Digital divide at individual level: Evidence for Eastern and Western European countries

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Digital Divide at individual level: Evidence for eastern and western European countries

Abstract

The current study explores the digital divide by checking the phenomenon at the individual level. It digs into the individual pattern of adoption and use of a broad set of information and communications technologies (ICT) by introducing a conceptual model combining the extended unified theory of acceptance and use of technology (UTAUT2) and the five-factor model of personality. By doing so it provides insights on factors affecting technology adoption and the role of personality on individual usage behavior. Most of the UTAUT2 hypotheses are supported, with performance expectancy being the strongest predictor. Openness is a significant predictor of behavioral intention, whereas for usage behavior the significant personality predictors are openness, extraversion, and agreeableness. Moreover, as data were collected in Bulgaria and Portugal, a multi-group analysis revealed significant country differences. The effect of performance expectancy, habit, agreeableness, and neuroticism on behavioral intention, as well as the effect of age on usage, are stronger for Bulgaria, whereas the effect of hedonic motivation on behavioral intention and the effect of behavioral intention on usage are stronger for Portugal.

Keywords: Information and communications technologies (ICT); digital divide, extended unified theory of acceptance and use of technology (UTAUT2); personality

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1. Introduction

Information and communication technologies (ICT) have become more integrated across all sectors of economy and society (European Commission, 2015). Research has shown that investment and evaluation of ICT is associated with economic benefits, such as higher productivity, lower costs, new economic opportunities, job creation, innovation, and increased trade (Irani, 2002; Weerakkody, Irani, Lee, Osman, & Hindi, 2015). According to the International Telecommunications Union (ITU, 2014), ICT will continue to play a major role in facilitating access to information, knowledge, and key services. As more people join the information society and high-speed communication networks, the tracking and measurement of ICT development become even more important. Continuous monitoring and measurement of ICT developments will help to identify progress and gaps.

The advancement and diffusion of technology have evolved at record-setting rates. For example, global internet penetration grew from 6.5% in 2000 to 47% in 2016 and many developed countries are experiencing penetration rates of more than 90% (ITU, 2016). The ongoing development of ICT in all its forms, applications and infrastructure technology (such as broadband) is driving radical change in our lives, with the constant creation of new products and services, new ways of conducting business, new markets and investment opportunities, new social and cultural expressions, and new channels for citizens and government to interact (Dwivedi & Irani, 2009; OECD, 2003). Hence, the continued existence of a digital divide, however defined, is an obstacle to any agenda of social inclusion. If societies are today partly, and will in the future more or less be completely structured around ICT, then the demand of economic efficiency as well as social and political equality, require that no social group finds itself excluded from participation (Alvares et al., 2014). Hence, understanding how ICT are adopted can help to reduce the digital divide.

This study seeks to contribute to the literature in this respect, through exploring the digital divide phenomenon from the perspective of individual ICT acceptance, and in which personality characteristics of the would-be adopters are also contemplated. It digs into the individual pattern of behavioral intention and usage behavior of a set of ICT, going behind the more traditional information technology (IT) adoption studies, which usually include only one technology and the potential drivers are related mainly with its direct or indirect characteristics/perceptions, toward a more comprehensive approach. Therefore, its main contributions are threefold: First, it adds to the current knowledge on digital divide by checking the phenomenon in a broader context at the individual level.

Second, the study proposes a theoretical model for the acceptance of the ICT at the individual level that combines the extended unified theory of acceptance and use of technology (UTAUT2) (Venkatesh, Thong, & Xu, 2012) with the big five personality traits (Costa & McCrae, 1992; Digman, 1990). By doing so, it provides insights on factors affecting technology adoption and explores if and how the big five personality traits (openness, extraversion, agreeableness, conscientiousness, and neuroticism) influence usage behavior, empirically testing its applicability in the context of Eastern and Western European countries, which to the best of the authors' knowledge has not yet been done. Third, it seeks to identify what factors in the proposed model differ the most across cultures (in the context of Eastern and Western European countries). Together, these three contributions will provide an innovative and comprehensive lens for researchers and policy-makers to develop accurate policies to engender ICT acceptance, including e-government and other e-services. Studies on individual-level digital divide usually focus on socio–demographic characteristics of individuals, usually in a limited environment (e.g., a country or a region), whereas the present study also includes one's attitudes toward ICT and personality traits, as well as individuals from two different settings, i.e., countries.

Research has revealed a difference in the speed at which various countries have adopted ICT, which is known as the global digital divide. Even in countries belonging to the European Union, which is one of the international entities that pays more attention to the issue of the digital divide (European Commission, 2010a, 2010b, 2015), meaningful digital asymmetries still exist across its member states (Cruz-Jesus, Oliveira, & Bacao, 2012). In the context of this study, we have chosen two European countries that belong to the two ends of the spectrum in terms of geographical location - Bulgaria and Portugal - as there is evidence that geography plays an important role in the digital divide (Cruz-Jesus, Vicente, Bacao, & Oliveira, 2016; Maria Rosalia Vicente & Lopez, 2010a). Note that besides the geographic aspect, these two countries also joined the EU in very different contexts: Portugal was among the EU-15 (joining in 1986), while Bulgaria joined, together with Romania, in 2007. Moreover, these two countries also present different digital development stages (Cruz-Jesus, Oliveira, & Bacao, 2018; Cruz-Jesus, Oliveira, Bacao, & Irani, 2017). For example, according to the World Bank Database, the percentage of Internet users differs across the two countries in question – 56.7% in Bulgaria versus 68.6% in Portugal. Besides factors such as government policy, industry lead, and market environment, heterogeneity in the diffusion process of newly introduced goods or services has shown to be affected by collective national characteristics as well (Hwang, Jung, & Salvendy, 2006). Moreover, from a personality point of view, Bulgaria and Portugal also have considerable differences. According to Hofstede's cultural dimensions, Bulgaria and Portugal show noticeable differences in long-term orientation, indulgence, and uncertainty avoidance. In other words, Bulgarians tend to consider their own past in assessing present and future challenges, whereas Portuguese are, according to The

Hofstede Centre, less prone to regulate their wishes and instincts as well as less comfortable in unknown situations.

The remainder of the paper is structured as follows. First, a theoretical background of the problem is presented, introducing the concept of digital divide, previous research on the phenomenon, overview of adoption models at the individual level, and personality traits concept. Second, a research model is proposed, and hypotheses are developed. Third, the research method is described, and study results are reported. Finally, a discussion, implications, and conclusions are presented.

2. Theoretical background

2.1 The Digital Divide

The digital divide is a complex phenomenon that hinges on many different factors (Hilbert, 2011). Among others, the study of the digital divide comprises different levels of ICT adoption (e.g., access and use) as well as different adoption units (individual-, firm-, and country-level) (Dewan & Riggins, 2005).

Initially, the digital divide was defined as the gap between *"those who have access to digital ICT and those who do not"* (OECD, 2001). Studies conducted in the 1990s were primarily concerned with issues surrounding access, where access was measured in terms of having, or not, a computer at home that connects to the internet. Representative surveys of this period that were focused on the number and categories of people with access to a computer and Internet, are the first "Falling Through the Net" reports from the US Department of Commerce's National Telecommunications and Information Administration (NTIA) (U. S. Department of Commerce, 1995, 1998, 1999). These reports concluded that those with lower income, educational attendance, with disabilities; as well as those belonging to ethnic minorities, the elderly and women were the most likely to be digitally excluded. At country level, one of the first papers addressing the global digital divide was the one from Hargittai (1999), which concluded that although aspects related with economic, educational, language, legal, environmental, and technological infrastructure of countries could explain the digital divide. Economic wealth and telecommunications policy were the ones identified as the most important.

However, in the year 2000 the physical access among the different categories of people in the developed countries started to decline (U. S. Department of Commerce, 2000). Throughout the years researcher have reframing the overly technical concept of the digital divide, to go beyond access and pay more attention to social, psychological, and cultural backgrounds (van Dijk, 2006). Hargittai (2002) argued that there was a difference between PC and Internet access (later labeled as the first-order digital divide) to the skills to effectively use these technologies. This represented a shift in the awareness toward the digital divide problem as, until this point, it was common to believe that technology access would (almost) automatically lead to its use. Accordingly, DiMaggio and Shafer (2004) expanded the context of digital divide by referring to not just differences in access, but autonomy of use, skills, social support, and the purposes for which the technology is employed, labeled as the second-order digital divide. Indeed, as the majority of the participants in any social system have obtained access to a technology, the second-order divide starts to become more important than the first-order divide (Dewan & Riggins, 2005).

Within this context, Hsieh, Rai, and Keil (2008), for example, used a local governmental project that provided free Internet to its residents to study how different people who are socio-economically advantaged or disadvantaged made use of the Internet given that they already had access to it. In their study, they used the theory of planned behavior (TPB) with the personal network exposure, demonstrating that economically advantaged and disadvantaged people indeed have very different post-implementation behavior regarding the use of ICT. These authors concluded that economically advantaged people have a "higher tendency to respond to network exposure", using these technologies with much more confidence than the disadvantaged. This is one of the few studies that used adoption models to assess the individual-level digital divide. Usually, research at individual-level digital divide takes place in the western world, which provides a biased view on the digital divide's determinants, as they change across countries/regions. As one example, whereas in western countries the gender-related digital divide has been strongly narrowed, in other areas of the globe that is not the case (see, e.g., Mumporeze & Prieler, 2017).

Accordingly, from a methodological standpoint, multivariate methods started to be employed as the subject start to be perceived as a multidimensional issue. Blank and Groselj (2014) used principal components analysis to find the main dimensions of ICT activities in UK users and ordinary least squares (OLS) model to identify its characteristics (age, gender, urban–rural, ethnicity, education, life stage, and marital status). At country-level, Cuervo and Menéndez (2006), for example, used factor and cluster analysis to identify the latent dimensions on the European digital divide as well as the countries' profiles on those dimensions. Çigdem ArIcIgil Çilan, Bolat, and Coskun (2009) used MANOVA to assess the differences in terms of ICT adoption between member-states and candidates of the European Union. Cruz-Jesus et al. (2018) made use of factor analysis and OLS models to assess the global digital divide's drivers across different periods. The digital divide is, therefore, a multidimensional and complex phenomenon that extends beyond access to technology and incorporates several perspectives.

In this paper the phenomenon is analyzed at the individual level and the concept "digital divide" refers to the difference in usage of ICT, and correspondingly to information content and any socio-economic opportunities related to it. According to Xiao, Califf, Sarker, and Sarker (2013), little attention has been paid to the individual level of analysis of ICT adoption. Moreover, these authors also concluded that studies comparing different countries are scarce.

In terms of indicators used to measure the digital divide, these have changed over time due to the changing characteristics and introduction of new ICT applications. Over time, international institutions tracking digital development have been introducing new indicators to measure the information society. While indicators initially concentrated on access and connectivity issues, their scope has later been extended to cover new product groups and means of delivering communication technologies to end-users. For example, in its latest module examining the information society, Eurostat's statistics include the use of cloud computing services. Studies have examined digital divide in the context of various technologies, e.g., there are studies that focus on differences in Internet use (Brandtzæg, Heim, & Karahasanović, 2011; Zhang, 2013), mobile devices adoption (see, e.g., Lee, Park, & Hwang, 2015; Magsamen-Conrad, Upadhyaya, Joa, & Dowd, 2015; Shim, You, Lee, & Go, 2015), advanced e-services such as e-learning, e-banking, e-government, etc. (see, e.g., Aparicio, Bacao, & Oliveira, 2017; Goncalo Baptista & Oliveira, 2017; Ebbers, Jansen, & van Deursen, 2016; Gulati, Williams, & Yates, 2014; Hung, Chang, & Kuo, 2013; Okunola, Rowley, & Johnson, 2017; Tam & Oliveira, 2017), and social networks (Hargittaia & Hsiehb, 2010), among others. Research in the digital divide has often used variables from international institutions such as the EUROSTAT, the OECD, the World Bank, the United Nations Development Program (UNDP), the International Data Corporation (IDC), and the International Telecommunication Union (ITU) to measure the phenomenon. In this paper the indicators applied to measure ICT use are based on the research literature and are described in Table 1.

