign activity, the negative effect of Conscientiousness becomes larger and also more statistically significant (Mondak et al 2010). Gallego and Oberski’s research also
supports this notion when they show that Conscientiousness’ effect on voter turnout is fully mediated by civic duty (Gallego and Oberski 2012).

Previous research has also yielded mixed results when it comes to Emotional Stability. Studying the direct effects of Emotional Stability on different forms of political participation, Mondak et al. find that there is a consistent negative association between Emotional Stability, and all sorts of political activities, e.g., electoral turnout, canvassing, and donation. However, far from all, reach statistical significance (Mondak et al. 2010). Other studies have been able to show signs of negative associations as well between the variables (Gerber et al. 2012; Anderson 2008). At the same time, some scientists have observed a positive association between Emotional Stability and some political activities. For instance, Gerber et al. find a positive association between the trait dimension and voter turnout, and Ha et al. find a positive association to Internet activity (although insignificant) (Gerber et al. 2012; Ha et al. 2013).

One thing that research consistently has shown is that high levels of Emotional Stability are positively associated with political interest and knowledge (see e.g. Gerber et al. 2011c; Gerber et al. 2012). According to Gerber et al., those high in Emotional Stability also tend to discuss more. They believe that this is due to them being more politically knowledgeable and interested, but also related to the fact that they do not get upset as easily (Gerber et al. 2012).

2.2.3 The Big Five and Online Political Participation

With the technological development of the last decades, political participation has set on to yet another arena: the Internet. Some research has followed, but, to the best of my knowledge, relatively little has been done on the Big Five Model and online political participation. In the next section, I account for four studies I have found exploring the topic. Table 1. on p. 21 also presents a summary of samples and operationalizations used. These four studies help deepen our understanding of personality and online political participation significantly. However, their findings do not tell one collected, unambiguous story. Perhaps due to their different aims and diverging designs, but it may also emphasize the need for more research.

“Online Political Engagement, Facebook, and Personality Traits” by Quintelier and Theocharis (2012)

In the article “Online Political Engagement, Facebook, and Personality Traits” (2012), Quintelier and Theocharis investigate how personality affects people’s propensity to participate politically online, using a sample of Belgian university students. Quintelier and Theocharis make a distinction between online political engagement and Facebook engagement, arguing that the latter captures a more
socially driven and transparent form of participation, while the former measures more general, less sociable activities.

Quintelier and Theocharis find that Openness is related to more political participation in all forms, Facebook and general. This is also the trait dimension that in their study reaches the strongest significance, it is statistically significant at p>0,001. Extraversion also has a positive effect on Facebook engagement and online political engagement. For online political engagement the effect is statistically significant at p<0,01 and for Facebook engagement at p>0,001.

For the remaining trait dimensions, the results are mixed and not as significant. When it comes to Agreeableness the authors find that people who score high on this trait dimension are a little bit more likely to participate politically online but not on Facebook. However, these results are significant at p<0,1. Quintelier and Theocharis believe their results suggest that Agreeable people prefer online engagement where they can distance themselves from confrontation by remaining anonymous.

Conscientiousness and Emotional Stability yield negative estimates. The results for Conscientiousness have low significance. The effect of Emotional Stability on online political engagement is also low, but for Facebook engagement, it is statistically significant at p<0,05. All in all, Quintelier and Theocharis conclude that their results regarding online political participation generally replicate previous findings in the offline sphere.

“Personality Traits and Political Participation: Evidence from South Korea” by Ha et al. (2013)

In the article “Personality Traits and Political Participation: Evidence from South Korea”. Ha et al. focus on the relationship between trait dimensions and different modes of political participation in South Korea. The authors highlight the fact that most studies use Western samples (primarily American samples). Therefore, their aim is the explore whether personality relates differently to several types of political participation in a non-European and non-American setting, using the 2009 Korean General Social Survey as their sample. Ha et al. include one variable that measures what they call “Internet-based activities” (see table for exact phrasing).

Ha et al. find that there is a negative association between Agreeableness and online political participation that is statistically significant at p<0,01. When it comes to Openness, they observe a positive association between the trait dimension and Internet-based activities, significant at p<0,05.

Conscientiousness is negatively linked; however, the estimate is not significant. Ha et al. comment on the results, suggesting that the internet does not appeal to Conscientious people, who prefer “individual acts requiring deliberation before action” (Ha et al 2013, p. 526). They highlight the alleged difference between
offline and online modes of political participation; according to Ha et al., the latter does not require "thoughtful action". I interpret it as if they make an implicit assumption that there is a lower threshold to participate in online political activities (Ha et al. 2013, p. 526).

When they examine Emotional Stability and Internet-based activity, they also find a negative correlation; however, it is also not statistically significant. The results for the association between Extraversion and Internet-based activity is positive but once again not statistically significant. Ha et al. refrain from commenting on these two trait dimensions since the results did not reach statistical relevance. (Ha et al. 2013).

“The Relationship Between Openness to Experience and Willingness to Engage in Online Political Participation Is Influenced by News Consumption” by Jordan et al. (2014)

In the “The Relationship Between Openness to Experience and Willingness to Engage in Online Political Participation Is Influenced by News Consumption” (2013), Jordan et al. refer to Mondak et al. (2010) and argue that personality primarily influences political participation through mediating factors, such as news consumption. News consumption, they add, serves a vital role in a healthy democracy. They hypothesize that news consumption makes us informed as well as knowledgeable about how to take civic action and thus can lead to internal political efficacy. So, the quantity of news consumed matter, but so, they argue, does also the quality. Public news sources they state are more likely to cover political issues in-depth and to equip citizens with more thorough political information. Therefore, in their study, they let two objectives guide them. Firstly, they ask to what degree does internal political efficacy and time spent on online news consumption function as mediators to online political participation. The second question they focus on is whether the propensity to participate politically online vary with a preference for different news sources.

Consistent with previous research, Jordan et al. find that Openness is positively associated with online political participation, and the estimated effect is statistically significant at p<0,01. Furthermore, their results show that indeed, this association is mediated by news consumption and internal political efficacy. Just like Quintelier and Theocharis, Jordan et al. choose to focus on young people when they examine political Internet behavior through the lens of the Big Five, namely a group of Canadian university students.


Russo and Amnå’s study is comprehensive as they take into regard the multidimensionality of online political participation, build their analysis on different modes of online political participation, and use extensive operationalizations of the
concept. Inspired by Gibson and Cantijoch (2013), they derive three sub-categories from online political participation: e-targeted, e-expressive, and e-news (excluding e-party). Russo and Amnå then study how these dependent variables vary with different values of the trait dimensions, directly or indirectly, through some mediating variables (Russo and Amnå 2016). For reasons that will become clear in the next chapter, I will only account for the results of e-expressive.

Russo and Amnå find that the mediating variables, political interest and political efficacy, have a positive impact on e-expressive. The estimates are statistically significant at p<0.001.

Openness has a positive direct effect on e-expressive, statistically significant at p<0.001. There is also a significant positive association between Openness and political efficacy as well as political interest.

When it comes to Extraversion, Russo and Amnå do not detect any direct effects. However, Extraversion has a positive effect on political efficacy, and thus, an indirect positive effect on e-expressive.

Russo and Amnå’s findings regarding Conscientiousness suggest that this trait dimension has a direct, negative effect on E-expressive, statistically significant at p<0.01. They also observe a positive effect on political interest.

As concerns Agreeableness, Russo and Amnå’s results indicate the trait dimension has a negative direct effect on e-expressive. The estimated effect is statistically significant at p<0.01. What is more, there is a negative association between Agreeableness and political efficacy.

Lastly, Russo and Amnå’s results indicate that Neuroticism (an inverted measure of Emotional Stability) does not have a direct impact on e-expressive. Nevertheless, it is negatively related to political efficacy. (Russo and Amnå 2016.)

2.3 Aim of the Thesis

The Big Five Model has been used to quite an extensive degree to explore the relationship between personality and political participation. The examples I gave here before only represent a small fraction of the work dedicated to the application of the trait dimensions on political behavior. Online political participation, however, has not been blessed with the same amount of attention. Lamentably so, one could argue, since there are good reasons for considering online political participation as a distinct phenomenon that is only increasing in importance, as I discussed earlier. When more people are increasingly attracted to
online platforms for political activity, it becomes more important for us to understand the role personality could play in this regard to truly understand the state of contemporary political involvement (Quintelier and Theocharis, 2012). Although the merits of previous research on the Big Five and online political participation that do exist are many, the field could gain from further research simply by the gathering of more empirical results. The first aim of my thesis is thus to provide more empirical results on the relationship between personality and online political participation. But I also believe my study can contribute in two other ways: by using a different sample and a different operationalization of online political participation.

2.3.1. A Different Sample

I use data from the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands) (LISS Panel 2019)⁴. LISS data has been used for studying political psychology before (e.g. van Ingen, and Bekkers 2015 and Rooduijn et al. 2016). CentERdata provides reliable data (e.g., they received the international Data Seal of Approval (LISS, n.d.)) and appears to be one of the few databases which collect (extensive) Big Five personality data.

To the best of my knowledge, there is no study combining the “Personality LISS Core Study” and the particular LISS Assemble Study “Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media and in Surveys”⁵ for the purpose of exploring the relationship between personality and online political participation. As a matter of fact, I believe there is not yet any study combining these sets. The novelty in itself could be interesting. What is more, LISS allows me to apply these research questions to the Dutch population. Ha et al. point out that American samples dominate in personality and political participation research. Therefore, there is value to exploring this relationship further by using samples from other countries. Although still a Western sample, my sample is not an American one, and as far as I know, there has not been much done on Dutch data when it comes to personality and online political participation.

The Netherlands also makes a particularly interesting country to study since it was the EU country with the highest level of domestic Internet access and, along with Sweden, also had the highest internet use on mobile devices in 2017. (CBS 2018a; CBS 2018b). Netherlands’ widespread use of the Internet also makes you wonder whether significant differences in digital behavior between adults and children or teenagers might be withering away. It bears considering if the Internet has not been in public domain long enough to be widely used across all ages. Dutch statistics partially supports this perspective, e.g., social media use in the ages of 12-54 does not differ much (in 2017 12-17 years: 96,9%, 18-24 years: 99,1%, 25-

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⁴ (for more information, see LISS: [https://www.lissdata.nl/about-panel](https://www.lissdata.nl/about-panel) and the Methodology section).
⁵ More information on these datasets will be given in the chapter Sources and Methodology.
and there is a reported rise of social media use among seniors. (CBS 2018a; CBS 2018b).

For the abovementioned reasons, it may make sense to not restrict the sample to youth only, especially in the Netherlands. Since my sample is a cross-section of the Dutch population, it includes all ages, which does not appear to be the norm in this type of research. Three out of the four studies I study here use a sample of youth respondents (Quintelier and Theocharis, Jordan et al. and Russo and Amnå, see Table 1 for an overview of the operationalizations). On top of that, two studies look at university students. Students are a quite homogenous group, at least in terms of several SES indicators. This makes it difficult to generalize the results beyond to say, e.g., youth in general.

