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# Extending the Understanding of the Impact of User Knowledge on It Adoption and User Performance: Under-Subjective Knowledge and Compatibility

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**Abstract**

*The purpose of the current study is to explore under-subjective knowledge, a concept we develop here in the context of information technology innovations adoption and implementation research and to investigate its unique impact. In addition, this study examines the impact of compatibility on the relationship between under-subjective knowledge and IT innovations adoption and performance. To do so, we develop two versions of mobile systems for a controlled experiment: 1) high compatible system and 2) low compatible system. The experiments with 340 participants are designed to test four hypotheses. The results of the study show that the impact of under-subjective knowledge is negatively related to intention to adopt IT innovations while users in the condition demonstrated higher performance than those in over-subjective knowledge condition. The results also indicate that compatibility attenuate the negative impact of under-subjective knowledge on IT innovations adoption intention and improve IT implementation performance by triggering a transformation from under-subjective knowledge to a condition of objective knowledge (and possibly, and less ideally, to a condition of over-subjective knowledge).*

**Keywords:** IT innovation, User Performance, Knowledge, Compatibility, Over-subjective knowledge, Under-subjective knowledge

## 1. Introduction

In recent years, there has been a proliferation of information technology (IT) innovation such as smartphones in organizations as well as in daily personal life that are equipped with powerful features with a variety of functions (Sun, 2013). In response to the pervasiveness and complexity of computing technology in all aspects of the personal lives of individuals, consumer IT innovations, defined as a product that is perceived as new, requires some significant changes on the part of adopter, and is embodied in or enabled by IT[1], for individuals constantly require users to learn how to use their features that have continuously evolved and enhanced (Billeter, Kalra, and Loewenstein, 2011). The learning often serves as a barrier to new IT innovation adoption and use (Ouden, Sonnemans, and Brombacher, 2006). There is considerable anecdotal evidence that users do not fully use their smartphones. According to research by the Pew Research Center, 81 percent of the smartphone users send text messages but only half of the users download apps and read or send e-mail. Harry interactive poll found that only 5 percent of Americans used their smartphones to show codes for movie admission or to display an airline boarding pass (Larry, 2012). Another survey found that 30 percent of participants ranked "not knowing what features are available" as their top complaint and that people consider their smartphones as expensive cameras that can make calls (Michael, 2014).

[1] The definition is adopted from Fishman *et al*., 2014 and adapted to this study.

That is, a smartphone, as a multifunctional information system, requires more effort to acquire the corresponding knowledge to use the features of the devices than any other systems do. The corollary to this is that to accomplish high performance with the consumer IT innovations such as smartphones, users require a large volume of knowledge to understand and use it effectively.

Knowledge (consumer knowledge) has been investigated across a wide variety of domains, including a range of information technology adoption and use. Demonstrated to affect information search, information processing, and adoption of new products decision making, prior knowledge that is information stored in memory remains an important topic to adoption decision making and use of a new technology2 (Brucks, 1985; Carlson *et al*., 2009; Petter, DeLone, and McLean, 2013). To improve an understanding of the impact of knowledge on decision making, consumer knowledge research distinguishes actual knowledge from perceived knowledge, referred to as objective knowledge and subjective knowledge. While objective knowledge refers to what users actually know, subjective knowledge refers to what consumers perceive they know. Many previous studies assert that there are independent effects of these two knowledge types on user behavior such as information search, information processing, and decision making (Brucks, 1985; Metcalfe, 1986; Park and Lessig, 1981; Punj and Staelin, 1983; Raju, Lonial and Mangold, 1995; Schater, 1983).

Despite the progress in research made using each of these theoretical perspectives of knowledge to explain the impact of the different types of knowledge on the adoption decision making process, studies have overlooked another type of knowledge: under-subjective knowledge, referring to the extent to which users feel they have little or no knowledge even though they actually do. Prior research has found that effect of subjective knowledge by considering over-subjective knowledge, referring to the extent to which users feel they have knowledge they actually do not, as subjective knowledge with limited perspective (Brucks, 1985; Metcalfe, 1986; Park and Lessig, 1981; Punj and Staelin, 1983; Raju, Lonial and Mangold, 1995; Schater, 1983).

