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Understanding workers' adoption of productivity mobile applications: a fuzzy set qualitative comparative analysis (fsQCA)

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ABSTRACT

Mobile devices such as smartphones and tablets become more present in our lives every day. Most of these devices use the Android operating system (O.S.), becoming the most popular O.S. for mobile devices. For these devices, there is a huge offer of application software that provides answers to users' different needs. This study aims to analyse how combinations of personality factors, sociodemographic variables and Internet use influence the adoption of productivity mobile apps by workers. To achieve this, a combination of these variables is analysed using fuzzy set Qualitative Comparative Analysis (fsQCA.) that allows us to analyse complex complementarities among factors. The results show the importance of distinct personality traits – extraversion and agreeableness – to understand the adoption of these services. Our study also provides relevant insight for software developers to target segments interested in the use of productivity software in their mobile devices.

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1. Introduction

Mobile devices such as smartphones and tablets are increasingly present in our lives. According to a recent market analysis, 78% of the world's population own a smartphone, more than 50% have tablets and some 10% already own a smartwatch device (Deloitte, 2017). Notably, more than 80% of these devices use the Android operating system (O.S.), which is now the most popular operating system (O.S.) for mobile devices (ONTSI, 2016).

For these devices, a wealth of application software (apps) provides answers to users' needs. One of the most popular apps categories is that of productivity apps, that is to say, applications dedicated to creating and modifying information provided in the form of documents, presentations, worksheets, databases, charts, graphs, etc. (Davis, 2017). This type of application, which increases the productivity of office workers and transforms the way we work, is fast becoming essential in the economy knowledge of today (Burning Glass Technologies, 2015).

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Given the relevance of productivity apps, it is important for all businesses, not just mobile technology developers, to have a firm understanding of the personal characteristics of workers who use productivity apps, since this may influence their productivity at the workplace. It is also important from a theoretical perspective to examine whether productivity apps can be adapted to users' personal characteristics as well as other types of information such as sociodemographic and Internet-usage information. Hence, this study aims to analyse how combinations of personality factors, sociodemographic variables and Internet use influence the adoption of productivity mobile apps by workers.

Previous work has shown the relevance of personality in relation to technology adoption (Vishwanath, 2005), including adoption of social media (Ross et al., 2009), location-based services (Chorley, Whitaker, & Allen, 2015) or mobile apps (Xu, Frey, Fleisch, & Ilic, 2016). However, scientific literature is scarce when it comes to studies of adoption based on a combination of personality, sociodemographic and Internet use factors.

This paper contributes to the literature on technology adoption by uncovering the relevance of extraversion and agreeableness factors for the adoption of productivity apps. Our study also provides relevant insights for software developers who wish to target specific segments interested in the use of productivity software on their mobile devices.

The present work is structured as follows: firstly, the different characteristics of the personality and sociodemographic variables that will be used as antecedents of adoption of mobile productivity applications are defined, with a review of the influence of these factors on the adoption of information systems. The methodology section explains the double strategy used for the collection of data through questionnaires and the collection of applications directly from Android phones. After a brief explanation of the analysis technique used, namely fsQCA, we present the conclusions, contributions and limitations of the work as well as suggestions for future research.

1.1. Personality, sociodemographic variables and Internet usage as antecedents to the adoption and use of technology

Research on technology adoption began in the late 1970s with work that focused broadly on users' views of technology and their satisfaction. The theories in this stream incorporate some of the central concepts from social and behaviour sciences in order to predict and understand users' adoption of technology, notably the Theory of Planned Behaviour (Ajzen, 1991), the general theory underlying multiple information-systems specific theories such as the Technology Acceptance Model (Davis, 1989) and the Unified Theory for Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003).

Ever since the mass adoption of the Internet in the early 1990s, researchers have begun to study the influence of sociodemographic and personality variables, arriving at the conclusion that research on the use of the Internet needs more variance than the traditional adoption models (McElroy, Hendrickson, Townsend, & DeMarie, 2007). Hence, following the call of McElroy et al. (2007), this study analyses the impact of personality, sociodemographic and Internet use variables on the adoption of productivity applications by workers.

