

Using social media to predict personality and innovative behavior

Personality prediction with the use of Twitter data.

Nick Bombay

S475460

0628081803

nick.bombay@gmail.com

Supervisor: Dr. H. Weigand

Second reader: Prof. dr. ir. H.A.M. Daniels

Table of Contents

Abstract.....	4
1. Introduction	5
1.1 Problem Indication	5
1.2 Problem statement.....	6
1.3 Scope	7
1.4 Research Questions.....	7
1.5 Research Design.....	7
2. Literature review	8
2.1 Big five personality domains.....	8
2.1.1 Emergence of the taxonomy.....	8
2.1.2 Interpretation.....	9
2.1.3 Cultural differences	10
2.1.4 Limitations	10
2.1.5 Applications.....	11
2.2 Social media	12
2.3 Adoption lifecycle.....	13
2.4 Conceptual framework.....	14
3. Methodology.....	15
3.1 Big five personality.....	15
3.2 Social media usage	15
3.3 Adoption of innovation	16
3.4 Demographics	17
3.5 Twitter data	17
3.6 Pretest.....	17
4. Results	18
4.1 Survey.....	18
4.2 Construct Validity	18
4.3 Twitter data and Personality.....	20
4.4 Social media and Personality.....	21
4.5 Personality and adoption of innovation	25
5. Conclusion.....	27
5.1 Summary of main findings	27
5.2 Managerial implications	27

5.3 Discussion	28
5.4 Future research	28
References.....	30
Appendix A: Constructs.....	36
Appendix B: Reliability.....	39
Appendix C: Twitter tests	40
Appendix D: Social media	42
Social Media usage.....	42
Social media behavior	46
Appendix E: Adoption of innovation.....	50

Abstract

Because social media platforms have witnessed a huge growth over the last couple of years, data of almost every consumer is available and accessible on a large scale. In this paper, we investigate the possibility of social media use to predict consumer personality traits. In addition, we investigate innovative behavior as a new application of the personality traits by linking these constructs together. By analyzing the content of over 13,000 tweets, we find that Twitter content can predict conscientiousness, one of the big five personality domains, to some extent. Furthermore, we find that the use of several other social media platforms can also give a predictive indication on other personality traits. Finally, we found a connection of each of the five personality domains with at least one of the two innovation constructs, establishing a new application for the big five.

Keywords: Social Media, Twitter, Big Five, Personality, Adoption lifecycle, Adoption of Innovation, Innovative Behavior, EAP, EIS.

1. Introduction

1.1 Problem Indication

Social media has increased tremendously the last couple of years. In Q1 of 2010, Facebook had 431 Million users, while this grew to a total of almost 1,4 Billion at Q4 of 2014 (Statista, 2014). In January 2015, Twitter had a total of 284 million (Statista, 2015). The emergence of social media has enabled companies to reach consumers in a new way rather than with the traditional channels like TV and printed media.

Besides new opportunities for targeting, companies can also gain better insight in consumer characteristics in general, as consumers make a lot of personal data available within the use of social media. Many companies would like to obtain more information about their consumers or persons of interest before interacting with them. One of the main advantages of obtaining more information is the ability to distinguish behavior and human characteristics, with which decisions or strategies can be adjusted individually.

One of the ways to distinguish human behavior is by determining the big five personality dimensions. The big five illustrate that a personality can be divided into five different independent measures, which provide meaningful individual differences. According to Barrick and Mount (1991), the big five personality dimensions are currently the most accepted by researchers and have been tested for robustness in several methods. The personality dimensions consist of openness, conscientiousness, extroversion, agreeableness and neuroticism.

The big five personality dimensions have been used to describe several characteristics and behavior and allow improved decision making for companies. Several studies have demonstrated value of personality in a professional environment. Certain dimensions are for example found to have an impact on job performance (Barrick & Mount, 1991) and career success (Judge et al 1999). However, the big five personality dimensions also have an impact in the marketing field. Whelan and Davies (2006) found a distinction between the preference of own brands and national brands, based on some of the personality characteristics.

Although the theoretical foundations for these effects have been found, it would be considerably hard for companies to actually obtain all necessary data needed to determine the big five personality traits. Some of the concepts should be feasible. For example, new potential employees could receive a personality test, so companies can estimate parameters such as job performance and career success. However, when a certain function has a large number of applicants, it can already be troublesome. Also, when using personality dimensions for consumers, it is often no longer feasible to gather all required data from each and every consumer with interviews or surveys.

1.2 Problem statement

Companies benefit from more individual data, which can more easily be obtained these days with the emergence of social media in the past decade. Golbeck et al (2011) investigated a personality prediction from Twitter in the English language. Markovikj et al (2013) researched the big five characteristics based on English Facebook data. Schwartz et al (2013) also investigated Facebook data, although using another method. However, there is an absence of personality research in social media in different languages. At this moment, the main stream of literature and language models are based on the English language, which leaves the question if similar methods can work for all non-native English speaking countries. In this study, we would like to address language differences and differences in a social media platform.

Having a model to predict personalities is relevant for all companies or institutions that want to individually target consumers in order to have a higher or more positive response. The fields of these companies can be quite diverse. On the one hand, it can be used externally for targeted marketing and preference, as mentioned in Whelan and Davies (2006). Product portfolios or advertisements could be tailored to individual desires, and thus improving attention, attitude or perceived value. On the other hand, it could be used internally, for recruiting purposes, as personality traits have been predictors of job performance (Barrick & Mount, 1991). Recruitment in general is a tough process which includes quite some uncertainty, considering there is often little known about the applicant. Certain known personality traits could improve the recruitment process of companies. All in all, although there have been quite some papers and discussions about personality characteristics, the possible applications are still somewhat limited. Therefore, we want to explore an additional application of personality in our study, by looking at innovative behavior.

The goal of this research is thus to investigate whether the connection between personalities and social media holds in different languages. In order to do this, we will link the five personality dimensions with words used in a public social media platform (Twitter) in another language (Dutch). We will establish a vocabulary, initially based on the English vocabulary of Schwartz et al (2013), which makes it possible for Dutch companies to analyze written text for personality dimensions. Furthermore, we will indicate the impact of other Twitter measurements, such as connections (followers, mentions) and interactions (replies, retweets) as well as general use of other social media platforms. Finally we will look at the impact of the personality dimensions on innovative behavior.

1.3 Scope

The scope of this study is limited to Twitter as social media platform for the word analysis. Despite Facebook being the largest social media platform to date, the numerous privacy settings make it difficult to analyze. In addition, a lot of content on Facebook is combined with pictures, movies or other shared content rather than plain text, making text analysis a difficult process. The distinction between Twitter as more informal and LinkedIn as a formal platform should give a decent overview of the mechanics of different media platforms and its accompanying content. Another limitation of this research is the selection of one language (Dutch), due to limited resources. Although positive effects in the Dutch language could be a sign that personality traits and measurements are universal.

1.4 Research Questions

In order to answer the problem statement, we have to formulate a research question. The research question for this study is:

“To what extent can social media platforms be used in order to predict individual personalities and innovative behavior in the Dutch language?”

To answer this inclusive research question, we make a distinction between several sub questions.

“What are the methods that can be used to analyze individual personalities?”

“Which social media platforms can be used to predict individual personalities?”

“What are the major differences between the English and Dutch language for predicting personality dimensions?”

“What personalities have an influence on innovative behavior?”

“How feasible is social media platform analysis on a large scale?”

1.5 Research Design

To answer our research question, we have to link the big five personality dimensions with available social media data. First, we gather the individual personality dimensions with the means of a survey, which will determine an actual value of the different dimensions. Denissen et al (2008) already have a tested Dutch translation of the big five dimensions. After obtaining the individual dimensions, we can gather social media data from the same respondents in order to match them with the data of the survey. Here, we will start with a Dutch translation of the vocabulary that Schwartz et al (2013) established. The method of Schwartz et al (2013) proved to explain more variability in personality than the Linguistic Inquiry and Word Count (LIWC) from Pennebaker et al (2001). Then, other Twitter and other social media data, such as amount and kind of use can be measured to see the impact on the big five personality dimensions. Finally, the link between personality and innovative behavior will be predicted by measuring the impact of personality on innovation constructs.

2. Literature review

This section is divided into three parts. First, we take a look at the establishment of the big five personality domains. Second, we examine the emergence of social media and investigate what possibilities social media can bring us. Finally, we look at research which predicts adoption of innovation.

2.1 Big five personality domains

Within the big five personality domains, we examine different sections. First, we explain the emergence of the personality domains. After looking at the emergence, we set the interpretation of each of the personality domains. Then, we investigate if the personality domains differ within cultures. Given the fact that this study is focused on a Dutch word list to see if results can be applied universally, it is important to take cultural differences into consideration. Next, several limitations and reservations of the big five personality domains will be pointed out. Finally, we will discuss several applications that have been found by using the big five factor model.

2.1.1 Emergence of the taxonomy

The need of personality taxonomy was first mentioned by McDougall (1932), who wrote the first article of the first *Journal of Personality*. In that article, he discusses the complexity of personality and refers to an earlier suggestion (McDougall, 1929) where he mentions five distinguishable factors. These five factors are intellect, character, temperament, disposition and temper. Eysenck (1947) came up with two personality dimensions in his book, namely extraversion and neuroticism. Later, Eysenck (1976) added psychoticism as a third dimension. Cattell (1943, 1946, 1947, 1948) proposed a more complex model in 1946, by merging almost 200 personality items to 35 terms which eventually led to 16 factors by using factor analysis. The questionnaire, which he developed in 1949 was quite extensive and could take upwards of an hour to complete. Many researchers criticized the model, since it has never been entirely replicated. In addition, the factor analysis at the time was done by hand and thus prone to error, rather than by specialized computer programs nowadays.

Fiske (1949) could not find evidence for more than five factors. Despite being published in a journal, his research seemed to have little effect on the perception of the 16 factor model. Tupes & Christal (1961) also found that only five factors worked well for their observations. The terms of the five factors were named surgency, agreeableness, dependability, emotional stability and culture. However, their study was for an Air Force technical report and remained relatively unknown at the time. Later, several other studies (Borgatta 1964, Norman 1963, 1967, Smith 1967) confirmed the studies of Fiske (1949) and Tupes & Christal (1961), which then got more recognition. Norman (1963) named the labels surgency, agreeableness, conscientiousness, emotional stability, which are similar to the big five we use today. Meanwhile, the 16 factors of Cattell received more criticism. Howarth & Browne (1971) carried out the 16 personality factors and only found 10 interpretable factors and concluded that the 16 factors do not measure the primary personality level. Kline & Barret (1983) replicated Cattell's

methodology and only found seven factors, with only four of which directly corresponded the 16 of Cattell.

After comparing several studies who investigated the five factors, Goldberg (1981) mentioned that any model for personality should at least entail some level of the big five personality dimensions. Costa & McCrae (1992) state that there are four lines of evidence that make the five factors strong and widely accepted. First, it is proven longitudinally and enduring. Second, the factors are represented in personality, language and traits. Third, the factors are found in a variety (age, sex, race) of groups. Finally, the factors seem to have some biological basis. Although literature is still divided about the exact labels for the big five personality traits, they are nowadays usually described conform Costa & McCrae (1985) as extraversion, agreeableness, conscientiousness, neuroticism and openness.

2.1.2 Interpretation

While general consensus has been reached about the number of personality dimensions, the interpretation and labels of the dimensions are still quite diverse in literature. The definitions used in this study are similar to the ones that are used in Digman (1990) and Barrick & Mount (1991), which will now briefly be explained. The first dimension is called extraversion, which includes being talkative, assertive and sociable. The second dimension, agreeableness, covers traits like flexibility, cooperation and tolerance. The third dimension, conscientiousness, involves being dependable, careful, responsible and organized. The fourth dimension is neuroticism, and covers being anxious, angry, emotional and insecure. The final dimension, openness, includes traits such as being imaginative, broad-minded and intelligent. All the personality dimensions that we use in this study are, together with the labels in other literature, summarized in Table 1.