Table 1. ICT and support

Code	ICT Application	Support
Int	Individuals regularly using the Internet	(Billon, Ezcurra, & Lera-López, 2008; Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; Haight, Quan-Haase, & Corbett, 2014; María Rosalía Vicente & López, 2011)
Mobile	Individuals accessing the Internet via a mobile device	(Cruz-Jesus et al., 2016; ITU, 2014; María Rosalía Vicente & Lopez, 2006; M. R. Vicente & López, 2008)
eBank	Individuals using banking services online	(Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; European Commission, 2010a)
eHealth	Individuals seeking health-related information online	(Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; European Commission, 2010a)
eLearn	Individuals looking for information about education online	(Çiğdem¸ a Çilan, Bolat, & Coşkun, 2009; Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; European Commission, 2010a)
eGov	Individuals interacting with public authorities online	(Çiğdem¸ a Çilan et al., 2009; Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; Ebbers et al., 2016; European Commission, 2010a; Fietkiewicz, Mainka, & Stock, 2017; Okunola et al., 2017)
IntSrc	Individuals looking for information about goods and services online	(Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; Lian & Yen, 2014)
eCom	Individuals ordering goods or services online	(Cruz-Jesus et al., 2012; Cruz-Jesus et al., 2016; European Commission, 2010a; Oliveira, Alhinho, Rita, & Dhillon, 2017; Vicente Cuervo & López Menéndez, 2006)

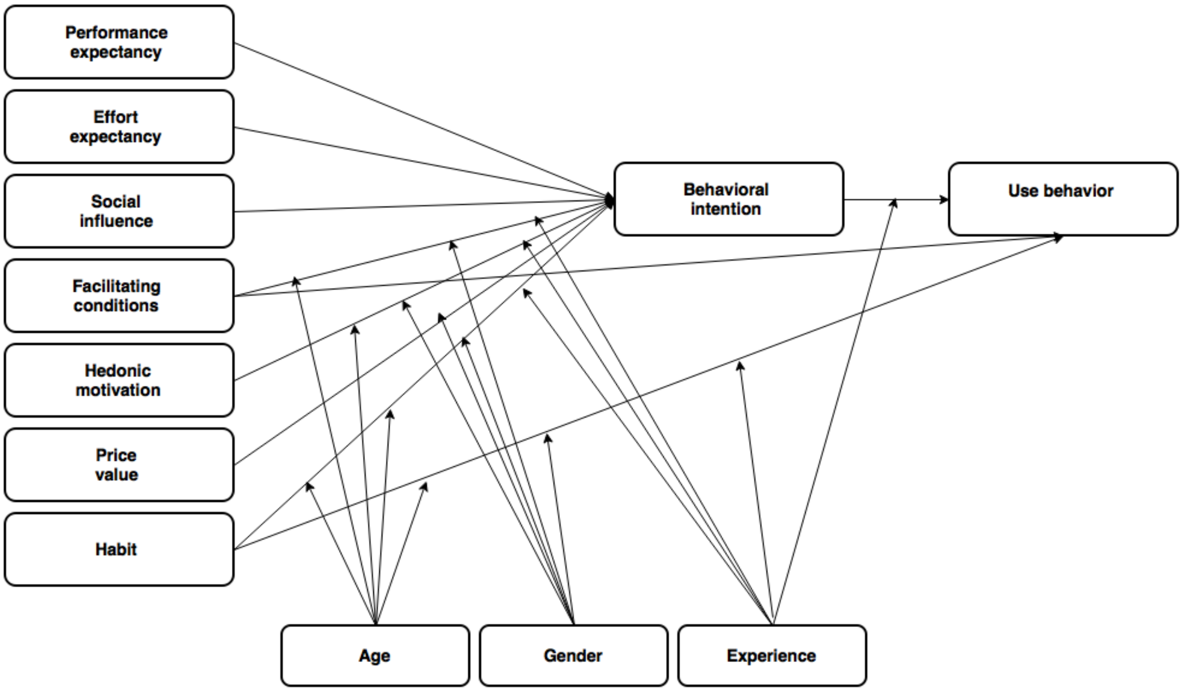
eCom_CB	Individuals ordering goods or services online, from sellers from other EU countries	(Cruz-Jesus et al., 2016; European Commission, 2013)
eCivic	Individuals active in online public participation	(Cruz-Jesus et al., 2016; Epstein, Newhart, & Vernon, 2014; Fietkiewicz et al., 2017; María Rosalía Vicente & Novo, 2014; Wattal, Schuff, & Mandviwalla, 2010)
SNS	Individuals participating in social networks online (e.g., Facebook, Twitter)	(Haight et al., 2014; Sato & Costa-i-Font, 2013; María Rosalía Vicente & Novo, 2014)
Cloud	Individuals using storage space on the Internet (Cloud) to save files for private purposes	(European Commission, 2012)

2.2 Adoption models at the individual level

Several technology acceptance theories and models have been developed and used to better understand the aspects that influence information technology acceptance in terms of behavioral intention (BI) and usage. The theory of reasoned action (TRA), for example, states that an individual's behavioral intentions determine his or her actual behavior. Behavioral intention is in turn determined by the individual's attitude toward this behavior and subjective norms with regard to the performance of this behavior (Fishbein & Ajzen, 1975). Based on the theory of reasoned action, Davis (1989) developed the technology acceptance model (TAM) to find out what factors cause people to accept or reject an information technology on the job. He suggests that perceived usefulness and perceived ease of use are the two most important individual beliefs about using an information technology. The theory of perceived behavior (TPB) is also based on the TRA and developed by Ajzen (1991), who adds a new construct - perceived behavioral control defined as the perceived ease or difficulty of performing the behavior. Another example, which is perhaps one of the most popular comprehensive frameworks to address technology acceptance at multiple levels, is the diffusion of innovations (DOI) (Rogers, 1995), which investigates innovations' characteristics that influence its adoption.

Considering the lack of a unified view on technology acceptance theory, Venkatesh, Morris, Davis, and Davi (2003) combined previous acceptance models and introduced the unified theory of acceptance and use of technology (UTAUT) built on eight previously developed theories: TRA, TAM, the motivational model (MM) (Davis, Bagozzi, & Warshaw, 1992) TPB, the PC utilization model (MPCU) (Thompson, Higgins, & Howell, 1991), DOI (Rogers, 1995), social cognitive theory (SCT) (Rogers, 1995), and an integrated model of technology acceptance and planned behavior (TAM-TPB) (Taylor & Todd, 1995). The model proposes four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. It also proposes four moderator variables: gender, age, experience, and voluntariness of use. Later Venkatesh et al. (2012), revised the UTAUT and adapted the original model to the context of consumer services, adding three new constructs: hedonic motivation, price value, and habit. This extended UTAUT model (UTAUT2) is thus composed of seven constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (please, see Figure 1). As in UTAUT, age, gender, and experience are still moderating variables, but voluntariness is dropped. Another difference in this revised version is that experience is proposed to also moderate the effect of behavioral intention on use. Another change is that UTAUT2 facilitating conditions influence not only actual behavior (as in UTAUT), but also behavioral intention. The construct of habit is also hypothesized to influence both behavioral intention and actual usage.

Figure 1. Extended unified theory of acceptance and use of technology (UTAUT2) model.



2.3 Personality traits

Personality refers to an individual's unique internal traits (Walczuch & Lundgren, 2004). Prior research on personality has demonstrated several traits that have been a subject of investigation since 1930, when 4500 descriptive terms were identified for personality by Allport and Odbert (1936). Although a universal view on the dimensions of personality is lacking, it is widely accepted among psychologists that the domain of personality can be described by five constructs (Barrick, Mount, & Judge, 2001; Digman, 1990). This theoretical approach to personality classification has become known as the Five Factor Model (FFM) and its dimensions are referred to as the big five. It consists of five broad personality traits, namely, openness, extraversion, agreeableness, conscientiousness and neuroticism. These basic tendencies are inborn and develop throughout one's life, influencing an individual's thoughts, feelings, and actions (Costa & McCrae, 1992). Thus, being able to include one's characteristics, such as these, as would-be drivers of adoption and use of ICT, is something well-worth investigating.

In fact, research in social psychology has shown that personality traits often determine an individual's beliefs and behavior across different aspects of life (Digman, 1990). Studies have tested the role of personality in a variety of contexts, such as behavior in trading activities (Kleine, Wagner, & Weller, 2015), eco-friendly behavior (Fraj & Martinez, 2006; Kvasova, 2015), and social networks use (see, e.g., Yair Amichai-Hamburger & Vinitzky, 2010; Hughes, Rowe, Batey, & Lee, 2012; Kokkinos, Baltzidis, & Xynogala, 2016).

There has been a growing interest in personality as an explanatory tool in technology acceptance (Li, Tan, Teo, & Tan, 2006). Although some studies have investigated links between personality and technology use (see, e.g., Behrenbruch, Söllner, Leimeister, & Schmidt, 2013; Tang, Chen, Yang, Chung, & Lee, 2016) research in this area is still scarce. Considering this gap in the technology acceptance literature, one of the contributions of this paper is to expand knowledge in the area and incorporate personality in the UTAUT2 to examine if and how personality influences technology adoption. It analyzes the effects of personality not as an external variable that may impact intention and use through the other constructs of UTAUT2, but as directly affecting intention and use.

Table 2 summarizes previous research on personality regarding technology adoption. It shows the research model applied (where applicable), main findings in terms of significant personality predictors, and the technology context of the research. Although Information Systems (IS) research has demonstrated the relevance of personality regarding technology adoption behaviors, e.g. within the framework of TAM, the research is still scant. Of the illustrative studies shown in Table 2, personality traits are examined as having an impact on behavioral intention via other constructs, and only one paper (Picazo-Vela, Chou, Melcher, & Pearson, 2010) hypothesizes a direct effect of personality on behavioral intention. As for the papers in which personality is not incorporated in an established technology adoption model, the direct relationship between personality traits and ICT use is examined. Therefore, one of the contributions of the current study is that it hypothesizes direct relationships to both behavioral intention and usage behavior.

Table 2. Summary of previous research on personality traits in technology adoption context published in peer review journals

Reference	Underlying theory/Relationship	Main findings	Technology context
(Landers & Lounsbury, 2006)	Examines the relationship between personality traits and Internet use	Internet use is negatively related to agreeableness, conscientiousness, and extraversion as well as two narrow traits – optimism and work drive, and positively related to tough-mindedness	Internet use
(Devaraj, Easley, & Grant, 2008)	TAM and big five personality traits	conscientiousness, extraversion, neuroticism, and agreeableness affect perceived usefulness and subjective norms toward the acceptance and use of technology	commercial collaborative system (e-project)
(Butt & Phillips, 2008)	Examines the relationship between personality and mobile phone use	agreeableness, extraversion and neuroticism explain patterns of mobile phone use	mobile phones use
(Hunsinger, Poirier, & Feldman, 2008)	Examines the relationship between personality and attitudes toward Individual response technology (IRT) use	extraversion and conscientiousness are positively related to IRT use	Individual response technology
(Picazo-Vela et al., 2010)	TPB and big five personality framework	neuroticism and conscientiousness are significant predictors of an individual's intention to provide an online review	providing an online review
(Yair Amichai-Hamburger & Vinitzky, 2010)	Examines how personality is related to behavior on Facebook	each of the personality factors examined is relevant to aspects of Facebook use	Facebook
(Svendsen, Johnsen, Almås-Sørensen, & Vittersø, 2011)	TAM and the big five personality traits	extraversion has significant, positive relations to BI; neuroticism is related to BI; openness to experience is significantly and positively related to perceived ease of use, but does not influence BI	a software tool designed to take care of digital contents, like images, music, and files
(Terzis, Moridis, & Economides, 2012)	Computer Based Assessment Acceptance Model (CBAAM) and big five personality framework	neuroticism has significant negative effect on perceived usefulness and on goal expectancy; agreeableness determines social influence and perceived ease of use, conscientiousness defines perceived ease of use; extroversion and openness explain perceived importance	computer based assessment
(Xu, Frey, Fleisch, & Ilic, 2016)	Examines impact of the big five personality traits on mobile applications use	personality traits have significant impact on the adoption of different types of mobile apps	mobile apps
(Tang et al., 2016)	Examines the relationship between the big five personality traits on Facebook use	agreeableness, conscientiousness, and neuroticism were negatively associated with Facebook addiction	Facebook
(Noë, Whitaker, Chorley, & Pollet, 2016)	Examines relationship between personality and online check-ins in common locations by location-based social networks (LBSNs)	conscientious, open, or agreeable people tend to check-in in locations in common; neurotic individuals do not tend to have locations in common	location-based social networks (LBSNs): Foursquare

3. Research model and hypotheses

The research model used in this study combines the UTAUT2 with the big five theory of personality traits. The UTAUT2 model has shown to improve the variation explained in behavioral intention and usage behavior compared to UTAUT (Venkatesh et al., 2012) and is therefore chosen for this study. Having in mind that personality may affect individuals' adoption of ICT, as shown in Table 1, personality traits are also used in our research model.