1.2. Personality factors

A vast amount of research work has focused on the relationship between personality factors and technology. Previous work concentrated on technology adoption (Ross et al., 2009; Vishwanath, 2005), Internet use (Landers & Lounsbury, 2006), problems in the use of mobile devices (Bianchi & Phillips, 2005) and the adoption of specific types of applications (Chorley et al., 2015). This section reviews the different characteristics that influence personality factors, the relationship between personality factors and the adoption of new technologies, and the propensity to adopt productivity applications. Our aim is to determine the current state of the art on the level of adoption of productivity applications according to the personality of individuals.

The Big Five Inventory scale (BFI-10) has been used extensively in scientific literature to measure five personality factors: extraversion, agreeableness, conscientiousness, neuroticism and openness to experience (Rammstedt & John, 2007).

The extraversion factor implies an energetic focus on both the social and the material world, including features such as being a social, active, assertive and emotionally positive person (John, Naumann, & Soto, 2008). Focusing on the impact of personality aspects on mobile phone adoption and usage, it should be noted how extroverted people are most likely to possess a smartphone. Extroverts do not replace offline relationships with online ones, although they are prone to using the Internet to maintain them, and are inclined to share information with others (Amiel & Sargent, 2004). Extraversion is one of the key characteristics associated with the use of social networking applications (Xu et al., 2016). However, extraversion is negatively associated with the use of computer games (Chittaranjan, Blom, & Gatica-Perez, 2013) and mobile game applications (Xu et al., 2016). In relation to education, extraversion is associated with the professional study of economics, law, political science and medicine (Vedel, 2016). As for extraversion and its relation to productivity apps, it is worth referring to the study by Lane and Manner (2012), who also tried to understand the personality characteristics associated with the use of smartphone applications. They came to the conclusion that extroverted individuals gave greater importance to gaming applications, while giving less importance to those apps corresponding to productivity (Lane & Manner, 2012). By contrast, Chittaranjan et al. (2013) point to a positive relationship between this personality factor and the use of Office applications and calendars. Thus, the studies relating to extraversion and productivity apps show contradictory results.

On the other hand, the agreeableness factor presents a community vision, showing characteristics such as altruism, confidence and modesty (John et al., 2008). Different studies agree that the tolerance and permissiveness which characterises agreeable people makes them more likely to accept new technologies easily and spend more time on the Internet (Devaraj, Easley, & Crant, 2008). The agreeableness factor is not a significant predictor of good work performance (Barrick & Mount, 1991) and shows little relationship to law, business and economic studies (Vedel, 2016). Lastly, although agreeable people use mobile phones extensively to make calls (Lane & Manner, 2012), the agreeableness factor has been found to be negatively correlated with the use of Office and Calendar applications, as well as video / audio / music, mail and SMS services on the Internet (Chittaranjan et al., 2013).

The conscientiousness factor is characterised by the control of impulses, facilitating the accomplishment of tasks and the achievement of objectives. Conscientious people think before acting, follow norms and rules, as well as planning, organising and prioritising tasks

(John et al., 2008). The practicality that characterises conscientious people would make them less interested in entertainment applications, such as music and video (Chittaranjan et al., 2013) or social networks (Hughes, Rowe, Batey, & Lee, 2012; Ryan & Xenos, 2011). Although it would be reasonable to expect people with these characteristics to be attracted to the use of productivity apps, there are no conclusive results that support such beliefs (Xu et al., 2016). The conscientiousness factor is important for all kinds of jobs (Barrick & Mount, 1991), although it shows a low relation to branches of study such as the arts and humanities (Vedel, 2016).