Personality dimension	Literature
Extraversion - Dimension I	Extraversion (Eysenk 1947), Social adaptability (Fiske 1949), Surgency (Tupes & Christal 1961, Norman 1963), Assertiveness (Borgatta 1964)
Agreeableness - Dimension II	Conformity (Fiske 1949), Agreeableness (Tupes & Christal 1961, Norman 1963), Likeability (Borgatta 1964), Psychoticism (Eysenk 1976),
Conscientiousness - Dimension III	Will to achieve (Fiske 1949), Dependability (Tupes & Christal 1961), Conscientiousness (Norman 1963), Psychoticism (Eysenk 1976)
Neuroticism - Dimension IV	Neuroticism (Eysenk 1947), Emotional control (Fiske 1949), Emotionality (Tupes & Christal 1961, Norman 1963, Borgatta 1964)
Openness - Dimension V	Inquiring intellect (Fiske 1949), Culture (Tupes & Christal 1961, Norman 1963), Intelligence (Borgatta 1964)

Table 1: Personality dimensions in this study and corresponding literature

2.1.3 Cultural differences

Although there has been quite some research on the validity of the big five in general, there are also quite some studies that have investigated the differences in culture. Guthrie & Bennett (1971) tested the big five personality dimensions on Filipinians. They found that extraversion and agreeableness were quite similar, but conscientiousness and openness were merged together while neuroticism was split into two factors. Bond, Nakazato & Shiraishi (1975) replicated the study of Norman (1963) with Japanese respondents and also compared it with the results from Guthrie & Bennett (1971). They found that the Japanese aggregated dimensions were similar to the American ones and that the Filipinian results only differed from the other two in the fifth dimension (openness/culture). The authors argue that the culture difference might be due to modernization of the American and Japanese culture compared to that of the Philippines. In the 90's, there were replications in quite some languages, such as Spanish (Psychological Assessment Resources 1994), Dutch (Hoekstra, Ormel & De Fruyt 1996), Korean (Piedmont & Chae 1997, McCrae & Costa 1997), Russian (Martin et al 1997), German, Portuguese, Hebrew, Chinese and Japanese (McCrae & Costa 1997). McCrae et al (1998) tested data in a Filipinian and French translation. Although there were some small variations in Filipinian results with regard to the extraversion and agreeableness facets, the factor congruence compared with the American structure was still very high. The authors further mention that not all American findings can be exported as a whole since some cultures vary slightly on one or more facets, but the model as a whole is quite representative. McCrae & Terracciano (2005) compared 51 cultures with the American structure and found that it was clearly replicated in most cultures and recognizable in all. In addition, they also found sex differences, although stronger in the western cultures, and age differences, which diminish slightly after the age of 40. The authors further found that although the five dimensions are present in all of the cultures, their average values do differ across cultures. These findings are in line with an earlier study (Hofstede & McCrae 2004), where the mean personality scores from 33 countries were significantly correlated with culture dimension scores of Hofstede. All in all, it can be concluded that the big five can be generalized for all cultures, although sometimes caution with culture related elements is necessary. For the purposes of our study, it is important to mention that Denissen et al (2008) developed and validated a Dutch translation of the big five inventory.

2.1.4 Limitations

While many researchers support the big five personality dimensions, there has also been some criticism, which should be pointed out. Block (1995, 2010) names some uncertainties which should be looked into. He argues that we should not restrict ourselves to the current position and re-examine the conceptual and empirical requirements, especially since some of the dimensions tend to correlate. In addition, Block (2010) points out some limitations about the factor analysis approach. Although it is a valid approach, it is also the only statistical approach that is used for personality dimensions, which therefore immediately inherits the drawbacks of the methodology itself. There are some variants in factor analysis which result in a different number of factors. The unsure number of factors combined with the fact that the big five are data-

driven rather than theory-driven, makes the selection of a certain number of factors evermore troublesome. Block (1995) also addresses the lexical hypothesis, where he states the difficulty of single-word descriptors for personality, especially since the context is quite important. Other studies (Paunonen & Jackson 2000, Paunonen et al 2003) question the scope of the personality domains, claiming that there are neglected domains within the big five. Paunonen et al (2003) formed supernumerary personality inventory (SPI) scales and created three additional factors. He created machiavellian as first factor, consisting of seductiveness, egotism, manipulativeness and thriftiness. The second factor was traditional, including conventionality and religiosity. Finally, masculine-feminine was the third factor, covering femininity, integrity, risk taking and humorousness. All three factors had little correlation with the existing big five, meaning they could be used as additional dimensions. However, these new dimensions seem to be closely related to Hofstede's cultural dimensions and might therefore not be included in the personality dimensions.

2.1.5 Applications

While many studies focus on reliability and validity of the big five, there has also been some research on the applications. A first stream of applications is with regard to a professional context. Barrick & Mount (1990) found a significant relation between conscientiousness and job performance on all three investigated performance criteria across five occupations. Extraversion was a predictor for more social professions (managers and sales). In addition, openness and extraversion also predicted training proficiency across occupations. Later, Barrick and Mount (1993) added autonomy as moderator and found that with managers in high-autonomy jobs, the validity was higher for higher conscientiousness, extraversion and lower agreeableness. Along the same line, Berr, Church & Waclawski (2000) found personality related manager behavior, albeit with the Myers-Briggs dimensions. They for example found that extraverts were more optimistic, and rated themselves higher, while introverts were perceived more ethical by peers. On the negative side, Salgado (2002) states that conscientiousness predicted employee deviant behavior (e.g. theft) and turnover, while the other four dimensions also predicted the turnover criterion. Zhao & Siebert (2006) found that entrepreneurs scored higher on conscientiousness and openness and lower on neuroticism and agreeableness. Finally, team performance is also related to the personality domains (Neuman, Wagner & Christiansen 1999), where a higher team average on the traits conscientiousness, agreeableness and openness and where more team diversity on extraversion and neuroticism was positively related to team performance.

The second stream of personality applications is more related to consumer profiling and preferences. Rentfrow & Gosling (2003) structured four dimensions for music preferences, of which openness correlated with three, and with which extraversion and agreeableness correlated with two. In the marketing field, Whelan & Davies (2006) show that consumers with higher openness bought corporately named products and extraverts bought more national brands. Consumers who bought own (retailer) brands score higher on the dimensions agreeableness and extraversion. Even preferences

towards dog and cat people (Gosling, Sandy & Potter 2010) and US presidential voting behavior (Jost, West & Gosling 2008) have been determined by using the big five personality dimensions. Although these kinds of studies might seem uncommon to investigate, it shows that the big five personality dimensions can be applied to numerous fields and can predict many human characteristics and behavior.

2.2 Social media

As mentioned before, social media has immensely emerged the last decade. These days, the number of Facebook users exceeds the population of the largest country in the world (The Huffington Post 2015). The unfolding of social media also enabled researchers to gather public data. In this subsection, we will discuss the predictive research that social media data has allowed.

Gruhl et al (2005) investigated blog mentions with online book sales and ranks of Amazon. They indeed found a correlation with the amount of book sales and blog mentions. The results sometimes indicated blog mentions preceding the sales spike. However, they could also happen simultaneously (e.g. consumers buying a book and then writing a blog post about it). Asur & Huberman (2010) analyzed tweets of Twitter to predict box-office revenues for movies. They found that a simple linear model on rate of tweets and movies already outperformed artificial money markets such as the Hollywood Stock Exchange. They also added sentiment analysis of people in tweets after the movie release and successfully indicated trends in later weekend sales compared to the prior. Tumasjan et al (2010) discusses a Twitter analysis of the 2009 German election. Solely the number of tweets already gave a close prediction of the actual election results and is comparable with traditional election polls. Bollen, Mao & Zeng (2010) even found that the sentiment of Twitter feeds were able to predict the stock market. Although they tested several dimensions, the only one which had results was the calm dimension of the Google-profile of Mood State measurements, which indicated the up and down changes of the Dow Jones Industrial Average with a 3-4 day delay.

Recently, there has been a small stream of literature focusing on the link between social media and personality. Hughes et al (2012) researched the big five dimensions on the usage of both Facebook and Twitter. They found several correlations between the personality dimensions and social media usage. For example, the dimensions extraversion had a negative impact on Twitter if used for informative purposes, while it had a positive effect on Facebook for information purposes. Openness to experience was positively related to Twitter usage for social purposes and Facebook usage for information purposes. These results show that distinct personalities use different kind of social media platforms. Golbeck, Robles & Turner (2011) found that Facebook data could be used to predict the big five personality dimensions. The error for each dimension was a little over 11%. The personality results still give a good indication about the global characteristics, which could be used for some practical implications. The study of Golbeck et al (2011) was similar but instead used Twitter data to predict personality dimensions. Here they found that openness and agreeableness were easier

to predict than the other personality domains. The predicted results differed between 11-18% of the actual values. Given their relatively small sample size of fifty respondents and the short message allowance of Twitter, the personality prediction with more respondents or several social media channels could give even better results.

2.3 Adoption of innovation

The final section of this chapter is dedicated to the innovation adoption lifecycle. The lifecycle is based on the diffusion of innovations of Rogers (2010), whose first version dates back to 1962. The theory of diffusions explains the rate at which new concepts or technology spread through a population. Typically, a population is a successive group consisting of innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%). These subgroups consecutively form a normal distribution of adoption. Every widely accepted product goes through this stage, ranging from electricity and telephones to television and smart phones, although some products complete the cycle faster than others. The Bass diffusion model (Bass 2004) is tightly linked to the diffusion of innovations. It explains that there is a certain coefficient of innovation, called p , which is the rate of new adopters. In addition there is the coefficient of imitation, called q , which explains the rate of followers. Together with the base value, they can estimate the time in which new products are adopted by the entire population. The amount of adopters over time is often shaped like an s-curve. First, the growth is slow due to only a few innovators, then it grows rapidly among the large amount of imitators, after which growth stagnates, as most of the population has already been reached.

There has been quite some research on identifying indicators of subgroups, especially innovators and early adopters, of the adoption lifecycle. Dickerson & Gentry (1983) performed extensive research on many characteristics of adopters of home computers. Their results indicate a profile of adopters to be a married, highly educated, middle-aged homeowner. In addition, the adoption of a home computer correlated with many other new products at the time, such as video recorders, credit cards and microwave ovens. Goldsmith and Hofacker (1991) developed measurement for innovation and adoption, using items about rock albums, which gave a good indication for often purchased type of products. Chau & Hui (1998) investigated elements of adopting new IT products. The authors found that opinion leadership and consumer novelty seeking was higher among the early adopters of Windows 95, while there was no effect found on independent judgement making (e.g. consulting friends or experts). In 1998, Agarwal et al investigated the construct personal innovativeness in the domain of information technology (PIIT), and found that it indeed had some extra effect on the perception of compatibility on new IT. Wood & Swait (2002) developed two constructs, need for cognition and need for change, which could predict general change behavior of consumers.

2.4 Conceptual framework

The previous three subchapters make up the conceptual framework depicted in Figure 1. We will first investigate to what extent several social media usage and behavior can predict the big five personality dimensions. Then, the impact of personality dimensions on adoption of innovation will be measured. Eventually, the goal is to predict some extent of innovative behavior by using open data of individual social media platforms through the use of the big five.



Figure 1: Conceptual framework

3. Methodology

In this chapter, we will discuss the procedure and instruments that will be used to investigate the conceptual framework of the previous chapter. First, we will discuss the measurement of the big five personality. Then, different types of social media usage are investigated. Next, we will discuss several constructs measuring adoption of innovations. Then, some demographic variables will be added. Finally, we conclude by gathering the word use of public data of Twitter accounts.

3.1 Big five personality

For the measurement of the big five personality dimensions, we will use the Big Five Inventory (BFI), an instrument originally set up by John & Srivastava (1999). Denissen et al (2008) developed and validated a Dutch translation of the BFI. In their paper, two independent persons translated the items, after which judges chose the best translation. Then, two Dutch-English bilingual students were asked to reverse the translation back to English to check whether it yielded the same as the original. If the translations differed, the final translation was chosen by consensus between the authors and the bilingual students. Both the average primary loadings and average cross-loadings the big five constructs were equal or slightly more favorable than their English (Benet-Martínez & John 1998), German (Lang, Ludtke & Asendorpf 2001) and Spanish (Benet-Martínez & John 1998) counterparts. The Tuckers phi, which is a measure of congruence between factors of a factor analysis were .92 for English, .87 for German and .90 for Spanish. A coefficient of .90 or higher indicates a similar structure (Bentler & Bonett 1980), which thus demonstrates correspondence with other languages. Next, all internal consistencies were high, with a Cronbach α ranging from .73 to .86 for the five personality dimensions. Finally, it was mentioned that all the scales were relatively independent from each other, except for extraversion and neuroticism, which had a negative significant correlation. Considering the Dutch variant of the BFI passed all the necessary tests, the current items and constructs of Denissen et al (2008) are all sound and valid and will therefore be directly used in our survey. The English questions and their Dutch counterparts can be found in Table 1A in Appendix A

3.2 Social media usage

First of all, we would like to know which social media platforms people are active in. One could hypothesize that people scoring high on extraversion also are more active on social media and might be active on more platforms. Furthermore, LinkedIn could be correlated with conscientiousness, since it is a professional platform and conscientiousness is found to be related to job performance (Barrick & Mount 1990). For our questionnaire, we ask the usage of the most popular social media platforms in the Netherlands. According to the national social media examination of Newscom (2015), which had over 10.000 participants, the most popular social media platforms are, in order, Facebook, YouTube, Google+, LinkedIn, Twitter, Instagram, Pinterest, Snapchat, Tumblr, Foursquare and WeChat. In addition, we added an empty text field to indicate remaining used social media. Next, we ask the reason for usage of each selected social media. As mentioned in Hughes, Rowe and Lee (2012), there is a

difference between an informative and social use of social media. There, extraversion was found to be negatively correlated on using twitter as information source, while it positively correlated with using Facebook as information source. Finally, we ask our respondents to indicate the amount of usage (both reading and posting) of each selected social media platform. Again, people scoring high on extraversion could also post more, while those who score high on for example openness to experience might read a lot in order to stay up to date to possible events or activities.

