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The Role of User Resistance and Social Influences on the Adoption of Smartphone:
Moderating Effect of Age

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ABSTRACT

This study examines the factors affecting users' adoption of the smartphone as an innovative device. Prior studies on the acceptance of computing devices have primarily focused on the impact of the technological benefits and characteristics. Meanwhile, there is a lack of research approaching user resistance, which hinders the diffusion of an innovation. In particular, the smartphone is a highly communication-oriented device that people's attitude and evaluation critically influence its further diffusion. However, few studies have validated this link in the smartphone adoption context. Therefore, this study has attempted to build a research model that explains factors affecting user's resistance to smartphone adoption by integrating technological and social antecedents forming the resistance, and empirically analyzes the data obtained through a survey. As a result, the relative complexity and relative advantages presented in the theory of innovation diffusion had a direct impact on the user's resistance.

KEYWORDS

Age, Informational Influences, Innovation Attributes, Normative Social Influences, Smartphone, User Resistance

INTRODUCTION

After the introduction of Apple's iPhone in 2007, the mobile phone market has been rapidly replaced by the smartphone. What kind of factors affected the rapid diffusion of innovation and why did the previous version of smartphone largely led by Nokia and Blackberry failed to take off in the market? According to the Diffusion of Innovation Theory(DIT) suggested by Rogers (1995), key factors such as relative advantage, compatibility, complexity, trialability, and observability play a significant role in the diffusion of innovation. Dramatic technological enhancement in user interface, full browsing, aesthetic design, and wireless network connection have given the iPhone relative advantages compared to previous smartphone models. The graphical user interfaces of icons on the smartphone and the full browsing internet are highly compatible with the ways people use a personal computer. The dialing technique is also exactly the same in feature phones, except for the touch-screen (Oulasvirta et al. 2012). The innovative user interfaces enable the users to operate the smartphone in a more convenient

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way by overcoming the limitations of feature phones such as a small-sized keypad, small display, and low computing performance, as well as limited features of wireless communications.

Despite the enhancements in the technological and economic values of an innovation, the speed of diffusion depends on the user's resistance towards the innovation (Ram and Sheth 1989). User resistance can be cognitive, affective, or opposing behaviors toward an innovation (Kim and Kankanhalli 2009). These kinds of behavior come from the users' motivation to keep the status quo or unwillingness to change from the current position to another. User resistance increases when the expected loss is higher than the expected benefits from adopting the innovation or switching to the alternative. High uncertainties and risks regarding the performance or values of the innovation also exist (Bagozzi and Lee 1999). In order to diffuse an innovation, it is inevitable to overcome the non-adopters' user resistance. According to Rogers' theory, the potential users are classified as innovators, early adopters, early majority, late majority, and laggard (Martinez et al. 1998). Rogers categorized the groups by their innovativeness, in other words, an individual's willingness to use an innovation. In general, the more innovative people show less resistance in adopting a new technology or product. People with high resistance are likely to remain non-adopters or laggards (Szmigin 1998). Therefore, it is crucial for innovation makers to reduce the innovation resistance of non-adopters and to make these people their customers. In order to do this, it is necessary to identify the impact of user resistance in the pre-adoption stage, and to figure out a way to reduce it with other factors including technological and social factors.

The smartphone is an innovative device that is highly communications-oriented and socially connected. To understand the impact of user resistance on smartphone adoption, it is not enough to investigate the influence of technological improvements. Rather, it is more important to unveil the impact of social influence and the interacting effects between technological and social influences on user resistance (Okazaki 2009). Indeed, the impacts of social factors are large, particularly in which the diffusion of innovative technologies relies on network effect or the size of the user base. Since the social influence can reinforce an individual's resistance in either a positive or negative way, the perceived risk and uncertainty inherent in an innovation can be increased or decreased by the social influence (Schierz et al. 2010). Although it is generally known that older people are relatively unfavorable with new technologies compared to younger people (Karim and Oyefolahan 2009; Kumar and Lim 2008a), it is still unclear how the social influences on user resistance varies across the user's age. The impact of social influences, which varies by age, should be empirically examined.

Hence, we proposed a research model that includes (1) the relationships between the technological attributes of an innovation such as relative advantage, compatibility, complexity, and user resistance, (2) the relationship between social influence and user resistance, and (3) the relationship between user resistance and adoption intention. In particular, the social influences are divided into two different types: normative social influence and informational social influence, according to Deutsch and Gerard (1995) (Deutsch and Gerard 1955). To examine the model empirically, we collected data from 250 non-adopters of smartphones in Korea. The partial least square method was used to analyze the research model using SmartPLS 2.0.

As a result, innovative attributes of a technology such as the perceived relative advantage and ease of use (complexity) reduce the user resistance while the compatibility has no direct effect on either user resistance or intention to use smartphones. However, both normative and informational social influences affect the level of user resistance. In respect to age, the impact of user resistance on the decision to adopt was greater in those older than in those younger. In addition, the impacts of social influences on the user resistance in those older were greater than those younger. However, the impacts of technological attributes were not significantly different by age.

This paper consists of the following sections: We briefly review related studies on smartphones, innovation, user resistance, and social influence in the next section. Then, we suggest hypotheses and build a research model. In the following section, we explain the methodology for data collection and the development of instruments, and then present the results of analysis. Finally, we discuss the theoretical and practical implications, as well as limitations of this study, and suggest some issues for further study.

THEORETICAL BASIS AND RESEARCH MODEL

Smartphone Adoption

The smartphone is an innovative mobile device with multiple functions enabling various tasks including telephoning, instant messaging, internet browsing, watching video clips and real-time broadcasts, listening to music, taking pictures, mobile gaming, and banking (Oulasvirta et al. 2012). As an innovative product, the smartphone has inherent uncertainties due to the immature technology and the lack of information on the actual performance. The technological uncertainty and risks involved in purchasing the smartphones make people hesitate to adopt it (Kim and Kankanhalli 2009; Rogers 1995). According to Rogers's Diffusion of Innovation Theory (DIT), the personal perception of the innovation attributes of a technology determined the adoption. These innovation attributes include relative advantages, compatibility, complexity, trialability, and observability. Among these innovation attributes, relative advantage, ease of use (complexity), and compatibility were found to be the most frequently identified factors for adopting and diffusing technologies (Liao et al. 1999; Szmigin 1998). The relative advantage refers to the individual's perception of performance or usefulness offered by an innovation. Compatibility is defined as the degree to which an innovation is perceived as consistent with existing values, habits, and past experiences of the potential adopter. Also, complexity means the degree to which the smartphone is perceived as relatively difficult to understand and use (Rogers 1995) . While the three technological attributes of an innovation, including relative advantage, complexity, and compatibility, are relatively more influential in the pre-adoption stage, the impacts of trialability and observability are more easily revealed in the post-adoption stage of an innovation (Rogers 1995). Users can perceive the trialability and observability as the innovation is diffused more widely through the market. As more manufacturers sell similar smartphones and more people adopt them, the possibility to test the innovation (trialability) and to observe how people use it (observability) also increases.