People with characteristics of the neuroticism category counterpoise emotional stability with negative emotionality, expressed by anxious feelings, nervousness, sadness and tension (John et al., 2008). The lack of confidence characteristic of this group of people prompts them to consider new technologies and services as threatening and stressful, resulting in less Internet use (Devaraj et al., 2008; Tuten & Bosnjak, 2001). Additionally, this factor is negatively related to the perception of utility and behaviour control, which reduces the intention to incorporate new technologies into daily life (Uffen, Kaemmerer, & Breitner, 2013). However, there are also studies that support the view that this personality factor pushes individuals to turn to new technologies to face their problems, either by looking to increase sociability via social networks (Ryan & Xenos, 2011) or by modulating their bad feelings through online shopping (Tuten & Bosnjak, 2001). In relation to studies, these individuals tend to study the arts, humanities and psychology (Vedel, 2016). As for the preferences of applications of neurotic people, the associated literature is not conclusive. According to Lane and Manner (2012), neurotics give greater importance to travel applications, while productivity and utility applications are the least important to them. However, Chittaranjan et al. (2013) indicate that emotional stability is negatively correlated with the use of Office and Calendar applications. These results show that both emotional stability and its opposite, neurotic personality, would have a negative relationship with the adoption of useful applications.

Finally, openness corresponds to an original, deep person with a curious mind (John et al., 2008). People with this characteristic are more likely to adopt new technologies (Constantiou, Damsgaard, & Knutsen, 2006; Tuten & Bosnjak, 2001). In the work environment, openness to experience is shown as a predictor of learning (Barrick & Mount, 1991), and stands out for its relation to humanities, the arts, psychology and political science (Vedel, 2016). In relation to the adoption of productivity apps, according to Chittaranjan et al. (2013), this factor is negatively correlated with Office, Calendar and SMS applications.

1.3. Sociodemographic variables and Internet usage

Along with the personality characteristics of users of Android applications, this study focuses on sociodemographic variables. The analysis includes the variables of gender, age and level of studies for workers who are Android users. In addition, in order to contextualise the degree of relationship of the users with new technologies, the analysis also includes the variable of Internet usage.

Sociodemographic variables have been taken into account to study the adoption of technologies. Some previous studies have focused on the technological impact of technology on users according to their profile (Pedersen & Ling, 2003), while others have focused on

relating users' characteristics to the operation of mobile terminals and their satisfaction with them (Balakrishnan & Yeow, 2007).

In relation to age, Walsh, White, and McD Young (2010) point out that young users are more likely to adopt mobile devices, while Plaza, Martín, Martín, and Medrano (2011) point out that older people use phones to communicate with their relatives, as aids to memory and daily life, enjoyment, self-realisation and as tools to feel safe.

According to the gender variable, Castells, Fernandez-Ardevol, Qiu, and Sey (2004) indicate that female users give greater value to their mobile terminal as a fashionable object, and as a key channel for maintaining personal relationships; in contrast, male users give more value to their mobile terminal as an instrument for achieving their goals.

In the adoption of mobile phones, the experience and aptitude of individuals towards new technologies have proven to be relevant since users who are more technologically advanced and technologically oriented can influence the perception of ease of use (Van Biljon & Kotzé, 2007). As a result, level of Internet use, understood as the number of online services used, can reflect the capacity and technological orientation of individuals, as well as their capacity to deal with new technologies such as productivity apps.

Concerning the adoption of specific applications, Chittaranjan et al. (2013) indicate that men are more likely to use Office applications, in addition to games and YouTube. Veríssimo (2016) shows through the fsQCA analysis that age can explain the non-use of mobile banking applications. Thus, the characteristic of being younger than 35 years old is present in different models explaining the non-use of the app (Veríssimo, 2016).

From the literature review and analysis, the following proposition emerged: the adoption or non-adoption of productivity apps can be explained as a combination of personality factors and sociodemographic variables. According to the previous antecedents, Figure 1 presents the study's model.