3.3 Adoption of innovation

The final construct that we measure is adoption of innovation. Although there are many indicators for adoption, such as ease of use, relative advantage and compatibility, we solely focus on personality characteristics in our paper. While there is a lot of research done on the big five and its constructs, the literature about personality and innovation is more divided and ambiguous. Goldsmith & Hofacker (1991) created an own scale of consumer innovativeness by measuring the purchases of new rock albums. They started with two 11-item scales, a positive and negative variant for each item. Then, the authors measured the items against variables such as product awareness, purchase, magazine readership and store visits. Finally, they picked three positive and three negative items with the largest validity, leaving a total construct of six items for innovativeness. While the construct is strong on validity, it is designed for repeatedly purchased products with lower involvement and is designed for a quite specific product domain (albums). Another possible innovation construct is that of Baugartner & Steenkamp (1996). They distinguish exploratory information seeking (EIS) and exploratory acquisition of products (EAP), which differently relate to optimum stimulation level (OSL), sensory stimulation (SS) and cognitive stimulation (CS), proving that there are different kind of innovation constructs. Next, there are two possible constructs from Wood & Swait (2002), namely, the need for cognition and need for change. These two constructs combined make a two by two matrix, with each field showing different behavior. Respondents indicating a high need for change and high cognition were innovative users considering many attributes. On the other hand, respondents with a low need for change and low need for cognition were not using innovative services, considered fewer attributes and were influenced a lot by their current provider. Finally, we consider a construct measuring personal innovativeness is the domain of information technology (PIIT) of Agarwal & Prasad (2008). Their construct was found to be different from computer playfulness and was found correlating with usage intentions and had a mediating effect on compatibility. Their results however, only indicated a small effect and will therefore not be used in this study. While all above mentioned constructs could be feasible, there are still quite some differences among them. Roehrich (2004) makes a clear distinction between different types of innovation scales. There are scales which either predict general behavior, product consumption or domain-specific consumption. The constructs of Goldsmith & Hofacker (1991) can achieve high prediction but are very domain-specific, which therefore makes it hard to be generalized for other domains. The constructs of Wood & Swait on the other hand, are very general and might therefore be too broad and vague to really determine specific innovation. The study of Baugartner & Steenkamp (1996)

lies in the middle by having its constructs predict product consumption while still achieving average predictability. We therefore chose to adapt EIS and EAP as constructs for adoption of innovation, since those constructs can be used to make some general conclusions while still having a reasonable level of prediction. The two measurement exploratory information seeking and exploratory acquisition of products in both English and Dutch can be found in Table 2A in Appendix A, together with the accompanying item measurement.

3.4 Demographics

In the final section of our survey, we will include some demographic variables. In Denissen et al (2008) age was positively correlated with openness, conscientiousness and agreeableness, while negatively correlated with neuroticism. Extraversion had no significant effect. Furthermore, women were observed to score higher on neuroticism and agreeableness (Feingold 1994, Costa, Terracciano and McCrae 2001). Finally, education level was positively related with openness and conscientiousness in a previous study (Paunonen 2003). We therefore include the demographic variables age, gender and education level in our survey.

3.5 Twitter data

Finally, we ask the Twitter account of the respondent. In addition to this question, a statement will be placed, describing that the account will be used to gather data, but that no individual posts or other individual data will be published. Like in Golbeck et al (2011), we gather the amount of followers and amount of following from the user accounts. Furthermore, we include the number of favorites and lists (a subset of some users someone is following). Finally, we collect the last 200 tweets of each user, which is the maximum allowed by the Twitter API restrictions. Besides the word use of these 200 tweets, some other statistics, such as the number of mentions, number of hashtags, number of links per person will also be gathered.

3.6 Pretest

Before launching the actual survey, we conducted a pretest. The pretest was conducted online by using Qualtrics. With the use of this software, we made the survey adaptable and conditional depending on earlier answers. For example, if users indicated that they were not using Facebook, no further questions regarding Facebook use were requested. Furthermore, for all mandatory questions a response was required in order to continue the survey, making sure no questions were accidentally forgotten. First, five close friends were asked to extensively review the survey. Here, mainly some clarity issues regarding the introducing text of the constructs were addressed. After making some changes, we asked another eight persons to fill in the survey, who had no further comments regarding clarity.

4. Results

In this section, the results of the survey and analysis will be discussed. First, we will look at the results of the survey and its respondents. Next, we estimate the validity of each construct used in this study, which are the five personality dimensions and the two measurements for adoption of innovation. After confirming validity, the twitter data can be gathered to predict personality with an established word list, translated from Schwartz et al (2003). The word list will be compared with the actual personality dimensions the respondents provided. Then, we will look at the other social media platforms, reason for usage and intensity of usage of those platforms in order to establish additional relationships with the big five personality dimensions. Finally, the impact five personality dimensions on the adoption of innovation will be determined.

4.1 Survey

The survey was accessible to both respondents who had Twitter accounts, as well as those who did not, for two reasons. First, the data from the survey of respondents that have no Twitter are still useful in estimating the link between personality and innovative behavior. Second, the respondents that have no Twitter are useful as a base case and can therefore be used to compare differences in personality with Twitter users. In total, 246 respondents finished the survey, out of the 375 who started the survey (66%). Out of these 246 respondents, 103 filled in the field regarding the Twitter account. However, some indicated that they already removed their Twitter account. Additionally, some users only had a few tweets. Accounts with less than 20 tweets were removed from this group. Other respondents used company accounts that were shared by several persons, making it useless for our research. After removing all these accounts, a total of 78 usable Twitter accounts (76%) remained. Out of the completed surveys, 61% of the respondents were male and the average age of the respondents was 31. The median completion time of the survey was 07:52 minutes and the majority of the respondents (87%) completed the survey within 15 minutes.

4.2 Construct Validity

As mentioned before, we measured the Dutch translation of the big five personality dimensions used in Denissen et al (2008), as well as the two personality innovativeness constructs used by Baugartner & Steenkamp (1996). Each of these 7 constructs has between 8 and 10 items to measure it. Before merging these items into a single construct, we have to check for validity and coherence between the different items, in order to conclude that they indeed measure the same construct. We will use the Cronbach's Alpha to measure internal consistency of these constructs. The Cronbach's Alpha coefficient ranges from 0 to 1, where a higher value means greater internal consistency of the scale. Nunnally & Bernstein (1994) mention a minimum score of 0.7, which often is in literature as a minimum threshold. However, as Lance, Butts & Michels (2006) describe, this is the lowest sufficient number and only modestly reliable. Most research has a recommended score of 0.8 and sometimes even higher for exact scores, in cases where almost no error is permitted. This is in line with George & Mallery (2003), who use the following rule of thumb: >0.9 – excellent, >0.8 – good, >0.7 – acceptable, >0.6 – questionable, >.5 – poor and < 0.5 unacceptable. The

Cronbach's Alpha tests in SPSS for the seven constructs that are used in this study can be found in Appendix B and are summarized in Table 2. Here, agreeableness has the lowest value (0.714), which is acceptable, but not really strong. The remaining four constructs of the big five are close to 0.8 or are higher, which makes the big five in total still good to use. Results in reliability are quite similar to those of Denissen et al (2008), which also reported lower values in agreeableness (0.73) and conscientiousness (0.79). In addition, we also looked at the number of items and whether removal of an item would lead to a higher score of the construct. Fortunately, none of Cronbach's Alphas for the big five personality dimensions would reach a higher score by removing an item, meaning that all of the items were sufficiently related to the construct. The other two constructs, measuring adoption of innovation, both show a Cronbach's Alpha of higher than 0.8, which means a good reliability. Again, this is in line with the literature (Baugartner & Steenkamp 1996), which found alphas of 0.80 for EAP and 0.84 for EIS. When looking at the removal of items however, we see that EIS can receive a higher alpha by removing an item. The question that is not similar to the other items is "I generally read even my junk mail just to know what it is about". This question has a low mean of 1.87, while all other nine items of the construct have a mean between 2.43 and 3.42. In addition, the item has a very small correlation with almost all of the other items. The unexpected results of this item could be attributed to the good spam filters of email providers these days, especially compared to the time that the constructs of Baugartner & Steenkamp (1996) were founded. The results of our survey indicated that almost no one reads the mails in their spam filter anymore and the item is not explaining exploratory information seeking anymore. Therefore, we will remove this item from the construct. For all the other constructs, all items were included. Each construct received a value by taking an average of all the accepted items.

Construct	Number of items	Cronbach's Alpha	Cronbach's Alpha by removing an item (highest)
Extraversion	8	0.827	0.826
Agreeableness	9	0.714	0.714
Conscientiousness	9	0.787	0.782
Neuroticism	8	0.816	0.807
Openness	10	0.776	0.776
Exploratory acquisition of products	10	0.819	0.816
Exploratory information seeking	10	0.825	0.840

Table 2: Constructs, number of items and Chronbach's Alpha of the big five personality dimensions and the adoption of innovation measurements.

4.3 Twitter data and Personality

As the big five personality dimensions are formed, we can look at the prediction of the Twitter data on the dimensions. The tweets of the 78 respondents were collected by making use of the Twitter API. After receiving keys and tokens from Twitter, we gathered the last 200 tweets of each user by using a PHP script. The restriction of 200 tweets was required by Twitter's standard regulations. Furthermore, either only public accounts or accounts that followed the requested account, could be accessed to collect the data. Not every respondent had more than 200 tweets, but respondents with less than 20 tweets were already removed from the sample. In total, 13896 tweets were collected, resulting in a little more than 178 tweets per person on average. To determine the personality from the tweets, we used an extensive word list constructed by Schwartz et al (2013). In their study, they analyzed over 15.4 million Facebook messages from almost 75,000 respondents using an open-vocabulary approach. With this differential language analysis (DLA), they set correlations with certain words for each of the personality dimension, with both positive and negative words or sections (1-3 words) for each dimension. Schwartz et al (2013) also ran DLA analysis on smaller random subsamples and concluded that smaller samples sizes, which are closer to 50 or 500, are not strong enough for the DLA creation of individual words. For this study, we therefore translate the established wordlist in their study. We took the top 650 highest correlating words for each dimension, both positive and negative, resulting in a total of 6500 translated Dutch words for the analysis. Next, we counted each of these words for all the tweets of each individual respondent and multiplied it by the given correlation. By doing this, stronger correlated words also got a stronger influence on that personality. Then, each value was divided by the total number of words in the list, to avoid respondents who use many words in all their tweets to score higher on each personality. The total scores of each personality are simply the sum of the value of all the individual words. To estimate the ultimate five personality scores, we subtracted the total of negatively related words from the total of positively related words, which could either be a positive or a negative score. These scores were loaded into SPSS to compare with the scores from the respondents of the survey. Here, we used a simple linear regression with the big five personality values of the survey as dependent variable and the estimated twitter personality as independent variable. The results of these tests can be found in Appendix C and are outlined in Table 3. Unfortunately, out of the five personality dimensions, only conscientiousness shows a good significant result ($p = .002$). There might be several reasons for these results. First, the dataset of 78 respondents is quite small, resulting in insignificant results. Second, the gathered data is from Twitter, while the list was established from Facebook posts. While both are social media platforms, the goals of the platforms are quite different. Additionally, Twitter messages are limited to 140 characters, which could change the way people phrase their posts. Finally, the translation from English to Dutch could not be sufficient. It might be that cultural word use differs so greatly that a translated list is not good enough to estimate personality in other languages. However, the fact that at least one dimension still shows a strong significance could indicate that the word list does work to some extent. Furthermore, the R^2 of .123 is higher than the reported R^2

of .116 of Schwartz et al (2013) and is also stronger than the R² of .084 of their LIWC method.