The smartphone is an innovative artifact that is designed to offer a faster and more convenient way to communicate with others and connect to the web with advanced multi-functionalities and user interface (Oulasvirta et al. 2012). However, the technological advancements of smartphones contain both advantages and disadvantages. While smartphones are equipped with useful new functionalities and a convenient user interface, smartphones can also make users feel uncomfortable or irritated. For example, users often complain about the small screen and unfamiliar touch-screen based user interface, short battery lifetime, relatively low speed for internet connection and computing power and frequent software(applications) updates of smartphones. These dissatisfactory factors increase resistance to the innovation because of the unfamiliarity and incompatibility. Therefore, the usefulness and complexity of using a smartphone may be perceived differently based on how compatible the potential user sees it to be. Chau and Hu (2001) mentioned that the extent of perceived compatibility negatively affects the perception of complexity (opposite of ease of use). Also, the effect of compatibility was positively associated with the perceived relative advantages (perceived usefulness) about an innovation (Chau and Hu 2001). Likewise, previous studies have investigated compatibility, resulting in support for its impact on the relative advantages and complexity (Huang and Hsieh 2012; Schierz et al. 2010). Based on previous research, the following hypotheses were proposed:

H1: Perceived compatibility of the smartphone will increase its perceived relative advantage.
H2: Perceived compatibility of the smartphone has a negative effect on its perceived complexity.

With respect to perceived innovation attributes, previous research suggests that intention to use is increased by higher relative advantages and compatibility and lower complexity (Chau and Hu 2001; Huang and Hsieh 2012; Kim et al. 2010; Yu 2012). Based on the previous studies, the following hypotheses were proposed:

H3: Perceived compatibility will increase intention to adopt smartphone.
H4: Perceived relative advantage will increase intention to adopt smartphone.
H5: Perceived complexity will decrease intention to adopt smartphone.

User Resistance and Innovation Adoption

While the innovation adoption theory such as Diffusion of Innovation Theory (DIT) (Rogers 1995) and Technology Acceptance Model (TAM) have found the underlying factors influencing the adoption of an innovation (V Venkatesh and Davis 2000; Viswanath Venkatesh et al. 2003), there is a lack of empirical studies showing how the individual's perceptions on technological attributes are associated with user resistance and adoption decision. Although it can be presumed that linear relations exist between these attributes, no empirical studies have attempted to examine the significance of the relationships in the context of smartphone adoption.

In the real world, not all innovations are accepted by customers. Contrary to expectation, many new technologies or services have disappeared immediately upon release to the market. Also, in some cases, they might be substituted by another new technology or service (Moore and Benbasat 1991). For instance, in the case of the mobile communications industry, despite 3G service having been launched more than 10 years ago, there are still many non-users of the service. With regards to this non-adoption, Ram and Sheth (1989) claimed that there must be more attention paid to the users' resistance, which is the result of a natural response to the customers' adoption process. According to Ram, user resistance is defined as "the resistance offered by consumers to an innovation, either because it poses potential from a satisfactory status quo or because it conflicts with their belief structure." More importantly, user resistance is not the same as non-adoption of innovation. Kuisma et al. (2007) argued that user resistance needs to be understood as another factor of the decision process rather than a determinant that necessarily leads users to non-adoption. When users are uncertain about likely outcomes of the innovation acceptance, when combined with an existence of physical and economical inherent risk, the user resistance becomes prominent (Featherman 2003; Ram 1987a; Schierz et al. 2010).

Previous studies on user resistance to new information technology have centered their studies on the mandatory implementation of new systems in organizations (Hirschheim and Newman 1988; Kim and Kankanhalli 2009; Ram and Jung 1991). The user resistance has also been conceptualized as rejection, postponement, and opposition (Laukkanen et al. 2008; Szmigin 1998). Previous research indicates that the user resistance to change is a multifaceted concept that includes the user's affection, cognition, and behavior (Kim and Kankanhalli 2009; Knowles and Linn 2004; Piderit 2000). Knowles and Lin (2004) identified three components to resistance as affective (favorance), cognitive (beliefs), and behavioral (intention or action). Recently, several studies have attempted to investigate the impact of user resistance to the adoption of new information systems and services: user resistance towards 4G wireless network services (Kang and Kim 2009), mobile banking (Laukkanen and Cruz 2009), mobile payment (Kim et al. 2010; Schierz et al. 2010), mobile data service (Sanford and Oh 2010), and e-book devices (Huang and Hsieh 2012).

Despite the importance of user resistance for innovation adoption and diffusion, few academic endeavors have attempted to unveil the black box of user resistance (Lapointe and Rivard 2005). Ram (1987) insisted that in his innovation resistance model, the determinants of a consumer's innovation resistance are affected by perceived innovation attributes (Ram 1987b). He argued relative advantages and compatibility as important perceived characteristics in reducing resistance. A recent study by Ooi and Tan (2016) assumed that perceived compatibility is an important prerequisite for the acceptance of NFC-enabled smartphone credit card systems. Another study on the acceptability of Telehealthcare in older adults has shown that not only functional advantages but also life-style compatibility and observability in the surrounding area are important for daily use of the system (Frennert et al., 2013). On the other hand, he claimed that the perceived complexity of innovation can increase the resistance. A research studied students' resistance to mandatory use of learning management systems, confirming that perceived ease of use had an impact on actual performance (Strang and Vajjahala, 2019). According to numerous studies, perceived innovation attributes such as relative advantage, compatibility, and complexity significantly influence not only innovation adoption, but also user resistance (Huang and Hsieh 2012; Schierz et al. 2010). Based on the previous studies, the following hypotheses were proposed:

H6: Perceived compatibility will decrease user resistance to smartphone adoption.
H7: Perceived relative advantages will decrease user resistance to smartphone adoption.
H8: Perceived complexity will decrease user resistance to smartphone adoption.