2. Methods

2.1. Data collection and measures

This study collected data directly from users' mobile phones, and from an online questionnaire. Participants installed an application on their phone called Pinkerton, following a process similar to that used in other works (Seneviratne, Seneviratne, Mohapatra, & Mahanti, 2014; Xu et al., 2016). For each mobile phone, the following data were collected: O.S. version; status of the option about download from unknown sources; if it was in developer mode; or if it had been routed. For each application on the phone, the following data were collected: name of the application; package; version; source from which it had been downloaded; categories of the application following Google Play or Amazon classification; and if the application included a launcher.

The direct collection of data from the individual's personal phone through a mobile app solved problems of bias derived from the use of self-completed surveys. Previous work has shown significant differences between the self-responses of research participants and their actual behaviour, especially in the number and duration of mobile calls (Vanden Abeele, Beullens, & Roe, 2013). Other studies have also shown that due to the large number of applications that the user may have installed, the user may find it difficult to enumerate

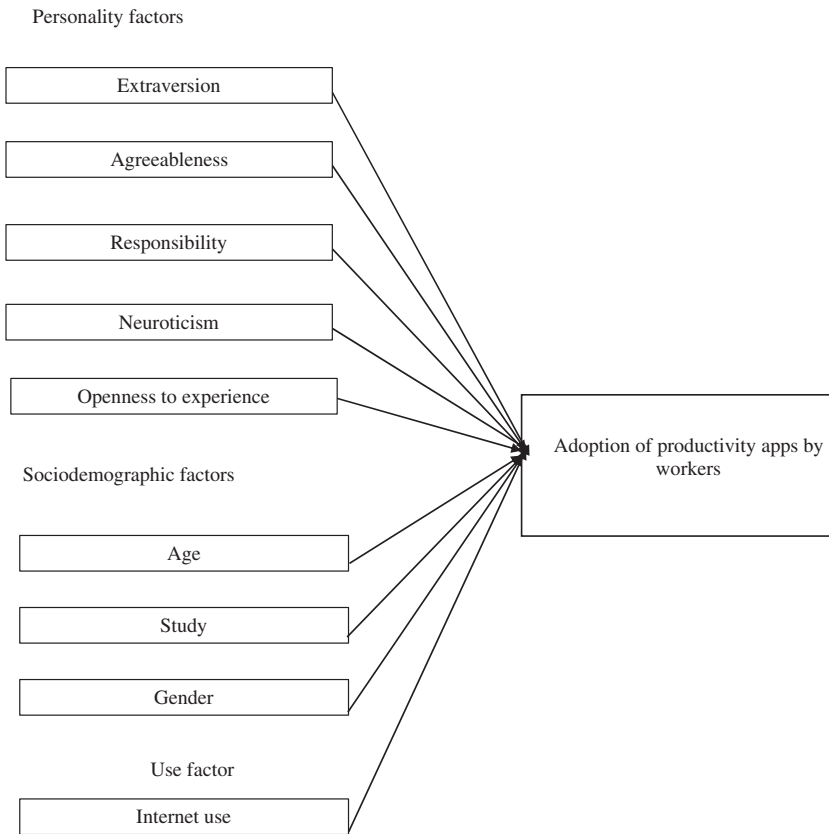


Figure 1. Research model. Source: Created by the authors.

all the installed applications and their daily use (Xu et al., 2016), thereby ruling out the possibility of introducing biases of answers by social desirability.

Sociodemographic variables (studies, age and sex), frequency of Internet use and personality (extraversion, agreeableness, responsibility, neuroticism and openness to experience) were collected through an online questionnaire. To study users’ personalities, we drew on the Big Five Inventory personality model in its 10-item version (BFI-10), which summarises the information of 44 items (BFI-44). The use of this instrument allowed us to include variables related to personality without excessive loss of information.

For the study, 701 mobile devices were analysed, of which 699 devices presented useful information for this study. The scanning of these devices collected a total of 27,740 applications, after obviating those corresponding to the device O.S. Thus, on average, users had 39.69 applications installed on their devices. Of the 701 devices, we selected the 497 that were owned by working users. Table 1 shows the sociodemographic characteristics of the 699 users sampled.