Thus, our primary objective in this research is to define a new type of knowledge and to investigate its unique impact on smartphone adoption and performance since perceived knowledge plays a relatively important role in the adoption decision making process while actual knowledge is associated to user performance, referring to users' effectiveness and efficiency of task accomplishment. We seek to do so through developing the concept of under-subjective knowledge, applying the classification of user knowledge in terms of actual knowledge and perceived knowledge. Our premise is that people with under-subjective knowledge are less likely to adopt new technology due to a lack of confidence about their knowledge while people with over-subjective knowledge would show less performance than they expected due to a lack of actual knowledge. Improving the theoretical clarity of the under-subjective knowledge and over-subjective knowledge should help scholars in both the MIS and marketing disciplines to improve the methodology and consistency of empirical support for continued research on the knowledge and innovation adoption relationship. We believe that differentiating under-subjective knowledge from over-subjective knowledge will open new areas to explore to understand a phenomena related to an innovation in IS research.

In addition to delineating a new knowledge type, the current study explores how compatibility influences the relationships between under-subjective knowledge and technology adoption and use. Compatibility refers to the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters. It is not clear whether different kinds of knowledge are more or less beneficial when the IT innovation has different types of compatibility. Finally, this study focuses on a specific type of knowledge condition, that of having under-subjective knowledge, and investigates the two research questions:

1) what is the impact of under-subjective knowledge on technology adoption intention and performance?
2) and what is the impact of compatibility on the relationships between under-subjective knowledge and technology adoption intention and performance?"

This paper begins with a summary of the literature on knowledge, and then reviews and discusses prior work on knowledge to develop the concept of under-subjective knowledge, with a special focus on the nature of under-subjective knowledge.

[2] Prior knowledge refers to the information held in an individual memory about a technology or the technology class while information refers to the knowledge required to adopt and use a new technology.

In the next section, we then develop the four hypotheses to explain the under-subjective knowledge's relationship to IT innovation adoption and use, and the impact of compatibility on the relationship. In the following section, we describe an experiment to test the hypotheses. We propose that this experiment would help explain adoption of new technologies in terms of cognitive aspects and consumer knowledge aspects. Finally, implications are discussed.

## 2. Theoretical Background

### *2.1 Customer Knowledge*

A large body of research suggests knowledge has been one of the most important drivers of the process of new technology adoption (Gatignon and Robertson, 1985; Mahajan, Muller and Bass, 1995; Moreau, Lehmann and, Markman, 2001; Moreau, Markman and Lehmann, 2001; Sheth, 1981). Knowledge (consumer knowledge) is defined as "the amount of accurate information held in memory about product alternatives as well as buyers' self-perceptions of this prior knowledge" (Rao and Monroe, 1988, p.255). The definition includes two types of consumer knowledge; 1) objective knowledge and 2) subjective knowledge (Park, Mothersbaugh and Feick 1994; Raju, Lonial and Mangold, 1995). While objective knowledge refers to what users actually know, subjective knowledge refers to what users perceive they know. Many previous studies assert that there are independent effects of these two knowledge types on consumer behavior (Brucks, 1985; Metcalfe, 1986; Park and Lessig, 1981; Punj and Staelin, 1983; Raju, Lonial and Mangold, 1995; Schater, 1983). Empirically, the distinct roles of these two knowledge types have been tested and demonstrated in information search and decision-making processes in the psychology and marketing disciplines (Bearden, Hardesty, and Rose, 2001; Brucks, 1985; Moorman, Diehl, Brinberg and Kidwell, 2004; Radecki and Jaccard, 1995; Raju, Lonial and Mangold, 1995; Schacter, 1983). While subjective knowledge leads users to a small amount of attribute evaluation, objective knowledge enables users to evaluate large amount of attributes with low search cost and high efficiency (Brucks, 1985). In addition, objective knowledge facilitates deliberation and use of newly acquired information, while subjective knowledge increase the reliance on internal information (Rudell, 1979).