Many studies have proved the negative relationship between user resistance and intent to use new technologies (Kleijnen et al. 2009; Kuisma et al. 2007; Laukkanen and Cruz 2009; Sanford and Oh 2010; Szmigin 1998). Although the smartphone is an innovative product that has greatly altered our lifestyles in a short time, the users' resistance to innovation and unwillingness to change standard lifestyle could negatively affect its adoption. Thus, we suggest the following hypothesis:

H9: User resistance will decrease intention to adopt smartphone.

Role of Social influences

The matter of how the social influences of the referent group or individuals affect the adoption of innovation has been an important theme for a long time in technology adoption research (Viswanath Venkatesh and Davis 2000; Viswanath Venkatesh et al. 2003). Potential users estimate the usefulness of an innovation based on their prior experience with similar products and information from reliable sources, including those considered important (Lee et al. 2003). The social influence from the referent people is an important antecedent of new technology/service adoption intention (Okazaki 2009; Schierz et al. 2010).

According to Deutsch and Gerard (1995), the social influences can be classified into two: normative influence and informational influence (Burnkrant and Cousineau 1975; Deutsch and Gerard 1955; Kaplan and Miller 1987). Normative influence is compliance to pressure by a social group, and this influence can occur when an individual desires to fulfill the respective expectation in the reference group in which the person holds strong ties. It can also trigger an adoption intention, regardless of individual will or belief (Fishbein and Ajzen 1975).

In IS research fields, the origin of study of normative influence can be found in the subjective norm of Fishbein's Theory of Reasoned Action (TRA) (Fishbein and Ajzen 1975). The subjective norm as a salient determinant of individual's behavioral intention can be expressed as a total set of a person's normative beliefs. Subjective norm is generally defined as the perceived social pressure to perform or not to perform a behavior (Liao et al. 2007). Recent studies on the adoption of new media and mobile service reveal that the perceived normative social influence has a very high influence on behavioral intention (Hau and Kim 2011; Sanford and Oh 2010; Schierz et al. 2010). Abdulfattah (2019) considered social influence as a critical influencer along with various technical, environmental, psychological, and personal factors related to the introduction of mobile cloud computing (Abdulfattah, 2019). This is because new media and mobile phones are fundamentally devised to communicate with others and are vulnerable to the network effect under which the volume of users is a key determinant of total utility (Gorbacheva et al. 2011). That is, if one's peers make use of innovation, even if one does not personally need it, the person probably feels a psychological burden or obligation to conform (Liao et al. 2007). Hence, if an individual perceives using a smartphone as a socially desirable act, the individual will prefer to adopt it. Thus, we suggest the following hypothesis:

H10: Normative social influence positively affects a user's intention to adopt smartphone.

On the other hand, the normative social influence can increase the user resistance when an individual feels certain psychological burden or pressure to comply with the normative values of a society. The psychological burden or implicit and explicit pressure from a subjective norm often conflict with the user's free will to choose alternative behaviors, which in turn, raises psychological or behavioral resistance (Burnkrant and Cousineau 1975).

For example, if a person who does not normally feel the need to have a smartphone were to feel social pressure to accept the smartphone and feel compelled to comply with this pressure against their perceived norm, this will increase adoption intention via normative influence, but also simultaneously raises the user's internal resistance.

If people are supposed to comply with perceived social norms, their intention for adopting a smartphone can be enhanced due to the normative influence. However, the fact that their intention is not related to the individual's freewill can increase psychological burden. As a result, the following hypothesis is proposed:

H11: Normative social influence can increase the user's resistance to smartphone adoption.

In the case of informational influence, in order to resolve people's uncertainty towards innovations, the choices of others were observed and compared in order to determine the reasonableness of one's own choice (Burnkrant and Cousineau 1975). Informational social influence is referred to the degree to which the individual accepts and applies the information from others as evidence about reality (Deutsch and Gerard 1955). An individual's judgment is affected by factual information or signals generated by social groups (Kaplan and Miller 1987). The informational influence reveals the potential risks involved in a new product and reduces the product's uncertainty. The reduced risk decreases user resistance, thus making it more possible to adopt the innovation. Once a consumer adopts an innovation, he or she uses external information to confirm his/her decision. According to a study, groups with strong ties tend to share knowledge and information and firmly believe in the truth of both (Garton et al. 1997).

Informational social influence is related to the perceived volume of the adopters. A greater number of people accepting an innovation indicates that the innovation is acceptable despite the inherent uncertainty and risks. People obtain information by observing others evaluating the product's favorability, the state of diffusion of the product, and sharing information with others. People use this explicit and implicit information as a basis for inferring that the innovation is, indeed, a better and reliable product (Burnkrant and Cousineau 1975). Consumers tend to compare one's actions to that of others in order to evaluate the reasonableness of one's consumption. Especially, in the occasion of accepting convergent products like a smartphone, selecting products with mere nominal information is hard. Accordingly, the effect brought by the individual's reference group is remarkable in this case.

In the case of smartphone use, user resistance could be reduced by sharing the advantages of the functionalities, performance, or usability of the smartphone compared to alternatives. Positive experiences and evaluations from others enhance one's motivation to use a smartphone. Hence, we developed the following hypotheses:

H12: Informational social influence increases the user's intention to adopt a smartphone.
H13: Informational social influence decreases the user's resistance to adopt a smartphone.

Moderating Effect of Age

Age was considered as an important personal trait in previous innovation adoption studies. Many research studies demonstrated that younger people are more likely to adopt new information technologies compared to older people (Viswanath Venkatesh et al. 2003)(Ansari et al. 2012; Bruner and Kumar 2005; Karim and Oyefolahan 2009; Kim et al. 2010; Kumar and Lim 2008a; Laukkanen et al. 2007; Schierz et al. 2010). User's age plays an important role in the explanation of variability in innovation acceptance and performance. For example, the perceived usefulness of a technology is lower in older adults because they weigh the perceived usefulness against the time to learn how to operate the system.

Older adults often think they are too old to learn a new technology and have low self-efficacy in its use (Arning and Ziefle 2007). Previous studies have found a positive relationship between age and perceived difficulty of learning a new software application (Viswanath Venkatesh et al. 2003). There is also ample evidence that older adults have a higher level of computer anxiety than their younger counterparts (Chaffin and Harlow 2005). A higher level of computer anxiety is also associated with greater reluctance to engage in opportunities to learn new internet skills (Chung et al. 2010).