From the 497 working users, the characteristics with greater representation are: men (57.95%), over 34 years old (71.03%) and with studies in higher education (university level) (60.76%). Regarding the adoption of productivity applications, it can be seen that 19.92% of users do not use any such applications, while about half (48.09%) have one or

Table 1. Sociodemographic characteristics of the sample.

Variable	Response category	N	%
Gender	Female (0)	340	48,64%
	Male (1)	359	51,36%
	Total	699	100%
Age	≤ 34 years old (0)	235	33,62%
	> 34 years old (1)	464	66,38%
	Total	699	100%
Level of Studies	Primary level (0)	5	0,72%
	Secondary level (0,5)	300	42,92%
	Higher education level (1)	394	56,37%
	Total	699	100%
Productivity Apps	0 app (0)	145	20,74%
	Between 1 and 2 apps (0,5)	333	47,64%
	>2 apps (1)	221	31,62%
	Total	699	100%

Note: The value of the response categories in parentheses corresponds to the value they take for the fsQCA analysis.
Source: Created by the authors.

two applications on their device, the remaining 31.99% corresponding to those with the greatest adoption of these types of applications.

2.2. Research methodology

In order to validate the previously posed proposition, we applied an fsQCA analysis, since its focus on ‘causal recipes’ (Ragin, 2008) makes it uniquely suited to analyse complex complementarities among factors (Ganter & Hacker, 2014; Henik, 2015; Woodside, 2013; Cova & Rodríguez-Monroy, 2016; Ryan, 2017), as is the case in our research. This analysis was carried out in three phases (Ragin, 2008; Schneider & Wagemann, 2012). Firstly, we performed a calibration of the conditions and outputs. Secondly, an analysis of necessary conditions was completed with the objective of determining if the independent variables were the necessary conditions needed to produce the output. Thirdly, an analysis of sufficiency conditions was carried out in order to determine the conditions or combinations that would be sufficient to cause the output. To carry out this analysis the fsQCA 2.5 software was used (Ragin, 2008).

In the calibration, the dichotomous variables (labour activity, age and sex) took either 0 or 1, with the first value corresponding to non-inclusion and the second corresponding to inclusion. Continuous variables were calibrated by taking the percentile less than 5 as 0, and therefore as not pertaining; the 50th percentile with 0.5, referred to the maximum level of uncertainty; and the 95th percentile as 1, corresponding to the most pertaining. In the case of adoption of productivity apps, the absence of application took the value 0; between 1 and 2 apps were given the value of maximum uncertainty, 0.5, with 1 being the case of those with more than two applications. The personality variables were calibrated as 1 non-membership value (given value 0); maximum uncertainty at 3 (value 0.5), mean value of the scale; and pertaining to 5 (value 1).

Following Ragin (2000), cut-off points with values of 0.80 of consistency were used to explain the adoption of applications. However, in the case of non-adoption, lower cut-off points were used due to the lack of cases reaching those values, with the intention of obtaining results that could be used for orientation purposes, but which were not conclusive. It

is also important to note the importance of consistency and coverage values in the fsQCA analysis. These parameters were between 0 and 1, the first responding to the proportion in which the model covered the studied solution, and the second, to the proportion presented by the proposed model among the cases containing the studied solution. The consistency value was similar to the correlation coefficient, constituting a test of solution adequacy, while the coverage value resembled the coefficient of determination (R^2) (Woodside, 2013). Thus, we considered a solution when the consistency value was above 0.65 (Ragin, 2000), although values above 0.75 were recommended; in addition, the coverage should have been between 0.25 and 0.65, although it was accepted when the values differed from these slightly (Urueña & Hidalgo, 2016).

3. Main findings

Table 2 shows that studies and responsibility variables are close to constituting a necessary condition for the adoption or not of productivity apps, showing a value close to 1 (Legewie, 2013). Other variables showed a sufficient relation in which these would constitute a subset of the condition presence of productivity apps. This means that this presence occurs if the variable showing a sufficient relation is present, but other conditions can also produce this fact (Legewie, 2013). Therefore, this first analysis corroborates the need for further study of how the combination of these variables influences the presence of productivity apps.