Performance expectancy is the degree to which an individual believes that using a technology provides benefits in performing certain activities and is considered to be similar to the perceived usefulness of TAM and the relative advantage of DOI (Venkatesh et al., 2003). The performance expectancy construct has proved to be the strongest predictor of use intention (Venkatesh et al., 2003; Venkatesh et al., 2012). In the specific case of ICT, performance expectancy has been proven to be a significant driver of, e.g., e-banking (see, e.g., Martins, Oliveira, & Popovič, 2014; Zhou, Lu, & Wang, 2010), mobile services (Paulo Rita, Tiago Oliveira, António Estorninho, & Sérgio Moro, 2018), among others. Note that in the specific case of ICT, one of the main reasons for individuals to be digitally excluded is that they do not perceive ICT as bringing added value to their lives. Hence, those who do see them as value adding technologies, we hypothesize, will be more likely to adopt them:

H1: The impact of performance expectancy (PE) on behavioral intention (BI) will be positive.

Effort expectancy is the degree of ease associated with the use of technology (Venkatesh et al., 2003) and it has proven to be a significant predictor of intention to use ICT (Venkatesh et al., 2012). Effort expectancy importance in technology adoption is in line with what was defined by Rogers (1995) DOI as complexity, i.e., "*the degree to which an innovation is perceived as relatively difficult to understand and use*". If a technology is perceived as easy to use, there is a greater likelihood that it will be accepted by users (Davis, 1989). Hence, in the context of ICT, we believe this construct will play a key role, especially because of the well-known role that education has on the digital divide (see, e.g., Cruz-Jesus et al., 2016; Shirazi, Ngwenyama, & Morawczynski, 2010). If it is true that the easier a technology is perceived to be used, or the less the effort expectancy is, the faster is its adoption rate, then it is also acknowledged that more educated individuals are more likely to effectively cope with technology complexity (see, e.g., Hsieh et al., 2008; Zhao, Kim, Suh, & Du, 2007). Hence, education contributed to lower complexity and effort expectancy, and is a reason why less educated individuals are more likely to be digitally excluded. This statement has been acknowledged throughout the years, making it one of the main arguments sustaining Tichenor, Donohue, and Olien (1970) knowledge gap theory (KGT). As demonstrated by Venkatesh, effort expectancy is an ICT key driver, as it positively convinces individuals to overcome ICT complexity (Venkatesh et al., 2003; Venkatesh et al., 2012). Therefore, we hypothesize:

H2: The impact of effort expectancy (EE) on behavioral intention (BI) will be positive.

Social influence is the extent to which individuals perceive that others, especially friends and family, believe they should use technology (Venkatesh et al., 2003; Venkatesh et al., 2012). It is considered to be similar to the subjective norm of TRA. It has been validated as a significant predictor of intention to adopt a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). ICT, in general, have become an indispensable way for individuals to create new ways to communicate, aggregate, and share information. Everyday actions like using email, messaging and VoIP applications, e-services, participating in social networks, watching multimedia streaming, among many others, are examples of new activities that consist of new types of communications and interactions between individuals, organizations, and public authorities (Castells, 2012; European Commission, 2006; Maria Rosalia Vicente & Lopez, 2010b). Almost every example requires peers for users to communicate with. In this sense, social influence, exercised by others, sometimes through ICT itself, is hypothesized to positively affect one's intention to adopt general ICT, under the penalty of being excluded, given its widespread use. Thus, we hypothesize the following:

H3: The impact of social influence (SI) on behavioral intention (BI) will be positive.

Facilitating conditions refers to how people believe that technical infrastructures exist to help them to use the system whenever necessary (Venkatesh et al., 2003). ICT usage is related to having digital skills varying from basic (low-level individual know-how for elementary uses of ICT) to more complex capabilities (higher-level literacy for creative engagement in digital media and ability for ICT-mediated interaction) (Mendonca, Crespo, & Simoes, 2015). As pointed out by J. van Dijk (2005), lack of such skills would make individuals perceive a difficulty in ICT use, so the presence of a favorable set of facilitating conditions would positively influence users in their decision to adopt ICT. Hence, one must have the proper skills to use the Internet and other ICT-related activities, a conclusion later supported by other authors (see, e.g., Hargittai & Hinnant, 2008; Scheerder, van Deursen, & van Dijk, 2017). Therefore, we hypothesize:

H4a: The impact of facilitating conditions (FC) on behavioral intention (BI) will be positive.

H4b: The impact of facilitating conditions (FC) on usage behavior (UB) will be positive.

Hedonic motivation is defined as the fun or pleasure derived from using technology (Venkatesh et al., 2012). In the context of specific ICT adoption, hedonic motivation has been identified as a relevant predictor of technology adoption (see, e.g., Gonçalo Baptista & Oliveira, 2015; Morosan & DeFranco, 2016). With the diversification of ICT and its uses i.e., the appearance of state-of-the-art applications such as online multimedia streaming, online gaming, social networks and all its capabilities, among others, the fun derived from conducting such activities is a critical issue. van Deursen and van Dijk (2014), for example, used principal components analysis and cluster analysis to find the main types of ICT usage, and found that in seven dimensions, at least two have strong hedonic characteristics (labeled by the authors as Leisure and Gaming). Therefore, we hypothesize:

H5: The impact of hedonic motivation (HM) on behavioral intention (BI) will be positive.

Price value is the consumer's cognitive trade-off between the perceived benefits of using a technology and the monetary cost of using it (Venkatesh et al., 2012). The concept of price value is defined as "consumers cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them'' (Dodds, Monroe, & Grewal, 1991), in which respondents bear the cost of the ICT in question, like device costs or fees to Internet service provider (ISP) companies. In the literature, higher costs are usually identified as an important inhibitor of ICT acceptance (see, e.g., Dewan, Ganley, & Kraemer, 2009; Unwin & de Bastion, 2009). Therefore, as lower costs usually correspond to higher perceived price value, we hypothesize:

H6: The impact of price value (PV) on behavioral intention (BI) will be positive.

Habit reflects the multiple results of previous experiences (Venkatesh et al., 2012). UTAUT2 adopts the concept of habit from Limayem, Hirt, and Cheung (2007), who consider habit as a self-reported perception and show that habit has a direct effect on technology use. Once a behavior becomes a habit, it becomes automatic and is practiced without conscious decision (Ouellette & Wood, 1998). Moreover, Internet and other ICT-related activities are potentially addictive (Lyvers, Karantonis, Edwards, & Thorberg, 2016). There is evidence in the literature that as one increases his or her extent of ICT use (e.g., for shopping, messaging, or participating in social networks), the more likely that person is to become addicted (see, e.g., Kuss & Griffiths, 2011; Kuss, Griffiths, & Binder, 2013). Therefore, when habit is stronger, individuals would rely more on their habit rather than external information and conscious decisions, thus increasing ICT behavioral intention and usage behavior. Therefore,

H7a: The impact of habit (HB) on behavioral intention (BI) will be positive.

H7b: The impact of habit (HB) on usage behavior (UB) will be positive.

UTAUT2 is consistent with previous models and maintains that behavioral intention has a substantial influence on technology use (Venkatesh et al., 2003). Therefore, it can be postulated that:

H8: The impact of behavioral intention (BI) on usage behavior (UB) will be positive.

As for those constructs originating in personality traits, we have:

Openness is one of the big five personality traits and represents one's receptivity to new ideas and experiences (Korukonda, 2007). It is a characteristic of individuals who have broad interests, seek novelty, who are creative, original, curious, flexible, adventurous, and non-conformist (Li et al., 2006), contrasting with those that prefer stable routines, are uneventful and conformers (Yoon & Barker Steege, 2013). In the literature, one can find evidence that openness is positively associated with technology adoption (see, e.g., Mouakket, 2017). Korukonda (2007) found that openness to experience results in lower levels of computer anxiety and McElroy, Hendrickson, and Townsend (2007) showed that open people use Internet more intensively. Guadagno, Okdie, and Eno (2008), analyzed two distinct samples of bloggers to assess personality traits effects on blogging. In both, openness was the strongest predictor of blogging. Yoon and Barker Steege (2013) also found evidence that openness positively influences Internet banking use. Therefore, as individuals who score high on openness are non-conformists and experimentalist in nature, we hypothesize:

H9a: Openness to experience (OPE) will positively affect behavioral intention (BI).

H9b: Openness to experience (OPE) will positively affect usage behavior (UB).

In general, extraverts feel comfortable with social relations, possess positive emotions, like to be stimulated, are adventurous, sociable, and talkative, whereas introverts are typically quiet and shy (Costa & McCrae, 1992; Yi-Shun, Hsin-Hui, & Yi-Wen, 2012). Those high in extraversion naturally care about their image, have larger social networks, and like presenting themselves to others. It is more likely that those who score high on extraversion are more active on social networks and similar technologies, therefore having greater information exposure to new technologies due to larger social networks. Also, other characteristics of extraverts are dominance and ambition (Judge, Higgins, Thoresen, & Barrick, 1999), implying that extraverts may consider advantages and gains from technology adoptions as more important than introverts would. In the IS literature, extraversion has been found to be positively associated with innovativeness, as extraverts were found to be more prone to use, e.g., the Internet (Y. Amichai-Hamburger & Ben-Artzi, 2003) or social networks (Chen, 2013). In the specific context of social networks activities, Liu and Campbell (2017) concluded that extraversion, along with openness, are its strongest predictors. As many ICT applications provide new and sometimes obliquus ways of communication such as emails, instant messaging, video sharing, video-broadcast, among others, we hypothesize:

H10a: Extraversion (EXS) will positively affect behavioral intention (BI).

H10b: Extraversion (EXS) will positively affect usage behavior (UB).

The personality trait agreeableness refers to the level of empathy, compassion, forgiveness, warmth, and generosity of an individual (Costa & McCrae, 1992) thus reflecting one’s orientation to others (Liu & Campbell, 2017). Agreeableness is therefore associated with presenting positive emotions in the relationships with others (DeYoung, 2015). Individuals that score high on agreeableness exhibit a lower level of computer anxiety (Korukonda, 2007). Also, more agreeable individuals are more likely to relate to technology beliefs when the technology is related to collaboration and cooperation (Devaraj, Easley, & Grant, 2008) and tend to build trust in service providers more easily in exchange for the service providers’ trust in them (Walczuch & Lundgren, 2004). On the other hand, it also seems plausible that those that are less agreeable may be more likely to have difficulties in relating with others in traditional (offline) ways (Ross et al., 2009), thus be tempted to use ICT applications, such as social networks, as a way to bypass this constraint. Nevertheless, we believe that agreeable people are more likely to build positive beliefs about technology adoption, and so we hypothesize that:

H11a: Agreeableness (AGR) will positively affect behavioral intention (BI).

H11b: Agreeableness (AGR) will positively affect usage behavior (UB).

Conscientious people are better organized and efficient in carrying out tasks, and self-discipline is a major characteristic of a conscientious person (Costa & McCrae, 1992). Individuals who score high on conscientiousness are self-motivated, achievement-oriented, systematic, and task-oriented (Barrick, 2001). Because higher levels of conscientiousness are associated with one's ability to follow explicit rules and prioritize long-term objectives, thus being able to adapt their behavior accordingly, conscientiousness is usually pointed as the strongest of the five personality traits, in predicting one's life outcomes, such as success, positive ageing or health/longevity (DeYoung, 2015; Roberts, Lejuez, F Krueger, M Richards, & L Hill, 2012). Thus, it is likely that more conscientious people would use technology more to achieve their goals, cooperate with others, and obtain information, especially given ICT pervasiveness in almost every aspect of our lives nowadays, including professional ones. Therefore, we hypothesize:

H12a: Conscientiousness (CON) will positively affect behavioral intention (BI).

H12b: Conscientiousness (CON) will positively affect usage behavior (UB).