### *2.2 Under-subjective knowledge*

The proposed concept, under-subjective knowledge, begins with a typology of knowledge (Figure 1). Each knowledge is classified according to two dimensions: actual knowledge and perceived knowledge. Actual knowledge reflects objective knowledge or accuracy of memory while perceived knowledge reflects subjective knowledge or confidence of memory (Alba and Hutchinson, 2000). Subjective knowledge refers to self-assessed knowledge as a judgment process in which users scan their memory for cues that will help them evaluate their level of knowledge. Subjective knowledge can be thought of as including an individual's degree of confidence in his/her knowledge, while objective knowledge refers only to what an individual actually knows (Brucks, 1985). In the context of this study, actual knowledge is dependent on one's ability to perform tasks with a smartphone while perceived knowledge the extent to which a user feels capable and assured with respect to his/her ability to perform tasks with a smartphone (Bearden, Hardesty, and Rose, 2001). Confidence is defined as a state of feeling sure and certain about users' knowledge about a smartphone.

Previous research in the marketing discipline has found the two types of knowledge are not always confirmed (Raju, Lonial and Mangold, 1995; Carlson *et al*., 2009). For example, users might be not confident that they think they don't know about a smartphone. If they have realized that their knowledge about the smartphone is good enough to use it, we would say their knowledge is not well calibrated (Alba and Hutchinson, 2000). Clearly, this is miscalibration of accuracy with confidence, reflecting the difference between actual knowledge and perceived knowledge since confidence may alter while leaving accuracy unchanged (Alba and Hutchinson, 1987). Thus, accuracy reflects what they know, confidence reflects what they think they know, and calibration reflects their correspondence (Alba and Hutchinson, 2000). Building upon Alba and Hutchinson's study, the current research proposes that miscalibration results in two ways: 1) positive miscalibration: confidence is higher than accuracy and 2) negative miscalibration: accuracy is higher than confidence. Finally, the current study conceptualizes the positive miscalibration as over-subjective knowledge and the negative miscalibration as under-subjective knowledge. Put all together, this research categorizes three types of consumer knowledge: 1) objective knowledge, the same level of perceived knowledge with actual knowledge, 2) over-subjective knowledge, higher perceived than actual knowledge, and 3) under-subjective knowledge, higher actual knowledge then low perceived knowledge (Figure 1).