Personality	B	Std. Error	Beta	T	Sig.	R ²
Extraversion	6,048	18,102	,038	,334	,739	.001
Agreeableness	20,991	40,084	,060	,524	,602	.004
Conscientiousness	58,744	18,023	,350	3,259	,002	.123
Neuroticism	-64,786	48,689	-,151	-1,331	,187	.023
Openness	6,111	6,420	,109	,952	,344	.012

Table 3: Prediction of estimated twitter personality on the big five dimensions.

4.4 Social media and Personality

In this section, we will look at usage and behavior of several social media platforms and link them to the big five personality dimensions. First, the effect of usage of social media platforms will be estimated. As mentioned before, we selected the top eleven social media platforms. The usage of social media platforms of all respondents is shown in Table 4. Almost all (96%) of the respondents uses Facebook and most of them also use YouTube (76%) and LinkedIn (86%). Tumblr and WeChat are barely used, with only 6% and 2% of the respondents respectively. Finally, 11% of the respondents indicated other social media platforms. Most of these included Whatsapp or Happening, which are both phone apps that are more oriented in direct messaging than actual being a social media platform and thus were not included in further analysis.

Platform	N	Minimum	Maximum	Mean	Std. Deviation
Facebook	246	0	1	.96	.207
YouTube	246	0	1	.76	.428
Google+	246	0	1	.33	.472
LinkedIn	246	0	1	.86	.346
Twitter	246	0	1	.56	.498
Instagram	246	0	1	.37	.485
Pinterest	246	0	1	.26	.437
Snapchat	246	0	1	.33	.472
Tumblr	246	0	1	.06	.240
Foursquare	246	0	1	.10	.297
WeChat	246	0	1	.02	.141
Other	246	0	1	.11	.308

Table 4: descriptive statistics of the eleven selected social media platforms.

To estimate the effect of social media platforms on personality, we used a multiple regression model for each big five construct individually as the dependent variable and the dichotomous usage of all eleven social media platforms as independent variables. The model summary and effect of coefficients can be found in Appendix D. All the social media platforms with at least a significance of .1 have been summarized in Table 5. Only five out of the eleven social media platforms have a significant effect on any of the personality dimensions. The reason for this is that some of the platforms are used by almost all of the respondents (Facebook, YouTube), while others were barely used

by anyone (Tumblr, WeChat). Still, there is a significant effect for almost every dimension, which will now briefly be discussed. First, extraversion shows a positive relationship with LinkedIn, Instagram and Foursquare. Extravert people are described as outgoing, which explains sharing of their experiences on Instagram or Foursquare. It is not surprising that the construct extraversion has the most significant effects of all personality domains. Extraverts are more social and might be expected to participate more in some social media platforms than introverts. Agreeableness and conscientiousness are not significantly influenced by any social media platform. Apparently, social media platforms are not only used by individuals who value cooperation and social harmony, but just as much by critics and skeptics. For conscientiousness, which was positively related to job performance (Barrick & Mount 1990), a relationship with LinkedIn might be expected, since LinkedIn is a more serious platform focused on finding jobs and networking with business partners. Still, LinkedIn is used by almost all respondents (86%), meaning it might not be exclusively for conscientious people who have strict control and order in their lives. Neuroticism on the other hand, did show a significant influence of LinkedIn. This effect, however, was negative, which indicates that respondents who have a high value on neuroticism did not use LinkedIn. A possible explanation might be that those who score high on neuroticism often tend to be anxious and cannot cope effectively with stress, which might explain avoidance of use of a social media platform related to work and networking. Finally, the construct openness is affected by both Twitter and Snapchat, which none of the other dimensions were related to. Here, Twitter has a positive effect, while Snapchat has a negative effect. Open people are considered curious to new experiences, which explains the use of Twitter, since it is considered an information sharing platform. Snapchat on the other hand, is a platform which shares mostly pictures between known people, leaving little room to explore new things. The total explanation of the constructs, indicated by the R^2 , remains relatively low. The three constructs with significant results each explain the variance between 7-11%. Of course, a low explanation of variance is not very surprising, as only the use of social media platforms was not expected to say much about a complete personality.

Construct	Platform	B	Std. Error	Beta	t	Sig.	R ²
Extraversion	LinkedIn	.246	.118	.139	2.083	.038	.075
	Instagram	.220	.100	.175	2.210	.028	
	Foursquare	.297	.149	.145	1.997	.047	
Agreeableness	Foursquare	.238	.123	.143	1.929	.055	.034
Conscientiousness	LinkedIn	.195	.106	.125	1.840	.067	.041
Neuroticism	LinkedIn	-.331	.124	-.178	-2.660	.008	.074
	Foursquare	-.280	.157	-.129	-1.785	.076	
Openness	Twitter	.164	.068	.170	2.421	.016	.116
	Pinterest	.132	.078	.121	1.701	.090	
	Snapchat	-.164	.069	-.162	-2.382	.018	

Table 5: Effects of social media platforms on the big five personality dimensions

In the survey, we further asked if respondents used a social media platform to spread information and/or to stay in touch with friends or colleagues. To see whether there is a difference in the use of social media when looking at personality, we conducted a multivariate multiple linear regression, with the big five dimensions as dependent variables, and each of the two options per platform as independent variables. However, none of the platforms shows any significant results in the multivariate tests (Pilai's trace, Wilks' lambda, Hotelling's trace and Roy's largest root), although there were a few significant results in the between-subject tests. Apparently, whether or not someone uses a platform is a better indication for personality, while the reason why is of little impact. Next, we summed the total of all the platforms each respondent used, as well as the percentage of the reason of usage (information seeking or staying connected). These results can be found in Table 6. Respondents use an average of 4.6 of the 11 most popular social media platforms. Furthermore, most respondents use social media platforms to share information (72%), while connecting to friends or colleagues has only been chosen a little over half (53%) as reason. A multiple regression model was used to estimate the effect of these three variables on each of the big five dimensions. Here, the only significant effect was total amount of platforms on openness, although the actual impact was quite small. Also across platforms, there did not seem to be a difference between the reasons of use of social media platforms. The reason for the significant effect for openness might be because of most social media is used to find information, which could thus be related to the curious traits of open people.

Platform	N	Minimum	Maximum	Mean	Std. Deviation
Total platforms	246	1,00	11,00	4,61	2,00
Information	246	,00	1,00	,72	,25
Connect friends	246	,00	1,00	,53	,24

Table 6: descriptive statistics of platform usage and reason for usage.

Finally, we investigated the intensiveness of usage of social media. Respondents indicated how often they looked at or read at the social media platform, as well as how many times they posted something. The descriptive statistics of these results can be found in Appendix D. Facebook is the social media platform that people check the most, with an average somewhere between several times a day and daily. For posting content, Snapchat is the most popular social media platform, with an average between weekly and several times a month. Again, a multivariate multiple linear regression was performed for each of the social media platform on all the big five personality dimensions. The only social media platform that passed Wilks' lambda multivariate test the amount of posts on Twitter, of which the results are in Appendix D and summarized in Table 7. Both conscientiousness and openness are significantly impacted by the amount of posts on Twitter. The fact that there is a relationship with Twitter is not surprising with earlier results in this study. When analyzing the word usage in tweets, conscientiousness was the only personality characteristic that was significantly predicted. Additionally, with analyzing the general social media data, Twitter and Snapchat were able to predict openness.

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Post on Twitter	Extraversion	4,989	7	,713	1,976	,065
	Agreeableness	1,230	7	,176	,633	,727
	Conscientiousness ^a	4,157	7	,594	2,151	,045
	Neuroticism	1,907	7	,272	,605	,750
	Openness ^b	4,383	7	,626	3,333	,003

Table 7: Effects of intensiveness of Twitter posting on the big five personality dimensions. a = R Squared = .286 (Adjusted R Squared = .057). b = R Squared = .377 (Adjusted R Squared = .177).

An estimated direction of the impact of both conscientiousness and openness can be found in Figure 2. While the graph shifts somewhat up and down, the line tends to drop towards lower posts. In other words, people who post more often on Twitter generally score higher on both conscientiousness and openness. It has to be mentioned that the effect on openness is somewhat stronger. Conscientiousness and openness have an adjusted R² of .057 and .177 respectively. Especially the adjusted score of openness is quite high compared to scores that we have seen before. The reported score on the word list from Schwartz et al (2013) scored .168 on openness, which means that the amount of Twitter posts explains an equal amount of variance.

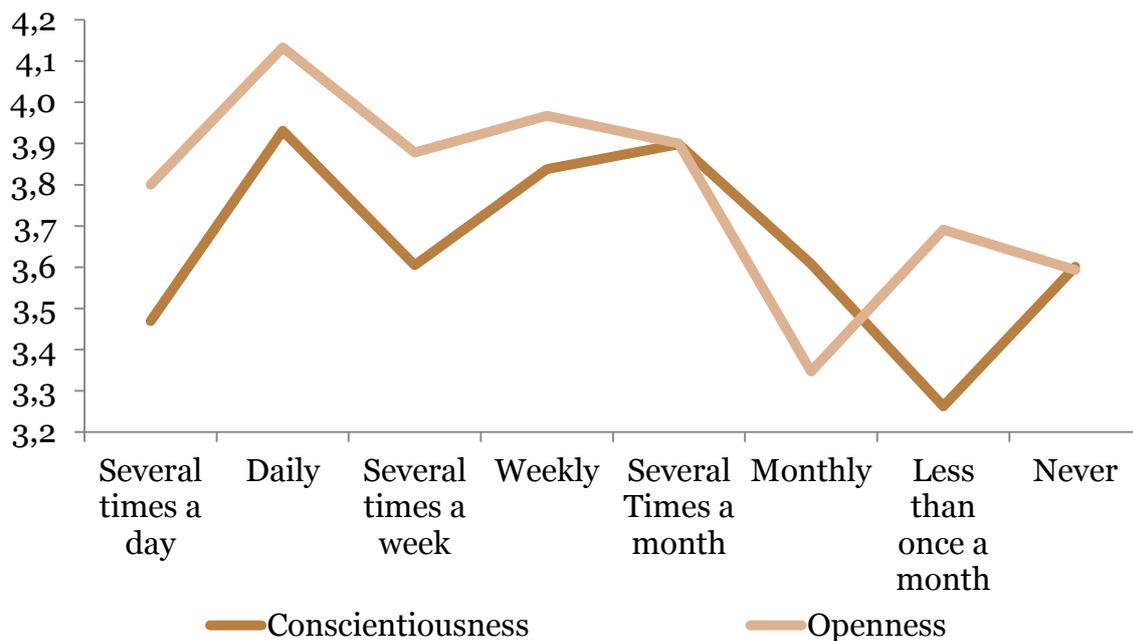


Figure 2: Effects of intensiveness of Twitter posting on conscientiousness and openness.

4.5 Personality and adoption of innovation

To conclude this section, we investigate the relation between personality and adoption of innovation. Since we expect that the five personality dimensions are having an impact on innovative behavior, we perform a multivariate multiple linear regression with the innovation as dependent variables and the big five dimensions as independent variables. The results of the statistical tests can be found in Appendix E. The different multivariate tests (Pilai's trace, Wilks' lambda, Hotelling's trace and Roy's largest root) all show significance for each of the big five personality dimensions, meaning that a part of the variance of at least either exploratory acquisition of products (EAP) or exploratory information seeking (EIS) is explained by each of these variables. The parameter estimates are summarized in Table 8.

For EAP, the personality dimensions extraversion, conscientiousness and openness are found to be significant influencers. Extraversion has a positive effect on EAP, meaning that more extravert people also purchase new products more often. Introverts on the other hand, tend to stay with familiar products. Chakrapani (1974) found that brand loyal consumers scored lower on extraversion and neuroticism and thus show similar results. Conscientiousness has a negative effect on EAP. People who are conscientious are organized and prefer planned behavior. Buying new products to explore other options is often more impulsive behavior which goes without planning, such as for example encountering a new product in the supermarket while doing your daily groceries. Finally, openness to experience has a positive relationship with EAP. Considering that description of openness is related to curiosity and variety of experience, it is not very surprising that it has an effect on EAP.

The personality dimensions extraversion, agreeableness and neuroticism are significant for EIS. Extraversion has a positive effect and is the only personality dimension that has an effect on both innovation variables. Extraverts often have more energy and seek stimulation, which might explain the need for more information seeking. Second, agreeableness shows a positive impact on EIS, which is a bit surprising. People who score high on agreeableness are compassionate, cooperative and trusting. However, despite being trusting, agreeable persons still seek information more. Finally, neuroticism has a positive effect on EIS. Neuroticism is also the parameter with the strongest effect on EIS. People who are nervous or have anxiety tend to pursue more information seeking behavior. Logically, persons who are more vulnerable or anxious could try to negate their traits somewhat by extensively seeking information before a purchase. That way, they minimize their risks of unpleasant emotions.