Individuals who score high on neuroticism are considered to be more sensitive and nervous, with a propensity to worry (Costa & McCrae, 1992). Neurotic people are less able to control impulses, cope poorly with stress, and respond emotionally to situations that would not influence most people (McCrae & John, 1992). Consequently, those high in neuroticism have a tendency to undergo negative emotions in situations in situations they perceive as adverse (DeYoung, 2015). Korukonda (2007) has shown that neurotic individuals show higher levels of computer anxiety. Devaraj, Easley, and Crant (2008) hypothesized that those with higher levels of neuroticism "are likely to view technological advances in their work as threatening and stressful, and to have generally negative thought processes when considering it". In their study, they demonstrated that neuroticism is negatively associated with perceived usefulness of a collaborative system. In the same way, but in the context of social networks, Mouakket (2017) hypothesized that neurotic individuals would are less likely to find a new technology to be useful and, as a result of low expectations towards it, they will be less likely to adopt it. Therefore, we hypothesize that, as those who score high on neuroticism tend to regard technology as stressful and worry that things can go wrong easily:

H13a: Neuroticism (NEU) will negatively affect behavioral intention (BI).

H13b: Neuroticism (NEU) will negatively affect usage behavior (UB).

In terms of demographic variables, the model includes gender and age. Although some studies have shown that one gender (male) tends to use technology more than the other, over time research has demonstrated that this gap is closing in a broader context of technology use (Lee et al., 2015). In the field of the digital divide, gender-related asymmetries are a disputable topic, as there is no consensus on the fact if the gender-related digital divide still exists. In developing countries findings usually point out that women are less likely to use or usually deal with ICT, whereas in western countries the gender-related digital divide appears to have been strongly narrowed (see, e.g., Mumporeze & Prieler, 2017; Okunola et al., 2017; World Bank, 2016). Hence, as the present study is confined to two countries of the European Union, we hypothesize that:

H14a: Gender will have no impact on behavioral intention (BI).

H14b: Gender will have no impact on usage behavior (UB).

Generation differences have been studied in several technology adoption papers. Age has proven to be a significant predictor in intention and usage in the context of technology use (see, e.g., Lian & Yen, 2014; Magsamen-Conrad et al., 2015; Bjoern Niehaves & Ralf Plattfaut, 2013). Accordingly, in the context of the digital divide, age is perhaps one of its most important drivers, an issue known as age-related digital divide (Björn Niehaves & Ralf Plattfaut, 2013). Friemel (2016), for example, recently found that in Switzerland, "*with every additional year of age, the likelihood of Internet usage decreases by 8%*". At the base of the age-related digital divide are the differences between those who were born and grew up with ICT and those who did not, i.e., those who had, at some point in their lives, to adapt to ICT with all the consequences and implications this adaptation has. These two groups are usually known as the "digital natives" and the "digital immigrants" (Prensky, 2001) . Adding to this fact, as a normal result from the ageing process, generally speaking the elderly almost inevitably are more likely to present physical and cognitive disabilities (e.g., problems with memory, reduced visual and auditory ability, and restricted mobility issues), affecting the ability to assimilate new knowledge, in particular handling ICT, which may cause digital exclusion (Czaja & Lee, 2007; Fozard & Gordon-Salant, 2001). Therefore, we hypothesize:

H15a: Age will negatively affect behavioral intention (BI).

H15b: Age will negatively affect usage behavior (UB).

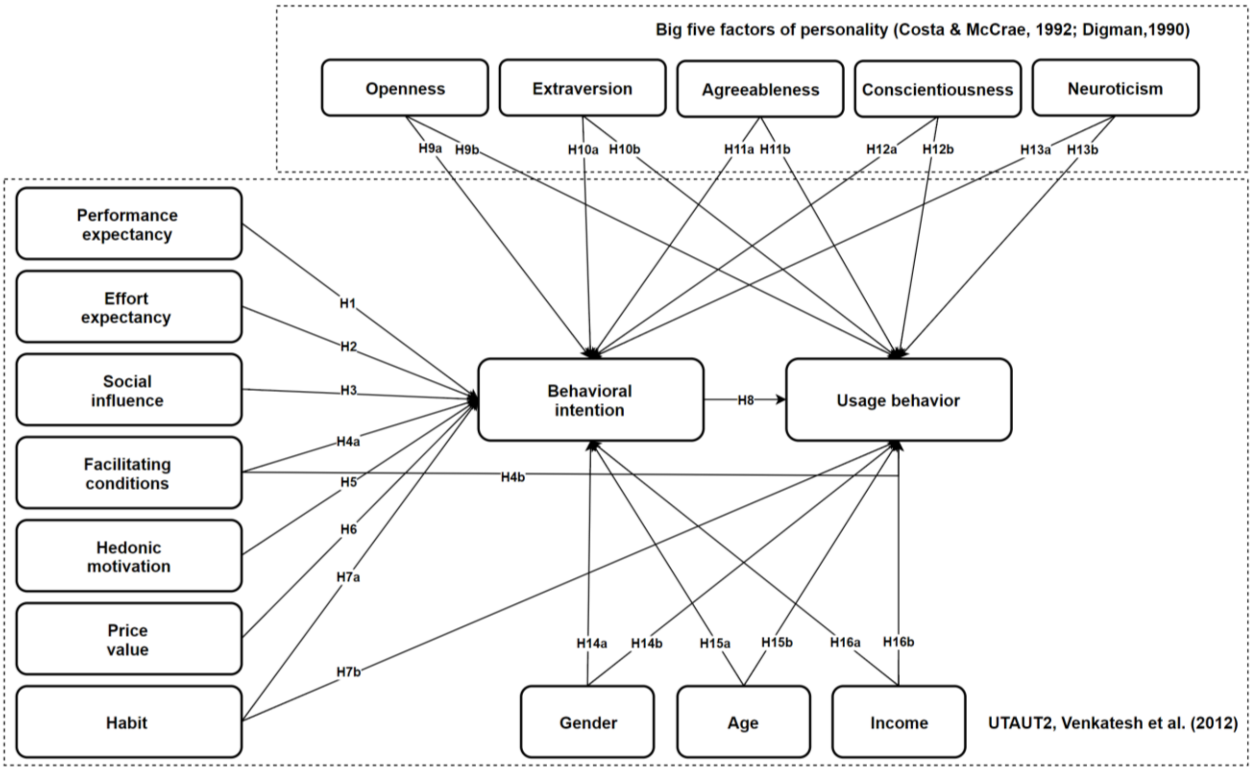
In the digital divide literature, income has been long recognized as, perhaps, the most important antecedent of ICT acceptance (see, e.g., Cruz-Jesus et al., 2018; Dewan & Riggins, 2005). In most cases, the very first obstacle that one faces in considering starting to use ICT is having the financial capability to do so. Hence, in the first years of the ICT revolution, the "haves" were strongly limited to those who were economically advantaged (U. S. Department of Commerce, 1999). Accordingly, income is expected to affect behavior intention of ICT adoption. Moreover, considering that newer ICT and applications (e.g., services and capabilities) tend to be more expensive than their predecessors, financial conditions also constrain its adoption even for those who have adopted the preceding ones (Rogers, 1995). Even in the 2000s, there is evidence than those who made a more advanced use (and "profit") of ICT were still those who were economically advantaged, despite the fact even those who were not already had access (Hsieh et al., 2008). Thus, income is also expected to affect ICT usage behavior.

H16a: Income will positively affect behavioral intention (BI).

H16b: Income will positively affect usage behavior (UB).

The proposed conceptual model applied in this study was built on the above listed hypotheses and is shown in Figure 2.

Figure 2. Conceptual model



4. Data collection research methodology

4.1 Measurement items

All items used to measure the model constructs were adapted from the literature with slight modifications to fit the context of the ICT in question. PE, EE, SI, FC, and BI were adopted from (Venkatesh et al., 2003; Venkatesh et al., 2012), HM, PV, and HB from (Venkatesh et al., 2012). As for the personality traits, they were operationalized using a short 20-item version of the 50-item international personality item pool - five-factor model measure - the mini-IPIP developed by (Donnellan, Oswald, Baird, & Lucas, 2006). This scale showed convergent, discriminant, and criterion-related validity with other big five measures (Cooper, Smillie, & Corr, 2010). The advantages of shortened versions of questionnaires include low cost and the short time that it takes to fill them in, which makes it possible to include personality measurement in studies whose time is limited, such as those conducted online (Gosling, Rentfrow, & Swann, 2003). Moreover, four socio-demographic questions related to gender, age, income, and professional status were included in the questions.

Most items were measured using seven-point range scales, ranging from totally disagree (1) to totally agree (7). Behavioral intention (BI) was measured by asking respondents about their intentions and plans to use the technology in the future. Personality traits were measured on a seven-point range scale, ranging from very inaccurate (1) to very accurate (7). Usage behavior was measured by asking respondents about their frequency of use of a set of ICT, ranging from (1) never to (7) many times per day. Age was measured in years. Gender was coded using a 0 or 1 dummy variable where 1 represented women. All constructs were modeled using reflective indicators, except for usage behavior, which was measured by formative indicators. The items for all constructs are included in Appendix A.

4.2 Data collection

The research design is presented as a robust structure in Figure 3. The questionnaire was developed having drawn upon the normative literature and experience of the research team. The questionnaire (developed in English) was then translated to Bulgarian and Portuguese respectively by professional native translators. Every attempt to reduce embedded bias was taken by checking and cross checking the translation and through the constructs in the research design. An online questionnaire survey approach was employed as this was considered the most appropriate way of ‘reaching out’ to participants and ensuring heightened levels of responses. The online questionnaire was sent via email to university alumni groups in Bulgaria and Portugal respectively. Participation in the survey was voluntary and satisfied the ethical standards of the lead-University.

A pilot study was initially conducted to test the measurement instrument. Its purpose was to ensure that appropriate data were collected (as necessary to test the hypotheses) and, to verify the reliability and validity of the measurement scales and check whether the interpretation and answering of the questions was clear to respondents. The pilot survey was answered by 30 respondents, confirming preliminary validity and reliability of the measurement instrument. All items were kept, with some minor linguistic modifications to reduce ambiguity and clearer interpretation of the questions thus, demonstrating the robustness of the research design. The data from the pilot survey were not included in the main study as a means to ensure maximum levels of data reliability and to reduce potential bias; in effect, as a means of triangulation.

Data were collected in Bulgaria and Portugal in the second semester of 2016. A survey was addressed to 2,362 individuals (976 in Bulgaria and 1,386 in Portugal). Although some cultural differences in the two audiences addressed were expected, it was reasonable to assume that the two samples were compatible in terms of background and work experience. The total number of complete questionnaires received was 498 (254 for Bulgaria and 244 for Portugal). Hence, the initial response rates were 26.1% in Bulgaria and 17.6% in Portugal. After removing all incomplete questionnaires, the final number of valid questionnaires was 245 (Bulgaria) and 229 (Portugal) respectively. These levels of response are in line with other studies that follow a similar research design, with the total sample has 474 valid questionnaires. The common method bias, i.e., variations in responses caused by the instrument, was examined as follows: first, using Harman's one-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), which confirmed that none of the factors alone explained the majority of the variance (the first factor explained only 34.5% of the total variance); second, using a marker-variable (Lindell & Whitney, 2001), which consists of adding a theoretically irrelevant marker variable in the model. This variable has 0.04 (4.0%) as the maximum shared variance with other variables, a value that is considered low (Johnson, Rosen, & Djurdjevic, 2010). Hence, no evidence of common method bias was found.