As for the results of the analysis of sufficiency conditions, regarding the adoption of applications according to personality factors, the model differentiates three subsets (paths 1a, 1b, 1c in Table 3). It is worth noting the positive values of the extraversion and agreeableness factors.

According to the first subset, the output of the adoption of productivity apps is determined by the presence of the characteristics of agreeableness in individuals, whereas it

Table 2. Necessary conditions.

Condition	Productivity apps			
	Adoption		Non-adoption	
	Consistency	Coverage	Consistency	Coverage
Age	0.70	0.55	0.72	0.45
~ Age	0.30	0.58	0.28	0.42
Studies	0.88	0.64	0.90	0.51
~ Studies	0.33	0.81	0.36	0.70
Gender	0.62	0.60	0.52	0.40
~ Gender	0.38	0.50	0.48	0.50
Internet usage	0.74	0.69	0.76	0.56
~ Internet usage	0.52	0.74	0.57	0.63
Extraversion	0.68	0.68	0.70	0.56
~ Extraversion	0.56	0.71	0.60	0.59
Agreeableness	0.75	0.68	0.77	0.55
~ Agreeableness	0.51	0.74	0.56	0.64
Responsibility	0.83	0.62	0.88	0.51
~ Responsibility	0.35	0.78	0.36	0.63
Neuroticism	0.53	0.73	0.55	0.60
~ Neuroticism	0.71	0.67	0.75	0.56
Openness to Experience	0.78	0.66	0.81	0.54
~ Openness to Experience	0.45	0.75	0.49	0.64
Age	0.70	0.55	0.72	0.45
~ Age	0.30	0.58	0.28	0.42

Notes: Values below 0.65 do not meet the criteria for necessary conditions.

Source: Created by the authors.

would present negative values of responsibility, neuroticism and openness to experience. The second subset establishes how the characteristics that must be present are extraversion, agreeableness, not responsibility and not neuroticism. The third model includes the factors of extraversion, agreeableness, responsibility, neuroticism and openness to experience.

The results of the analysis of non-adoption of productivity apps according to personality factors do not provide values of consistency that reach the recommended acceptance criteria of consistency (between 75% and 80%), given that it was not possible to determine a cut-off point greater than 0.75. Therefore, these kinds of results need to be treated carefully. This solution contemplates two subsets (paths 2a, 2b) of factors to explain that there is no adoption, highlighting the absence of agreeableness and neuroticism and the presence of responsibility.

As for the sociodemographic characteristics of the individuals who adopt the applications, two subsets were obtained (paths 1a and 1b in Table 4). In both subsets, it is worth noting the presence of higher education studies and males. The first subset is characterised by being men, with studies and low use of Internet services. Likewise, young men with studies define the second subset.

With reference to the explanation of non-adoption and sociodemographic variables, we also obtained low-level consistency and coverage values. However, the results of the model

Table 3. Results of the complex solution (personality factors).

	Adoption*			Non-adoption**	
	1a	1b	1c	2a	2b
Extraversion		●	●	●	
Agreeableness	●	●	●	○	
Responsibility	○	○	●	●	●
Neuroticism	○	○	●	○	○
Openness to Experience	○		●		●
Consistency	0.81	0.81	0.80	0.70	0.69
Raw coverage	0.24	0.27	0.38	0.43	0.46
Unique coverage	0.02	0.02	0.16	0.02	0.05
Solution coverage	0.45			0.47	
Solution consistency	0.81			0.69	

Note: Black circles represent the presence of a condition while void circles indicate negation.

*Complex Solution. Cut-off point= 0.80.

**Complex Solution. Cut-off point= 0.72.

Source: Created by the authors.

Table 4. Results of the complex solution (sociodemographic variables and Internet usage).