With respect to age differences in perceptions of online communities, Chung et al. (2010) found that age was negatively associated with internet self-efficacy, perceived quality of online community sites, perceived usefulness, and behavioral intention. They argued that the negative associations between age and perception of the usefulness of online communities, as well as behavioral intention, indicate that significant generational gaps still exist despite the rapid growth in internet use among older adults. Furthermore, the negative associations between age and internet self-efficacy, as well as perceived quality of online community sties, suggest that older adults still experience difficulties in fully enjoying internet applications because of their lack of confidence or the poor quality of the sites they visit.

Karim and Oyefolahan (2009) found similar results in a study. They discovered that the older users' primary purpose of mobile phones is family contact that is highly communications-oriented. However, young people use mobile phones for a variety of reasons such as listening to music, watching multimedia, gaming, instant messaging, and shopping, which is highly experience-centric. While the utilitarian performance, like call quality, is relatively easily measured and assured, the hedonic values that are attainable by direct experience is hardly predictable and recognized. This is in line with previous findings that indicate that a high level of computer anxiety is a key factor in older adults' reluctance to use computers. Thus, the unpredictability of and uncertainty regarding the hedonic values of smartphones make older people hesitate to adopt it.

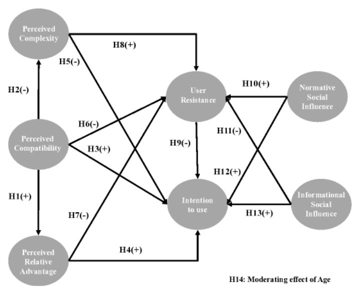
Furthermore, older people have a tendency to maintain their status quo, so they are unwilling to change from their current state to another, even though the alternative shows a superior performance and offers better benefits (Ansari et al. 2012; Karim and Oyefolahan 2009). Also, the older users who have a relatively long usage period with their current solution are likely to perceive a higher switching cost, including financial, relational, and procedural costs (Featherman 2003; Huang and Hsieh 2012; Kim and Perera 2008). In general, older people tend to have a conservative attitude towards their value systems, which has been accumulating throughout their lives. They feel comfortable when they follow the normative values of a social group while young people are relatively active in searching for information and are particularly sensitive to information about recent trends in new technologies in (Laukkanen et al. 2007). This is why the innovators and early adopters are usually young people who are risk-takers, innovative, and curious to use new technology while the older people are likely to stay behind with innovation adoption.

On the other hand, the users' behavioral intention is affected by not only the normative values of a society, but also the information itself offered by referents and others in a society. Prior studies found that older people are more strongly attached to the information provided by others considered important such as family, friends, and colleagues (Kim and Kankanhalli 2009) because they believe the information from these people is more credible. Thus, the informational social influence would have a greater effect on the resistance and behavioral intention of older people rather than on those of younger people. Therefore, we assume that age has a moderating effect on the social influences, users' resistance, and adoption intention.

Previous studies indicate that age has a moderating effect on the levels of individual perception on the innovative attributes of emerging technologies, as well as user resistance and adoption intention (Kumar and Lim 2008b; V Venkatesh et al. 2003; Venkatesh et al. 2012). Furthermore, the impact of social influence on user resistance will be more strongly found in the older group than in the younger group. Thus, we suggest there is a moderating effect of age on the user resistance and decision to adopt a smartphone.

H14: The effect of each path in the research model will be different for older adults than younger adults.

Figure 1. Conceptual research model



RESEARH METHODOLOGY

Data Collection

In order to collect data for testing the hypotheses, we conducted an online survey with a professional survey agency which has the largest panel numbers in Korea. We surveyed mobile phone users aged between 12 and 59 using stratified sampling and assigning fixed portions of samples based on age and gender distribution. We extracted the demographic information of the Korean mobile phone users from a report published by the Korea Internet & Security Agency. The respondents were offered an incentive such as an online gift coupon of about $2. The online survey continued for one week, and a total of 270 valid samples were collected.

Measurements

All measurement items were selected from previous studies but adapted to this study context. All questionnaires were developed with a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). Table 1 shows the constructs and measurement items with their sources. Our research model consists of seven latent variables in four categories and one moderating variable: (1) perceived innovation attributes (relative advantage, complexity, and compatibility), (2) user resistance, (3) social influences (normative and informational social influence), (4) intention to use while age was the moderating variable.

First, perceived innovation attributes consists of three constructs: perceived compatibility, perceived relative advantages, and perceived complexity. The definitions of the variables were employed by Rogers (1995) and measurement scales were adopted from Moore and Benbasat (1991). Second, in this study, we defined user resistance as the "user's negative cognition and affection, and opposition to smartphone use", which was operationally based from reviewing previous studies. Its measurement was conducted by four items employed by Cho and Chang (2008) and Kim and Kankanhalli (2009). Third, as one aspect of social influences, the normative social influence is defined by subjective norms mentioned in the Theory of Planned Behavior (TPB) (Viswanath Venkatesh et al. 2003) and measured with two items used in previous studies by Venkatesh et al. (2003) and Taylor and Todd (1995). This study defined another effect of social influences, informational social influence, as the degree to which users perceive the acceptance volume of the smartphone by their important others such as colleagues and friends. Its measurement was employed by three items modified from Lu et al. (2010) and Levin and Cross (2004). Finally, the users' intention to adopt was measured using three items suggested by Davis (1989) and Venkatesh et al. (2012)). To investigate the moderating effect of age, we divided the samples into two groups for age (Mean=35.7, S.D=12.42). The respondents whose age was less than the median scores (35 years old) were defined as the young aged group (Mean=24.92, SD=6.09, Min=14, Max=34), while the others were defined as the old aged group (Mean=46.32, SD=6.47, Min=35, Max=58). Table 1 shows the operational definition of the constructs and measurement items used in this study.

RESULTS

Data were analyzed by Partial Least Squares (PLS), one of the structural equations modeling (SEM) technique. PLS is known as an appropriate approach for complex causal relationships with many constructs. It also requires relatively weak constraints in terms of sample size and residual distributions (Gefen and Straub 2005; Hair et al. 2011) To test for path significance (β), we used bootstrapping with 500 resamples for 270 cases. Statistic tools smart-PLS 2.0 and SPSS 18.0 were used.

Sample Characteristics

Among all the respondents (N=270), 51.1% were male and 48.9% were female. The average age was 35.7. There were 134 people from the young aged group (49.4%) and 136 from the old aged group (50.4%) who responded. Most of the respondents were in their 30s (24.1%). More than 65% of the respondents held advanced degrees including postgraduate studies, and 21.5% of them had a monthly household income between $2,000 and $3,000. Table 2 summarizes the social demographic statistics of the respondents.