Figure 3. Data collection process flow

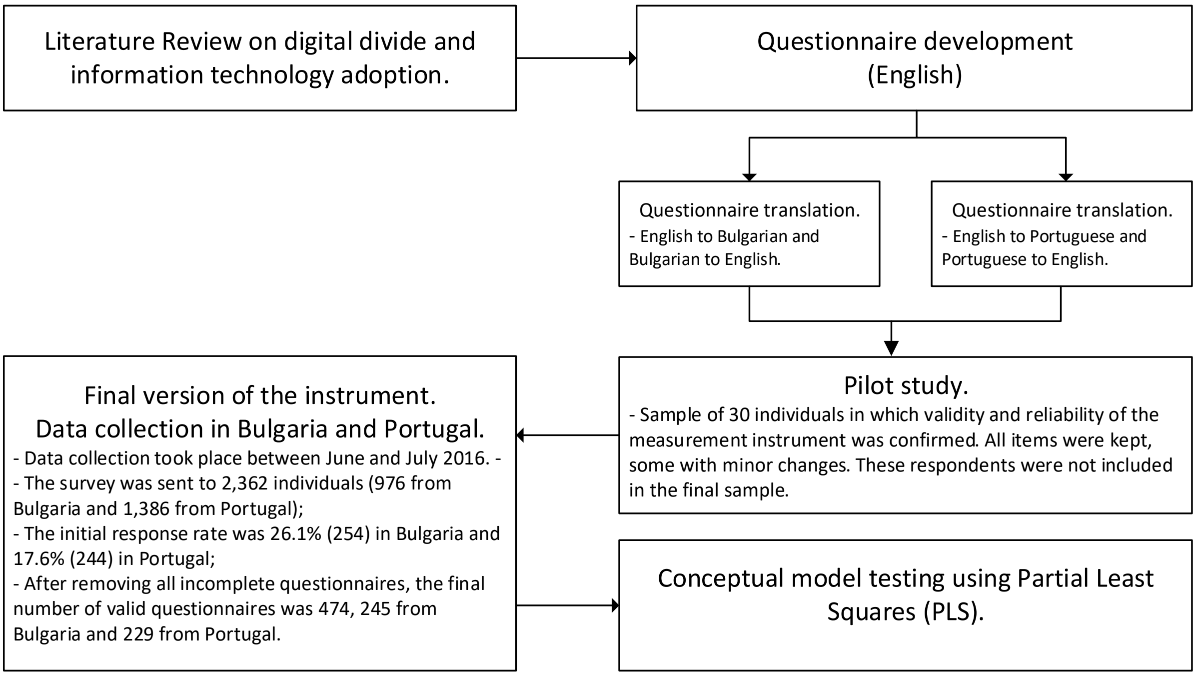


Table 3 shows sample characteristics for the total sample, as well as for the Bulgarian and Portuguese samples. Referring to the total sample, the split between male and female participants is respectively 50.8% vs. 49.2%, representing a sample almost equally distributed by gender, with a marginal surplus of men. The largest group of respondents belongs to the 25-34 age group (56.3%), which is also the largest group in the subsamples per country. Note that while in Bulgaria there are representatives from the last two age groups (55-64 and 65+) corresponding to 6.1% and 4.1%, for the Portuguese sample the participation of these age groups amounts to 0.4% and 0%. Most respondents reported to be employed (70.0%).

Table 3. Sample characteristics (n=474)

		Total Sample		**Bulgaria**		**Portugal**	
Measure	**Value**	**%**	**Frequency**	**%**	**Frequency**	**%**	**Frequency**
Gender	Male	50.8%	241	54.3%	133	47.2%	108
	Female	49.2%	233	45.7%	112	52.8%	121
Age	18 – 24	22.4%	106	20.4%	50	24.5%	56
	25 - 34	56.3%	267	57.1%	140	55.5%	127
	35 - 44	10.3%	49	8.2%	20	12.7%	29
	45 - 54	5.5%	26	4.1%	10	7.0%	16
	55 - 64	3.4%	16	6.1%	15	0.4%	1
	65+	2.1%	10	4.1%	10	0.0%	0
Income	less than 500 EUR	3.6%	17	5.3%	13	1.7%	4
	between 500 and 1000 EUR	23.2%	110	29.0%	71	17.0%	39
	between 1000 and 1500 EUR	34.0%	161	41.6%	102	25.8%	59
	between 1500 and 2000 EUR	14.8%	70	13.1%	32	16.6%	38

	between 2000 and 2500 EUR	9.7%	46	3.3%	8	16.6%	38
	between 2500 and 3000 EUR	3.4%	16	1.2%	3	5.7%	13
	more than 3000 EUR	6.3%	30	4.1%	10	8.7%	20
	Don´t know / Don´t want to answer	5.1%	24	2.4%	6	7.9%	18
Professional status	Employed or Self Employed	70.0%	332	65.3%	160	75.1%	172
	Unemployed	2.5%	12	2.4%	6	2.6%	6
	Retired	3.8%	18	7.3%	18	0.0%	0
	Student	22.4%	106	22.9%	56	21.8%	50
	Other	1.3%	6	2.0%	5	0.4%	1

5. Data analysis and results

In the current study measurement model validation and structural model testing were conducted using partial least squares (PLS), a variance-based structural equation modeling technique. This technique is chosen over the covariance-based structural equation modeling as it is less demanding on the sample size and distribution and allows the use of formatively measured constructs (J. Henseler, Ringleand, & Sinkovics, 2009). To assess the measurement and structural model, SmartPLS 3 software was used (Ringle, Wende, & Becker, 2015).

5.1 Measurement model

The conceptual model has both reflective and formative constructs. First, reflective measures are analyzed for indicator reliability, composite reliability, and convergent and discriminant validity. Second, formative measures are tested for collinearity issues, significance, and relevance of outer weights.

To confirm indicator reliability outer loadings were analyzed. The criteria that all outer loadings should be preferably higher than 0.7 and the ones below 0.4 have to be eliminated has been applied (Churchil, 1979; J. Henseler et al., 2009). CON2R, NEU1, and NEU3 were dropped due to low outer loadings. All other indicators have outer loadings higher than 0.7, with the exception of EXS4R with an outer loading value of 0.67, which is on the threshold. All indicators are statistically significant at 0.05, as illustrated in Table 4. Therefore, indicator reliability can be confirmed. To assess the constructs' reliability, we examined the composite reliability (CR) and Cronbach's alpha (Table 4). The CR and Cronbach's alpha are higher than the cut-off of 0.7. Therefore, both criteria are met and internal consistency is ensured (Hair & Anderson, 2010). Convergence validity has been validated against the criteria that average variance extracted (AVE) should be higher than 0.5 (Fornell & Larcker, 1981; J. Henseler et al., 2009). As shown in Table 4, this criterion is met.

Table 4. AVE, CR, Cronbach's alpha, and loadings

Construct	Item	AVE	CR	Cronbach's alpha	Loading	t-statistics
Performance expectancy (PE)	PE1	0.885	0.969	0.957	0.927	86.406
	PE2				0.948	128.147
	PE3				0.950	119.138
	PE4				0.939	97.008
Effort expectancy (EE)	EE1	0.890	0.970	0.959	0.944	130.391
	EE2				0.948	163.665
	EE3				0.954	160.414
	EE4				0.928	109.978
Social influence (SI)	SI1	0.740	0.919	0.881	0.883	57.553
	SI2				0.899	80.506
	SI3				0.742	22.906
	SI4				0.908	88.769
Facilitating conditions (FC)	FC1	0.771	0.931	0.901	0.879	41.951
	FC2				0.893	72.018
	FC3				0.884	51.071
	FC4				0.856	36.827
Hedonic motivation (HM)	HM1	0.879	0.956	0.931	0.934	84.441
	HM2				0.948	153.558
	HM3				0.932	89.963
Price value (PV)	PV1	0.887	0.959	0.936	0.934	100.556
	PV2				0.951	159.615
	PV3				0.941	121.702
Habit (HB)	HB1	0.671	0.890	0.835	0.867	59.468
	HB2				0.715	24.403
	HB3				0.773	27.590
	HB4				0.908	102.265
Behavioral intention (BI)	BI1	0.852	0.945	0.913	0.912	75.389
	BI2				0.900	51.891
	BI3				0.957	161.194
Openness (OPE)	OPE1	0.720	0.911	0.872	0.874	63.192
	OPE2				0.809	28.438
	OPE3				0.833	37.796
	OPE4				0.875	49.456
Extraversion (EXS)	EXS1	0.681	0.893	0.892	0.952	6.492
	EXS2				0.731	3.836
	EXS3				0.915	5.987
	EXS4				0.669	3.126
Agreeableness (AGR)	AGR1	0.814	0.946	0.924	0.919	92.085
	AGR2				0.910	66.401
	AGR3				0.873	47.309
	AGR4				0.906	63.145
Conscientiousness (CON)	CON1	0.672	0.860	0.757	0.792	4.385
	CON3				0.888	5.114
	CON4				0.775	3.948
Neuroticism (NEU)	NEU2	0.822	0.903	0.786	0.886	48.457
	NEU4				0.927	91.312

Note: R - Reversed items

To evaluate discriminant validity, we applied three criteria – Fornell-Larcker, cross-loadings, and Heterotrait-Monotrait Ratio (HTMT) (Jörg Henseler, Ringle, & Sarstedt, 2015). First, according to the Fornell-Larcker criterion, discriminant validity is supported if the square root of AVE for each construct is greater than its correlation with any other construct (Fornell & Larcker, 1981). This criterion is met, as shown in Table 5. Second, discriminant validity was assessed by examining cross-loadings, all indicators' outer loadings (in bold) on a construct should be higher than its cross-loadings (Chin, 1998).

This is illustrated in Appendix B. As for the HTMT ratios, all are below the threshold of 0.9 (please see Appendix C). Therefore, all the measures satisfy the discriminant validity of the constructs. Hence, it can be concluded that discriminant validity is supported.

Table 5. Correlation Matrix

Construct	PE	EE	SI	FC	HM	PV	HB	BI	UB	OPE	EXS	AGR	CON	NEU	Gen	Age	Inc
PE	**0.941**																
EE	0.649	**0.944**															
SI	0.396	0.374	**0.860**														
FC	0.700	0.701	0.399	**0.878**													
HM	0.619	0.622	0.362	0.591	**0.938**												
PV	0.407	0.474	0.396	0.487	0.517	**0.942**											
HB	0.575	0.555	0.503	0.566	0.517	0.420	**0.819**										
BI	0.764	0.585	0.489	0.626	0.607	0.384	0.657	**0.923**									
UB	0.478	0.478	0.378	0.461	0.324	0.293	0.458	0.506	**NA**								
OPE	0.425	0.471	0.266	0.432	0.279	0.268	0.342	0.428	0.610	**0.848**							
EXS	-0.060	-0.042	-0.074	-0.032	-0.009	-0.006	0.014	-0.046	0.144	0.133	**0.825**						
AGR	0.255	0.262	0.328	0.275	0.234	0.201	0.239	0.308	0.397	0.375	-0.226	**0.902**					
CON	0.172	0.082	-0.088	0.116	0.188	0.085	0.025	0.125	0.046	-0.055	-0.103	0.097	**0.820**				
NEU	-0.277	-0.348	-0.280	-0.270	-0.207	-0.266	-0.308	-0.319	-0.287	-0.308	-0.091	-0.064	-0.041	**0.907**			
Gender	-0.107	-0.084	0.004	-0.037	0.047	-0.003	-0.101	-0.087	-0.038	-0.031	-0.122	0.205	0.047	0.221	**NA**		
Age	0.041	-0.157	-0.095	-0.072	0.047	-0.014	-0.109	-0.007	-0.418	-0.309	-0.139	-0.184	0.240	0.055	-0.026	**NA**	
Income	0.061	0.100	-0.014	0.168	0.096	0.082	0.079	0.100	0.130	0.120	0.064	0.171	0.111	0.005	-0.024	0.057	**NA**

Notes: Diagonal elements in bold are square root of average variance extracted (AVE); NA – Not Applicable; PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions; HM: hedonic motivation; PV: price value; HB: habit; BI: behavioral intention; UB: usage behavior; OPE: openness; EXS: extraversion; AGR: agreeableness: CON: conscientiousness: NEU: neuroticism

Second, the construct usage behavior (UB), measured by 12 formative indicators, is analyzed. The evaluation of this construct includes assessing collinearity issues. We apply the variance inflation factor (VIF) measure to check for collinearity. In this case the maximum VIF for all items is below the conservative threshold of five, thus suggesting no issues of collinearity. Second, the significance and relevance of each indicator’s outer weights are checked by means of bootstrapping (5,000 iterations). In Table 6 VIF, outer weights, t-statistics for outer weights, and outer loadings are shown. All formative indicators’ outer weights are significant except for IntSrc, eBank, eCom, eLearn, eGov, eHealth, and eCivic. Referring to these indicators’ outer loadings, they are all above 0.5 (except eGov, eHealth, and eCivic, which were eliminated). The formative indicators retained are presented in Table 6.