In sum, LISS is one of few databases of its kinds to collect reliable data based on the Big Five Model. Furthermore, LISS has data on political Twitter use. Therefore, LISS data is very useful for my thesis. What is more, a Dutch sample may contribute to the field by adding some knowledge on cross-national variation of the relationship between personality and online political participation. High Internet usage across all ages also makes it especially interesting and easier to study a cross-section of the Dutch population in particular.

2.3.2 A Different Operationalization

With the data from the LISS Assemble Study “Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media and in Surveys”, I also offer a different operationalization of online political participation. Table 1 shows a summary of the operationalizations of online political participation that the four mentioned articles utilize. From Table 1, we conclude that there are multiple ways to go about turning this abstract phenomenon into a measurable, distinguishable concept that can be observed empirically. For example, the authors use different amounts of items to measure online political participation. Ha et al. use one question while Russo and Amnå use as many as thirteen, in turn, divided into subgroups capturing different modes of online political participation, i.e., the scopes of the operationalizations differ. With thirteen questions divided into subcategories, Russo and Amnå’s operationalization capture a wide range of online political activity that reflects a multidimensionality of the concept. But some choose to focus on a specific set or area of online political activity.

Quintelier and Theocharis partly focus on a particular social network site (SNS), which is Facebook. Quintelier and Theocharis choose to distinguish Facebook engagement to other political participation online, arguing as mentioned that Facebook engagement is a more socially driven and transparent form of participation than other online participation. Being the largest SNS, Facebook is, of
course, interesting and valuable to study. However, Twitter could also make a compelling case with its focus on opinion- and information sharing rather than social interaction, as well as the anonymity that may relieve social pressure and shift focus from who you are to what you have to say. (Hughes et al. 2012).

Nevertheless, it seems as though Twitter has not received the same attention that Facebook has. Jordan et al. are the only ones to mention Twitter explicitly in their operationalizations, although several questions could apply to Twitter, e.g., linking news to friends (Russo and Amnå 2016) or disseminating a political message (Quintelier and Theocharis 2012). Being such an important but rather forgotten SNS makes it especially interesting to focus on online political participation through Twitter.

Gibson and Cantijoch refer to the contemporary debate of how well Western democracies meet citizen demand and reiterate Dalton’s claim that more and more people are turning away from official modes of participation in favor of more expressive ones. At the same time, Gibson and Cantijoch stress that the birth of social media is transforming formerly considered passive forms of political activity into more active forms. Due to technological change, expressive activities are becoming more active, collective, and networked online. (Gibson and Cantijoch 2013). I believe the result is an increasing relative importance of the e-expressive mode. Twitter, apart from being an SNS of great importance that has somewhat escaped the attention of personality and online political participation research, is also a forum that emphasizes the e-expressive mode of online political participation. This makes a another reason why it is particularly interesting to study online political participation on Twitter through the lens of the Big Five.

To summarize, Twitter is interesting to study because it is an important SNS that has not been subject to much research on personality and online political participation. It is also interesting to study as it becomes increasingly important; it is a place where e-expressive and e-news modes of participation are used and are being "upgraded" to more active forms. By using data from the LISS assembled study, I am able to operationalize Twitter political participation in a new way and thereby add to the field of personality and online political participation with more research on Twitter and the e-expressive mode of participation.
<table>
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<td>1. &quot;Supporting a sociopolitical group&quot;</td>
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<td>2. &quot;Using the share button of a news website or other site to share a link&quot;</td>
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<td>3. &quot;Posting of articles or videos about news or politics&quot;</td>
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<td>4. &quot;Responding positively to an invitation for a political meeting by a friend or group&quot;</td>
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<td>6. &quot;Posting opinion about politics on a wall&quot;</td>
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<td>7. &quot;Using the share button of a website of a politician or political party to share a link, article, or video about the news or politics&quot;</td>
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<td>Online Political Engagement</td>
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<td>1. &quot;Signing an online petition&quot;</td>
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<td>Ha et al. (2013)</td>
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<td>1. &quot;Have you joined an Internet political forum or discussion group? Yes=1; No=0&quot;</td>
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<td>Jordan et al. (2014)</td>
<td>Canadian university students (n=419)</td>
<td>Online questionnaire</td>
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<td>How likely is it that you</td>
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<td>1. &quot;Use a cell phone to record or transmit videos or text messages that are political in nature?&quot;</td>
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<td>2. &quot;Upload a video or a social networking website to draw attention to a political or social issue?&quot;</td>
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<td>3. &quot;Create a status update or tweet with the intent of drawing attention to a political or social issue?&quot;</td>
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<td>4. &quot;Join a social or political group on a social networking site?&quot;</td>
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<td>5. &quot;Blog about a political or social issue?&quot;</td>
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<td>6. &quot;Sign an online petition?&quot;</td>
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<td>(4-point scale ranging from 0=Extremely unlikely to 3=Extremely likely)</td>
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<tr>
<td>Russo &amp; Amnå (2015)</td>
<td>20-year-old and 22-year-olds in Örebro (n=134)</td>
<td>Online and mail questionnaires</td>
<td>The Big Five Inventory - Versions 4a and 54 (John, Donahue &amp; Kentle, 1991)</td>
<td>How many of the following have you done in the last 2 months? Response options: Several times (3), Occasionally (2), or Never (1)</td>
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<td>E-agenda</td>
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<td>1. Signed an online petition</td>
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<td>2. Taken part in an Internet-based protest</td>
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<td>3. Sent an e-mail to a politician</td>
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<td>4. Linked news to my friends</td>
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<td>5. Discussed political or quantitative issues with friends on the net</td>
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<td>6. Linked videos to a political content</td>
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<td>7. Chatted with friends on the Internet about something I've seen on the news</td>
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<td>8. Connected to a group on Facebook (or similar) dealing with societal issues</td>
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<td>9. Sent music in or linked content about music that I think has a good political and social message</td>
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<td>10. Visited a political website</td>
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<td>11. Single information about politics or societal issues on the Internet</td>
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<td>12. Read about politics via blog</td>
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<td>13. Watched videos on my channel about societal issues or politics*</td>
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<td>(Russo &amp; Amnå, 2015, p. 275)</td>
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Sources mentioned:
3 Theoretical Framework and Hypotheses

3.1 Twitter as an Example of E-expressive and E-news

“The Internet has become an essential component in the navigation of everyday life. The Internet influences all aspects of human endeavor from the way in which organizations operate to the way people shop and spend their leisure time. Yet, perhaps the biggest transformations have been in the way in which we socialize and seek-out and spread information (Amichai-Hamburger and Ben-Artzi 2000). Via the internet, vast amounts of information can be disseminated to world wide audiences whilst the web simultaneously offers an arena for public and private social interaction.”

(Hughes et al. 2012, p.561)

In the article “A Tale of Two Sites: Twitter vs. Facebook and the Personality Predictors of Social Media Usage” (2012), Hughes et al. state that the Internet has changed how we interact socially and seek and share information. Many are the SNS where you can go online for social interaction and information sharing. However, they differ somewhat in the services they offer and functions they employ. Among the various SNS that exist, Twitter, with its special focus on opinion and information sharing rather than socializing activities, stands out (Hughes et al. 2012).

As was mentioned in Previous Research, early participation research focused only on a few election-related political activities, whereas subsequent studies have explored more of the multidimensionality of political participation. Online political participation research has also studied multidimensionality. Russo and Amnå state that the 2013 study by Gibson and Cantijoch is the most ambitious work dedicated to the multidimensionality of online political participation (Russo and Amnå 2016). To the best of my knowledge, three years later, this statement still holds. So I imitate Russo and Amnå and use Gibson and Cantijoch’s framework of online political participation, but I focus on e-expressive and e-news because of their peculiarity.

E-news refers to reading online newspapers, blogs, watching video clips online, etc., anything that includes news that regards politics and can be consumed through online news sources. E-expressive captures activities that relate to discussion or expression of political content and takes place mainly on social media with activities such as posting, forward, or embedding political messages or engaging in discussion in the comments (Gibson and Cantijoch 2013; Russo and Amnå 2016). As I describe in the Previous Research section, Gibson and Cantijoch
see signs of an “upgrading” taking place in the online arena of formerly passive
types of political activities, transforming into more participatory forms of
engagement (Gibson and Cantijoch 2013). I argue that this makes it even more
interesting to focus on e-expressive and e-news. Twitter is a good SNS to study for
this purpose, and here, I attempt to explain why I believe political participation on
Twitter is a good example of e-expressive and e-news.

Twitter was launched in October 2006 and has since become one of the most
popular microblogging platforms (Java et al. 2007). Here, registered users can go
online to post and interact, e.g., like, comment, or re-post with messages known as
tweets. A tweet is restricted to 240 characters (in Japanese, Korean, and Chinese,
the character limitation is half the size). In the first quarter of 2019, Twitter had
330 millions monthly active users spread out all over the globe but with the highest
level of adoption being in North America, Europe, and Asia (Java et al. 2007;
Statista 2019a; Statista 2019b). One could argue that Twitter has some distinct
features that make it stand out among other SNS. Heavy emphasis on information
sharing, lack of required reciprocity, perceived anonymity to mention a few. To
follow someone on Twitter does not require that you follow them back. In fact,
studies suggest that only a small portion of followers are followed by any of their
followings on Twitter. One plausible explanation to this relatively low level of
reciprocity is that most users see Twitter as a source of information rather than a
forum for socializing. Twitter, compared to Facebook, for example, also relieves its
users from some social pressure as it is easier to stay anonymous. (Kwak et al.
2010; Hughes et al. 2012; Java et al. 2007). Twitter users can be sorted into three
categories: information sources, friends, and information seekers (Java et al. 2007)
Zhao and Rosson mention a couple of Twitter’s characteristics they believe
motivate people to use it. Part of the Twitter-allure, Zhao and Rosson say, is that it
is basically “a people-based RSS feed” (Zhao and Rosson 2009, p. 245). In other
words, users can subscribe to information updates from people they know or trust
or for whatever other reason they choose to follow. The most common motivation
behind following a Twitter account is that the follower shares his or her interests.
The user interface, defined by brevity, accessibility, and perspicuity, is also a reason
why people go on Twitter (one example being the hashtag as a function). For the
individual user, it offers her a way to browse and take in vast amounts of
information (Zhao and Rosson 2009). Moreover, empirical analyses have shown
that the primary user intentions on Twitter are daily chatter, conversations, sharing
information/ URLs and reporting news.