	Adoption*		Non Adoption**	
	1a	1b	2a	2b
Age		○	●	●
Studies	●	●	●	○
Gender	●	●	○	○
Internet usage	○		○	●
Consistency	0.83	0.71	0.74	0.75
Raw coverage	0.33	0.13	0.18	0.09
Unique coverage	0.25	0.05	0.11	0.02
Solution coverage	0.38		0.20	
Solution consistency	0.78		0.74	

Note: Black circles represent the presence of a condition while void circles indicate negation.

*Complex Solution. Cut-off point = 0.80.

**Complex Solution. Cut-off point = 0.72.

Source: Created by the authors.

are shown for guidance. Thus, the presence of women and age above 35 years should be noted. On the other hand, the first subset, in addition to the two common characteristics, presents higher education studies and a low use of Internet services, while the second subset is characterised by no higher level in studies and high use of Internet services.

To strengthen our understanding of the adoption of productivity apps, we also analysed the age variable and personality factors (Table 5). The choice of age is determined by not being present in all subsets of the explanatory model of adoption, in addition to showing both positive and negative values. In addition, it is considered a variable of great importance when it comes to understanding technological adoption (Morris & Venkatesh, 2000).

From the analysis of the variables age and personality together, we obtained a model formed by six subsets (paths 1a–1f) that explain the adoption of productivity apps. It is worth mentioning the positive presence of the factors of agreeableness and extraversion, as opposed to the negative values of neuroticism and age in the results.

The most relevant differences are found when addressing the responsibility factor. This personality factor presents high values only when the users of the devices are under 35 years old, also making it possible to present high values of openness to the experience. On the contrary, when users are not responsible, age may not be present in the solution. Thus, if the values of responsibility are low, age seems to play a less relevant role.

4. Discussion

Our literature review has shown the influence of both personality factors and sociodemographic variables on the adoption of new technologies and mobile applications. This study delves into the different combinations of personality factors and sociodemographic characteristics that create the conditions for the adoption – or non-adoption – of productivity apps by workers.

We highlight the positive value of the factors of extraversion and agreeableness for the adoption of productivity apps. Thus, the relevance of the extroverted character factor in the subsets that explain the adoption of productivity apps contradicts the studies that indicated that extroverted people give less importance to these kind of applications (Lane & Manner, 2012). Likewise, the relevance of the agreeableness factor contrasts with the studies that

Table 5. Results of the complex solution (personality and age).

	Adoption*						Non Adoption**		
	1a	1b	1c	1d	1e	1f	2a	2b	2c
Extraversion	●	●	●	●	●	○	●	●	○
Agreeableness	●	●	●	●	●	●		○	○
Responsibility	○	○		●	●	○	●	●	●
Neuroticism	○	○	○	○		○	○	○	○
Openness to Experience	●		●		●	○	○		●
Age		●	○	○	○	○	●	●	○
Consistency	0.81	0.80	0.81	0.80	0.80	0.80	0.70	0.70	0.70
Raw coverage	0.26	0.18	0.15	0.15	0.15	0.07	0.28	0.30	0.11
Unique coverage	0.00	0.00	0.00	0.01	0.01	0.01	0.05	0.08	0.11
Solution coverage							0.47		
Solution consistency		0.80					0.70		

Note: Black circles represent the presence of a condition while void circles indicate negation.

*Complex Solution. Cut-off point = 0.80.

**Complex Solution. Cut-off point = 0.72.

Source: Created by the authors.

reported a negative correlation of this factor with the use of productive apps such as Office and Calendar (Chittaranjan et al., 2013). Our results are aligned with studies showing the capability of agreeable people to adopt new technologies (Devaraj et al., 2008), and their willingness to use them in the work environment.

In addition, these factors with positive values have a limited presence in the subsets that explain the non-adoption of productivity apps, being combined in these cases with positive values of responsibility, factors that would appear highly relevant when explaining non-adoption, especially when combined with an age over 35 years old.