Table 6. VIF, outer weights and outer loadings

Item	VIF	Outer Weights	T-Statistics	Outer Loadings
Cloud	1.842	0.112	1.986	0.678
Int	1.952	0.459	4.756	0.866
IntSrc	2.208	0.039	0.456	0.621
Mob	1.930	0.209	2.689	0.781
SNS	1.807	0.261	2.949	0.735
eBank	1.385	-0.007	0.121	0.504
eCom	3.111	-0.023	0.262	0.639
eCom_CB	2.313	0.231	2.514	0.604
eLearn	1.688	0.050	0.800	0.513

5.2 Structural model and hypotheses testing

As the measurement model results validate a good construct reliability, indicator reliability, convergent and discriminant validity for reflective measures, as well as a validation for formative measures, we next proceed with testing the structural model. First, the three models tested are compared – UTAUT, Personality, UTAUT + Personality + Income. The models are assessed and compared by adjusted R^2 and path coefficients, all shown in Table 7. To analyze the hypotheses and association between constructs standardized paths coefficients are examined, in which path significance levels are analyzed using the bootstrap resampling method (Hair & Anderson, 2010; J. Henseler et al., 2009) with 5,000 iterations of sampling (Chin, 1998). Finally, a multi-group analysis is performed to compare the differences at country level.

A comparison of the estimated models reveals that when adding personality to UTAUT2, there is an increase in the adjusted R^2 on usage, with it being 0.45 for UTAUT2, 0.49 for Personality, and 0.56 for UTAUT + Personality + Income. When analyzing behavioral intention, the adjusted R^2 for UTAUT2 and UTAUT2 + Personality remains the same (0.68). Therefore, the proposed conceptual model (UTAUT2 + Personality + Income) has the highest R^2 on usage behavior as compared to the other two (UTAUT2 and Personality). Next, the analysis focuses on the model combining UTAUT + Personality + Income.

As can be seen in the last column of Table 7, the conceptual model explains 69% of the variation in behavioral intention. Performance expectancy, social influence, hedonic motivation, price value, habit, and openness are found to be statistically significant in explaining behavioral intention, whereas effort expectancy, facilitating conditions, extraversion, agreeableness, conscientiousness and neuroticism are not found to have a statistically significant effect on behavioral intention. Regarding usage behavior significant predictors are habit, behavioral intention, openness, extraversion, agreeableness, and age. Facilitating conditions, conscientiousness, and neuroticism are not statistically significant predictors. Our model explains 57% of the variation in usage behavior.

Table 7. Structural model with path coefficients and R^2 for UTAUT2, Personality, and UTAUT2 + Personality + Income

	UTAUT2	**Personality**	**UTAUT2 + Personality + Income**
Behavioral intention			
R^2	0.68	0.27	0.69
Adj. R^2	0.68	0.26	0.68
Performance expectancy (PE)	0.47***		0.44***
Effort expectancy (EE)	-0.002		-0.04
Social Influence (SI)	0.14***		0.12***
Facilitating conditions (FC)	0.05		0.04
Hedonic motivation (HM)	0.15***		0.16***
Price value (PV)	0.05*		0.07**
Habit (HB)	0.24***		0.24***
Openness (OPE)		0.32***	0.08**
Extraversion (EXS)		-0.06	-0.01
Agreeableness (AGR)		0.15***	0.05
Conscientiousness (CON)		0.11**	0.02
Neuroticism (NEU)		-0.21***	-0.05
Gender	-0.02		-0.03
Age	0.007		0.03
Income			0.03
Usage Behavior			
R^2	0.46	0.50	0.57
Adj. R^2	0.45	0.49	0.56
Facilitating conditions (FC)	0.15***		0.07
Habit (HB)	0.13*		0.10*
Behavioral intention (BI)	0.33***	0.29***	0.20***
Openness (OPE)		0.39***	0.29***
Extraversion (EXS)		0.12**	0.11**
Agreeableness (AGR)		0.19***	0.15***
Conscientiousness (CON)		0.07**	0.09
Neuroticism (NEU)		-0.04	-0.04
Gender	0.02		-0.02
Age	-0.39***		-0.29***
Income			0.01

Notes: *p<0.10; **p<0.05; ***p<0.01

Next, the analysis proceeds with comparison between Bulgaria and Portugal to detect country differences. To capture significant differences between the two countries, PLS Multi-group analysis is performed (J. Henseler et al., 2009). Table 8 summarizes the differences for all relationships in the model between the two countries. As shown in Table 8, there are several statistically significant relationships.

Table 8. PLS Multi-group analysis

	Bulgaria UTAUT2 + Personality + Income	Portugal UTAUT2 + Personality + Income	Comparison Path Coefficients-diff (|Bulgaria - Portugal|)
Behavioral intention			
R2	0.73	0.71	
PE -> BI	0.554***	0.375***	0.179*
EE -> BI	-0.095	-0.047	0.048
SI -> BI	0.071	0.162***	0.090
FC -> BI	-0.032	0.108	0.140
HM -> BI	0.028	0.285***	0.257**
PV -> BI	-0.068	-0.043	0.024
HB -> BI	0.332***	0.155***	0.177**
OPE -> BI	0.060	0.083	0.024
EXS -> BI	0.018	0.029	0.011
AGR -> BI	0.091*	-0.032	0.123*
CON -> BI	0.037	0.015	0.021
NEU -> BI	-0.129**	0.042	0.171**
Gender -> BI	0.006	-0.062	0.068
Age -> BI	0.062	-0.022	0.040
Income → BI	0.005	0.002	0.003
Usage behavior			
R2	0.67	0.49	
FC -> UB	0.066	0.113	0.047
HB -> UB	0.221***	0.049	0.173
BI -> UB	-0.004	0.407***	0.412**
OPE -> UB	0.321***	0.174*	0.157
EXS -> UB	0.168**	0.045	0.123
AGR -> UB	0.205***	0.157	0.048
CON -> UB	0.101	-0.036	0.137
NEU -> UB	-0.023	-0.134	0.111
Gender -> UB	0.003	-0.033	0.030
Age -> UB	-0.360***	0.043	0.404*
Income → BI	0.013	-0.122	0.135

Notes: *p<0.10; **p<0.05; ***p<0.01; PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions; HM: hedonic motivation; PV: price value; HB: habit; BI: behavioral intention; UB: usage behavior; OPE: openness; EXS: extraversion; AGR: agreeableness: CON: conscientiousness: NEU: neuroticism.

6. Discussion

6.1 Discussion of findings

Before discussing the results regarding personality traits, we review UTAUT2 hypotheses, most of which are supported. In line with previous research (Venkatesh et al., 2012), the strongest predictor of behavioral intention (BI) turns out to be performance expectancy (PE), showing that individuals treat the outcomes of ICT as very important. The impact of behavioral intention (BI) on usage behavior (UB) is also significant, indicating that ICT users are more likely to use technology if they have the intention to use them. Another significant predictor is social influence (SI), revealing that an individual's social environment affects the decision of technology use, like friends and family's opinion. A possible reason is that the social and communication functionalities of some ICT (e.g., social networks and VoIP) magnify this effect. Moreover, hedonic motivation (HM) is a significant predictor of behavioral intention (BI), showing that individuals use ICT not only to complete tasks but for entertainment purposes as well, which makes sense for some ICT such as online games, blogs, and social networks. This finding is in line with previous research (e.g., Morosan & DeFranco, 2016; Venkatesh et al., 2012). As expected, habit (HB) has a significant positive effect on both behavioral intention and use, an indication that individual's automatic behavior positively influences their intention and use of technology. As socio–demographic characteristics, in line with other researchers who found that gender differences were no longer very relevant in technology acceptance, at least in modern and technology-literate societies (Workman, 2014), our study appears to support this hypothesis as gender is significant only in Bulgaria, the less digitally developed country of the two countries (Cruz-Jesus et al., 2018), and only for usage behavior (women use technology less). However, some caution should be taken as the context of this study is within the European Union. It seems reasonable, and there is evidence, that in other (mainly developing) countries, gender may (still) have its influence in ICT acceptance (Okunola et al., 2017). Income turned out to not be a statistically significant driver of ICT acceptance in the full sample or in the two individual country samples. Although digital divide scholars consistently identify income as one of its major drivers, studies also point out that once the financial requirements for acquiring ICT are met, other factors come into play for influencing ICT acceptance. Hence, as with gender, some cautions must be considered because we suspect that in other contexts, especially developing countries, income would be a major driver of ICT acceptance. On the other hand, as expected, age affects technology behaviors such that older individuals tend to use technology less. Prior research has identified the increased risk of an European age-related digital divide (Niehaves & Plattfaut, 2014). According to the literature, one of the most important age-related digital divide drivers is based on the differences between those who were born and grew up with ICT from those who did not. Prensky (2001) explains that these two groups are often referred to as "digital natives" and "digital immigrants" (Prensky, 2001). The first ones were born surrounded by technology such as computers, digital music players, and the Internet, whereas the second ones, which are older, needed to adapt themselves to these and other technologies at some point during their lifetime.

Contrary to our expectations, effort expectancy (EE) and facilitating conditions (FC) turn out to be non-significant predictors of technology adoption. A possible explanation behind this might be that as the technologies in question are widespread, users get used to them more quickly and find them easy to use, therefore, putting less importance on the effort expected and the facilitating conditions (like infrastructure and capabilities). Price value (PV) is significant, and contrarily to what we have hypothesized, only in the full sample, not in Bulgaria or Portugal alone, which led us to think that it does not affect ICT acceptance, as it does not in neither of the two countries separately. Hence, individuals do not consider the price value of ICT an important thing, probably for the same reasons as income is not important – this study takes place in (two) developed countries.

Next, the effect of personality traits is discussed. Three out of the five personality traits explored (openness, extraversion, and agreeableness) have a direct effect on either one of the constructs of behavioral intention or usage behavior, or on both. Specifically, openness (OPE) is positively associated with both behavioral intention (BI) and usage behavior (UB), indicating that individuals who are more open are more likely to adopt technology. Although some prior studies state that openness has no effect on technology use (e.g., Behrenbruch et al., 2013; Devaraj, Easley, & Grant, 2008), in line with our findings, others have shown that openness positively affects social network usage (Yair Amichai-Hamburger & Vinitzky, 2010; Hughes et al., 2012) and that it is positively correlated with the use of social apps (Butt & Phillips, 2008; Correa, 2010). As for extraversion (EXS), consistent with previous research, we confirm that extroverts use technology more than introverts. It has been demonstrated that extraversion positively affects the use of technology (see, e.g., Correa, 2010; Hunsinger et al., 2008; Zhou & Lu, 2011). Furthermore, the current study reveals that individuals who score high on agreeableness (AGR) tend to build positive beliefs about technology adoption in contrast to more disagreeable people. This finding is in line with previous research indicating that agreeableness is positively associated with technology beliefs, especially when the outcomes of technology use are related to cooperation, task accomplishment and communication (Butt & Phillips, 2008; Xu et al., 2016). Although extraversion and agreeableness show a positive relationship with usage behavior (UB) as hypothesized, neither of them is a significant predictor of behavioral intention (BI). A possible explanation behind this might be that although extraverted and agreeable people are more likely to become early adopters, the set of technologies in the context of this study are widespread and intent of early adoption is weakened and non-significant in this context.

Regarding conscientiousness (CON) and neuroticism (NEU), none of the hypotheses is supported. Thus, whether and individual scores high or low in conscientiousness or neuroticism, this would have no effect on the decision to adopt ICT. Even though conscientious individuals tend to use ICT when they believe it would help them be more efficient (Devaraj, Easley, & Grant, 2008), studies have shown that conscientious people are less likely to adopt socially-based ICT (Xu et al., 2016). Similarly, previous research has shown that individuals high in neuroticism tend to reduce their use of Internet due to higher levels of anxiety and stress (Devaraj, Easley, & Grant, 2008), but at the same time they tend to spend more time on social and shopping apps (Xu et al., 2016). Therefore, a possible explanation behind the non-significance of these predictors might be that the current study encompasses a broader set of ICT characterized by both efficiency and enjoyment outcomes.

6.2 Theoretical implications

From a theoretical point of view, results suggest that by adding personality to UTAUT2, the variation explained in usage behavior increased some 11 p.p. (45% vs 56%). Hence, the theoretical development and empirical results of the present study appear to show that combining the perspectives of technology adoption with the digital divide's, provides a more effective lens, regardless of the technology under consideration, for understanding its diffusion process. As income and personality traits improved UTAUT2, we encourage future research to reassess UTAUT2, and test a larger set of socio-demographic variables than only gender or age.