Results of Measurement Model Analysis

Prior to hypotheses assessment, the reliability and validity of our measurement model were conducted. First, the reliability verification of each construct used Cronbach's alpha and the composite reliability (CR). Cronbach's alpha and composite reliability are widely used for testing internal consistency reliability of measurement items. Cronbach's alpha represents the expected correlation of the item and the construct. It assumes that items are equally related to the construct. However, Composite reliability assumes the factor loadings of each item can be different. Thus, CR is a less biased estimate of reliability than Cronbach's Alpha. It is viewed as an indicator of the shared variance among the observed variables used as an indicator of a latent construct. The acceptable level of Cronbach's alpha is 0.7, and 0.8 or greater is preferred. The acceptable value of CR is 0.7 and above (Fornell and Larcker 1981). As shown in Table 3, all constructs satisfied these criteria.

For the convergent validity, if each construct has an Average Variance Extract (AVE) of at least 0.5, the convergent validity is satisfactory. As shown in Table 3, the AVE scores of all nine constructs exceeded 0.5. For evaluating the discriminant validity of the measurement model, the square root of the AVE of each construct and cross-loadings of each latent variable were used. The square root of each construct's AVE should be greater than its correlations between the construct and each of the other constructs, and the item loadings belonging to a factor should be higher than the correlations

Table 1. Operational definition and measurement items of each construct

Construct	Measurement Items	References
Perceived Relative Advantages	Def.:The degree to which a user perceives that using a smartphone results in more benefits than its precursor(feature phone) does. PRA1: Smartphones are more useful than feature phones. PRA2: Smartphones are more convenient than feature phones. PRA3: Smartphones are more effective than feature phones.	Rogers (1995) Moore and Benbast (1991)
Perceived Complexity	Def.: The degree to which the smartphone is difficult to use and understand. PCPLX1: It is difficult to understand how smartphones work. PCPLX2: Learning how to use a smartphone is difficult for me. PCPLX3: It is not easy to operate a smartphone.	Moore and Benbast (1991)
Perceived Compatibility	Def.: The degree to which the smartphone is perceived as consistent with existing values, habits, and past experiences of the potential adopter. PCOM1: Using a smartphone is compatible with all aspects of my work. PCOM2: Adopting a smartphone fits well with the way I like to manage my ICT device. PCOM3: Using a smartphone is compatible with my lifestyle.	Moore and Benbast (1991)
User Resistance	Def.: User's negative cognition and affection and opposition to smartphone use. UR1: I have critical thoughts about using a smartphone. UR2: I refuse to use a smartphone. UR3: I oppose using a smartphone. UR4: I am discontent with using a smartphone.	Cho and Chang (2008) Kim and Kankanhalli (2009)
Intention to Use	Def.: User's intention to use a smartphone. INT1: I will intend to use a smartphone as soon as possible. INT2: I plan to adopt a smartphone in the future. INT3: I will strongly recommend others to use a smartphone.	Davis (1989) Venkatesh et al. (2012)
Normative Social Influence	Def.: The degree to which users perceive that most people who are important to him or her think he or she should or should not perform the behavior in question. NSI1: People who influence my behavior think that I should use a smartphone. NSI2: People who are important to me think I should use a smartphone.	Venkatesh e al. (2003) Taylor and Tood (1995)
Informational Social Influence	Def.: The degree to which users perceive acceptance volume of the smartphone by their important others such as colleagues and friends. ISI1: My family or friends use a smartphone. ISI2: People who are important to me use a smartphone. ISI3: My colleagues use a smartphone.	Bansal and Voyer (2000) Levin and Cross (2004) Lu et al. (2010)

between the construct and other items (Gefen and Straub 2005) (see the Appendix). As shown in Table 3, the results support the discriminant validity of this measurement model.

Results of Hypothesis Testing

Figure 2 and Table 4 present the results of the hypotheses proposed in this study. As shown in Figure 2, nine of 13 paths were supported at a 5% significant level.

First, the hypothesized relationships from perceived compatibility (PCOM) to perceived relative advantage (PRA) and perceived complexity (PCPLX) were supported. The coefficients of paths from PCOM to PRA and PCPLX were .454($p<.001$) and -.396($p<.001$), respectively. Thus, H1 and H2 cannot be rejected.

Second, H3 to H5 focused on the relationships between perceived innovation attributes (PIA) and intention to adopt (INT). No significant relationships between PCOM and INT and PCPLX and INT

Table 2. Demographic statistics of the respondents

	Overall (N=270)	Young Aged (N=134)	Old Aged (N=136)
Gender			
Male	138(51.1%)	65(48.5%)	73(53.7%)
Female	132(48.9%)	69(51.5%)	63(46.3%)
Age			
12-19	41(15.2%)	41(30.6%)	-
20-29	58(21.5%)	58(43.3%)	-
30-39	65(24.1%)	35(26.1%)	30(22.1%)
40-49	63(23.3%)	-	63(46.3%)
50-59	43(15.9%)	-	43(31.6%)
Education			
Less than High School	94(34.8%)	40(37.3%)	44(32.4%)
Bachelor's degree	155(57.4%)	75(56.0%)	80(59.8%)
Higher than Bachelor's degree	21(7.8%)	9(6.7%)	12(8.8%)
Monthly Income			
Less than $1K	68(25.2%)	54(40.3%)	14(10.3%)
$1K - $2K	57(21.1%)	37(27.6%)	20(14.7%)
$2K - $3K	70(25.9%)	30(22.4%)	40(29.4%)
$3K - $4K	39(14.4%)	9(6.7%)	30(22.1%)
More than $4K	36(13.3%)	4(3.0%)	32(23.5%)

were found. Thus, H3 and H5 were not supported. However, the user's intention was significantly influenced by PRA ($b = .233$, $p < .001$). This result supports H4.

The results of hypotheses corresponding to user resistance are as follows. First, H6 to H8 hypothesized causal linkages between PIA (PRA, PCPLX, and PCOM) and UR. The negative effect of the perceived relative advantage on user resistance was significant ($b=-.358$, $p < .001$). Also, perceived complexity had a positive relationship with user resistance ($b=.119$, $p < .05$). Therefore, H7 and H8 were supported. However, contrary to our expectations, the negative path from perceived compatibility to user resistance was not significant. Hence, H6 was rejected.

Finally, the results of hypotheses related to two types of social influence were as follows. H10 and H11 hypothesized the effects of two kinds of social influence on user resistance. H10, which posits that normative social influence enhances user resistance, was significant ($b=.209$ $p<.001$) Also, we confirmed H11, which claims that informational social influence resolves user resistance, cannot be rejected ($b = -.157$, $p<.01$).