So why then could Twitter be seen as a good example of e-expressive and e-news?
Well, for one, two out of the three user categories are related to information
(information sources and information seekers). Furthermore, two out of the four
identified main user intentions, sharing information and reporting news, I believe is
best sorted under the mode e-news. The fact that Zhao and Rosson call Twitter “a
people-based RSS feed” (Zhao and Rosson 2009, p. 245), enhances my suspicions.
When it comes to the other two user intentions, conversation and chatter, at first
glance, it might look as if Twitter functions as a social outlet. But you could
question what the driving force behind microblogging is. Consider the fact that
very few people are followed by the people they follow, which suggests that a majority of users are not precisely making Twitter-friends. As the low level of reciprocity might be a sign of, the motivation behind conversation or chatter or tweeting could be to express oneself rather than socializing. This seems likelier in the light of quotes by scientists reinforcing ideas such as: “its focus seems to be on opinion and information rather than reciprocal social interaction” Hughes et al. 2012, p. 561. Now, recall that e-expressive captures modes that relate to discussion or expression of political content and could mean activities such as posting, forwarding, and commenting political messages on social media (Gibson and Cantijoch 2013; Russo and Amnå 2016). For these reasons, I believe Twitter activity, especially the speaking up parts and not just the monitoring information parts, also resonates with e-expressive. However, the data from LISS only cover the latter mode (I give an account of the variables in the Methodology section). Therefore, when I proceed to study the relationship between personality and online political participation on Twitter, the focus from now on will solely be on the e-expressive mode.

3.2 Hypotheses

How does personality relate to online political participation on Twitter? My thesis differs from previous personality and online political participation research in two ways: I conduct it on a different sample, and I utilize a different operationalization of online political participation. But my expectations can still be informed by previous research, online and offline, and this is what I intend to do in this section. What follows is an account of my hypotheses and how I ended up formulating them.

Openness

In sum, previous research on personality and political participation has shown that Openness is positively related to all kinds of offline political participation (see, for example, Mondak et al. 2010). Some argue that this is because high levels of this trait dimension make a person more positive towards new experience and, therefore, more willing to participate in political activity, even if the form of participation is new to them. With this information in mind, we may expect people high in Openness to engage politically on Twitter more than those with low levels since they do not shy away from new forms of participation and Twitter is a relatively new platform.

Individuals high in Openness seek intellectual stimulation and a deeper understanding. Therefore, they are generally more updated on current events and better at navigating contemporary politics (Mondak et al. 2010; Vecchione and Caprara 2009). As a result, Open people may also be more self-confident, which in turn could be an advantage when taking a stance publicly or entering a discussion. Twitter, as a platform, emphasizes self-expression and opinion sharing. The brevity
and potential reach often lead to quick exchanges and a contentious debate climate. So, being self-confident could make it easier to participate politically on Twitter. It is also possible that Twitter attracts Open people who search for information and stimuli. This may also be reasons for expecting a positive relationship between Openness and Twitter political participation.

What then is there to gather from research that involves personality and online political participation? Openness is actually where the most evident association between a trait dimension and online political participation appears. All four studies report a significant association between Openness and online political participation. Again, it may not be so surprising that people who are Open to new experiences and have curious mindsets, would seek new areas and outlets to satisfy their need for intellectual stimulation. Russo and Amnå, for example, find that Openness has a positive and significant direct effect on the e-expressive mode of online political participation. Ha et al. find that people high on Openness tend to engage more in online political forums and discussions. There is an element of intellectual exchange to e-expressive activities as Russo and Amnä defines them as well as Ha et al.’s “Internet-based activity”. These activities all involve sharing ideas and arguing for or against different positions, which presuppose intellectual flexibility and curiosity, the very linchpins of the Openness. What is more, Jordan et al.’s find that Openness has a positive effect on news consumption. (Russo and Amnä 2016; Ha et al. 2013; Jordan et al. 2014). Since my twitter variables are best described as e-expressive, and Twitter emphasizes discussion, it seems reasonable to expect a positive association between Openness and online political participation through Twitter.

**H1: There is a positive association between Openness and Twitter political participation.**

**Extraversion**

In offline political participation research, Extraversion is the trait dimension that has yielded the most consistent findings (Gerber et al. 2011). Generally speaking, studies have found a positive relationship between Extraversion and political participation. However, Mondak et al. argued that this positive relationship only adheres to political activities that involve social interaction (Mondak et al. 2010). The question then becomes, to what extent does Twitter present its members communicative and socializing opportunities? Hughes et al.’s research suggests that there is an informational focus on Twitter rather than a strong socializing element. Many users prefer to follow and read other’s tweets to sharing content themselves. Would this sort of behavior count as social and communicative? Some research also shows that Extraverts are more comfortable with heterogeneity, discussion, and disagreement in their network (Mondak 2010; Gebrer et al. 2012). A useful quality to possess indeed on social media platforms, not the least on Twitter, which is known for its, sometimes, contentious climate. What is more, it has also been shown that there is a positive relationship between Extraversion and political interest.
The findings of online political participation research, to some extent, replicate those offline, suggesting at large a positive relationship between Extraversion and online political participation. Quintelier and Theocharis find that Extraversion is positively related to online political participation. However, contrary to what they expected, Quintelier and Theocharis cannot find support for their hypothesis that Extraversion would have a stronger effect on Facebook engagement, i.e., the more social form of online political participation according to them. Ha et al. observe a positive association, but the results are not statistically significant. Russo and Amnå do not detect a direct effect of Extraversion on e-expressive. Nevertheless, they find a positive indirect effect through mediation of political efficacy. (Quintelier and Theocharis 2012; Ha et al. 2013; Russo and Amnå 2016).

There is another aspect of Extraversion, which tends to be sidelined by the need for social stimulation: need for attention. Twitter may not be the most social SNS, but it is a place where users easily can gain attention, tons of attention, and quickly. As Gibson and Cantijoch write: “online expressive activity is arguably more influential than its offline counterpart.” (Gibson and Cantijoch 2013, p.704), pointing out that social media users can access a far broader and more diverse audience than those who stay put with traditional forms of political participation can. Many assume and have shown that social interaction is a driving force for Extraverts to engage, but it is possible that the need for attention also matters, and for this, Twitter could be an outlet. With these thoughts in mind, I expect that there will be a positive relationship between Extraversion and online political participation through Twitter.

H2: There is a positive association between Extraversion and Twitter political participation.

Agreeableness

It is difficult to make predictions about the relationship between Agreeableness and online political participation since previous research has yielded such mixed results. Studies that explore how personality relates to offline political participation generally struggle to reach statistically significant results, and estimates are both negative and positive.

What does online political participation research then have to offer? Yet again, the findings from previous research are mixed. As presented before, Quintelier and Theocharis find that people high on Agreeableness are a little bit more likely to engage politically online but not on Facebook. They believe this means that Agreeable people are more likely to engage politically online through activities where they can remain anonymous, perhaps to avoid potential confrontation (Quintelier and Theocharis 2012). According to this reasoning, Twitter might repel those with high levels of Agreeableness since it is a contentious SNS. But at the same time, Twitter does offer anonymity. However, one may wonder to what extent anonymity helps. It still may be the contentious environment in itself that repels Agreeable people and not the reprisals that may follow from engaging in it.
Ha et al. find that there is a significant negative association between Agreeableness and Internet-based activities. Ha et al.’s operationalization (“Have you joined an Internet political forum or discussion group”) could also involve activities that expose participants to conflict (Ha et al. 2013). So does Russo and Amnå’s e-expressive mode, with acts such as “discuss societal or political questions with friends on the net” or “link video clips with a political content”, activities that implicate taking a stance and invite opinion sharing. Russo and Amnå’s results show that Agreeableness has a direct significant negative effect on e-expressive participation (Russo and Amnå 2016).

Taking these results, I expect Agreeableness to be negatively related to online political participation through Twitter. Two out three studies suggest so, and the one that does not has an operationalization that I believe is furthest away from mine. However, since previous studies have struggled to reach statistical significance, I do not expect my results to be statistically significant either.

**H3: There is a negative association between Agreeableness and Twitter political participation; however, it is not significant.**

**Conscientiousness**

When it comes to Conscientiousness, it is also difficult to make predictions based on previous political participation research as it yet again has shown mixed results. As was mentioned in the Previous Research section, some studies suggest there is a positive relationship between Conscientiousness and some political activities, e.g., contacting government officials or media, but a negative association with others, e.g., attending a rally. Other studies consistently show a negative association between the trait dimension and all forms of participatory acts (Ha et al. 2013; Mondak and Halperin 2008; Gerber et al. 2011; Mondak et al. 2010).

Some scholars believe that when we study Conscientiousness and political participation, we must take into account the individual’s perception of duty. Conscientious people will participate at high levels if they believe a participatory act to be part of her civic duty (Mondak et al. 2010). So perhaps we can expect that the Conscientious will partake in communicational or informational use of Twitter if they believe this is the norm-abiding behavior. Recall that Gibson and Cantijoch refer to Dalton and his idea that a growing number of people nowadays prefer expressive modes of participation to duty-based. At some point, it may be that new patterns of influence are changing the notion of what constitutes a political duty. We could, for example, imagine that high levels of Conscientiousness coupled with the conviction that political discussion is vital to democracy and a central part of the democratic citizen’s duty may lead to a positive association between Conscientiousness and Online Political Participation through Twitter. However, to test that hypothesis would require a way to measure, e.g., perceived importance of political discussion, and at this time I do not have an appropriate mediating variable for this.
What then is there to gather from research that involves personality and online political participation? Both Quintelier and Theocharis and Ha et al.’s studies yield negative results; however, their estimates are not statistically significant. Russo and Amnå find there to be a significant, negative direct effect of Conscientiousness on e-expressive. Therefore, I expect a negative association between Conscientiousness and Twitter online political participation. But, since previous studies have struggled to reach statistical significance and since perception of duty might be interacting, I do not expect my results to be statistically significant either.

H4: There is a negative association between Conscientiousness and Twitter political participation; however, it is not significant.

Emotional Stability
Just like with Conscientiousness and Agreeableness, scientists have struggled to find any consistent patterns between the trait dimension Emotional Stability and different sorts of political participation. In the offline sphere, some studies suggest there might be a negative relationship between Emotional Stability and political activity of all kinds (Mondak et al. 2010; Gerber et al. 2012; Anderson 2008). Yet many of these results do not reach statistical significance, and what is more, once in a while, research has pointed towards a positive relationship (e.g., Gerber et al. 2011). One thing that does seem more certain, however, is that Emotional Stability is positively associated with political interest and frequency of discussion. The implications of this, if any, may be that people that have political interest and do not mind an argumentative climate are more likely to enjoy Twitter.

Turning to online political participation research, the results viewed here indicate only a negative association between the trait dimension and online political participation. Quintelier and Theocharis’ findings suggest a negative association between Emotional Stability and Facebook engagement and online political engagement and Ha et al. observe a negative association between the trait dimension and Internet-based activities. Although these results are not statistically significant, I find it intriguing that they indicate a negative association. Perhaps the psychical distance of the Internet has a particular appeal to people who more easily find certain situations uncomfortable and feel vulnerable. It may also be that the less Emotionally Stable you are, the more attractive an SNS may seem as a medium for social stimulus and as a place to express anxiety and direct worry as well as frustration. Russo and Amnå, however, do not find any direct effect of Emotional stability on e-expressive. (Quintelier and Theocharis 2012; Ha et al. 2013; Jordan et al. 2014).

In aggregate, I find the results of previous research too inconsistent and insignificant to be able to build any particular expectations on for the relationship between Emotional Stability and Twitter online political participation.