Therefore, the responsibility factor plays a critical role in the non-adoption of productivity apps. It appears positive in all subsets explaining non-adoption and negative in three of the subsets that explain adoption. This factor could be key in the case of users over 35 years old, given the combination of responsibility and age over 35 as a result of non-adoption (although the model did not achieve the established consistency level for acceptance by five tenths). However, the presence of high values of responsibility resulted in adoption in the event of users being under 35 years old.

As a hypothesis, we can state that people with high scores in responsibility are not mobile workers, since they are more efficient while in their workplace and within working hours, and use their mobile device to perform other productive activities. Thus, relating this hypothesis to the results of responsible people in their working life, Judge, Higgins, Thoresen, and Barrick (1999) point out that the responsibility factor positively predicted success in a professional career. Additionally, responsible people are positively related to a beneficial interaction between work and non-work roles (Michel, Clark, & Jaramillo, 2011) and negatively correlated with the interference of family life in the workplace (Kinnunen, Vermulst, Gerris, & Mäkikangas, 2003), i.e., they separate private life and work. Therefore, the use of productivity apps in mobile devices may have less relevance in the working life of responsible people.

In relation to the subsets that explain adoption and present positive values of responsibility, it should be noted that for users under 35 years old, the presence of productivity apps may be due to the level of technological savviness of these users, and the high degree of integration of new technologies in their lives. These people also present high values of openness to the experience and will be inclined to try different kinds of applications.

On the other hand, neuroticism shows a negative relation with the adoption of productivity apps. These results are in agreement with previous work (Ryan & Xenos, 2011), besides granting less importance to productivity apps, compared to other types of applications such as travel.

Finally, in relation to gender and study level, it is worth noticing the presence of the male and the level of studies variables in the different subsets that explain the adoption of productivity apps.

5. Conclusions

The mobile revolution has changed our daily experiences, including the way we work. Productivity apps are a key element in such a revolution. This study contributes to the research on the adoption of productivity apps by identifying the personality traits of individual users and correlating them to the adoption or non-adoption of productivity apps. We have focused on users of Android applications.

Our analysis combines personality factors, sociodemographic variables and Internet usage to study the adoption of productivity apps. The extraversion and agreeableness factors emerged as central to the adoption of productivity apps, while the responsibility factor constrained the adoption among those over 35 years old, but did not preclude adoption among those under 35. This work reinforces theories that point out the importance of personality in adopting mobile apps. In the same way, it serves to contrast previous research that provides contradictory results on the characteristics that affect the adoption of mobile apps. Applying fsQCA to study the adoption of productivity applications has proven to be correct and to be an interesting alternative to traditional statistical analysis.

Our study has management-related implications for business in general, and application developers in particular. Firstly, previous studies have identified how productivity apps can drive efficiency and effectiveness in different areas of business organisation (Väättäjä, 2012). If companies want to encourage their adoption, they need to pay special attention to those who have a responsible personality and are over 35 years old. Such a group may require specific awareness programmes and training about the advantages and use of productivity apps. Secondly, research on interface designs revealed that some design features are more or less effective depending on personality characteristics; for instance, badges work better on introverts while the progress bar method is preferred by people with a high level of agreeableness (Codish & Ravid, 2014). Developers of productivity apps may need to include features to maintain engagement with the app by extroverted and agreeable people, possibly including gamification techniques (Kumar, 2013). In contrast, responsible people are less likely to be motivated by socially based technologies and different techniques may need to be applied.

Future research could take this study further by addressing several limitations. Firstly, our sample was drawn from Android users, leaving out those who have other O.S. such as i.O.S. or Windows Phone. Future investigations will need to extend the study to users of other O.S., and to examine potential differences between the different user groups. Likewise, it would be interesting to extend the study to apps outside the productivity category, and to extend it to other domains such as tourism or transportation. Finally, this research analyses the information collected by scanning mobile terminals at a given time. Hence, it is not possible to analyse issues such as evolution in the use of applications, which is another potential line of future research.

Disclosure statement

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