H12 and H13 concerned casual paths from social influences to adoption intention. The results showed that normative social influence has a significantly strong effect on adoption ($b=.362$, $p<.001$). Thus, H12 was supported. However, the direct effect from informational social influence to adoption intention was insignificant. Hence, H13 was not supported.

Comparison of Aged Groups

The moderating role of age in the smartphone adoption process was demonstrated. Moderating effects were tested by comparing the path coefficients between the two groups produced for age. T-values for comparing path coefficients were calculated using the equation suggested by Chin et al. (2003) (Chin, Marcolin, and Newsted 2003). Table 4 shows the results of the path coefficient comparisons.

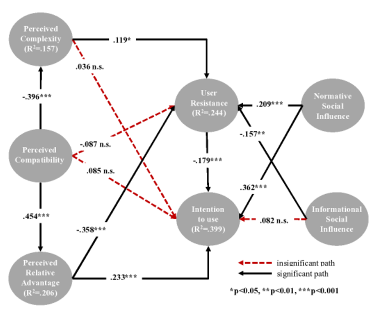
According to age, some significant differences between the young and old aged groups were found. UR is a more important factor among older than younger people in their hesitation using a smartphone. The results indicate that the user resistance negatively affects the adoption intention ($b=.228$, $p<0.05$) in the old aged group. However, this was not significant in the young aged group.

Table 3. Discriminant Validity Test

Construct	Mean	S.D.	Cronbach's α	C.R.	AVE	Correlations						
						(1)	(2)	(3)	(4)	(5)	(6)	(7)
Overall												
(1)PCPLX	4.06	1.27	.899	.937	.832	**.912**						
(2)PCOM	4.57	.93	.819	.892	.733	-.396	**.856**					
(3)PRA	5.41	.95	.877	.924	.803	-.152	.454	**.896**				
(4)UR	2.78	1.15	.929	.950	.825	.221	-.303	-.412	**.908**			
(5)INT	4.96	1.30	.931	.956	.879	-.058	.330	.465	-.303	**.937**		
(6)NSI	4.00	1.47	.962	.982	.964	.047	.202	.269	.015	.485	**.982**	
(7)ISI	4.81	1.17	.879	.925	.804	-.026	.315	.341	-.196	.419	.545	**.897**
Young												
(1)PCPLX	3.92	1.35	.887	.929	.813	**.902**						
(2)PCOM	4.69	1.02	.833	.900	.751	-.408	**.867**					
(3)PRA	5.44	.98	.880	.925	.805	-.216	.455	**.897**				
(4)UR	2.59	1.12	.926	.948	.819	.215	-.318	-.487	**.905**			
(5)INT	4.95	1.31	.911	.944	.849	-.073	.339	.427	-.246	**.922**		
(6)NSI	3.93	1.55	.950	.975	.952	.072	.220	.112	.031	.443	**.976**	
(7)ISI	5.31	1.28	.874	.922	.798	-.012	.359	.215	-.136	.354	.428	**.893**
Old												
(1)PCPLX	4.19	1.18	.913	.945	.852	**.923**						
(2)PCOM	4.46	.87	.794	.878	.706	-.372	**.840**					
(3)PRA	5.36	.92	.875	.923	.800	-.074	.455	**.894**				
(4)UR	2.98	1.14	.931	.950	.827	.210	-.259	-.349	**.909**			
(5)INT	4.95	1.29	.953	.969	.913	-.046	.329	.521	-.379	**.956**		
(6)NSI	4.06	1.39	.978	.989	.978	.007	.197	.458	-.021	.534	**.989**	
(7)ISI	4.94	1.22	.885	.928	.812	-.022	.253	.489	-.249	.495	.695	**.901**

Note: PCPLX: Perceived Complexity; PCOM: Perceived Compatibility; PRA: Perceived Relative Advantages; INT: Intention to Use; UR: User Resistance; NSI: Normative Social Influence; ISI: Informational Social Influence

Figure 2. PLS results for research model



In the paths from NSI and ISI to UR, the coefficient from older people was significantly stronger than those from younger people. Interestingly, the normative social influence significantly increased user resistance, but the impact was greater in the old age group. Similarly, the informational social influence contributed in reducing the user resistance (b=-.329, $p<0.05$) while the effect was not significant in the young aged group. However, there were no significant differences in the effect of perceived innovation attributes (relative advantage, complexity, compatibility) on either the user resistance and adoption intention. As a result, we confirm that user resistance and the adoption decision of old aged people were more strongly affected by social influences both in negative and positive ways. Young people also have more concerns regarding the technological attributes of the smartphone and they take into account the normative value of a society in the adoption process.

DISCUSSION

Theoretical Implications

First, the results of this study show that user resistance mediates the perceived innovation attributes and social influences on the adoption intention of the smartphone and exercises a significant negative influence upon it. Among the technological attributes of the smartphone, the perceived relative advantage is the most crucial in that it directly affects adoption intention and directly affects it by lowering user resistance. Perceived complexity is only significant in the reinforcement of user resistance. However, unlike our expectation, the perceived compatibility was not significant in this study. This implies that the compatibility issue of smartphone is not a concern. The smartphone is a convergent product that inherits the previous mobile phone and personal computers, so it supports cultural and technological compatibilities. Such results clearly suggest a need for the theoretical expansion of user resistance in the field of conventional technology acceptance theories.

Second, social influence has a meaningful effect upon user resistance and adoption intention. In the case of informational social influence, although it has no direct positive relationship with adoption intention, through reducing user resistance, it indirectly facilitates the growth of positive adoption intention. On the other hand, normative social influence has shown the greatest impact in raising users' adoption intention. This confirms that the smartphone, in essence, is a social medium for communications and information acquisition. Therefore, the impact of social influence should be carefully examined, particularly in studies on the adoption of communication-oriented or socially interconnected technologies.