No hypothesis.
4 Sources and Methodology

4.1 Data Used

In this paper, I make use of cross-sectional data of the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands). The LISS panel consists of 4500 households, compromising 7000 individuals. Panel members complete online questionnaires every month and are paid for each completed questionnaire (LISS: https://www.lissdata.nl/about-panel). I merge four datasets on household id: the sixth wave of the “Personality LISS Core Study” collected in May up to and including June 2013 (sample: LISS panel members aged 16 years and older; sample size: 5708; response rate: 90.6%), the sixth wave of the “Politics and Value LISS Core Study” collected in December 2012 up to and including January 2013 (sample: LISS panel members aged 16 years and older; sample size 6,692; response rate 85.7%), “Background Variables” collected in October 2013 and the “Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media” LISS Assembled Study collected in October 2013 (sample: LISS panel members aged 16

<table>
<thead>
<tr>
<th>Name of Study</th>
<th>Study type</th>
<th>Wave</th>
<th>Data Collection Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personality LISS Core Study</td>
<td>Longitudinal Study</td>
<td>6th wave</td>
<td>May- Jun 2013</td>
</tr>
<tr>
<td>Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media and in Surveys</td>
<td>Single Wave Study</td>
<td>-</td>
<td>Oct 2013</td>
</tr>
<tr>
<td>Background Variables</td>
<td>Single Wave Study</td>
<td>-</td>
<td>Oct 2013</td>
</tr>
<tr>
<td>Politics and Value LISS Core Study</td>
<td>Longitudinal Study</td>
<td>6th wave</td>
<td>Dec 2012-Jan 2013</td>
</tr>
</tbody>
</table>

Sources: LISS Panel (2019)
years and older; sample size 6261; response rate: 83.2%). Although the data collection periods are not identical, the studies were conducted over a rather small window of time. Therefore, I assume there is no significant variation over time that may bias my estimates.

4.2 Variables

4.2.1 Outcome Variables

Online political participation, as I have defined it here, cannot be directly observed. Therefore, I need proxy measurements that can stand in for or indicate whether the latent variable is present or not. In the previous chapter, I argue that political participation on Twitter can be seen as a particularly good example of the modes e-expressive and e-news. For this reason, I searched for variables that measure a person’s propensity to e-expressive and e-news political behavior through Twitter. The LISS study “Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media and in Surveys” includes five questions that grouped, I believe, could serve well as a proxy of e-expressive online political participation. Table 3. presents these variables as well as their descriptive statistics. The responses are based on a five-point ordinal scale, where 1 stands for “Never”, 2 for “1-2 days a week”, 3 for “3-4 days a week” 4 for “5-6 days a week”, and 5 for “Every day”. (LISS Panel 2019).

4.2.2 Twitter Political Participation Index: TPPI and bi_TPPI

An index is a statistical device that creates a compounded measure by aggregating observations of different variables. Together the five Twitter variables are a much stronger indicator of political participation on Twitter than apart. Hence, I create an index, Twitter political participation index (TPPI). In my analysis, I use an additive index as opposed to a weighted index because, based on my literature review, I find no reason to suspect that these variables should affect online political participation asymmetrically.

For reasons that are described in the analysis chapter, I turn the TPPI into a binary outcome variable, that I call bi_TPPI. The bi_TPPI indicates the presence of online political participation on Twitter. If bi_TPPI takes on the value 0 that means the respondent does not participate politically on Twitter. If bi_TPPI takes on the value 1, the respondent participates politically on Twitter.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable name</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>How often do you use Twitter for the following activities?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>… Express political opinion?</td>
<td>jz13a042</td>
<td>240</td>
<td>1,263</td>
<td>0,648</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>… Circulate political information by posting news links?</td>
<td>jz13a043</td>
<td>240</td>
<td>1,238</td>
<td>0,645</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>… Circulate political information by retweeting political message?</td>
<td>jz13a044</td>
<td>240</td>
<td>1,258</td>
<td>0,64</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>… Engage in conversation about a political topic?</td>
<td>jz13a045</td>
<td>240</td>
<td>1,25</td>
<td>0,637</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>… Convince others to participate in politics?</td>
<td>jz13a046</td>
<td>240</td>
<td>1,096</td>
<td>0,461</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Twitter Political Participation Index</td>
<td>TPPI</td>
<td>240</td>
<td>6,1</td>
<td>2,7</td>
<td>5</td>
<td>25</td>
</tr>
</tbody>
</table>
4.2.3 Independent Variables of Interest

As was discussed in the chapter Previous Research, prior studies indicate that personality influences online political participation. I use a set of personality variables from the Personality LISS Core Study to find out if and how personality might correlate with online political participation on Twitter. In the Personality LISS Core Study, respondents are asked to use a five-item response scale to indicate how accurately a statement regarding personal behavior describes them, where 1 equals very inaccurate and 5 very accurate (LISS Panel 2019; see appendix for exact wording of the questionnaire). These variables are based on the 50-item IPIP representation of the Goldberg (1992) markers for the Big-Five factor structure, ten questions per trait domain. Simply by using addition, I calculate each respondent’s aggregate score on each trait domain.

Table 4. Independent Variables of Interest

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agreeableness</td>
<td>241</td>
<td>38.639</td>
<td>5.042</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>241</td>
<td>35.552</td>
<td>5.919</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>241</td>
<td>34.012</td>
<td>7.169</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Extraversion</td>
<td>241</td>
<td>34.838</td>
<td>6.4111</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Openness</td>
<td>241</td>
<td>36.647</td>
<td>4.873</td>
<td>10</td>
<td>50</td>
</tr>
</tbody>
</table>

However, some of the questions among the Goldberg markers are negatively keyed. For example, for Emotional Stability, respondents are asked to rate how well the statement “Often feel blue” would describe their character. Therefore, before creating a total score for each trait dimension, I must reverse the scales for the personality variables that are negatively keyed. In the analysis, it is the aggregated personality variables, the trait domains, that will be used as my independent variables of interest. Table 4. presents the trait domains as well as their descriptive statistics.

4.2.4 Control Variables

6 Goldberg (1992) uses the term Intellect and not Openness to Experience. However, these two are by many used interchangeably, also by those who use Goldberg’s framework.
One of the most common explanations to political participation is socioeconomic status (SES). For example, it is generally thought that income level is a good predictor of political participation. The underlying argument is that political participation demands resources that some lack, such as time and money. Among other things, an individual with a higher salary might be able to “buy themselves” more free time that can be devoted to political engagement. It may also be easier for high income-earners to put aside money for political donations, party fees, campaign events, etc. Educational level is another popular predictor of SES. Education can help people get certain civic skills that facilitate political participation. The list is long of studies that have tested or controlled for the relationship between time, money, and level of education and political participation. I can find plenty of examples in the studies I have reviewed as well. Difficulty in managing basic expenses, the highest level of education, the highest level of education of one’s mother, and income, to mention a few (Russo and Amnå 2016; Ha et al. 2013; Vissers and Stolle 2014; Kahne and Bowyer 2018).

In my analysis, I make use of two measures of SES: income and education. I measure income using a background variable from LISS Background variables dataset. Respondents were asked to state their net monthly income in Euros. Education is measured by a categorical variable. Respondents are asked to state their highest level of education, irrespective of diploma and get to choose between 9 categories (see codebook in the appendix for further details). In my analysis, I also control for age and gender, two well-established predictors of political participation (see e.g., Gallego and Oberski 2012; Bakker and de Vreese 2011; Russo and Amnå 2016, Vissers and Stolle 2014; Kahne and Bowyer 2018; Ha et al. 2013). The age and gender variables are also gathered from the LISS Background variables dataset. Age is a discreet variable and gender a binary categorical variable where 0 is female and 1 is male.7 (LISS Panel 2019).

4.2.5 Mediating Variables

I include two mediating variables: political interest and internal political efficacy. Several prior studies suggest there is a link between personality and political interest and in turn a link between political interest and political participation, offline and online (see for example Russo and Amnå; Gerber et al. 2011a, Mondak 2010, Mondak and Halperin; Gerber et al 2011c; Quintelier and Theocharis 2012). Therefore, some explore indirect relationships by adding mediating variables. For example, Russo and Amnå find that there is an indirect effect of Openness on e-expressive mediated by political efficacy and political interest (Russo and Amnå 2016). I, however, will not study mediating variables in themselves but only control for them.

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7 In LISS data female is actually denoted as 2 and male as 1 but for the sake of consistency I choose to code all my binary variables with 0 and 1.
In the Politics and Values LISS Core Study, I find a variable that could be used as a measure of an individual’s political interest. The respondents were asked “Are you very interested in political topics, fairly interested or not interested?” where the value 1 was assigned to those who chose to answer “very interested”, 2 for those who answered “fairly interested” and 3 to those who said “not interested”. The second mediating variable I include is internal political efficacy, as do, e.g., Russo and Amnå (2016) and Jordan et al (2014). Again, I make use of the Politics and Values LISS Core Study. The dataset includes a question where panel members are asked to state if they believe they are “well capable of playing an active role in politics”. The value 1 is given to people who claim that that is true and 0 if they do not believe this is true about them (LISS Panel 2019).

4.3 Linear Probability Models and Binary Choice Models

I model the probability of political participation on Twitter with a linear probability model and a binary choice model. For each analysis, I run three models: a baseline model (Model 1), a model with control variables (Model 2), and a model with control variables as well as mediating variables (Model 3).

4.3.1 Linear Probability Model: The OLS Regression

An OLS with a binary dependent variable is called a linear probability model. The linear regression is specified as follows:

\[ y_i = \beta_1 + \beta_2 x_{i,2} + \beta_3 x_{i,3} + \cdots + \beta_k x_{i,k} + \epsilon_i \quad i = 1, \ldots, n \]

If the \( x \)-variables are exogenous to the model, then the expression above is equal to the expected value of \( y_i \) given the \( x \)-variables.

\[ E(y_i|x_i) = \beta_1 + \beta_2 x_{i,2} + \beta_3 x_{i,3} + \cdots + \beta_k x_{i,k} + \epsilon_i \quad i = 1, \ldots, n \]

The expected value of any variable can be calculated by the following formula:

\[ E(X) = x_1 p_1 + \cdots + x_n p_n = \sum_{i=1}^{n} x_i p_i \]

Since the dependent variable is binary and can only take on the value zero or one, we can conclude that:

\[ E(y) = 1 \cdot P(y = 1) + 0 \cdot P(y = 0) = P(y = 1) \]

\(^8\) In LISS data not true is denoted as 2, but for the sake of consistency I choose to code all binary variables in the same way, with 0 and 1.
In other words, the conditional expectation can be written as a conditional probability. Hence, the expected value of the dependent variable $y$ is equal to the probability that $y = 1$. In the linear regression model the $\beta$-parameters are usually interpreted as the change in the expected value of $y$ when $x$ changes one unit and $\beta_1$ as the expected value of $y$ when all the $x$-variables take the value zero. However, when the dependent variable is binary, the parameters must be interpreted differently. Now we interpret $\beta_1$ as the probability that $y = 1$ when all the $x$-variables are zero. The other $\beta_1$-parameters are interpreted as the change in the probability that $y = 1$ when $x$ changes by one unit. (Jochumzen 2017a).