In previous research, personality traits have been incorporated in technology adoption models and their impact on technology adoption has been examined via constructs like usefulness or perceived ease of use (see, e.g., Devaraj, Easley, & Grant, 2008; Picazo-Vela et al., 2010; Terzis et al., 2012). Therefore, another theoretical contribution of the current study is incorporating personality in UTAUT2 and examining direct effects on both behavioral intention (BI) and usage behavior (UB), which proved to be useful as some of these relationships were confirmed. Moreover, it addresses a call for further research to understand the openness dimension as Devaraj, Easley, and Grant (2008) reveal that openness does not affect intention via other TAM constructs, but find some evidence that certain aspects of personality might have a more direct impact on intention to use technology.

Finally, another theoretical contribution of this paper is that it discerns patterns of cross-cultural variability (Eastern versus Western Europe), shows the main drivers for ICT acceptance in each of the countries, and detects significant differences (see Table 9). The differences appearing between the two countries can be sought behind the way personality traits and culture interact to shape the behavior of individuals, market maturity, and the stage of the "online evolution". For example, neuroticism is a significant predictor only in Bulgaria, which can be related to the idea that Latin people are more relaxed and exert less anxiety as compared to Balkan people. As has been previously shown, anxiety and stress reduce the use of Internet (Devaraj, Easley, & Grant, 2008). Moreover, neurotic people are less likely to feel enjoyment and pleasure from technology use (Xu et al., 2016). Therefore, they will rather tend to use technology when the outcome is related to performance gains, which might be related to the observation that hedonic motivation is a significant predictor only in Portugal, whereas in Bulgaria performance expectancy is the strongest driver on behavioral intention. Additionally, while in Bulgaria habit is a significant predictor on both behavioral intention (BI) and usage behavior (UB), indicating that past actions are transformed to usage behavior, in Portugal habit positively affects only intention. As suggested by Ouellette and Wood (1998), in domains where habits are less likely to develop, usage behavior might be controlled by deliberative reasoning processes, and the effects on usage behavior are mediated by intentions. As for the significance difference in agreeableness, it has been demonstrated by Hofstede (2016) that Bulgarians score high on long-term orientations as opposed to Portuguese who score low on this dimension. Therefore, Bulgarians show an ability to adapt traditions easily to changed conditions, indicating a more agreeable mindset, whereas Portuguese view societal change with suspicion.

Moreover, there is no significant impact of social influence on behavioral intention to use in Bulgaria, as opposed to Portugal. This means that views of opinion-makers and of those in a social circle do not significantly affect one's behavioral intention to use. An explanation could be that the utility factor of performance expectancy is the major determinant of behavioral intention in Bulgaria, leaving social influence as a weak explanatory variable. While the relationship between behavioral intention (BI) and usage behavior (UB) is significant in the Portuguese sample, it is not supported in the Bulgarian one. This non-significant relationship can be associated with individuals in Bulgaria poorly estimating their own behavior (Straub, Limayem, & Karahanna-Evaristo, 1995). As for age being significantly different between the two countries, the reasoning should be sought in the sample characteristics, which is addressed as one of the limitations of the current study.

Table 9. Significant ICT adoption factors and country differences

Relationship	**Hypothesis**	**Significance (full sample)**	**Significance (Bulgaria)**	**Significance (Portugal)**	**Significant difference**
H1: PE -> BI	positive	✓	✓	✓	✓
H2: EE -> BI	positive				
H3: SI -> BI	positive	✓		✓	
H4a: FC -> BI	positive			✓	
H4b: FC -> UB	positive				
H5: HM -> BI	positive	✓		✓	✓
H6: PV -> BI	positive	Supported with (-)			
H7a: HB -> BI	positive	✓	✓	✓	✓
H7b: HB -> UB	positive	✓	✓		
H8: BI -> UB	positive	✓		✓	✓
H9a: OPE -> BI	positive	✓		✓	
H9b: OPE -> UB	positive	✓	✓	✓	
H10a: EXS -> BI	positive				
H10b: EXS -> UB	positive	✓	✓		
H11a: AGR -> BI	positive		✓		✓
H11b: AGR -> UB	positive	✓	✓		
H12a: CON -> BI	positive				
H12b: CON -> UB	positive				
H13a: NEU -> BI	negative		✓		✓
H13b: NEU -> UB	negative				

H14a: Gender -> BI	no impact	✓	
H14b: Gender -> UB	no impact	✓	
H15a: Age -> BI	negative		
H15b: Age -> UB	negative	✓	✓
H16a: Income -> BI	Positive		
H15b: Income -> UB	Positive		

Notes: *p<0.10; **p<0.05;***p<0.01; PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions; HM: hedonic motivation; PV: price value; HB: habit; BI: behavioral intention; UB: usage behavior; OPE: openness; EXS: extraversion; AGR: agreeableness: CON: conscientiousness: NEU: neuroticism

6.3 Linkage between digital divide and technology adoption literature

Considering the importance of the digital divide and the popularity of technology adoption models, a major contribution of this paper is that it adds a bridge between these two fields by introducing and validating a conceptual model in the context of a broad set of ICT, instead of a specific technology. By linking personality traits directly to behavioral intention and use, additional support for including individual difference variables in the UTAUT2 is provided. Although these two fields are to some extent similar, they also present strong distinctions. Digital divide emphasizes one's socio–demographic characteristics and contexts, as well as cultural beliefs, to explain acceptance vs. non-acceptance behavior, whereas technology adoption models pay more attention to one's individuality in the sense that antecedents of acceptance are usually rational and autonomous. Moreover, in the technology adoption field, technologic adoption is dealt with individually. This paper combines both perspectives, grounding on UTAUT2, one's personality traits and socio-demographic status, namely age, gender, and income. Moreover, a set of technologies in opposition to only one, are examined.

Although UTAUT2 is recognized as one, if not the most, popular and effective lens for understanding technology adoption, it seems that in the context of the digital divide, i.e., focusing not on one specific but rather a comprehensive set of ICT, personality traits are more effective in shedding some light on the diffusion process. Comparing both theories, UTAUT2's adjusted-R^2 is 0.46, whereas Personality Traits' is 0.50.

6.4 Practical implications

The current study reveals that different personality characteristics influence individuals' intention and use of ICT. A better understanding of individual differences and how they impact adoption intent and usage behavior would have implications for a wide variety of practitioners, including psychologists, developers, marketers, and policy makers in developing, aligning, and designing ICT functionalities and creating proper stimuli regarding personality differences. For example, more open to experience, extraverted, and agreeable people are more likely to become ICT adopters. Therefore, personality traits should be considered in applying a more personalized approach on the targeted audience considering this audience's characteristics and the way that ICT is evaluated (Sharif & Irani, 2006). Additionally, although young users adapt ICT applications easily, developers should still focus on providing technical support to users who are less technologically advanced, e.g., the elderly. Furthermore, marketing practitioners should focus on the real value of their ICT applications by revising their marketing and pricing schemes to attract price-sensitive consumers.

From a policy-making point of view, as performance expectancy (PE) is the strongest antecedent of behavioral intention (BI) in both countries, whereas effort expectancy (EE) is not in neither, policy-makers should emphasize ICT usefulness and performance rather than its ease of use. Note that recent research in eGovernment indicates that, at least in developed countries, ICT skills – a major issue on the digital divide literature – seems to be losing relevance (see, e.g., Ebbers et al., 2016). The fact that there is social influence (SI) positively affects behavioral intention (BI), although not in Bulgaria, suggests that policy-makers should encourage adopters to share their positive experiences with ICT to those who are not adopters. Initiatives targeting this goal could be conducted at national level, even though a series of local ones would probably be more efficient (see, e.g., the Digital Birmingham's "Keep IT in the family" project). Age, the only socio-demographic characteristic proven to impact ICT acceptance in both countries, should raise policy-makers' awareness to the issue of the age-related digital divide, and its impact in empowering these citizens. As the elderly are a vulnerable and usually under-represented group, policy-makers involved in promoting ICT acceptance should provide special attention to initiatives intended to raise the awareness of the elderly to the benefits of ICT and how these technologies can improve their lives. As for the comparison in the two cultural contexts – an Eastern and a Western European country – there are variations in the magnitudes of the impacts of the factors of technology adoption across the two countries. This implies that policy-makers should consider different strategies when planning to engender ICT. For example, in Bulgaria it turns out that PE is a strong predictor, whereas in Portugal HM plays a very significant role as well. Therefore, in Portugal policy-makers should communicate not only ICT usefulness but also entertaining aspects as well. Additionally, habit and neuroticism are significant drivers in Bulgaria, indicating that there should be a focus on trying to constantly reinforce users' habit with value added services and incentives, as well as promote ICT applications in such a way that neurotic individuals do not see them as threatening or stressful.

6.5 Limitations and future research

Some limitations must be considered when interpreting the results of the current study. One of the limitations is related to the sampling, as most respondents are young workers and students. More than 50% of the respondents in the sample are in the age group of 25-34 and 92.4% are either students or workers, with some 70% being employed or self-employed. For this reason, to improve generalization and external validity, future research is thus called upon to confirm our findings among different age and professional groups, namely those unemployed. Future research is thus encouraged to confirm our findings among different age and professional groups. Second, the current study uses the personality traits of a five-factor model that encompasses five broad factors of personality. Although it has been recognized by researchers that this framework captures an individual's personality (Costa & McCrae, 1992; Digman, 1990), other more detailed personality dimensions have shown to have an impact in the context of technology use. For example, narrow personality traits, such as optimism and work drive, have been investigated in the context of Internet usage (Landers & Lounsbury, 2006). We focused on the big five personality traits as they have been widely applied in technology adoption studies. However, other personality frameworks may offer additional insights to both technology adoption and personality literature. Third, a further limitation is related to the scale used to measure personality traits, 20-item IPIP, a shorter version that is suitable for online questionnaires as it is time saving and results in a higher response rate. However, a recommendation for future research is to apply a longer and more rigorous version of the big five personality traits. Another limitation is related to the broad set of ICT on use as personality can affect the adoption of ICT differently depending on their specific functionalities and characteristics. Therefore, future researchers are called upon to examine the impact of personality on more specific types of IS adoption and use. Finally, although placed at different edges of Europe, similarities between Bulgaria and Portugal exist as, at least, both belong to the EU, thus sharing some of its values and culture. In other words, these two countries are not completely independent. Hence, caution should be taken when generalizing to other countries.

In addition, personality traits also depend on culture and region. This study focuses on only two European countries. However, these findings need to be tested in other cultures. Therefore, future research can use this model to replicate the study in other cultural contexts. Furthermore, this study is based on cross-sectional data and does not detect changes in the investigated relationships over time. A longitudinal investigation may provide additional insights on the consistency of the effects studied over time. Lastly, this paper used self-report survey measures, and individuals may be inaccurate when making self-assessment of their personality and usage behavior.

7. Conclusions

The authors of this research have sought to make a contribution to the normative literature in the broad domain of ICT and specifically when considering the information systems digital divide from a European perspective. In doing so, a conceptual model was developed UTAUT2, underpinned by five factors of personality that allowed for greater insights on the drivers influencing technology adoption at an individual level to be developed.

The proposed model was then empirically tested within a European context, following a robustly constructed research design. Our substantive findings are:

- The UTAUT2 hypotheses (8 out of 13) were empirically confirmed. Performance expectancy and habit turned out to be the strongest predictors of ICT acceptance;
- By including personality traits to UTAUT2 the adjusted R^2 increased by some 11 p.p. on usage intention, whereas the increase in behavioral intention was negligible;
- The personality characteristics of openness, extraversion, and agreeableness were found to be significant predictors of ICT acceptance;
- The cross-cultural comparison added further insights on how culture influences the predictors and outcomes of technology use among individuals: openness, extroversion, agreeableness, and neuroticism (only for behavioral intention) proved to be significant predictors of ICT acceptance for Bulgarian individuals, whereas, for Portuguese individuals, only openness did so.

There needs to be something added (a paragraph) here about what this means within the context of the conceptual model that was originally developed.