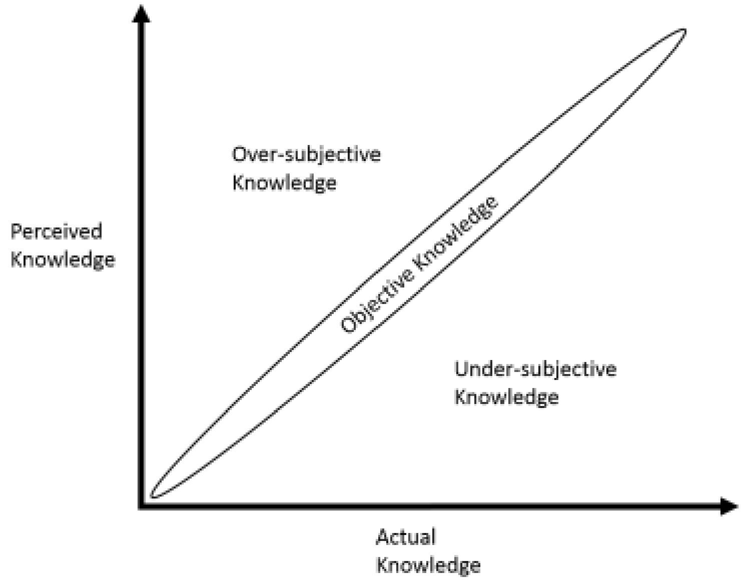



**Figure 1** Knowledge categorization

Over-subjective knowledge, that is a state where a user does not accurately perceive how much he/she actually knows and over-evaluates his/her knowledge, increases as confidence increases. Confidence is influenced by familiarity. Park and Lessig (1981) find that users who had a high level of familiarity felt confident and exhibited more decision-making biases and heuristics than consumers who had low and moderate levels of familiarity. Those with a high level of familiarity with a specific technology tend to develop heuristic rules that simplify the decision making process (Kinard, Capella, and Kinard 2009). In turn, heuristic rules developed by familiarity are apt to use more internal information by reducing cognitive efforts to analyze external or additional information during the decision making process (Maheswaran and Chaiken, 1991). While users get familiar with a category of technology, their perceived incremental knowledge about the technology might not be increasing, as they might be using only a relatively few features of the technology. That is, confidence forms as familiarity increases but actual knowledge about the technology, especially about the various features of the technology, does not increase (Park, Mothersbaugh, Feick, 1994). That is, a high level of confidence does not necessarily mean a high level of actual knowledge. As users become more familiar with the technology, they are less likely to be affected by external factors due to the high level of confidence. Finally, instead of the increment of actual knowledge, perceived knowledge increases.

Unlike over-subjective knowledge, under-subjective knowledge, which is a state where a user does not accurately perceive how much he/she actually knows and under-evaluates his/her knowledge, increases as fear or uncertainty to the use of a new technology increases. Among the many dimensions comprising the social cognitive theory, of particular relevance here is self-efficacy, beliefs about one’s ability to perform a specific behavior, recognizing that people’s expectations of positive outcomes of a behavior will be meaningless if they doubt their capacity to successfully perform the behavior (Bandura, 2001; Compeau, Higgins, and Huff, 1999). Despite of the similarity, under-subjective knowledge, as a new concept, has a distinctive value and is distinguished from self-efficacy. Conceptually, under-subjective knowledge is self-beliefs about their own knowledge, while self-efficacy is self-beliefs about their capabilities to perform a task (Badura, 1977, Thatcher and Perrewe, 2002). Empirically, under-subjective knowledge is a relevant value, while self-efficacy is an absolute value. Therefore, while under-subjective knowledge is manipulated by the level of confidence regarding a specific knowledge (Carlson et al. 2009, Moorman 2004), self-efficacy is measured by only the amount of confidence or beliefs. In sum, under-subjective knowledge can explain how users’ belief of their *knowledge* influences IT adoption and user performance, while self-efficacy describes the role of users’ belief of their *ability* on IT adoption and performance. Weary and Jacobson (1997) found that people with uncertainty of the causes of outcomes tend to seek more information to improve their predictability than those confident of causes of outcomes. Not only does information seeking compensate insufficient knowledge, but also it increases *feeling of effort* and *of difficulty*.

Tsai and McGill (2011) reveal that when subjective *feeling of difficulty* is interpreted as a hindrance in completing a task, which in turn decreases confidence. Given the expensive and complex nature of consumer IT innovations such as smartphones, this phenomenon is evident on the process of adoption and use (Billeter, Kalra, Loewenstein, 2011). When users perform a skill- and knowledge-based task such as computer programming, their estimates of their confidence regress downward since they believe that they are below average (Moore and Cain, 2007). Users may perceive more *feeling of effort* and less *feeling of knowing* due to the uncertainty and difficulty to use a smartphone when new features are added (Schacter, 1983). Thus, this study proposes that difficulty experienced in adopting process of smartphones could lead to feeling of low confidence, providing this difficulty is interpreted as the inability to perform tasks with the features of the smartphones. We assume that this phenomenon could prevent users not only from adopting IT innovations such as smartphones, but also from utilizing full functions of IT innovations with the limited access to a few features of IT innovations.