The straightforward computation and interpretation could be seen as two of the linear probability model’s strengths. However, there are some problems with the linear probability model. The linear probability model models the probability that $y = 1$ as a linear function of its independent variables. Linear functions are unbounded, upwards as well as downwards, which makes it possible for the $x$-variable to take on a value that leads to the probability to lie outside $0,1$. A common way to deal with this issue is to say that all estimated probabilities that end up greater than 1 are “set to one” and those smaller than zero “set to zero”. (Jochumzen 2017a).

The other problem concerns marginal effects. The linear probability model assumes that the marginal effect is constant, meaning it does not depend on any $x$-variable. In many cases, this is an unrealistic assumption, and especially when the dependent variable is binary. However, OLS regression analysis can provide sufficient estimates for marginal effect as long as you are satisfied with getting an estimate for the average individual of your data set and not a specific one. (Jochumzen 2017a). Nevertheless, due to the obvious limitations of the OLS regression on a binary dependent variable, I conduct additional analysis using a binary choice model instead.

### 4.3.2 The Logistic Model

One way to amend the problems that arise with the linear probability model is to model the probability that $y$ equals one conditionally on $x$ as a function of all the explanatory variables:

$$P(y = 1|x) = F(\zeta_i) \quad \text{where} \quad \zeta_i = \beta_1 + \beta_2 x_{i,2} + \beta_3 x_{i,3} + \cdots + \beta_k x_{i,k}, \ i = 1, \ldots, n$$

We can then restrict the function $F$ to have the range $0,1$ and find a function that satisfies this condition. One such function is the logistic function:

$$F(\zeta) = \frac{1}{1 + e^{-\zeta}} \Rightarrow \frac{1}{1 + e^{-(\beta_1 + \beta_2 x_{1,2} + \beta_3 x_{1,3} + \cdots + \beta_k x_{1,k})}}$$
In the logistic function, if \( x \) increases, \( e^{-x} \) will decrease, and \( F \) increases. As \( e^{-x} \) gets closer to zero, \( F \) will consequently get closer and closer to one but will always be at least slightly less than one. If \( x \) decreases, \( e^{-x} \) will increase and \( F \) decrease. As \( x \) decreases, \( F \) will, therefore, get closer and closer to zero but will always be greater than zero. Therefore, the logistic function will always lie inside the 0,1 bound and will take the form of an s-shape curve. (Jochumzen 2017b; Jochumzen 2017c).

The logistic model also circumvents the problem of constant marginal effect. The marginal effect is given by the derivative of

\[
\frac{dF(\zeta)}{dx} = \frac{e^x}{(1 + e^{-x})^2}
\]

and is not constant but changes with the value of \( x \). As the s-shaped curve suggests, the marginal effect decreases as \( y \) gets closer to 0 on the one end, and on the other end as \( y \) gets closer to 1. (Jochumzen 2017b; Jochumzen 2017c).

Although the logistic model restricts the probability to a 0,1 bound and allows for a changing marginal effect, there are some disadvantages associated with the use of it. In the logistic model, there is no immediate interpretation of the numeric values of the estimates of the \( \beta \)-parameters. Only the signs can be interpreted without further processing. If \( \beta_k > 0 \) then \( \zeta \) increases with \( x_k \) and \( P(y = 1|x) \) will increase with \( x_k \). But if \( \beta_k < 0 \) then \( \zeta \) decreases with \( x_k \) and \( P(y = 1|x) \) will decrease with \( x_k \). Naturally, if \( \beta_k = 0 \) then \( \zeta \) does not depend on \( x_k \) and then \( P(y = 1|x) \) will not depend on \( x_k \) either. (Jochumzen 2017b; Jochumzen 2017c)

There are a variety of methods that enable further analysis of estimates of the \( \beta \)-parameters. Predicted probabilities is one such method. Predicted probabilities is often described as intuitive and rather uncomplicated and is based on estimated margins at certain values of the covariates. In the Analysis, I describe what values I choose and why. As before, I run three models: a baseline model, a model with control variables, and a model with control variables as well as mediating variables.
5 Analysis

5.1 Dataset Preparation: Cleaning and Recoding

5.1.1 Simple Recoding of Variables

Some variables need recoding before I can conduct the analysis:

*Income*

The income variable (nettoink) is numerical, but when asked how much they earn, some respondents stated that they do not know, prefer not to say, or just refrain to answer. In the LISS dataset, these answers are given the values -13, -14, and -15 and thus need to be recoded to missing.

*Education*

The education variable (oplzon) is categorical. The values 7, 8, and 9 stand for “Other”, “Not yet completed any education”, and “Not (yet) started any education”. 8 and 9 are automatically dropped in the merge stage due to them not having a match in all datasets joined together.

During the modeling phase, it could be problematic if you have many categories with small frequencies. In my sample, there is only one respondent that chooses 7/ “Other” as an answer, therefore, I drop 7. I also create three categories out of the six, so that the categories each contain more observations. The categories now are: 1 (primary school and intermediate secondary education), 2 (secondary education, preparatory education and junior college), and 3 (college and university).

*Political interest*

The political interest variable is a categorical variable that can take on three values. To simplify things a bit, I add together two categories, very interested and fairly interested, and create a dummy variable where 1 denotes “interested” and 0 “not interested”.

5.1.3 Reversing Scales

Some personality variables are negatively keyed, meaning that agreement indicates a lower level of the trait dimension. In other words, the scale has been inverted. For example, the statement “Feel little concern for others” measures Agreeableness. But if you respond that the statement is very accurate, that means that you are not as Agreeable as a person who says that the statement is very
inaccurate. Therefore, I have to reverse the scales for the negatively keyed personality variables before I calculate respondents’ aggregate score in each trait domain. This is done by simply creating a new variable for every negatively keyed variable that will equal 6- the old value of the variable (see appendix for more information).

5.1.4 Missing Values

In LISS data, missing values are coded as such and not zero. When the above-mentioned changes are done, I drop all individuals that have a missing value on any of the variables since missing values can reduce statistical power and bias the estimates. The dataset is now considerably smaller. It has shrunken from 4317 to 240 individuals. Ideally, I would have conducted a response analysis to make sure that the responses that are being removed do not follow a pattern or systematically share characteristics. However, due to time constraints I have not been able to do so.

5.1.5 Creating Additive Indexes: TPPI and the Big Five Traits

Using an additive index means I summarize each score that an individual reports on a question or statement. For example, let’s say an individual has answered that he or she expresses political opinion on Twitter 1-2 days a week (2), circulates political information by posting news links 3-4 days a week (3), circulates political information by retweeting political message 3-4 days a week (3), engages in conversation about a political topic 1-2 days a week (2) and never convinces others to participate in politics (1). The individual would have an aggregate score of 11. This is TPPI for this respondent.

I calculate the aggregate score for each trait domain in the same manner. Each trait domain consists of ten statements, and by adding up the observations for each individual, after having reversed some of the scales, I get a total score for Openness, Conscientiousness, Emotional Stability, Extraversion, and Agreeableness.

Descriptive statistics also show that a large amount of the observations of TPPI cluster around 5, which indicates that many respondents answered “Never” to several of the questions regarding the political use of Twitter. For example, an overwhelming majority of the respondents chose to reply “Never” (1) when asked how often they circulate political information by retweeting political messages. In other words, the data was skewed. As my sample is rather small, keeping the scale would mean that in some categories, there would be very few data points which could lead to TPPI values with low frequency being outweighed by the more frequent ones. This can reduce the statistical power of the model. Therefore, I believe it is better to turn the outcome variable into a binary variable and study the
presence or absence of online political participation on Twitter rather than the degree.

5.1.7 Converting TPPI into a Binary Variable

I create a new binary variable based on the TPPI that I call bi_TPPI. If an individual scores a 1, meaning “Never”, on all five variables, the TPPI score would be 5. Consequently, a 5 indicates that the person in question does not engage politically at all through Twitter. Any number above that, suggests the individual answered 1-2 days a week or more on at least one of the variables, and hence, does participate politically to some degree on Twitter. The bi_TPPI assumes the value 1 if the TPPI score is greater than 5, otherwise bi_TPPI = 0.

Figure 1. Illustration of bi_TPPI

5.2 Analysis Part 1: Linear Probability Model

5.2.1 Results

I begin by analyzing the relationship between the Big Five and bi_TPPI using an OLS model without control variables and mediating variables. Table 5. shows that the trait domains Agreeableness, Conscientiousness and Emotional Stability all correlate negatively with the outcome variable. All else equal, the results indicate
Table 5. Results from OLS

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Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
that a one-unit increase of Agreeableness decreases the probability of an individual participating politically on Twitter on average with 1.25 percentage points.

For Conscientiousness and Emotional Stability, the results show a decrease in probability on average of 0.165 percentage points respectively. However, out of these three variables, the association between Agreeableness and TPPI is the only one that is statistically significant. The estimated effect is statistically significant at p<0.1. Nonetheless, the significant effect of Agreeableness disappears when control variables and mediating variables are included. Agreeableness, Conscientiousness, and Emotional Stability now turn out to be jointly negative and insignificant.

When it comes to Extraversion, there is a positive correlation between the trait domain and political activity on Twitter, however; it is not significant, and it remains insignificant through all three models.

Openness is the trait domain that yields the most significant estimates. It is also the largest effect in absolute value. In the first two models, the estimated effect is statistically significant at p<0.01, and in the third statistically significant at p<0.05. In the first model, holding everything else constant, a one-unit increase of Openness increases the probability of an individual participating in political activity on Twitter on average with 1.94 percentage points. With control variables, the estimated effect is slightly smaller: on average, a one-unit increase of Openness increases the probability with 1.63 percentage points. When mediating variables are added, the effect is further reduced.

5.3 Analysis Part 2: Logistic Model

5.3.1 Results

In logistic models, there is no direct interpretation of the coefficients. However, their signs can be interpreted. The logistic model yields negative coefficients for Agreeableness, Conscientiousness, and Emotional Stability, with and without control and mediating variables. These results suggest that as the value of Agreeableness, Conscientiousness, and Emotional Stability increase, the probability that bi_TPPi=1 will decrease. These results are consistent with the results of the OLS models.

In the baseline model, the estimates for Agreeableness reach statistical significance with a p-value lesser than 0.1. However, when control and mediating variables are added, the significance disappears. The results of Conscientiousness and Emotional Stability are insignificant.
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Observations 240 240 240

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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*0.geslacht, 1.oplzon, 0.cv13f012 and 0.cv13f050 are not presented in the table because they are the reference categories.
Just like the OLS model indicated, the association between Extraversion and online political activity on Twitter is positive. This implies that as the level of Extraversion increases, so will the probability that bi_TPPI=1. But, yet again, the results for this trait domain are not statistically significant.

Lastly, the coefficient of Openness is positive, which means that as the value of Openness increases, the probability of bi_TPPI=1 will increase. It also yields statistically significant results, at p<0.01 in the first model, and at p<0.05 in Model 2 and 3. In sum, the directions and significances of the estimates in logistic model replicate the OLS models.

5.3.2 Predicted Probabilities and Marginsplot

Since there is no direct interpretation of the coefficients in the logistic model, I need to conduct additional analyses of the output. Predictive probabilities is an intuitive and easily applicable method to interpret the output further.