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Appendix A – Instrument

Construct	Item	Code	Source
Performance expectancy (PE)	I find ICT useful in my daily life	PE1	Venkatesh et al.(2003;2012)
	Using ICT increases my productivity	PE2	
	Using ICT helps me accomplish things more quickly	PE3	
	Using ICT increases my chances of achieving things that are important to me	PE4	
Effort expectancy (EE)	Learning how to use ICT is easy for me	EE1	Venkatesh et al.(2003;2012)
	My interaction with ICT is clear and understandable	EE2	
	I find ICT easy to use	EE3	
	It is easy for me to become skillful at using ICT	EE4	
Social influence (SI)	People who are important to me think that I should use ICT	SI1	Venkatesh et al.(2003;2012)
	People who influence my behavior think that I should use ICT	SI2	
	ICT use is a status symbol in my environment	SI3	
	People whose opinions I value prefer that I use ICT	SI4	
Facilitating conditions (FC)	I have the resources necessary to use ICT	FC1	Venkatesh et al.(2003;2012)
	I have the knowledge necessary to use ICT	FC2	
	There is compatibility between the ICT I use	FC3	
	I can get help from others when I have difficulties using ICT	FC4	
Hedonic motivation (HM)	Using ICT is fun	HM1	(Venkatesh *et al.*, 2012)
	Using ICT is enjoyable	HM2	
	Using ICT is entertaining	HM3	
Price value (PV)	ICT are reasonably priced	PV1	(Venkatesh *et al.*, 2012)
	ICT are a good value for the money	PV2	
	At the current price, ICT provide a good value	PV3	
Habit (HB)	The use of ICT has become a habit for me	HB1	(Venkatesh *et al.*, 2012)
	I am addicted to using ICT	HB2	
	I must use ICT	HB3	
	Using ICT has become natural to me	HB4	
Behavioral intention (BI)	I intend to continue using ICT in the future	BI1	Venkatesh et al.(2003;2012)
	I will always try to use ICT in my daily life	BI2	
	I plan to continue to use ICT frequently	BI3	
Usage behavior (UB)	Please choose your usage frequency for each of the following ICT, where frequency ranges from “1-never” to “7-many times per day”: a) Internet b) access the Internet via a mobile device, away from home or work c) use online banking d) seek health-related information online e) look for information about education, training or course offers online f) interact with public authorities online g) look for information about goods and services online h) order goods or services online i) order goods or services online, from sellers from other EU countries j) online public participation (consultations or voting to define civic or political issues) k) social networks l) storage space on the Internet (e.g., Google Drive, Dropbox)	UB	(Venkatesh *et al.*, 2012)
Openness (OPE)	I have a vivid imagination	OPE1	(Donnellan *et al.*, 2006)
	I am not interested in abstract ideas (R)	OPE2	
	I have difficulty understanding abstract ideas (R)	OPE3	
	I do not have a good imagination (R)	OPE4	
Extraversion (EXS)	I am the life of the party	EXS1	(Donnellan *et al.*, 2006)
	I don’t talk a lot (R)	EXS2	
	I talk to a lot of different people at parties	EXS3	
	I keep in the background (R)	EXS4	
Agreeableness (AGR)	I sympathize with others’ feelings	AGR1	(Donnellan *et al.*, 2006)
	I am not interested in other people’s problems (R)	AGR2	
	I feel others’ emotions	AGR3	
	I am not really interested in others(R)	AGR4	
Conscientiousness (CON)	I get chores done right away	CON1	(Donnellan *et al.*, 2006)
	I often forget to put things back in their proper place (R)	CON2	
	I like order	CON3	
	I make a mess of things (R)	CON4	
Neuroticism (NEU)	I have frequent mood swings	NEU1	(Donnellan *et al.*, 2006)
	I am relaxed most of the time (R)	NEU2	
	I get upset easily	NEU3	
	I seldom feel blue (R)	NEU4	

Note: R: Reversed items

Appendix B – Loadings and cross-loadings

	PE	EE	SI	FC	HM	PV	HB	BI	OPE	EXS	AGR	CON	NEU
PE1	**0.927**	0.595	0.347	0.684	0.629	0.388	0.560	0.751	0.367	-0.076	0.276	0.198	-0.232
PE2	**0.948**	0.627	0.361	0.662	0.559	0.392	0.531	0.712	0.427	-0.050	0.244	0.143	-0.272
PE3	**0.950**	0.608	0.377	0.657	0.571	0.371	0.514	0.693	0.402	-0.053	0.213	0.198	-0.256
PE4	**0.939**	0.611	0.406	0.631	0.565	0.381	0.556	0.717	0.407	-0.045	0.226	0.108	-0.283
EE1	0.575	**0.944**	0.341	0.626	0.580	0.450	0.516	0.522	0.400	-0.050	0.214	0.052	-0.353
EE2	0.642	**0.948**	0.371	0.677	0.615	0.462	0.539	0.557	0.435	-0.047	0.269	0.087	-0.306
EE3	0.603	**0.954**	0.368	0.650	0.598	0.464	0.523	0.552	0.480	-0.004	0.265	0.079	-0.354
EE4	0.625	**0.928**	0.330	0.689	0.554	0.415	0.515	0.573	0.460	-0.059	0.239	0.089	-0.301
SI1	0.398	0.356	**0.883**	0.406	0.365	0.406	0.414	0.437	0.228	-0.058	0.268	-0.060	-0.279
SI2	0.382	0.335	**0.899**	0.402	0.339	0.395	0.438	0.433	0.231	-0.062	0.338	-0.068	-0.172
SI3	0.244	0.297	**0.742**	0.216	0.203	0.174	0.445	0.347	0.215	-0.067	0.265	-0.105	-0.201
SI4	0.326	0.301	**0.908**	0.330	0.321	0.357	0.443	0.458	0.240	-0.071	0.261	-0.076	-0.306
FC1	0.589	0.627	0.356	**0.879**	0.478	0.453	0.493	0.542	0.333	-0.022	0.208	0.073	-0.272
FC2	0.651	0.682	0.365	**0.893**	0.506	0.346	0.527	0.564	0.411	-0.047	0.259	0.091	-0.240
FC3	0.639	0.607	0.326	**0.884**	0.560	0.436	0.483	0.532	0.389	-0.014	0.251	0.129	-0.205
FC4	0.578	0.538	0.353	**0.856**	0.535	0.487	0.481	0.559	0.383	-0.027	0.245	0.118	-0.230
HM1	0.514	0.619	0.334	0.555	**0.934**	0.494	0.497	0.522	0.271	0.029	0.226	0.118	-0.203
HM2	0.619	0.605	0.332	0.569	**0.948**	0.480	0.487	0.622	0.261	-0.011	0.226	0.185	-0.203
HM3	0.599	0.526	0.352	0.538	**0.932**	0.482	0.473	0.555	0.255	-0.041	0.206	0.222	-0.176
PV1	0.319	0.438	0.386	0.411	0.466	**0.934**	0.372	0.320	0.242	0.014	0.181	0.041	-0.277
PV2	0.387	0.436	0.345	0.451	0.504	**0.951**	0.356	0.376	0.242	-0.007	0.178	0.081	-0.229
PV3	0.434	0.465	0.389	0.507	0.489	**0.941**	0.453	0.382	0.273	-0.021	0.207	0.113	-0.250
HB1	0.592	0.564	0.397	0.621	0.503	0.360	**0.867**	0.583	0.276	-0.037	0.206	0.077	-0.201
HB2	0.236	0.293	0.461	0.264	0.315	0.394	**0.715**	0.384	0.188	0.118	0.164	-0.144	-0.221
HB3	0.404	0.311	0.418	0.335	0.291	0.293	**0.773**	0.483	0.312	0.015	0.171	0.027	-0.275
HB4	0.580	0.581	0.404	0.561	0.536	0.345	**0.908**	0.659	0.332	-0.017	0.231	0.073	-0.312
BI1	0.765	0.575	0.446	0.650	0.614	0.414	0.605	**0.912**	0.412	-0.044	0.343	0.181	-0.263
BI2	0.628	0.468	0.428	0.497	0.472	0.332	0.566	**0.900**	0.366	-0.027	0.215	0.051	-0.306
BI3	0.716	0.569	0.480	0.578	0.586	0.315	0.645	**0.957**	0.405	-0.054	0.289	0.108	-0.317
OPE1	0.453	0.461	0.287	0.433	0.301	0.269	0.382	0.451	**0.874**	0.190	0.360	-0.018	-0.311
OPE2	0.291	0.372	0.176	0.329	0.209	0.208	0.223	0.279	**0.809**	0.045	0.254	-0.107	-0.210
OPE3	0.270	0.370	0.195	0.346	0.179	0.186	0.202	0.293	**0.833**	0.112	0.271	-0.065	-0.266
OPE4	0.386	0.380	0.217	0.340	0.233	0.232	0.310	0.387	**0.875**	0.075	0.360	-0.021	-0.241
EXS1	-0.044	-0.019	-0.046	-0.032	-0.008	-0.028	0.030	-0.026	0.147	**0.952**	-0.229	-0.110	-0.121
EXS2	-0.039	-0.122	-0.149	-0.035	-0.013	-0.026	-0.063	-0.059	0.089	**0.731**	-0.208	-0.035	0.075
EXS3	-0.065	-0.052	-0.096	-0.026	-0.008	0.020	-0.001	-0.053	0.086	**0.915**	-0.190	-0.066	-0.075
EXS4	0.002	-0.147	-0.214	-0.044	-0.014	-0.071	-0.103	-0.032	0.052	**0.669**	-0.259	0.058	0.075
AGR1	0.255	0.279	0.306	0.322	0.265	0.207	0.255	0.296	0.320	-0.207	**0.919**	0.085	-0.099
AGR2	0.225	0.212	0.249	0.194	0.168	0.167	0.200	0.280	0.356	-0.202	**0.910**	0.079	-0.023
AGR3	0.183	0.226	0.374	0.224	0.187	0.218	0.208	0.227	0.340	-0.199	**0.873**	0.051	-0.105
AGR4	0.251	0.225	0.264	0.242	0.217	0.137	0.195	0.303	0.340	-0.206	**0.906**	0.131	-0.009
CON1	0.145	0.055	-0.107	0.085	0.074	0.061	-0.046	0.075	0.022	-0.007	0.110	**0.792**	-0.021
CON3	0.173	0.105	-0.026	0.150	0.235	0.131	0.099	0.130	-0.069	-0.094	0.072	**0.888**	-0.043
CON4	0.094	0.027	-0.102	0.031	0.130	-0.007	-0.019	0.097	-0.087	-0.160	0.060	**0.775**	-0.034
NEU2	-0.224	-0.331	-0.251	-0.279	-0.208	-0.306	-0.257	-0.274	-0.248	-0.067	-0.086	-0.048	**0.886**
NEU4	-0.274	-0.304	-0.258	-0.218	-0.172	-0.190	-0.299	-0.303	-0.305	-0.095	-0.036	-0.028	**0.927**

Appendix C – Heterotrait-Monotrait Ratio (HTMT)

	PE	EE	SI	FC	HM	PV	HB	BI	OPE	EXS	AGR	CON	NEU	Age	Sex	Income
PE																
EE	0.676															
SI	0.428	0.408														
FC	0.753	0.751	0.442													
HM	0.651	0.658	0.395	0.646												
PV	0.426	0.500	0.428	0.531	0.553											
HB	0.619	0.597	0.604	0.627	0.570	0.480										
BI	0.814	0.621	0.543	0.687	0.652	0.412	0.737									
OPE	0.451	0.508	0.295	0.479	0.302	0.290	0.380	0.463								
EXS	0.049	0.110	0.166	0.050	0.028	0.046	0.099	0.057	0.115							
AGR	0.269	0.277	0.368	0.298	0.250	0.217	0.268	0.331	0.409	0.281						
CON	0.196	0.089	0.125	0.131	0.211	0.095	0.141	0.145	0.110	0.098	0.121					
NEU	0.317	0.403	0.335	0.325	0.245	0.320	0.378	0.376	0.361	0.120	0.087	0.053				
Age	0.042	0.160	0.104	0.082	0.056	0.014	0.127	0.047	0.328	0.112	0.192	0.281	0.059			
Sex	0.109	0.086	0.026	0.048	0.050	0.016	0.111	0.093	0.032	0.097	0.213	0.061	0.253	0.026		
Income	0.063	0.100	0.038	0.176	0.099	0.085	0.088	0.105	0.125	0.076	0.178	0.130	0.006	0.024	0.057	