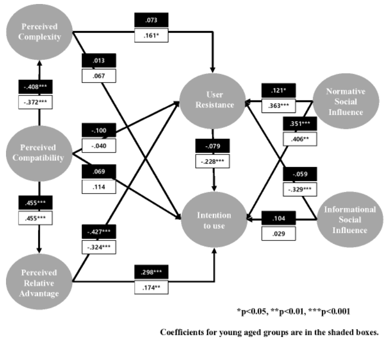
Table 4. Moderating effect of age

Path		Age		T-Value (Chin's Test)
		Young	Old	
PCOM → PRA	H1(+)	.455***	.455***	.001
PCOM → PCPLX	H2(-)	-.408***	-.372***	-.307
PCOM → INT	H3(+)	.069	.114	-.327
PRA → INT	H4(+)	.298***	.174**	1.155
PCPLX → INT	H5(+)	.013	.067	-.460
PCOM → UR	H6(-)	-.100	-.040	-.448
PRA → UR	H7(-)	-.427***	-.324***	-.975
PCPLX → UR	H8(+)	.073	.161*	-.737
UR → INT	H9(-)	**-.079**	**-.228*** **	**2.378** **
NSI → UR	H10(+)	**.121***	**.363*** **	**-2.064** **
ISI → UR	H11(-)	**-.059**	**-.329*** **	**2.350** **
NSI → INT	H12(+)	.351***	.406***	-.478
ISI → INT	H13(+)	.104	.029	.667

Note: PCOM: Perceived Compatibility; PRA: Perceived Relative Advantages; PCPLX: Perceived Complexity; INT: Intention to Use; UR: User Resistance; NSI: Normative Social Influence; ISI: Informational Social Influence

* p<.05, **p<.01, ***p<.001

Figure 3. PLS results for research model for the young and old aged group



Third, the current study demonstrates the significant moderating effect of age. The results highlight that the younger group is more sensitive to the technological attributes of innovation rather than social influences. The user resistance in the young group does not affect adoption intention, though it is significantly affected by the normative social influence. On the contrary, the user resistance of the older group plays a significant role in the adoption decision while the perception of the innovative attributes of technologies is equally important in reducing user resistance and increasing adoption intention. Furthermore, the role of both normative social influence and informational social influence was significant on user resistance formation process, particularly in the older group. This implies that the likelihood of older people adopting an innovation can be greatly increased by reducing user resistance and exposing them to positive information offered by the close referent group.

Practical Implications

First of all, the results suggest that manufacturers should focus on developing the relative advantages of the smartphone. The relative advantage includes some novel features that provide better productivity and utilities to users and are distinguished from previous models. The endeavors to improve ease of use and design more fitted to the users' lifestyle are important, but the investment in developing the relative advantages of the new model should precede other R&D activities.

Second, this study provides some strategic insights for practitioners to take advantage of social influence. In the early stage of innovation diffusion, the informational social influence does not effectively promote the adoption and reduction of user resistance. Instead, the normative social influence plays a critical role. However, it must be considered that the normative social influence has dual effects. The supportive opinions from the important others of non-adopters apparently have a positive effect on the adoption intention. However, the non-adopters can feel a psychological burden simultaneously because of the inclination to follow the suggestions of referent people. Thus, manufacturers need to make additional efforts to eliminate the psychological burden. The literature suggests that the information that supports one's decision can reduce cognitive dissonance or regret after decision. Thus, it is recommended for practitioners to provide additional information that helps assure the potential adopters of their decision and lowers the perceived risks of the innovation.

Finally, the practitioners should bear in mind that the impact of social influence differs by the age of non-adopters. This study manifests that young people are more innovative and less resistant to adopting a smartphone. They focus more on technological attributes than depending on information from others. However, they respect social norms and consider them in their adoption decision. Thus, it is recommended to focus on young people as the initial target customers and let them fully experience the advantages of the smartphone while helping them transition to the smartphone. This approach is effective in that young customers can act as advocators to disseminate positive information to their family, friends, and people in their social networks.

Limitations and Further Studies

The limitations of this study are as follows. First, this study focused on the influence user resistance has upon adoption intention, and the effect of two types of social influence has upon these two. Therefore, a simplified model of the antecedents to user resistance was implemented. Further studies will require an expanded model that takes into account the switching cost or perceived risks, which are known factors in the formation of user resistance.

Second, the study was conducted when smartphone proliferation in Korea had reached only 15 percent. The situation at the time of study may have significant differences with the current smartphone market that has passed the proliferation stage and reached full-fledged growth. However, there is still thirty percent of non-adopters as of 2014. Moreover, the manufacturers have been competing in launching new models with renewed design and advanced features. Thus, the theoretical implications and practical insights from this study are useful and valid to understand the adoptive process of those non-adopters of new smartphones. According to Rogers (1995), these people are considered as the late majority and laggards. Empirical studies for this group of people in the proliferation stage of smartphones might provide interesting results on the effect of perceived information attributes as well as the normative and information social influences on reducing user resistance and adoption intention.

Accordingly, there must be more longitudinal studies exploring perceived innovation attributes in accordance with the smartphone diffusion level, user resistance, and the role of social influence.

Finally, the current study is understood to reflect the strong social cohesion of Korea's cultural characteristics, and thus it would be a strain to reach a generalization based on it. Recent studies have pointed out that factors and their relative strength on technology acceptance may vary according to cultural backgrounds. Thus, if future studies take heed of this and integrate comparison with Western cultures, a clearer understanding of user resistance formation and relief, and the effect it has upon adoption intention, is likely.

CONCLUSION

Overcoming user resistance in the pre-adoption stage of smartphones is crucial for its initial adoption or its later diffusion. However, there have been few studies on user resistance, particularly in which the adoption decision is made in a voluntary manner. Thus, this study has tried to provide empirical evidence of the significant role of user resistance, which can be reduced by understanding the relationships between the user resistance and other primary factors associated with the adoption decision of non-adopters. In this study, we focused on the role of perceived innovation attributes such as perceived relative advantage, complexity, and compatibility, as well as the role of – normative and informational social influences. Moreover, the two different constructs related to social influence have not been empirically examined in previous studies.

The results of the empirical study provide some interesting theoretical and practical insights. Theoretically, we confirm that the user resistance plays a significant role as an inhibitor on smartphone adoption. However, the results of the moderating effect of age indicate that user resistance cannot be a serious concern for young non-adopters. Rather, it strongly prevents the older non-adopters from adopting the smartphone. Additionally, the results suggest that the user resistance can be theoretically decreased by enhancing technological features that enhance the user's productivity. Finally, the user resistance can be increased when non-adopters feel social pressure from the people closely related to them. Interestingly, this effect is greater for the older group than the younger group. The elderly people are more sensitive to the opinions from important others such as family and friends, and their adoption decision is also highly influenced by them.