The R^2 of EAP is 0.148 and the R^2 of EIS is 0.130, which means the personality dimensions only explain the adoption of innovation partially. Having a lower R^2 of these values is not necessarily bad considering this study attempts to predict human behavior, which is often far more unpredictable than for example physical processes. The fact that every type of personality dimension shows a significant effect on either EAP or EIS is a good sign for the importance of big five personality measurement.

Additionally, it has to be mentioned that the two adoption of innovation constructs of Baugartner & Steenkamp (1996) indeed seem to measure something different. Except for extraversion, none of the personality dimensions are having an effect on both EAP and EIS.

Variable	Parameter	B	Std. Error	t	Sig.	Lower Bound	Upper Bound
EAP^a	Intercept	2,177	,581	3,748	,000	1,033	3,321
	Extraversion	,254	,068	3,747	,000	,120	,387
	Agreeableness	,056	,085	,656	,513	-,112	,224
	Conscientiousness	-,157	,073	-2,145	,033	-,301	-,013
	Neuroticism	-,124	,068	-1,817	,071	-,259	,011
	Openness	,198	,083	2,400	,017	,036	,361
EIS^b	Intercept	-,078	,693	-,112	,911	-1,442	1,287
	Extraversion	,293	,081	3,628	,000	,134	,452
	Agreeableness	,301	,102	2,953	,003	,100	,501
	Conscientiousness	,124	,087	1,424	,156	-,048	,296
	Neuroticism	,369	,082	4,520	,000	,208	,530
	Openness	-,165	,099	-1,671	,096	-,359	,029

Table 8: Big five personality dimensions and adoption of innovation. a. R Squared = ,148 (Adjusted R Squared = ,130) b. R Squared = ,115 (Adjusted R Squared = ,096)

5. Conclusion

In this final section we will conclude the findings of this paper. First, we will give a brief summary of the most important findings. Then, managerial implications will be outlined, to determine the use for business. Next, we will discuss the findings of the paper and its implications and possible problems. Finally, future research will be mentioned in order to develop the area of social media for predictions.

5.1 Summary of main findings

The emergence of social media enables companies and researcher to gather consumer data. In our paper, we used public Twitter data by using an API to investigate personality and link it to innovation. First, we found a link of Twitter word use with the personality trait conscientiousness. With the use of an existing word list translated from English to Dutch from Schwartz et al (2013), we found a predicting effect. Although only one of the five personality dimensions had a significant effect, it is interesting that personality can partly be predicted by simply counting words of social media posts. Then, the use of several social media was linked to the personality dimensions. The use of social media platforms LinkedIn, Instagram and Foursquare were found to be significantly related to more extravert people. In addition, LinkedIn users also showed a lower score on neuroticism. Finally, the personality trait openness was higher for people who used Twitter, while it was lower for people using Snapchat. Even within the Twitter users, people who post Tweets more frequently, score higher on both conscientiousness and openness. After establishing links with social media data and personality dimensions, we investigated the relation between personality and two different types innovative behavior, adding to the application of the big five personality dimensions. We found that people who score explore products more often, score higher on extraversion and openness, but lower on conscientiousness. People who seek a lot of information on the other hand, score high on extraversion, agreeableness and neuroticism. These results show that different personality domains explain different types of innovative behavior.

5.2 Managerial implications

The findings in this paper have several implications for managers. First of all, they show that public data from social media can be used to predict some personality traits. One example is that Tweets can be used to estimate conscientiousness. Recruiters could use these estimates since the traits conscientiousness was found to be related to both job performance (Barrick & Mount, 1991) and career success (Judge et al 1999). Furthermore, there are several social media platforms that show extraverted people. Managers might target these kind of people for hiring (e.g. sales people), or could let these individuals test free products and post reviews about them. Extraverts are more social and thus have many friends and connections and therefore have a large reach which could be utilized. Finally, the results of innovative behavior could be used by managers. Acquisition of products are important for marketing new product. It is important that these new products reach the select group of innovative people in order to spread and become popular among the mass public. Therefore, managers should target extraverted, open people, while avoiding consumers that are very conscious. As

we have seen, Twitter users who post regularly are the type of consumers that could be focused on. Furthermore, the content of the tweets could be used to avoid those scoring high on conscientiousness. Information seeking consumers tend to be extravert, agreeable and neurotic. Managers should take extra care of these consumers by making reliable and accurate information available. This could be done via newsletters or by introducing tutorials or guidelines for their products.

5.3 Discussion

As mentioned before, there are some findings up for discussion. First al, not all gathered data could be used to predict all personality traits. Mainly extraversion, conscientiousness and openness were easier to predict with social media data and gave more insight in the personality domains. The translated word list of Schwartz et al (2013) was only able to hold for one personality trait. This might be due to language differences in other personality traits, but could also indicate differences between the social media platforms Facebook and Twitter. Furthermore, the social media usage was only able to explain personality traits to some extent. Although the direction of the trait is already important. Exact personality traits are hard to measure, but it is already useful to know whether people tend to lean towards either the introverted or extraverted part of the spectrum. Next, there is the question of the feasibility of using social media to predict personality. Not everyone makes their personal accounts publicly viewable. Even though the use of a platform can still be estimated, the actual retrieval of tweets or posts for investigating purposes can be troublesome. Privacy concerns are increasing and social media platforms are spending more effort to cope with the consumer needs. Still, some general info, such as simply the use of a social platform, can already indicate some personality traits and can be obtained regardless of set privacy settings.

5.4 Future research

Although we established some connections between social media platforms, personality and innovative behavior, there is still quite some potential for future research. First of all, new word lists should be established for other languages and other social media platforms. The fact that only conscientiousness could be predicted with the current translated list raises some questions about the uniformity of such lists. When other lists are constructed, they can be compared with existing ones to determine personality changes that are visible with language use. Furthermore, language use between social media should be investigated. The content of a Facebook post might be considerably different than the post on Twitter or LinkedIn. When using social media to predict behavior, there is a need to know how to interpret the messages. Additionally, more content of social media platforms could be used to predict a more precise personality profile. Next, due to the small sample size, not all social media platforms gave results. Facebook for example, was used by 96% of the sample and might thus lack concrete results. With the use of a larger sample, of both social media users and no social media users, additional effects could be found on the personality dimensions. Finally, future research could focus on other applications of the big five. Although there are enough papers about the big five personality dimensions and its

validity, there is still a low amount of applications for it. This paper set a new direction by looking at innovative behavior, but there are plenty of behavioral fields in which the personality dimensions could have an impact. Proven applications of the big five could also further improve the need for determination through social media or other publicly available consumer content.

References

- Agarwal, R., Ahuja, M., Carter, P. E., & Gans, M. (1998, September). Early and late adopters of IT innovations: extensions to innovation diffusion theory. In *Proceedings of the DIGIT Conference* (pp. 1-18).
- Asur, S., & Huberman, B. A. (2010, August). Predicting the future with social media. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on* (Vol. 1, pp. 492-499). IEEE.
- Bass, F. M. (2004). Comments on "A new product growth for model consumer durables the bass model". *Management science*, 50(12_supplement), 1833-1840.
- Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: a meta-analysis. *Personnel psychology*, 44(1), 1-26.
- Barrick, M. R., & Mount, M. K. (1993). Autonomy as a moderator of the relationships between the Big Five personality dimensions and job performance. *Journal of applied Psychology*, 78(1), 111.
- Benet-Martínez, V., & John, O. P. (1998). Los Cinco Grandes across cultures and ethnic groups: Multitrait-multimethod analyses of the Big Five in Spanish and English. *Journal of personality and social psychology*, 75(3), 729.
- Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological bulletin*, 88(3), 588.
- Berr, S. A., Church, A. H., & Waclawski, J. (2000). The right relationship is everything: Linking personality preferences to managerial behaviors. *Human Resource Development Quarterly*, 11(2), 133-157.
- Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1), 1-8.
- Bond, M. H., Nakazato, H., & Shiraishi, D. (1975). Universality and distinctiveness in dimensions of Japanese person perception. *Journal of Cross-Cultural Psychology*, 6(3), 346-357.
- Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological bulletin*, 117(2), 187.
- Block, J. (2010). The five-factor framing of personality and beyond: Some ruminations. *Psychological Inquiry*, 21(1), 2-25.
- Borgatta, E. F. (1964). The structure of personality characteristics. *Behavioral Science*, 9(1), 8-17.
- Cattell, R. B. (1943). The description of personality: basic traits resolved into clusters. *The journal of abnormal and social psychology*, 38(4), 476.

- Cattell, R. B. (1946). Description and measurement of personality.
- Cattell, R. B. (1947). Confirmation and clarification of primary personality factors. *Psychometrika*, 12(3), 197-220.
- Cattell, R. B. (1948). The primary personality factors in women compared with those in men. *British Journal of Statistical Psychology*, 1(2), 114-130.
- Chakrapani, T. K. (1974). Personality correlates of brand loyalty. *Psychological Studies*.
- Chau, P. Y., & Hui, K. L. (1998). Identifying early adopters of new IT products: A case of Windows 95. *Information & Management*, 33(5), 225-230.
- Costa, P. T., & McCrae, R. R. (1985). *The NEO Personality Inventory manual*. Odessa, FL: Psychological Assessment Resources.
- Costa, P. T., & McCrae, R. R. (1992). Four ways five factors are basic. *Personality and individual differences*, 13(6), 653-665.
- Denissen, J. J., Geenen, R., Van Aken, M. A., Gosling, S. D., & Potter, J. (2008). Development and validation of a Dutch translation of the Big Five Inventory (BFI). *Journal of personality assessment*, 90(2), 152-157.
- Dickerson, M. D., & Gentry, J. W. (1983). Characteristics of adopters and non-adopters of home computers. *Journal of Consumer research*, 225-235.
- Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual review of psychology*, 41(1), 417-440.
- Eysenck, H. J. 1947. *Dimensions of Personality*. New York: Praeger.
- Eysenck H. J. and Eysenck S. B. G. (1976) *Psychoticism as a Dimension of Personality*. Hodder & Stoughton, London.
- Fiske, D. W. (1949). Consistency of the factorial structures of personality ratings from different sources. *The Journal of Abnormal and Social Psychology*, 44(3), 329.
- George, D., & Mallery, P. (2003). *SPSS for Windows step by step: A simple guide and reference*. 11.0 update (4th ed.). Boston: Allyn & Bacon.
- Golbeck, J., Robles, C., & Turner, K. (2011, May). Predicting personality with social media. In *CHI'11 extended abstracts on human factors in computing systems* (pp. 253-262). ACM.
- Golbeck, J., Robles, C., Edmondson, M., & Turner, K. (2011, October). Predicting personality from twitter. In *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on* (pp. 149-156). IEEE.

- Goldberg, L. R. (1981). Language and individual differences: The search for universals in personality lexicons. *Review of personality and social psychology*, 2(1), 141-165.
- Goldsmith, R. E., & Hofacker, C. F. (1991). Measuring consumer innovativeness. *Journal of the Academy of Marketing Science*, 19(3), 209-221.
- Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in personality*, 37(6), 504-528.
- Gosling, S. D., Sandy, C. J., & Potter, J. (2010). Personalities of self-identified “dog people” and “cat people”. *Anthrozoos: A Multidisciplinary Journal of The Interactions of People & Animals*, 23(3), 213-222.
- Gruhl, D., Guha, R., Kumar, R., Novak, J., & Tomkins, A. (2005, August). The predictive power of online chatter. In *Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining* (pp. 78-87). ACM.
- Guthrie, G. M., & Bennett, A. B. (1971). Cultural differences in implicit personality theory. *International Journal of Psychology*, 6(4), 305-312.
- Hoekstra, H. A., Ormel, J., & De Fruyt, F. (1996). *Handleiding NEO Persoonlijkheidsvragen-lijsten NEO-PI-R en NEO-FFI*. The Netherlands: Swets & Zeitlinger
- Hofstede, G., & McCrae, R. R. (2004). Personality and culture revisited: Linking traits and dimensions of culture. *Cross-cultural research*, 38(1), 52-88.
- Howarth, E., & Browne, J. A. (1971). An item-factor-analysis of the 16 PF. *Personality: An International Journal*.
- Hughes, D. J., Rowe, M., Batey, M., & Lee, A. (2012). A tale of two sites: Twitter vs. Facebook and the personality predictors of social media usage. *Computers in Human Behavior*, 28(2), 561-569.
- John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research*, 2(1999), 102-138.
- Jost, J. T., West, T. V., & Gosling, S. D. (2009). Personality and ideology as determinants of candidate preferences and “Obama conversion” in the 2008 US presidential election. *Du Bois Review: Social Science Research on Race*, 6(01), 103-124.
- Judge, T. A., Higgins, C. A., Thoresen, C. J., & Barrick, M. R. (1999). The big five personality traits, general mental ability, and career success across the life span. *Personnel psychology*, 52(3), 621-652.
- Kline, P., & Barrett, P. (1983). The factors in personality questionnaires among normal subjects. *Advances in Behaviour Research and Therapy*, 5(3), 141-202.