## 3. Hypotheses Development

According to the theory of planned behavior (TPB), the resources available to a user will to some extent dictate the likelihood of development of intention to perform a behavior of interest (Ajzen, 1991). TPB asserts that users' perceptions of the ease or difficulty of performing the behavior of interest affect users' intention to perform the behavior of interest because people's intentions are strongly influenced by their confidence in their ability to perform it (Ajzen, 1991; Bandura, 1977). User confidence is conceptualized as a multidimensional concept reflecting information acquisition and processing confidence and self-protection confidence. The former is related to the users' perceived ability to acquire and use information and the latter is the perceived ability to protect themselves from being misled, deceived, or treated unfairly (Bearden, Hardesty, Rose, 2001). Building upon the argument, recent research that has examined the impact of an individual's beliefs that an organizational and technical infrastructure exists to support use of the system on the intention to adopt systems (Venkatesh, Morris, Davis, and Davis, 2003) reflects employees' beliefs about the support may increase self-protection confidence and result in increasing intention of adoption. Similarly, Bagozzi, Davis and Warshaw (1992) find that intention to adopt a new technology depends on users' expected reactions to success and failure. In addition, according to the innovation diffusion theory, complexity has a negative effect on adoption (Premkumar, Ramamurthy and Nilakanta, 1944; Rogers, 2003). Adoption decision of under-subjective knowledge users would be expected to be more intensively negatively affected by complex innovations because of their lack of confidence.

According to previous studies, users with high computer self-efficacy tend to form positive attitude of computers (Venkatesh and Davis, 1996), self-efficacy influences anti-spyware adoption intention through perceived behavioral control (Lee and Kozar, 2008), and users' confidence in their capabilities to conduct on-line shopping affects on-line shopping adoption intention (Vijayasarathy, 2004). Thus, this study proposes that confidence and self-efficacy affecting perceived knowledge has an impact on intention to adopt IT innovations. A high level of over-subjective knowledge from high self-confidence has been associated with the active adoption of new technologies because confidence about using a technology affects perceived knowledge of the technology (Radecki and Jaccard, 1995) and the over-subjective knowledge users' adoption decision will be based on familiarity with a technology category and is dependent on intrinsic information (Park and Lessig, 1981; Rao and Monroe, 1988; Raju, Lonial, and Mangold, 1995). At the other end of the adoption – the subjective knowledge spectrum - users with high levels of under-subjective knowledge are afraid of adopting a new technology because of their low self-protection confidence due to less perceived knowledge about the technology and because of their low information acquisition and processing confidence since they think they do not know. This leads to the following hypotheses:

*Hypothesis 1: Under-subjective knowledge about an IT innovation is less likely to be related to intention to adopt technology than over-subjective knowledge.*

User performance is defined as the degree to which user effectively and efficiently accomplishes the tasks that it are expected to be accomplished. Knowledge has been shown to have a positive impact on user IS performance (Karahanna and Preston, 2013; Kearns and Sabherwal, 2006-7). As discussed earlier, users' confidence is not always correlated with their actual knowledge. Users with a high level of confidence performing an IT innovation could have a high level of perceived knowledge that is higher than their actual knowledge. Implementation by these individuals of a technology may not be as successful as these over-subjective knowledge users had led themselves to believe should be the case due to the lack of actual knowledge.

Despite their high self-efficacy, over-confident users are more likely to have the negative effects on performance due to their unrealistically high expectations (Moores and Chang, 2009). Thus, their performance would be lower than expected because their actual knowledge is lower that they had thought.

Unlike over-subjective knowledge users, users with high levels of under-subjective knowledge of a technology tend to assess their knowledge less than the actual knowledge. Thus, user performance using the IT innovations would likely be higher than expected due to the lower expectations these users had prior to adoption and because they underestimated their ability to perform a technology. Thus, their performance would be higher than performance of over-subjective knowledge users under the same conditions.