To obtain predicted probabilities, I use the margins command in Stata. This gives me the predictive margins. With the margins, I am able to calculate the predicted probability of political participation on Twitter at different levels of a specific trait, holding all other variables in the model constant at a specific value.

Choosing Traits to Study
The trait domains Agreeableness and Openness stand out in Model 1 because of their results reaching statistical significance. Therefore, I look into these trait domains specifically. In Model 2 and 3, I look into Openness as it is then the only trait domains with estimates that are significant.

Choosing Fixed Values
Theoretically, the lowest value an individual can get on any trait is 10. That means that the individual in question has answered 1 on every statement. Conversely, the highest value an individual theoretically can receive is 50. Thus, I let the levels of the trait domains I study vary from 10 to 50. The other trait domains are held constant at their mean, so is the income and the age variable. The other variables are set to their median value because they are categorical. In other words, the predicted probabilities are calculated on a 36-year-old female, with higher secondary education/senior high school or junior college, and an average income that is interested in politics but do not believe she is cable of playing an active part in it.

The results are illustrated in the Figure 2-5, where the y-axis shows the probability that bi_TPPI=1, and the x-axis shows trait domain. The graphs also show confidence intervals.
Figure 2. Marginsplot of Openness in Model 1

Figure 3. Marginsplot of Openness in Model 2
Figure 2. is a marginsplot of the results of an estimation of the predictive margins for an individual at levels of Openness from 10 through 50 at intervals of 2. By graphical interpretation, we can discern a positive association between Openness and probability to engage in political Twitter participation. We can also see that the slope of the curve increases as the independent variable gets larger, which means that the higher the score of Openness, the larger the marginal effect. For example, an increase in Openness from level 40 to 41 has a greater effect on the probability to engage compared to a one-unit increase in Openness from 16 to 17.

The average score of Openness in my sample is 36.7. At this level the predicted probability of political participation on Twitter is approximately 30 percent, holding the other variables in the model constant at specific values. All else equal, if the score of Openness increases from the mean to the highest observed value in my sample, 50, the predicted probability of political participation on Twitter is raised roughly 30 percent, to nearly 60 percent. The smallest value is 23, where the predicted probability is a little bit less than 10 percent. The width appears to be at its narrowest around 36-38, where the median also lies. Knowing where the median is, it makes sense that where most individuals in the dataset are clustered is also where we will have the best precision in our estimates.

When control variables and mediating variables are added in Model 2 and 3 (Figure 3-4), the graphs change in two notable manners. Firstly, the slope does not increase at the same rate in Model 2 and 3. Secondly, in Model 2 and 3 the area of
the graph has grown larger compared the Model 1. This means that the confidence interval is larger; hence, we are not as sure of the predictions as we were in model 1.

Figure 5. Marginsplot of Agreeableness in Model 1

Figure 5. shows the result of the marginsplot of an estimation of the predictive margins for an individual at levels of Agreeableness from 10 through 50 at intervals of 2. A graphical interpretation tells us that there is a negative correlation between Agreeableness and probability to engage in political Twitter participation as the graph is decreasing. The slope of the curve also appears to be almost constant. Therefore, judging by this graph it seems as though the marginal effect remains rather constant as the level of Agreeableness increases.

In the sample, the mean score of Agreeableness is approximately 38.6. At the mean level, the predicted probability of political participation on Twitter is around 30 percent, holding the other variables in the model constant at specific values. All else equal, if the score of Agreeableness increases from the mean to the highest observed value in my sample, 50, the predicted probability decreases a little bit more than 10 percent. The smallest observed value is 21. At this level of Agreeableness, the predicted probability of political participation on Twitter is approximately 60 percent. It is worth noting that the area of graph 4 is considerably larger than graph 1, 2 and 3. This means that the confidence interval is larger, and the results are less precise.
6 Discussion and Closing Remarks

The 21st century saw a conceptual expansion of political participation. As our notion of democracy and citizenship changed, political participation entered new territories. The Internet was one. New forms of political participation on new arenas required broader definitions of the concept. Former definitions turned obsolete.

For this thesis, Brady’s 1998 definition has served as a point of departure. According to Brady, a political act does not have to take place inside the government sphere or be directed towards those in charge. As long as the participant aims for the act to have political consequences, it can be labeled political.

When political participation enters new arenas, the question sometimes arises whether or not the place makes participation inherently different. So has been the case with online political participation.

Gibson and Cantijoch (2013) argue that, although many forms of online political participation mirror their offline counterparts, some are actually transforming due to medium. The e-expressive mode is one such form. This, I would say, makes a particularly good reason for studying e-expressive, and Twitter is a particularly good example with activities, such as posting, forward or embedding political messages or engaging in discussion in the comments, being common.

Researchers from all types of fields have studied and continue to study political participation. Political psychology is no exception. One popular research area is how personality relates to political participation of different forms. However, there is considerably less research done on personality and online political participation, and Twitter especially has received little attention. This is unfortunate since Twitter is a big, important SNS which also emphasizes the e-expressive mode. With my thesis, I attempt to fill out a part of this research gap. My study also adds to debate on personality and online political participation because it is conducted on a sample that differs slightly from previous ones. First of all, it consists of Dutch people, a nationality that is not included in the studies I have come across. It is also a non-American sample, although Western, and what is more, it is a cross-section of the Dutch population and not constrained to young people or students. This is important because, in the long run, it could help generalize results of personality research.
6.1 How Does My Results Relate to Previous Research?

My results indicated that there is a positive association between Openness as well as Extraversion and bi_TPPI. This means that as the level of Openness and Extraversion increase, so does the probability that an individual will engage in political participation on Twitter. Between Agreeableness, Conscientiousness, and Emotional Stability and bi_TPPI, I observed negative associations. However, only Agreeableness (Model 1) and Openness (all three models) get significant results. In other words, my hypotheses for Openness, Conscientiousness and Emotional Stability were confirmed. However, when it comes to Agreeableness and Extraversion, the results were a bit surprising to me.

In offline political participation research, Extraversion is the trait domain that has yielded the most consistent findings. It is probably too early to draw conclusions about Extraversion and online political participation since there are still few studies. So far, however, it looks as though there is not as clear and strong of an association here. For example, Russo and Amnå (2016) find an indirect and not a direct effect and Ha et al. (2013) observe a positive association but it is not significant. The same goes for my study. It would be interesting to study this further to see if there is an actual tendency here. And if there is, to explore why.

Mondak et al. (2010) argued that social interaction is what drives the association between Extraversion and political activity. Following this line of thinking, it makes sense to expect that Extraverts would not be as attracted to online forms of engagement because the physical distance means a lesser return for them. On the other hand, the endless possibilities of networking and constant social exchange that the online sphere offers could be something that they find appealing. What is more, for a social, expressive, and attention-seeking person, the enormous reach on the internet might compensate what is lost by the physical distance.

For similar reasons, it would be interesting to study Openness and online political participation further. Judging by the studies I have accounted for here, as well as the results that I get, Openness, rather than Extraversion is the trait domain that yields the most consistent results. Intuitively it makes sense. After all, the Internet is a great source of stimulation with numerous opportunities for a curious person to learn and explore with a low entry threshold.

For Agreeableness, I expected a negative association between the trait dimension and bi_TPPI. However, I did not expect it to be significant. The reason was that the results from offline research were inconsistent. Quintelier and Theocharis’ results were not significant, and they found a positive association. Nevertheless, Russo and Amnå’s study showed significant direct association between Agreeableness and e-expressive. In retrospect, maybe I should have let Russo and Amnå’s study guide more since I partly used the same theoretical framework as they did. Again, I would argue, it is too early to draw any conclusions from the empirical findings of personality and online political participation research. However, it would be
interesting if future research further explored the relationship between Agreeableness and online political participation. Theoretically, it would make sense if a negative association is stronger for online activities, especially those that count as e-expressive. On Twitter, there is no shortage of discussion and contention. This might repel those who are high on Agreeableness. But then, online, you have physical distance and the possibility of anonymous participation, which could function mitigating. Yet, it is worth asking if social sanctions are what makes Agreeable people shy away from conflict, or is it that they genuinely do not like to upset people? Besides, anonymity may make it less daunting for Agreeable people to engage in an online forum characterized by discussion. However, at the same time, it most likely intensifies the debate climate as well. Furthermore, the physical distance and the anonymity might also take away what those high in Agreeableness feel they might otherwise gain.

To summarize, I think it might be theoretically motivated to expect a stronger negative association between Agreeableness and online political participation, in particular e-expressive. However, more research is needed. It would also be interesting if future research explored the relationship between Openness and the e-expressive mode of participation since so far this seems to be the strongest, and not Extraversion.

6.2 Methodological and Theoretical Choices

*Using OLS Regression on a Binary Variable*

There are differences of opinion regarding the use of OLS regression on a binary variable. Linear functions are unbounded, and thus, the outcome variable can take on a value lesser than 0 or greater than 1. The result is that the probability technically could be lesser than 0 or greater than 100%, which, of course, theoretically is not possible. Some argue that this disqualifies OLS as a method whenever you have a binary outcome variable. On the other hand, there are those who believe this need not be a problem as long as you are careful with how you interpret the outcome. The same goes for the problem of constant marginal effects that I also mentioned in the Sources and Methodology chapter. One could argue that as long as you interpret the results as the estimates of the “average individual” of your data set, it is not a problem.

Because of these opposing views, I decided it was best to use both OLS regressions and logistic models. Regardless of the methodological divide, I get similar results from the two methods. I cannot comment on whether this means that OLS regression is an appropriate method for binary outcome variables. That is beyond my knowledge, experience, and place. However, for my purposes, the OLS provided sufficient estimates.
Data Constraints
There are several control variables and mediating variables that I considered to include but, in the end, did not. For example, I considered controlling for Internet access and Internet usage. It makes sense to control for Internet access since it is a basic requirement for taking part in political participation on Twitter. Internet usage is a fairly common control variable in studies like mine. The idea is that people who are avid internet users are more likely to engage politically online, regardless of their personality. Political engagement and political knowledge are also two examples of common control and mediating variables I contemplated.

There are a variety of reasons I did not include these and other variables. First of all, there were some practical reasons. Sometimes, as in the case of, e.g., political knowledge, there was no suitable variable available in the LISS dataset. To add variables and datasets would most likely also make the sample even smaller. A small sample is problematic because it affects the reliability of the results. When adding many independent variables, you also risk overfitting the model. As more independent variables are added, it is more likely that the independent variables will be statistically significant despite there not being a causal relationship between the independent variables and the outcome variable.

Another data-related constraint that I came upon was the partial dropouts. When I dropped all individuals in my dataset with one or multiple missing values, a substantial amount was removed. This was primarily because the Twitter dataset had many partial dropouts. A small sample size can be a problem because it reduces the overall statistical power, it could make you inflate the effect size of the estimates, and it makes it more difficult to reproduce the study. Regrettably, I cannot be sure that the individuals I remove do not follow a certain pattern or systematically share characteristics since I do not conduct a response analysis. Nevertheless, the problem of a small sample size is not easily fixed because it depends on the data collection process. Hopefully, there will be more data at hand in the future.