- Lance, C. E., Butts, M. M., & Michels, L. C. (2006). The sources of four commonly reported cutoff criteria what did they really say?. *Organizational research methods*, 9(2), 202-220.
- Lang, F. R., Ludtke, O., & Asendorpf, J. B. (2001). Validity and psychometric equivalence of the German version of the Big Five Inventory in young, middle-aged and old adults. *Diagnostica*, 47(3), 111-121.
- Markovikj, D., Gievska, S., Kosinski, M., & Stillwell, D. (2013, June). Mining facebook data for predictive personality modeling. In *7th International AIII Conference On Weblogs And Social Media*.
- Martin, T. A., Draguns, J. G., Oryol, V. E., Senin, I. G., Rukavishnikov, A. A., & Klotz, M. L. (1997). Development of a Russian-language NEO-PI-R. In *Comunicación presentada en 105th Annual Convention of the American Psychological Association, Chicago, IL*.
- McCrae, R. R., & Costa Jr, P. T. (1997). Personality trait structure as a human universal. *American psychologist*, 52(5), 509.
- McCrae, R. R., Costa, P. T., Del Pilar, G. H., Rolland, J. P., & Parker, W. D. (1998). Cross-Cultural Assessment of the Five-Factor Model The Revised NEO Personality Inventory. *Journal of Cross-Cultural Psychology*, 29(1), 171-188.
- McCrae, R. R., & Terracciano, A. (2005). Personality profiles of cultures: aggregate personality traits. *Journal of personality and social psychology*, 89(3), 407.
- McDougall, W. (1932). Of the words character and personality. *Journal of Personality*, 1(1), 3-16.
- McDougall, W. I. L. L. I. A. M. (1929). The chemical theory of temperament applied to introversion and extroversion. *The Journal of Abnormal and Social Psychology*, 24(3), 293.
- Neuman, G. A., Wagner, S. H., & Christiansen, N. D. (1999). The relationship between work-team personality composition and the job performance of teams. *Group & Organization Management*, 24(1), 28-45.
- Newcom. Social media onderzoek 2015. Retrieved 26 March, 2015 from <http://www.newcom.nl/socialmedia2015>
- Norman, W. T. (1963). Toward an adequate taxonomy of personality attributes: Replicated factor structure in peer nomination personality ratings. *The Journal of Abnormal and Social Psychology*, 66(6), 574.
- Norman, W. T. (1967). 2800 Personality trait descriptors – Normative operating characteristics for a University population.

- Paunonen, S. V., & Jackson, D. N. (2000). What is beyond the big five? Plenty!. *Journal of personality*, 68(5), 821-835.
- Paunonen, S. V., Haddock, G., Forsterling, F., & Keinonen, M. (2003). Broad versus narrow personality measures and the prediction of behaviour across cultures. *European Journal of Personality*, 17(6), 413-433.
- Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). Linguistic inquiry and word count: LIWC 2001. *Mahway: Lawrence Erlbaum Associates*, 71, 2001.
- Piedmont, R. L., & Chae, J. H. (1997). Cross-cultural generalizability of the five-factor model of personality development and validation of the NEO PI-R for Koreans. *Journal of Cross-Cultural Psychology*, 28(2), 131-155.
- Psychological Assessment resources. (1994). *The revised NEO personality inventory: Manual Supplement for the Spanish Edition*. Odessa, FL: Author.
- Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: the structure and personality correlates of music preferences. *Journal of personality and social psychology*, 84(6), 1236.
- Roehrich, G. (2004). Consumer innovativeness: concepts and measurements. *Journal of Business Research*, 57(6), 671-677.
- Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.
- Salgado, J. F. (2002). The Big Five personality dimensions and counterproductive behaviors. *International Journal of Selection and Assessment*, 10(1-2), 117-125.
- Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Ramones, S. M., Agrawal, M., & Ungar, L. H. (2013). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one*, 8(9), e73791.
- Smith, G. M. (1967). Usefulness of Peer Ratings of Personality in Educational Research. *Educational and Psychological Measurement*, 27(4), 967-984.
- Statista. Number of monthly active Facebook users worldwide 2008-2014. Retrieved 15 February, 2015 from <http://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/>
- Statista. Global social networks ranked by number of users 2015. Retrieved 15 February, 2015 from <http://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/>
- The Huffington Post. Facebook is now bigger than the largest country on Earth. Retrieved 19 March, 2015 from http://www.huffingtonpost.com/2015/01/28/facebook-biggest-country_n_6565428.html

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social Science Computer Review*, 0894439310386557.

Tupes, E. C., & Christal, R. E. (1961). *Recurrent personality factors based on trait ratings* (No. ASD-TR-61-97). Personnel Research Lab Lackland AFB TX.

Whelan, S., & Davies, G. (2006). Profiling consumers of own brands and national brands using human personality. *Journal of Retailing and Consumer Services*, 13(6), 393-402.

Wood, S. L., & Swait, J. (2002). Psychological indicators of innovation adoption: Cross-classification based on need for cognition and need for change. *Journal of Consumer Psychology*, 12(1), 1-13.

Zhao, H., & Seibert, S. E. (2006). The big five personality dimensions and entrepreneurial status: a meta-analytical review. *Journal of Applied Psychology*, 91(2), 259.

Appendix A: Constructs

English	Dutch
Extraversion	
Is talkative	Spraakzaam is
Tends to be quiet (r)	Doorgaans stil is (r)
Generates a lot of enthusiasm	Veel enthousiasme opwekt
Is outgoing, sociable	Hartelijk, een gezelschapsmens is
Is reserved (r)	Terughoudend is (r)
Is sometimes shy, inhibited (r)	Soms verlegen, geremd is (r)
Is full of energy	Vol energie is
Has an assertive personality	Voor zichzelf opkomt
Agreeableness	
Is considerate and kind to almost everyone	Attent en aardig is voor bijna iedereen
Has a forgiving nature	Vergevingsgezind is
Is helpful and unselfish with others	Behulpzaam en onzelfzuchtig ten opzicht van anderen is
Starts quarrels with others (r)	Snel ruzie maakt (r)
Is sometimes rude to others (r)	Soms grof tegen anderen is (r)
Can be cold and aloof (r)	Koud en afstandelijk kan zijn (r)
Is generally trusting	Mensen over het algemeen vertrouwt
Tends to find fault with others (r)	Geneigd is kritiek te hebben op anderen (r)
Likes to cooperate with others	Graag samenwerkt met anderen
Conscientiousness	
Does a thorough job	Grondig te werk gaat
Perseveres until the task is finished	Volhoudt tot de taak af is
Tends to be disorganized (r)	Doorgaans geneigd is tot slordigheid (r)
Tends to be lazy (r)	Geneigd is lui te zijn (r)
Is a reliable worker	Een werker is waar men van op aan kan
Does things efficiently	Dingen efficiënt doet
Makes plans and follows through with them	Plannen maakt en deze doorzet
Is easily distracted (r)	Gemakkelijk afgeleid is (r)
Can be somewhat careless (r)	Een beetje nonchalant kan zijn (r)
Neuroticism	
Worries a lot	Zich veel zorgen maakt
Can be tense	Gespannen kan zijn
Is relaxed, handles stress well (r)	Ontspannen is, goed met stress kan omgaan (r)
Gets nervous easily	Gemakkelijk zenuwachtig wordt
Is emotionally stable, not easily upset (r)	Emotioneel stabiele is, niet gemakkelijk overstuur raakt (r)
Remains calm in tense situations (r)	Kalm blijft in gespannen situaties (r)
Is depressed, blue	Somber is
Can be moody	Humeurig kan zijn

Openness	
Likes to reflect, play with ideas	Graag nadenkt, met ideeën speelt
Is inventive	Vindingrijk is
Values artistic, aesthetic experiences	Waarde hecht aan kunstzinnige ervaringen
Is original, comes up with new ideas	Origineel is, met nieuwe ideeën komt
Is ingenious, a deep thinker	Scherpzinnig, een denker is
Has an active imagination	Een levendige fantasie heft
Is curious about many different things	Benieuwd is naar veel verschillende dingen
Is sophisticated in art, music or literature	Het fijne weet van kunst, muziek of literatuur
Has few artistic interests (r)	Weinig interesse voor kunst heeft (r)
Prefers work that is routine (r)	Een voorkeur heft voor werk dat routine is (r)

Table A1: Personality dimension measurement items (Denissen et al 2008). Negatively framed items which need to be reverse coded and are indicated by an (r).

English	Dutch
Exploratory acquisition of products (EAP)	
Even though certain food products are available in a number of different flavors, I tend to buy the same flavor (r)	Alhoewel bepaalde voedselproducten in verschillende smaken beschikbaar zijn, heb ik de neiging dezelfde smaak te kopen (r)
I would rather stick with a brand I usually buy than try something I am not sure of (r)	Ik blijf liever bij een merk dat ik doorgaans koop, dan dat ik iets probeer waar ik niet zeker van ben (r)
I think of myself as a brand-loyal consumer (r)	Ik zie mezelf als een merkloyale consument (r)
When I see a new brand on the shelf, I'm not afraid to giving it a try	Als ik een nieuw merk op het schap zie, aarzel ik niet om het een keer te proberen
When I go to a restaurant, I feel it is safer to order dishes I am familiar with (r)	Als ik naar een restaurant ga, voel ik me prettiger bij het bestellen van bekende gerechten (r)
If I like a brand, I rarely switch from it just to try something different (r)	Als ik een merk fijn vind, wissel ik zelden om iets anders te proberen (r)
I am very cautious in trying new or different products (r)	Ik ben erg voorzichtig met het proberen van nieuwe of andere producten (r)
I enjoy taking chances in buying unfamiliar brands just to get some variety in my purchases	Ik houd van kansen nemen in het kopen van onbekende producten om wat variëteit in mijn aankopen te hebben
I rarely buy brands about which I am uncertain how they will perform (r)	Ik koop zelden merken zonder te weten hoe ze presteren (r)
I usually eat the same kinds of foods on a regular basis (r)	Ik eet doorgaans hetzelfde soort eten op een regelmatige basis (r)
Exploratory information seeking (EIS)	
Reading mail advertising to find out what's new is a waste of time (r)	Het lezen van postadvertenties om wat nieuws te ontdekken is tijdsverspilling (r)

I like to go window shopping and find out about the latest styles	Ik houd van winkelen en achter de nieuwste stijlen te komen
I get very bored listening to others about their purchases (r)	Ik raak erg verveeld als ik luister naar anderen over hun aankopen (r)
I generally read even my junk mail just to know what it is about	Ik lees over het algemeen zelfs mijn spam mail, enkel om weten waar het over gaat
I don't like to shop around just out of curiosity (r)	Ik houd er niet van om rond te shoppen uit nieuwsgierigheid (r)
I like to browse through mail order catalogs even when I don't plan to buy anything	Ik blader door postorder catalogussen, zelfs wanneer ik niet van plan ben iets te kopen
I usually throw away mail advertisements without reading them (r)	Ik gooi doorgaans postadvertenties weg zonder ze te lezen (r)
I like to shop around and look at displays	Ik houd ervan om rond te shoppen en naar etalages te kijken
I don't like to talk to my friends about my purchases (r)	Ik houd er niet van om tegen vrienden over mijn aankopen te praten (r)
I often read advertisements just out of curiosity	Ik lees vaak advertenties uit nieuwsgierigheid

Table A2: Personality innovativeness measurement items (Baugartner & Steenkamp 1996). Negatively framed items which need to be reverse coded and are indicated by an (r).