> *Hypothesis 2: Under-subjective knowledge about an IT innovation is more likely to be related to performance than over-subjective knowledge.*

One of the main purposes of the current study is to reveal the moderating effect of compatibility on the relationship between under-subjective knowledge and adoption and use of IT innovations. As a multidimensional construct, compatibility disaggregates into four dimensions: 1) compatibility with preferred work style, 2) compatibility with existing work practices, 3) compatibility with prior experience, and 4) compatibility with values (Karahanna, Agarwal, and Angst, 2006). The first three dimensions refer to operational compatibility, that is, compatibility with what people do, capturing an individual's self-concept regarding the way they like to work and the reality as it is currently experienced, while the last dimension refers to cognitive compatibility, that is, compatibility with what people feel or think about a technology. We argue for the inclusion of all the dimensions as they would be expected to play a critical role in the adoption decision for a smartphone. The current study defines the conceptual notion of compatibility as the congruence between a new smartphone adoption and various aspects of the individual and the situation in which the technology will be utilized.

Compatibility has been shown to have significant effects on attitude and intentions of information technology adoption (Gatignon and Robertson, 1985; Moore and Benbasat, 1991; Rodger, 2003; Tornatzky and Klein, 1982). Further support for this is evidenced in the findings of innovation diffusion research that the adoption speed and success of an IT innovation depends on the adopter's characteristics as well as the characteristics of an IT innovation such as compatibility (Premkumar, Ramamurthy and Nilakanta, 1994; Roger, 2003). Positive relationships have been found between both organizational and technical compatibility and a managers' decision to adopt a website for their organization; this was found to be driven by the reduced effort needed to modify organizational culture, norms, and technical infrastructure (Betty, Shim, and Jones, 2001). That is, IT innovation adoption is accelerated when users are able to migrate knowledge of the legacy system to usage of the IT innovations, or knowledge transfer through analogy (Gustafsson and Roos, 2005). Acknowledging the effect of compatibility in reducing the effort to implement IT innovations, this study assumes that compatibility would result in reducing the *feeling of effort* which is one of the hindrances of confidence (Tsai and McGill, 2011). Thus, this study proposes that compatibility would strengthen the relationship between under-subjective knowledge on IT innovation adoption intention by mitigating the feeling of effort and, in turn, cultivating confidence and perceived knowledge. This leads us to hypothesis.

> *Hypothesis 3: Compatibility will moderate the relationship between under-subjective knowledge and intention to adopt technology such that high levels of compatibility will strengthen this relationships, with the strongest relationship occurring when under-subjective knowledge and compatibility are both high.*

Prior studies have argued that confidence is formed through the process in which pieces of information that are recalled from memory are integrated to form confidence (Biswas, Zhao, and Lehmann, 2011; Jacoby *et al*., 2002). Users' ability to recall from their memory would be improved through surface similarity between two situations affecting analogical transfer (Holyoak and Koh, 1987). In the context of this research, analogy is used to generate knowledge applicable to using a novel target IT innovation by transferring knowledge from a source IT innovation that is better understood through prior or vicarious experience. Therefore, a new IT innovation's compatibility with existing work practices is positively correlated with users' confidence to implement the IT innovation by improving users' ability to recall from their memory what they have done with the former technologies. In addition, when compatibility is high in a technology category, prior actual knowledge about the category is highly transferrable for using a device of the technology category (Moreau, Lehmann, and Markman, 2001; Monroe, 1976; Gregan-Paxton and John, 1997).

Thus, the current study suggests that compatibility will positively moderate the relationships between under-subjective knowledge and user performance of smartphone use.