The Use of an Additive Index
I also had to take into consideration which index type to use. I chose between additive index and weighted index and the fact is that my decision was more based on what index not to use rather than which index to use. I could not come up with any arguments for why any of the five questions the TPPI is based on would count more or less as e-expressive activity. Although the activities (expressing, retweeting, conversating, etc.) certainly differ, I do not see how they would represent political activity in different degrees.

The Cutoff Value in the bi_TPPI
The outcome variable takes on the value 1 if the TPPI score is greater than 5, meaning that a respondent has answered that he or she used Twitter one or more days a week for at least one of the five listed activities. This is somewhat an

10 The Swedish term is bortfall. I do not know if “dropout” is the correct term to use here.
arbitrary or subjectively chosen number; the cutoff value could have been set higher. For example, I could have chosen to study a little and a lot of Twitter political participation as well. I chose this cutoff value because I wanted to avoid having a category with very few observations. Few observations can reduce the statistical power. Furthermore, I considered it to be a theoretically interesting distinction.

**Theoretical Choices**

I have built my analysis on a theoretical framework and a few central concepts from pre-existing literature. The personality variables are based on the 50-item IPIP representation of the Goldberg (1992) markers for the Big Five factor structure, without alterations from either LISS or me. It is important to remember that although the Big Five Model is arguably the most comprehensive personality framework in existence, it has been subject to criticism. The Big Five Model is derived from lexical studies, and therefore, some argue that the framework measures how we describe personality rather than the actual, complex nature of it. Other common criticisms are that the framework is too descriptive and not sufficiently based on theory (Fiske 2010; Pervin 2009). It is also important to remember that, even among the Big five Model’s proponents, some things are debated, such as what personality-descriptive terms best describe each domain and how levels of each factor are best measured, e.g., debating the pros and cons with different kinds of scales, self-rating tests, peer tests, or whether there are actually more or fewer trait domains.

**6.3 Possible Implications of My Thesis**

There are three possible main implications of my thesis. Previous research undoubtedly has many qualities; however, the amount of studies is limited. Empirically, my thesis thus provides further evidence on the relationship between personality and online political participation, and in particular expressive forms that arguably are transforming on the Internet. Besides, as far as I know, there is no other study combining the datasets I have used for the same purposes.

Theoretically, the implication of my study is two-folded. First of all, I operationalize online political participation differently, allowing for a greater focus on the e-expressive mode of participation. Since I use a sample that is representative of the Dutch population, my results also add to the debate on cross-national variation of trait domains and political participation. This is interesting because we could learn more about the extent to which we can generalize results on personality and online political participation across country borders.

The political implications and relevance outside of research are related to my empirical findings. Participation is central to democratic society. However, political participation is a fluid concept. As our notion of democracy and citizenship
changes, so does the idea of what constitutes political participation. When some political participatory acts go in and out of fashion, some may follow while others will not. Today, some make the argument that more people are turning away from official modes of participation in favor of more expressive ones. Because participation is vital to a society’s democratic function, it is always useful to explore who participates and why. In the long term, this kind of knowledge could help us keep democracy healthy and inclusive. Personality is just one of the many possible explanations for political participation, but it has been and remains an important one, offline and online.
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Appendices

Codebook

In this codebook I include the parts of the questionnaires administered to the LISS panel that my variables are based on. The text makes use of data and text of the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands), unchanged. The information can be found on: https://www.dataarchive.lissdata.nl.

Please note that the variable names are printed in bold and correspond to the names in the dataset and that the questions are sorted by dataset.

Personality LISS Core Study

Title: Personality
Data file: cp13f
Funding sources: CentERdata – MESS project
Investigator: CentERdata
Project description: The survey focuses on personality and characteristics
Sample:
Selected number of household members: 5708 (100%)
Non-response: 539 (9.4%)
Response: 5169 (90.6%)
Complete:
Incomplete:
Date of data collection: May 2013, June 2013

On the following pages, there are phrases describing people's behaviors. Please use the rating scale below to describe how accurately each statement describes you. Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. Please read each statement carefully, and then fill in the bubble that corresponds to the number on the scale.

1 = very inaccurate
2 = moderately inaccurate
3 = neither inaccurate nor accurate
4 = moderately accurate
5 = very accurate

**cp13f020 - cp13f029**

Please use the rating scale below to describe how accurately each statement describes you.

**cp13f020** Am the life of the party.
**cp13f021** Feel little concern for others.
**cp13f022** Am always prepared.
**cp13f023** Get stressed out easily.
**cp13f024** Have a rich vocabulary.
**cp13f025** Don’t talk a lot.
**cp13f026** Am interested in people.
**cp13f027** Leave my belongings around.
**cp13f028** Am relaxed most of the time.
**cp13f029** Have difficulty understanding abstract ideas.

1 very inaccurate
2 moderately inaccurate
3 neither inaccurate nor accurate
4 moderately accurate
5 very accurate

**cp13f030 - cp13f039**

Please use the rating scale below to describe how accurately each statement describes you.

**cp13f030** Feel comfortable around people.
**cp13f031** Insult people.
**cp13f032** Pay attention to details.
**cp13f033** Worry about things.
**cp13f034** Have a vivid imagination.
**cp13f035** Keep in the background.
**cp13f036** Sympathize with others’ feelings.
**cp13f037** Make a mess of things.
**cp13f038** Seldom feel blue.
**cp13f039** Am not interested in abstract ideas.

1 very inaccurate
2 moderately inaccurate
3 neither inaccurate nor accurate
4 moderately accurate
5 very accurate

**cp13f040 - cp13f049**

Please use the rating scale below to describe how accurately each statement describes you.

**cp13f040** Start conversations.
**cp13f041** Am not interested in other people’s problems.
**cp13f042** Get chores done right away.
**cp13f043** Am easily disturbed.
**cp13f044** Have excellent ideas.
**cp13f045** Have little to say.
**cp13f046** Have a soft heart.
**cp13f047** Often forget to put things back in their proper place.
**cp13f048** Get upset easily.
**cp13f049** Do not have a good imagination.

1 very inaccurate
2 moderately inaccurate
3 neither inaccurate nor accurate
4 moderately accurate
5 very accurate

**cp13f050 - cp13f059**
Please use the rating scale below to describe how accurately each statement describes you.

**cp13f050** Talk to a lot of different people at parties.
**cp13f051** Am not really interested in others.
**cp13f052** Like order.
**cp13f053** Change my mood a lot.
**cp13f054** Am quick to understand things.
**cp13f055** Don’t like to draw attention to myself.
**cp13f056** Take time out for others.
**cp13f057** Shirk my duties.
**cp13f058** Have frequent mood swings.
**cp13f059** Use difficult words.

1 very inaccurate
2 moderately inaccurate
3 neither inaccurate nor accurate
4 moderately accurate
5 very accurate

**cp13f060 - cp13f069**
Please use the rating scale below to describe how accurately each statement describes you.

**cp13f060** Don’t mind being the center of attention.
**cp13f061** Feel others’ emotions.
**cp13f062** Follow a schedule.
**cp13f063** Get irritated easily.
**cp13f064** Spend time reflecting on things.
**cp13f065** Am quiet around strangers.
**cp13f066** Make people feel at ease.
**cp13f067** Am exacting in my work.
**cp13f068** Often feel blue.
**cp13f069** Am full of ideas.
1 very inaccurate
2 moderately inaccurate
3 neither inaccurate nor accurate
4 moderately accurate
5 very accurate

**Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media and in Surveys**

**Title:** Calibrating Twitter Data: Issue Salience and Issue Ownership in Social Media and in Surveys  
**Datafile:** jz13a  
**Funding sources:** MESS Project  
**Investigator:** Dr. B. Hosch-Dayican, Prof. Dr. K. Aarts, Dr. A. Dassen, and Dr. C. Amrit  
**Project description:** This questionnaire consists of questions about the knowledge of the views of different political parties and the use of Twitter for voicing political opinions.  
**Sample:** Panel members aged 16 years or older.  
**Overview of the response:**  
Selected number of household members: 6261 (100%)  
Non-response: 1050 (16.8%)  
Response: 5211 (83.2%)  
Complete: 5143 (82.1%)  
Incomplete: 68 (1.1%)  
**Date of data collection:** October 2013

**jz13a042 - jz13a046**  
How often do you use Twitter for the following activities?  
**jz13a042** Express political opinion?  
**jz13a043** Circulate political information by posting news links?  
**jz13a044** Circulate political information by retweeting political message?  
**jz13a045** Engage in conversation about a political topic?  
**jz13a046** Convince others to participate in politics?  
1 Never  
2 1-2 days per week  
3 3-4 days per week  
4 5-6 days per week  
5 Every day

**Background Variables LISS Panel**

**Title:** Background Variables
Datafile: avars_201310
Date of data collection: October 2013
Funding sources: MESS Project/CentERdata
Investigator: CentERdata
Sample: Contact person of each household

**geslacht**  Gender
1 Male
2 Female

**leeftijd**  Age of the household member

**oplzon**  Highest level of education irrespective of diploma
1 primary school
2 vmbo (intermediate secondary education, US: junior high school)
3 havo/vwo (higher secondary education/preparatory university education, US: senior high school)
4 mbo (intermediate vocational education, US: junior college)
5 hbo (higher vocational education, US: college)
6 wo (university)
7 other
8 Not yet completed any education*
9 Not (yet) started any education

**nettoink**  Personal net monthly income in Euros
-13 I don’t know
-14 Prefer not to say
-15 Unknown (missing)

---

**Politics and Values LISS Core Study**

Title: Politics and Values – wave 6
Datafile: cv13f
Funding sources: MESS Project/CentERdata
Investigator: CentERdata
Project description: The survey focuses on politics and values
Sample: panel members aged 16 years and older
Overview of the response:
Selected number of household members: 6,692 (100.0%)
Nonresponse: 960 (14.3%)
Response: 5,732 (85.7%)
Complete: 5,680 (84.9%)
Incomplete: 52 (0.8%)
Date of data collection: December 2012, January 2013

**cv13f012**
Are you very interested in political topics, fairly interested or not interested?
1 very interested
2 fairly interested
3 not interested

**cv13f047 - cv13f052**
What is your response to the following statements?

**cv13f050** I am well capable of playing an active role in politics.
1 this is true
2 this is not true
Do-file

*** DO-FILE FOR MASTER THESIS
*** Created by Angelica Dahl
*** last updated on 20 December 2019

This is the do-file for my quantitative analysis. The do-file includes all
the commands that I have run, even those that has not been accounted for in
the paper.