Appendix B: Reliability

Extraversion

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,827	,826	8

Agreeableness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,714	,723	9

Conscientiousness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,787	,792	9

Neuroticism

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,816	,815	8

Openness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,776	,781	10

Exploratory acquisition of products

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,819	,824	10

Exploratory information seeking

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,825	,823	10

Appendix C: Twitter tests

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,038 ^a	,001	-,012	,58267

a. Predictors: (Constant), ExtraversionTwitterC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,593	,213		16,905	,000
	ExtraversionTwitterC	6,048	18,102	,038	,334	,739

a. Dependent Variable: Extraversion

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,060 ^a	,004	-,010	,53055

a. Predictors: (Constant), AgreeablenessTwitterC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,741	,080		46,705	,000
	AgreeablenessTwitterC	20,991	40,084	,060	,524	,602

a. Dependent Variable: Agreeableness

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,350 ^a	,123	,111	,52945

a. Predictors: (Constant), ConscientiousnessTwitterC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,759	,087		43,012	,000
	ConscientiousnessTwitterC	58,744	18,023	,350	3,259	,002

a. Dependent Variable: Conscientiousness

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,151 ^a	,023	,010	,63554

a. Predictors: (Constant), NeuroticismTwitterC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,470	,085		29,058	,000
	NeuroticismTwitterC	-64,786	48,689	-,151	-1,331	,187

a. Dependent Variable: Neuroticism

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,109 ^a	,012	-,001	,44835

a. Predictors: (Constant), OpennessTwitterC

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,728	,089		41,842	,000
	OpennessTwitterC	6,111	6,420	,109	,952	,344

a. Dependent Variable: Openness

Appendix D: Social media

Social Media usage

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Gebruik Facebook	246	0	1	,96	,207
Gebruik YouTube	246	0	1	,76	,428
Gebruik Google+	246	0	1	,33	,472
Gebruik LinkedIn	246	0	1	,86	,346
Gebruik Twitter	246	0	1	,56	,498
Gebruik Instagram	246	0	1	,37	,485
Gebruik Pinterest	246	0	1	,26	,437
Gebruik Snapchat	246	0	1	,33	,472
Gebruik Tumblr	246	0	1	,06	,240
Gebruik Foursquare	246	0	1	,10	,297
Gebruik WeChat	246	0	1	,02	,141
Gebruik Other	246	0	1	,11	,308
Valid N (listwise)	246				

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,274 ^a	,075	,028	,60254

a. Predictors: (Constant), Gebruik Other, Gebruik Snapchat, Gebruik LinkedIn, Gebruik Google+, Gebruik Facebook, Gebruik Tumblr, Gebruik YouTube, Gebruik Pinterest, Gebruik Twitter, Gebruik Foursquare, Gebruik WeChat, Gebruik Instagram

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3,349	,214		15,683	,000
1 Gebruik Facebook	,111	,195	,038	,568	,570
Gebruik YouTube	-,113	,095	-,079	-1,196	,233
Gebruik Google+	-,012	,088	-,009	-,132	,895
Gebruik LinkedIn	,246	,118	,139	2,083	,038
Gebruik Twitter	-,053	,088	-,043	-,604	,547
Gebruik Instagram	,220	,100	,175	2,210	,028
Gebruik Pinterest	-,124	,102	-,089	-1,225	,222
Gebruik Snapchat	-,041	,090	-,032	-,459	,647

Gebruik Tumblr	-,232	,188	-,091	-1,234	,218
Gebruik Foursquare	,297	,149	,145	1,997	,047
Gebruik WeChat	-,056	,323	-,013	-,173	,863
Gebruik Other	-,161	,127	-,081	-1,266	,207

a. Dependent Variable: **Extraversion**

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,183 ^a	,034	-,016	,49889

a. Predictors: (Constant), Gebruik Other, Gebruik Snapchat, Gebruik LinkedIn, Gebruik Google+, Gebruik Facebook, Gebruik Tumblr, Gebruik YouTube, Gebruik Pinterest, Gebruik Twitter, Gebruik Foursquare, Gebruik WeChat, Gebruik Instagram

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,746	,177		21,189	,000
	Gebruik Facebook	-,092	,161	-,038	-,568	,571
	Gebruik YouTube	-,026	,078	-,022	-,328	,743
	Gebruik Google+	-,017	,073	-,016	-,232	,817
	Gebruik LinkedIn	,043	,098	,030	,441	,660
	Gebruik Twitter	,007	,073	,007	,093	,926
	Gebruik Instagram	,025	,082	,025	,304	,762
	Gebruik Pinterest	-,035	,084	-,031	-,418	,677
	Gebruik Snapchat	-,080	,074	-,076	-1,074	,284
	Gebruik Tumblr	-,213	,156	-,103	-1,365	,174
	Gebruik Foursquare	,238	,123	,143	1,929	,055
	Gebruik WeChat	-,039	,268	-,011	-,145	,885
	Gebruik Other	,114	,106	,071	1,082	,280

a. Dependent Variable: **Agreeableness**

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,201 ^a	,041	-,009	,54157

a. Predictors: (Constant), Gebruik Other, Gebruik Snapchat, Gebruik LinkedIn, Gebruik Google+, Gebruik Facebook, Gebruik Tumblr, Gebruik YouTube, Gebruik Pinterest, Gebruik Twitter, Gebruik Foursquare, Gebruik WeChat, Gebruik Instagram

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	3,349	,192		17,451	,000
Gebruik Facebook	,137	,175	,053	,785	,433
Gebruik YouTube	-,065	,085	-,052	-,769	,442
Gebruik Google+	,080	,079	,070	1,010	,313
Gebruik LinkedIn	,195	,106	,125	1,840	,067
Gebruik Twitter	-,059	,079	-,054	-,742	,459
Gebruik Instagram	-,065	,089	-,059	-,731	,466
Gebruik Pinterest	,052	,091	,042	,567	,571
Gebruik Snapchat	-,042	,081	-,037	-,518	,605
Gebruik Tumblr	-,142	,169	-,063	-,843	,400
Gebruik Foursquare	,035	,134	,019	,263	,793
Gebruik WeChat	-,051	,291	-,013	-,177	,860
Gebruik Other	-,117	,115	-,067	-1,018	,310

a. Dependent Variable: **Conscientiousness**

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,272 ^a	,074	,026	,63447

a. Predictors: (Constant), Gebruik Other, Gebruik Snapchat, Gebruik LinkedIn, Gebruik Google+, Gebruik Facebook, Gebruik Tumblr, Gebruik YouTube, Gebruik Pinterest, Gebruik Twitter, Gebruik Foursquare, Gebruik WeChat, Gebruik Instagram

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	3,135	,225		13,940	,000
Gebruik Facebook	-,219	,205	-,070	-1,066	,288
Gebruik YouTube	,088	,100	,059	,884	,378
Gebruik Google+	-,048	,092	-,035	-,517	,606
Gebruik LinkedIn	-,331	,124	-,178	-2,660	,008

Gebruik Twitter	-,106	,093	-,082	-1,135	,258
Gebruik Instagram	-,038	,105	-,028	-,359	,720
Gebruik Pinterest	,163	,107	,111	1,525	,129
Gebruik Snapchat	,058	,095	,043	,618	,537
Gebruik Tumblr	,264	,198	,098	1,331	,184
Gebruik Foursquare	-,280	,157	-,129	-1,785	,076
Gebruik WeChat	-,195	,340	-,043	-,574	,567
Gebruik Other	,022	,134	,010	,160	,873

a. Dependent Variable: **Neuroticism**

ANOVA^a

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	6,475	12	,540	2,537	,004 ^b
Residual	49,545	233	,213		
Total	56,020	245			

a. Dependent Variable: Openness

b. Predictors: (Constant), Gebruik Other, Gebruik Snapchat, Gebruik LinkedIn, Gebruik Google+, Gebruik Facebook, Gebruik Tumblr, Gebruik YouTube, Gebruik Pinterest, Gebruik Twitter, Gebruik Foursquare, Gebruik WeChat, Gebruik Instagram

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	3,546	,163		21,699	,000
Gebruik Facebook	-,128	,149	-,056	-,860	,390
Gebruik YouTube	,033	,072	,029	,454	,650
Gebruik Google+	-,011	,067	-,011	-,166	,868
Gebruik LinkedIn	,087	,090	,063	,965	,336
Gebruik Twitter	,164	,068	,170	2,421	,016
Gebruik Instagram	,071	,076	,072	,928	,354
Gebruik Pinterest	,132	,078	,121	1,701	,090
Gebruik Snapchat	-,164	,069	-,162	-2,382	,018
Gebruik Tumblr	,049	,144	,024	,339	,735
Gebruik Foursquare	-,166	,114	-,103	-1,454	,147
Gebruik WeChat	,369	,247	,109	1,490	,137
Gebruik Other	,073	,098	,047	,750	,454

a. Dependent Variable: **Openness**

Social media behavior

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Totalplatforms	246	1,00	11,00	4,6098	1,99646
Percentinfo	246	,00	1,00	,7180	,24689
Percentfriend	246	,00	1,00	,5260	,23692
Valid N (listwise)	246				

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Ik...-Kijk op Facebook	235	1	8	1,60	1,278
Ik...-Post op Facebook	235	1	8	5,55	1,786
Ik...-Kijk op YouTube	187	1	8	3,11	1,560
Ik...-Post op YouTube	187	2	8	7,61	,756
Ik...-Kijk op Google+	82	1	8	5,76	2,203
Ik...-Post op Google+	82	2	8	7,28	1,363
Ik...-Kijk op LinkedIn	212	1	8	3,50	1,702
Ik...-Post op LinkedIn	212	1	8	6,62	1,698
Ik...-Kijk op Twitter	137	1	8	3,36	2,601
Ik...-Post op Twitter	137	1	8	5,01	2,609
Ik...-Kijk op Instagram	92	1	8	2,92	2,190
Ik...-Post op Instagram	92	1	8	5,27	1,761
Ik...-Kijk op Pinterest	63	1	8	4,68	1,958
Ik...-Post op Pinterest	63	2	8	6,17	1,836
Ik...-Kijk op Snapchat	82	1	8	2,95	2,388
Ik...-Post op Snapchat	82	1	8	4,39	2,361
Ik...-Kijk op Tumblr	15	1	8	5,07	2,549
Ik...-Post op Tumblr	15	3	8	6,80	1,699
Ik...-Kijk op Foursquare	24	2	8	6,62	2,081
Ik...-Post op Foursquare	24	2	8	6,54	2,265
Ik...-Kijk op WeChat	5	4	8	5,00	1,732
Ik...-Post op WeChat	5	6	8	6,80	,837
Valid N (listwise)	3				

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,991	2309,336 ^b	5,000	99,000	,000
	Wilks' Lambda	,009	2309,336 ^b	5,000	99,000	,000
	Hotelling's Trace	116,633	2309,336 ^b	5,000	99,000	,000
	Roy's Largest Root	116,633	2309,336 ^b	5,000	99,000	,000
Ik...KijkopTwitter	Pillai's Trace	,430	1,386	35,000	515,000	,073
	Wilks' Lambda	,630	1,389	35,000	418,885	,073

Ik...PostopTwitter	Hotelling's Trace	,497	1,383	35,000	487,000	,075
	Roy's Largest Root	,212	3,120 ^c	7,000	103,000	,005
	Pillai's Trace	,454	1,471	35,000	515,000	,043
	Wilks' Lambda	,610	1,490	35,000	418,885	,039
	Hotelling's Trace	,538	1,498	35,000	487,000	,036
Ik...KijkopTwitter * Ik...PostopTwitter	Roy's Largest Root	,272	4,009 ^c	7,000	103,000	,001
	Pillai's Trace	,662	,828	95,000	515,000	,871
	Wilks' Lambda	,483	,826	95,000	486,318	,873
	Hotelling's Trace	,804	,824	95,000	487,000	,876
	Roy's Largest Root	,332	1,799 ^c	19,000	103,000	,032

a. Design: Intercept + Ik...KijkopTwitter + Ik...PostopTwitter + Ik...KijkopTwitter * Ik...PostopTwitter