*Hypothesis 4: Compatibility will moderate the relationship between under-subjective knowledge and performance such that high levels of compatibility will strengthen this relationship, with the strongest relationship occurring when under-subjective knowledge and compatibility are both high.*

## 4. Methodology

The hypotheses were tested in an experiment using two versions of the smartphone simulator that differed in compatibility by were consisted in content. The experiment is designed to examine the distinctive roles of over- and under-subjective knowledge on intention of adoption and task performance with the simulator. Objective knowledge is also included as a third, intermediate condition of accurate knowledge, that is, neither over-subjective nor under-subjective. The tasks used in this study that are related to smartphone performance are adopted by extending Fang *et al*. (2006)'s and Harris, Rettie, and Kwan (2005)'s study. In their studies, they looked at the moderating effect of task on the intention to use a handheld device, categorizing the tasks in the perspective of users' objectives: (1) general tasks that do not involve transactions and gaming, (2) transactional tasks, and (3) gaming tasks. The present experiment applies the three categories and extends them for more detailed investigation based on Harris, Rettie, and Kwan (2005) to four categories: (1) communication tasks, (2) informational tasks, (3) transactional tasks, and (4) entertainment tasks (Table 1).

**Table 1** Four categories of tasks

| *Tasks* | *Functions* |
|---|---|
| Communication task | Voice, short message service, multimedia message service, video call, and email |
| Informational task | Entertainment news, sports news, headline news, traffic news, weather forecast, local map, local information and navigation |
| Transactional task | Mobile payment, mobile banking, and ticket purchase |
| Entertainment task | Games, ring tone, wallpaper/screen paper, and browsing Internet |

Note: Harris, Rettie, and Kwan (2005)

### *4.1 Experimental smartphone simulator*

Experimental smartphone simulators were developed for the study. Two versions of simulators were designed with low compatibility to control the effect of prior knowledge of smartphones and with high compatibility to examine the moderating impact of compatibility on the relationships between under-subjective knowledge and IT innovations adoption intention and performance.

The operationalization of compatibility of the simulator in this study follows Karahanna, Agarwal, and Angst's research (2006). Compatibility is operationalized as the degree to which a simulator is perceived as being consistent with the prior experience, existing work practices, preferred work style, and values of potential adopters. Based on the concepts, two simulators were developed for this study. First of all, to reduce compatibility with existing work practices and with prior experience, the simulator with low compatibility is designed to negate the common interface of the smartphones by consisting of shapes or icons which are not related to the corresponding task and not aligned, by placing buttons in the middle of screen, and by randomly replacing a button with a hyperlinked text (Figure 2). Based upon their prior experience, for example, smartphone users expect to have an envelope shaped icon to write or read an email not a star shaped icon. Unlike the low compatible simulator, the simulator with high compatibility includes relatively reliable icons which are not exactly the same as any other icons used for existing smartphones in order to control for other unwanted effects. In addition, the low compatible simulator was vertically written making it less compatible with prior experience and value. Most smartphones and the mobile applications in U.S. market are designed with horizontal writing, which is the users' existing value and expectation toward a new smartphone (Figure 2). The simulators featured eight functions (see Figure 2): communication tasks (messaging and email), information (weather and sports), transaction (tickets and banking) and entertainment (music and wallpaper).


Figure 2 Eight functions of experimental smartphone simulator

Note: Low: low compatibility version used in study 1; High; high compatibility used in study 2. The high compatibility simulator is included here and used later for ease of comparison with the low compatibility simulator.