In conclusion, this study contributes in expanding our understanding on the role of user resistance in conjunction with the technological factors and different types of social influence on the user adoption of smartphone. Although the study has limitations of generalizability due to the nature of the cross-sectional study in a particular country, the proposed research model is useful as a basic model to extend with other meaningful factors that reveal significant antecedents and their consequences in the adoptive decision process of non-adopters. Also, cross-cultural and more empirical studies in the different domains of innovative technology are highly encouraged.

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APPENDIX

Table 5. Cross-Loadings of each construct in the proposed model

	PCPLX	PCOM	PRA	UR	INT	NSI	ISI
All Respondents							
PCPLX1	**0.933**	-0.392	-0.144	0.215	-0.059	0.041	-0.002
PCPLX2	**0.960**	-0.389	-0.162	0.248	-0.047	0.058	-0.039
PCPLX3	**0.839**	-0.289	-0.100	0.122	-0.054	0.025	-0.033
PCOM1	-0.196	**0.783**	0.378	-0.177	0.259	0.213	0.234
PCOM2	-0.444	**0.901**	0.389	-0.332	0.289	0.165	0.316
PCOM3	-0.342	**0.880**	0.405	-0.250	0.299	0.154	0.253
PRA1	-0.085	0.391	**0.902**	-0.371	0.386	0.240	0.279
PRA2	-0.212	0.476	**0.909**	-0.383	0.457	0.241	0.327
PRA3	-0.097	0.343	**0.876**	-0.353	0.402	0.243	0.309
UR1	0.112	-0.283	-0.297	**0.847**	-0.203	-0.014	-0.169
UR2	0.277	-0.308	-0.398	**0.942**	-0.338	-0.025	-0.201
UR3	0.210	-0.252	-0.409	**0.945**	-0.324	0.010	-0.180
UR4	0.179	-0.264	-0.379	**0.895**	-0.212	0.085	-0.158
INT1	-0.065	0.306	0.493	-0.365	**0.916**	0.390	0.387
INT2	-0.058	0.322	0.436	-0.254	**0.965**	0.471	0.401
INT3	-0.040	0.299	0.377	-0.233	**0.930**	0.504	0.390
NSI1	0.049	0.201	0.275	0.015	0.497	**0.983**	0.543
NSI2	0.043	0.197	0.253	0.014	0.455	**0.980**	0.526
ISI1	0.006	0.238	0.296	-0.151	0.302	0.467	**0.877**
ISI2	0.002	0.295	0.300	-0.164	0.389	0.503	**0.933**
ISI3	-0.067	0.305	0.318	-0.204	0.419	0.492	**0.879**
Young Aged Group							
PCPLX1	**0.929**	-0.376	-0.213	0.219	-0.073	0.053	0.018
PCPLX2	**0.965**	-0.433	-0.228	0.247	-0.064	0.090	-0.022
PCPLX3	**0.804**	-0.261	-0.119	0.069	-0.063	0.042	-0.039
PCOM1	-0.179	**0.790**	0.411	-0.222	0.284	0.245	0.293
PCOM2	-0.440	**0.906**	0.364	-0.343	0.280	0.164	0.330
PCOM3	-0.408	**0.900**	0.417	-0.254	0.320	0.179	0.311
PRA1	-0.133	0.377	**0.912**	-0.447	0.353	0.101	0.174
PRA2	-0.290	0.484	**0.918**	-0.492	0.451	0.112	0.237
PRA3	-0.133	0.341	**0.861**	-0.353	0.327	0.086	0.155
UR1	0.077	-0.287	-0.367	**0.828**	-0.220	-0.105	-0.198
UR2	0.242	-0.314	-0.438	**0.936**	-0.276	0.013	-0.123
UR3	0.196	-0.266	-0.452	**0.950**	-0.213	0.084	-0.063
UR4	0.240	-0.288	-0.494	**0.901**	-0.186	0.091	-0.123
INT1	-0.117	0.333	0.531	-0.366	**0.898**	0.331	0.326
INT2	-0.048	0.312	0.336	-0.176	**0.955**	0.403	0.335
INT3	-0.030	0.289	0.294	-0.121	**0.911**	0.496	0.316
NSI1	0.079	0.211	0.127	0.037	0.453	**0.978**	0.419
NSI2	0.061	0.220	0.090	0.022	0.409	**0.973**	0.416
ISI1	-0.048	0.274	0.191	-0.070	0.271	0.409	**0.877**
ISI2	-0.002	0.318	0.153	-0.103	0.328	0.395	**0.924**
ISI3	0.008	0.358	0.229	-0.175	0.339	0.352	**0.878**
Old Aged Group							
PCPLX1	**0.938**	-0.395	-0.053	0.186	-0.050	0.014	-0.008
PCPLX2	**0.951**	-0.315	-0.080	0.228	-0.034	0.007	-0.044
PCPLX3	**0.878**	-0.313	-0.076	0.166	-0.044	-0.004	-0.012

continued on following page

Table 5. Continued

	PCPLX	PCOM	PRA	UR	INT	NSI	ISI
PCOM1	-0.210	**0.772**	0.335	-0.106	0.235	0.184	0.152
PCOM2	-0.437	**0.896**	0.413	-0.291	0.307	0.181	0.288
PCOM3	-0.247	**0.848**	0.391	-0.220	0.280	0.135	0.172
PRA1	-0.016	0.402	**0.891**	-0.287	0.433	0.412	0.398
PRA2	-0.123	0.467	**0.900**	-0.279	0.473	0.388	0.422
PRA3	-0.056	0.349	**0.892**	-0.370	0.489	0.429	0.491
UR1	0.136	-0.262	-0.219	**0.863**	-0.191	0.086	-0.126
UR2	0.290	-0.271	-0.364	**0.946**	-0.419	-0.085	-0.269
UR3	0.209	-0.213	-0.371	**0.944**	-0.445	-0.082	-0.292
UR4	0.085	-0.203	-0.275	**0.881**	-0.251	0.066	-0.175
INT1	0.000	0.270	0.456	-0.364	**0.941**	0.464	0.452
INT2	-0.071	0.342	0.550	-0.344	**0.973**	0.551	0.478
INT3	-0.058	0.328	0.482	-0.381	**0.952**	0.513	0.488
NSI1	0.005	0.203	0.452	-0.026	0.546	**0.990**	0.702
NSI2	0.010	0.186	0.453	-0.015	0.509	**0.988**	0.672
ISI1	0.093	0.182	0.417	-0.223	0.338	0.547	**0.879**
ISI2	0.025	0.257	0.486	-0.224	0.465	0.650	**0.946**
ISI3	-0.144	0.234	0.417	-0.227	0.507	0.663	**0.877**

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