*** PART I: DATASET PREPARATION: Merge, recode and drop
// Set the directory to the appropriate folder
cd "\Users\angelicadahl\Documents\Stata"
// Begin a log file, specify the name and location of the file
log using 20dec_analysis, replace
// Open the dataset Personality Liss Core Study, 6th wave
use cp13f_EN_1.0p.dta
// Merge the dataset with the independent variables with the dependent variables
** The type of merge I will do is a 1:1 merge, where the Personality LISS
** Core Study will be the "master dataset" and Calibrating Twitter data will
** be "using" in the first merge.
merge 1:1 nomem_encr using jz13a_EN_1.0p.dta
** After the merge, a total of 1,230 observations do not match, 594 from the
** from the master dataset and 636 from the using dataset. 4,575
observations do match.
// Drop observations that do not match on the identifying variable, household id
drop if _merge==1
drop if _merge==2
** 1,230 observations are deleted and 4,575 remains.
// Merge with Background variables
** I repeat the process, but now with the Background Variables
** dataset being used.
drop _merge
merge 1:1 nomem_encr using avars_201310_EN_1.0p.dta
** After the merge, a total of 5,006 observations do not match,
2 from the
** from the master dataset and 5,004 from the using dataset.
drop if _merge==1
drop if _merge==2
58 ** 5,006 observations are deleted. A total of 4,573 remains.
// Merge with Politics and Value LISS Core Study,
** I repeat the process, but now with the Politics and Value
** dataset being used.
drop _merge
merge 1:1 nomem_encr using cvi3f_EN_1.0p.dta
** After the merge, a total of 1,671 observations do not match,
256 from the
** from the master dataset and 1,415 from the using dataset.
// Drop observations that do not match on the identifying variable
drop if _merge==1
drop if _merge==2
** 1,671 observations are deleted. A total of 4,317 remains.
// Drop all the variables not needed for the analysis
keep cp13f020 cp13f021 cp13f022 cp13f023 cp13f024 cp13f025
  cp13f026 cp13f027 cp13f028 cp13f029 cp13f030 cp13f031 cp13f032
  cp13f033 cp13f034 cp13f035 cp13f036 cp13f037 cp13f038 cp13f039
  cp13f040 cp13f041 cp13f042 cp13f043 cp13f044 cp13f045 cp13f046
  cp13f047 cp13f048 cp13f049 cp13f050 cp13f051 cp13f052 cp13f053
  cp13f054 cp13f055 cp13f056 cp13f057 cp13f058 cp13f059 cp13f060
  cp13f061 cp13f062 cp13f063 cp13f064 cp13f065 cp13f066 cp13f067
  cp13f068 cp13f069 geslacht leeftijd oplzon nettoink cvi3f012
cv13f050 jz13a042 jz13a043 jz13a044 jz13a045 jz13a046
85 // Recode variables that needs to be recoded
86 ** Before I can drop missing values from the dataset, income, education,
87 ** gender, political interest and internal political efficacy needs some
88 ** recoding (see codebook for more information).
89 // Recode observations on the income variable (nettoink) with
90 // the value of -13
91 // ("I don’t know"), -14 ("I prefer not to say") and -15
92 // (unknown) to missing.
93 foreach var of varlist nettoink{
94    recode `var' -13=.  
95    recode `var' -14=.  
96    recode `var' -15=.  
97 }  
98  
99 ** 223 changes were made.
100 // Recode observations on the education variable (oplzon) with
101 // the value of
102 // 7 ("Other"), 8 ("Not yet completed any education") or 9 ("Not (yet) started any
103 // education") to . Create three education categories out of the
104 // total 6.
105 foreach var of varlist oplzon{
106    recode `var' 7=.  
107    recode `var' 8=.  
108    recode `var' 9=.  
109    recode `var' 2=1  
110    recode `var' 3=2  
111    recode `var' 4=2  
112    recode `var' 5=3  
113    recode `var' 6=3  
114 } 
115  
116 ** 4160 changes were made.
117  
118 // Recode the gender variable
119 ** In LISS female is given the value 2 and male the value 1.
120 This will
121 ** be changed so that female is given the value of 0 instead.
** Male will still be denoted by the value of 1.

foreach var of varlist geslacht{
    recode `var' 2=0
}

** 2281 changes were made.

// Recode the variable political interest, creating a dummy variable where 1 stands for interested and 0 for not interested.

foreach var of varlist cv13f012{
    recode `var' 2=1
}

foreach var of varlist cv13f012{
    recode `var' 3=0
}

** 3629 changes were made.

// Recode the internal political efficacy variable, so that 2 becomes 0.

foreach var of varlist cv13f050{
    recode `var' 2=0
}

** 3311 changes were made.

//Drop the households that have one or multiple missing observations
// on any of the variables.


** 4,077 observations were deleted. I now have a total of 240
individuals to study.

// Reverse scales for negatively keyed personality variables
** Some personality variables are negatively keyed (see appendix (insert)
** reference) for more information). Therefore, I create a new
variable for every negatively keyed variable that will equal 6 –
the old value of the variable.

// Reverse scales for Agreeableness:
gen new_cp13f021=6-cp13f021

gen new_cp13f031=6-cp13f031

gen new_cp13f041=6-cp13f041

gen new_cp13f051=6-cp13f051

// Reverse scales for Conscientiousness:
gen new_cp13f027=6-cp13f027

gen new_cp13f037=6-cp13f037

gen new_cp13f047=6-cp13f047

gen new_cp13f057=6-cp13f057

// Reverse scales for Emotional Stability

gen new_cp13f023=6-cp13f023

gen new_cp13f033=6-cp13f033

gen new_cp13f043=6-cp13f043

gen new_cp13f048=6-cp13f048

gen new_cp13f053=6-cp13f053

gen new_cp13f058=6-cp13f058

gen new_cp13f063=6-cp13f063

gen new_cp13f068=6-cp13f068

// Reverse scales for Extraversion

gen new_cp13f025=6-cp13f025
gen new_cp13f035=6-cp13f035
gen new_cp13f045=6-cp13f045
gen new_cp13f055=6-cp13f055
// Reverse scales for Openness to Experience
gen new_cp13f029=6-cp13f029
gen new_cp13f039=6-cp13f039
gen new_cp13f049=6-cp13f049
// Drop negatively keyed variables
drop cp13f021 cp13f031 cp13f041 cp13f051 cp13f027 cp13f037
cp13f047 cp13f057 cp13f023 cp13f033 cp13f043 cp13f048 cp13f053
cp13f058 cp13f063 cp13f068 cp13f025 cp13f035 cp13f045 cp13f055
cp13f065 cp13f029 cp13f039 cp13f049
// Create scores for each personality dimension
** Now, the variables that belong to a certain trait dimension must be added
** together to create a total score for each personality dimension. This is done
** by creating a new variable, which equals the addition of all the personality
** variables belonging to a certain dimension.
// Create a total score of Agreeableness
eegen agreeableness= rowtotal (cp13f026 cp13f036 cp13f046 cp13f056
cp13f061 cp13f066 new_cp13f021 new_cp13f031 new_cp13f041
new_cp13f051)
// Create a total score of Conscientiousness
eegen conscientiousness= rowtotal (cp13f022 cp13f032 cp13f042
cp13f052 cp13f062 cp13f067 new_cp13f027 new_cp13f037 new_cp13f047
new_cp13f057)
// Create a total score of Emotional Stability
eegen emotionalstability= rowtotal (cp13f028 cp13f038 new_cp13f023
new_cp13f033 new_cp13f043 new_cp13f048 new_cp13f053 new_cp13f058
new_cp13f063 new_cp13f068)
// Create a total score of Extraversion
egen extraversion=rowtotal (cp13f020 cp13f030 cp13f040 cp13f050 cp13f060 new_cp13f025 new_cp13f035 new_cp13f045 new_cp13f055 new_cp13f065)
// Create a total score of Openness to Experience
egen openness=rowtotal (cp13f024 cp13f034 cp13f044 cp13f054 cp13f059 cp13f064 cp13f069 new_cp13f029 new_cp13f039 new_cp13f049)
// Create the Twitter Political Participation Index (TPPI)
** Create the Twitter Political Participation Index, generating a new variable
** by adding up the five variables from the “Calibrating Twitter Data...”
** =dataset.
egen TPPI=rowtotal (jz13a042 jz13a043 jz13a044 jz13a045 jz13a046)

*** PART 2: DESCRIPTIVE STATISTICS
summarize jz13a042 jz13a043 jz13a044 jz13a045 jz13a046, detail
summarize TPPI, detail
histogram TPPI, frequency
summarize agreeableness conscientiousness emotionalstability extraversion openness geslacht leeftijd oplzon nettoink cv13f012 cv13f050, detail

*** Revisiting PART 1: Creating a binary outcome variable
** Generate a binary outcome variable out of the TPPI called bi_TPPI,
** (detecting/showing) the occurrence of twitter political participation (1) or
** the absence of it (0).
gen bi_TPPI=0
replace bi_TPPI=1 if TPPI>5
histogram bi_TPPI, frequency

*** PART 3: LINEAR PROBABILITY MODELS
// Run LINEAR PROBABILITY MODEL 1: Independent variables of interest and outcome variable
ssc install outreg2

** Outreg2 is a user-written procedure that will help produce nice presentations** of results. Since it is user-written it needs to be installed.

reg bi_TPPI agreeableness conscientiousness emotionalstability extraversion openness
outreg2 using OLS_results.doc, replace ctitle(Model 1)

// Run LINEAR PROBABILITY MODEL 2: Control variables added
reg bi_TPPI agreeableness conscientiousness emotionalstability extraversion openness i.geslacht leeftijd i.oipzon nettoink
outreg2 using OLS_results.doc, append ctitle(Model 2)

** an "i" is put before the variables that are best not treated as continuous
** variables

// Run LINEAR PROBABILITY MODEL 3: Mediating Variables Added
reg bi_TPPI agreeableness conscientiousness emotionalstability extraversion openness i.geslacht leeftijd i.oipzon nettoink i. cv13f012 i.cv13f050
outreg2 using OLS_results.doc, append ctitle(Model 3)

*** PART 4: LOGISTIC MODELS

// Run logistic model and get odds ration model 1: Independent variables of interest and outcome variable

// Model 1
logit bi_TPPI agreeableness conscientiousness emotionalstability extraversion openness
outreg2 using BCM_results.doc, replace ctitle(Model 1)
margins, at((mean) openness conscientiousness emotionalstability extraversion agreeableness=(10(2)50))
marginsplot, xlabel(10(2)50) recast(line) recastci(rarea)
margins, at((mean) agreeableness conscientiousness emotionalstability extraversion openness=(10(2)50))
marginsplot, xlabel(10(2)50) recast(line) recastci(rarea)
// Model 2
logit bi_TPPi agreeableness conscientiousness emotionalstability extraversion openness i.geslacht leeftijd i.oplzon nettoink
outreg2 using BCM_results.doc, append ctitle(Model 2)
margins, at((mean) agreeableness conscientiousness emotionalstability extraversion openness=(10(2)50) nettoink leeftijd=36 oplzon=2 geslacht=0)
marginsplot, xlabel(10(2)50) recast(line) recastci(rarea)

//Model 3
logit bi_TPPi agreeableness conscientiousness emotionalstability extraversion openness i.geslacht leeftijd i.oplzon nettoink i. cv13f012 i.cv13f050
outreg2 using BCM_results.doc, append ctitle(Model 3)
margins, at((mean) agreeableness conscientiousness emotionalstability extraversion openness=(10(2)50) nettoink leeftijd=36 oplzon=2 geslacht=0 cv13f012=1 cv13f050=0)
marginsplot, xlabel(10(2)50) recast(line) recastci(rarea)