b. Exact statistic

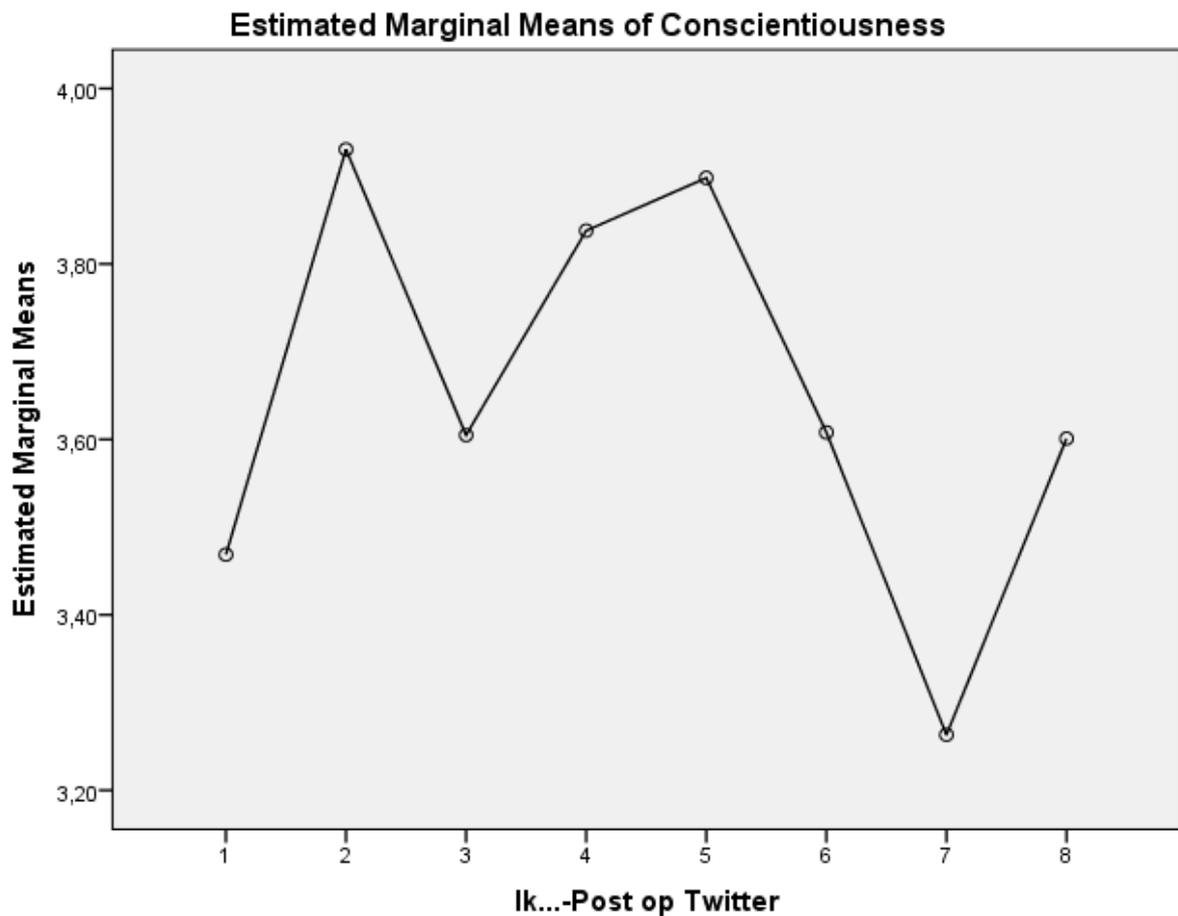
c. The statistic is an upper bound on F that yields a lower bound on the significance level.

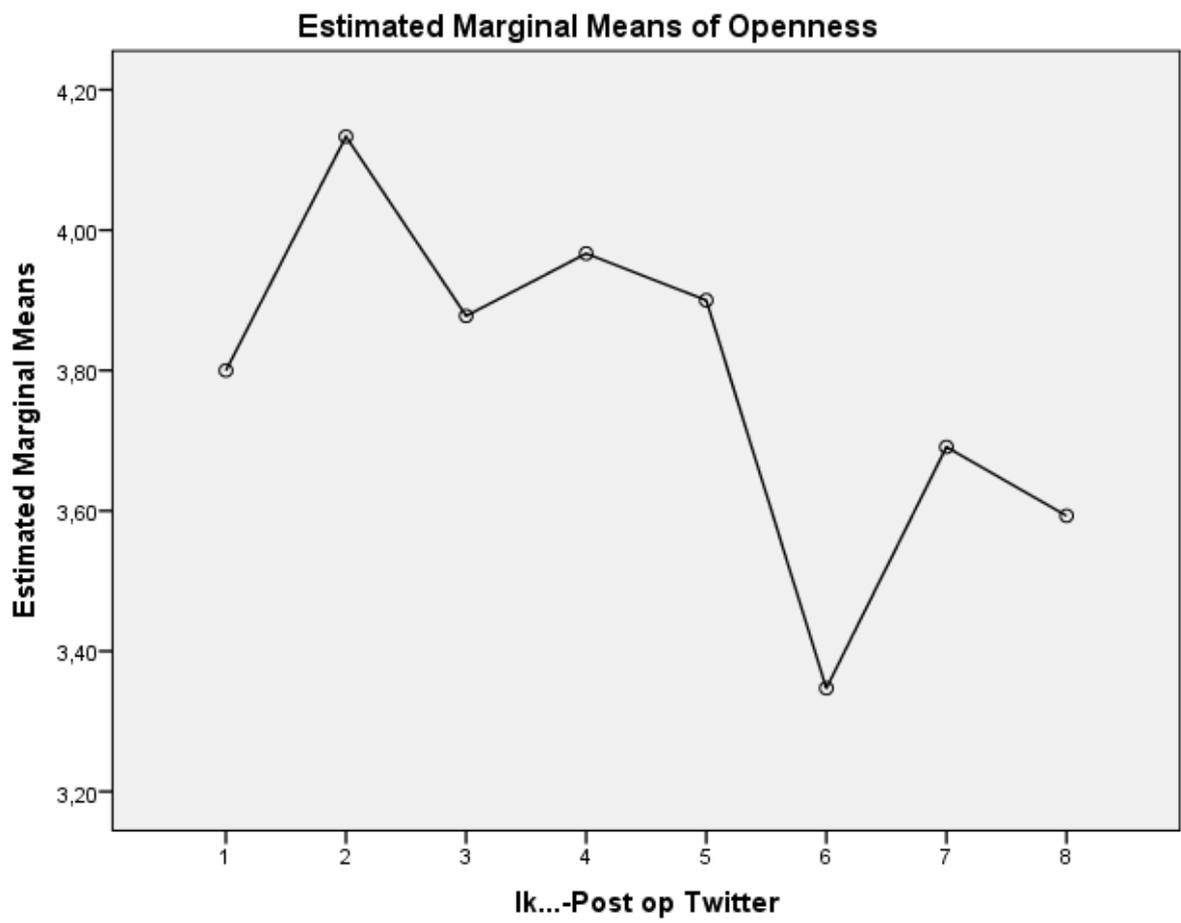
Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extraversion	12,180 ^a	33	,369	1,023	,449
	Agreeableness	9,273 ^b	33	,281	1,013	,463
	Conscientiousness	11,374 ^c	33	,345	1,248	,199
	Neuroticism	14,506 ^d	33	,440	,977	,514
	Openness	11,713 ^e	33	,355	1,889	,008
Intercept	Extraversion	820,505	1	820,505	2274,258	,000
	Agreeableness	794,507	1	794,507	2863,695	,000
	Conscientiousness	760,111	1	760,111	2752,938	,000
	Neuroticism	378,100	1	378,100	840,148	,000
	Openness	835,798	1	835,798	4448,343	,000
Ik...KijkopTwitter	Extraversion	3,171	7	,453	1,256	,280
	Agreeableness	,951	7	,136	,490	,840
	Conscientiousness	3,881	7	,554	2,008	,061
	Neuroticism	3,867	7	,552	1,227	,295
	Openness	2,353	7	,336	1,789	,097
Ik...PostopTwitter	Extraversion	4,989	7	,713	1,976	,065
	Agreeableness	1,230	7	,176	,633	,727
	Conscientiousness	4,157	7	,594	2,151	,045
	Neuroticism	1,907	7	,272	,605	,750
	Openness	4,383	7	,626	3,333	,003
Ik...KijkopTwitter * Ik...PostopTwitter	Extraversion	6,853	19	,361	1,000	,468
	Agreeableness	4,636	19	,244	,879	,608
	Conscientiousness	2,470	19	,130	,471	,969
	Neuroticism	7,724	19	,407	,903	,580
	Openness	4,579	19	,241	1,283	,211

Error	Extraversion	37,160	103	,361	
	Agreeableness	28,576	103	,277	
	Conscientiousness	28,439	103	,276	
	Neuroticism	46,354	103	,450	
	Openness	19,353	103	,188	
Total	Extraversion	1827,922	137		
	Agreeableness	1890,346	137		
	Conscientiousness	1748,926	137		
	Neuroticism	983,344	137		
	Openness	1916,970	137		
Corrected Total	Extraversion	49,341	136		
	Agreeableness	37,849	136		
	Conscientiousness	39,813	136		
	Neuroticism	60,860	136		
	Openness	31,066	136		

- a. R Squared = ,247 (Adjusted R Squared = ,006)
- b. R Squared = ,245 (Adjusted R Squared = ,003)
- c. R Squared = ,286 (Adjusted R Squared = ,057)
- d. R Squared = ,238 (Adjusted R Squared = -,006)
- e. R Squared = ,377 (Adjusted R Squared = ,177)





Appendix E: Adoption of innovation

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,059	7,517 ^b	2,000	239,000	,001
	Wilks' Lambda	,941	7,517 ^b	2,000	239,000	,001
	Hotelling's Trace	,063	7,517 ^b	2,000	239,000	,001
	Roy's Largest Root	,063	7,517 ^b	2,000	239,000	,001
Extraversion	Pillai's Trace	,084	10,965 ^b	2,000	239,000	,000
	Wilks' Lambda	,916	10,965 ^b	2,000	239,000	,000
	Hotelling's Trace	,092	10,965 ^b	2,000	239,000	,000
	Roy's Largest Root	,092	10,965 ^b	2,000	239,000	,000
Agreeableness	Pillai's Trace	,035	4,342 ^b	2,000	239,000	,014
	Wilks' Lambda	,965	4,342 ^b	2,000	239,000	,014
	Hotelling's Trace	,036	4,342 ^b	2,000	239,000	,014
	Roy's Largest Root	,036	4,342 ^b	2,000	239,000	,014
Conscientiousness	Pillai's Trace	,034	4,252 ^b	2,000	239,000	,015
	Wilks' Lambda	,966	4,252 ^b	2,000	239,000	,015
	Hotelling's Trace	,036	4,252 ^b	2,000	239,000	,015
	Roy's Largest Root	,036	4,252 ^b	2,000	239,000	,015
Neuroticism	Pillai's Trace	,109	14,554 ^b	2,000	239,000	,000
	Wilks' Lambda	,891	14,554 ^b	2,000	239,000	,000
	Hotelling's Trace	,122	14,554 ^b	2,000	239,000	,000
	Roy's Largest Root	,122	14,554 ^b	2,000	239,000	,000
Openness	Pillai's Trace	,044	5,504 ^b	2,000	239,000	,005
	Wilks' Lambda	,956	5,504 ^b	2,000	239,000	,005
	Hotelling's Trace	,046	5,504 ^b	2,000	239,000	,005
	Roy's Largest Root	,046	5,504 ^b	2,000	239,000	,005

a. Design: Intercept + Extraversion + Agreeableness + Conscientiousness + Neuroticism + Openness

b. Exact statistic

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	EAP	14,661 ^a	5	2,932	8,309	,000
	EIS	15,610 ^b	5	3,122	6,216	,000
Intercept	EAP	4,958	1	4,958	14,048	,000
	EIS	,006	1	,006	,013	,911
Extraversion	EAP	4,956	1	4,956	14,042	,000
	EIS	6,612	1	6,612	13,165	,000
Agreeableness	EAP	,152	1	,152	,430	,513
	EIS	4,379	1	4,379	8,718	,003
Conscientiousness	EAP	1,623	1	1,623	4,600	,033

Neuroticism	EIS	1,018	1	1,018	2,026	,156
	EAP	1,165	1	1,165	3,300	,071
Openness	EIS	10,263	1	10,263	20,435	,000
	EAP	2,032	1	2,032	5,758	,017
Error	EIS	1,402	1	1,402	2,792	,096
	EAP	84,699	240	,353		
Total	EIS	120,536	240	,502		
	EAP	2492,650	246			
Corrected Total	EIS	2209,778	246			
	EAP	99,360	245			
	EIS	136,146	245			

a. R Squared = ,148 (Adjusted R Squared = ,130)

b. R Squared = ,115 (Adjusted R Squared = ,096)

Parameter Estimates

Dependent Variable	Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
EAP	Intercept	2,177	,581	3,748	,000	1,033	3,321
	Extraversion	,254	,068	3,747	,000	,120	,387
	Agreeableness	,056	,085	,656	,513	-,112	,224
	Conscientiousness	-,157	,073	-2,145	,033	-,301	-,013
	Neuroticism	-,124	,068	-1,817	,071	-,259	,011
	Openness	,198	,083	2,400	,017	,036	,361
EIS	Intercept	-,078	,693	-,112	,911	-1,442	1,287
	Extraversion	,293	,081	3,628	,000	,134	,452
	Agreeableness	,301	,102	2,953	,003	,100	,501
	Conscientiousness	,124	,087	1,424	,156	-,048	,296
	Neuroticism	,369	,082	4,520	,000	,208	,530
	Openness	-,165	,099	-1,671	,096	-,359	,029