### *4.2 Subject*

Subjects were recruited from two southern state universities for extra credit in an Information Systems course. In addition, all participants are given a chance to win one of six $50 cash cards. Those choosing not to participate were provided the opportunity to earn course credits by completing an alternative assignment. Similar to other adoption research, we consider the use of student subjects to be appropriate because students frequently use a smartphone and because we are examining a basic psychological phenomenon (i.e., confidence) to which people in general should react similarly. In addition, to avoid confounding effects due to age differences, we selected student subject from the narrow age group 20 to 25 rather than using a blend of people from different age groups. A total of 283 subjects completed the experiment, with 47.7 percent being male, and with an average age of 20.8. We also carefully balanced the subject's prior experience with smartphones. To measure their prior knowledge about smartphones, subjects were asked to complete a survey which inquires about the length of usage, frequency of use, and the number of smartphones that they have used. On average, the subjects had 3.52 years of smartphone experience, 2.11 devices owned in their life, spent 71- 90 minutes smartphone daily, and use their smartphone every 15 minutes. Based on these responses, participants are evenly assigned into six cells to control for external effects. To do so, subjects are sorted by smartphone usage years and then the first subject, the participant with the most smartphone usage experience, is assigned to the first cell, the second subject, the participant with the second most smartphone usage years, is assigned to the second cell, and so on until the sixth subject to the sixth cell.

Then the seventh subject was assigned to the first cell. We assigned all subjects in this manner. This design allowed us to control for other unwanted influences. A one-way ANOVA test showed that subjects in the six cells weren't significantly different from each other based on 1) smartphone experience years ($F = 0.837$, $p = 0.524$), 2) the number of devices owned ($F = 0.326$, $p = 0.897$), 3) daily usage frequency ($F = 0.509$, $p = 0.770$), and 4) daily duration of smartphones usage ($F = 0.411$, $p = 0.841$). In addition to the general usage test, subjects' prior experience with smartphone features have been proven not significantly different by measuring six features of smartphones: 1) multimedia message service ($F = 0.952$, $p = 0.448$), 2) short message service ($F = 0.463$, $p = 0.804$), 3) ringtone ($F = 1.144$, $p = 0.337$), 4) games ($F = 1.085$, $p = 0.369$), 5) web surfing ($F = 0.888$, $p = 0.489$), and 6) email ($F = 0.059$, $p = 0.998$). Table 2 and 3 shows more information. Thus, it is proved that the subjects' prior experience with smartphones in each cell is approximately equal. In addition, a PLS test was conducted to test the impact of prior experience on intention to adoption and performance. The results, summarized in Appendix A, found there is no significant effect of prior smartphone experience on the intention of adoption of the simulators and performance.

Table 2 Prior experience with smartphones of experimental groups

| *Group* | *Years* | *# of Devices* | *First Time* | *Often** | *Minutes** | *Age* | *Male* | *Female* | *Total* |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 3.90 | 2.06 | 2009 | 3.15 | 4.13 | 21.4 | 21 | 27 | 48 |
| 2 | 3.33 | 1.98 | 2008 | 3.00 | 4.09 | 20.2 | 23 | 24 | 47 |
| 3 | 3.79 | 2.42 | 2010 | 2.98 | 3.84 | 21.2 | 24 | 21 | 45 |
| 4 | 3.17 | 2.10 | 2009 | 3.25 | 4.23 | 20.9 | 22 | 26 | 48 |
| 5 | 3.70 | 2.10 | 2009 | 3.33 | 4.06 | 20.0 | 23 | 26 | 49 |
| 6 | 3.27 | 2.00 | 2009 | 3.20 | 4.09 | 21.0 | 22 | 24 | 46 |
| Average/ *Total* | 3.52 | 2.11 | 2009 | 3.15 | 4.08 | 20.8 | *135* | *148* | *283* |

Note: Years: the experience years with smartphones; # of devices: the number of smartphones in their life, first time: the year where a subject owns a smartphone;

Note: * Five-point Likert scale was used. Often: frequency to use their smartphones daily - (1) less than an hour, (2) every 30 minutes, (3) every 15 minutes, (4) every 5 minutes, (5) more than every 5 minutes; Minutes: minutes spent for smartphones daily - (1) less than 30 minutes, (2) 31-50 minutes, (3) 51-70 minutes, (4) 71-90 minutes, (5) more than 90 minutes

Table 3 Smartphones usage information of experimental groups

| Group | SMS | MMS | Ringtone | Games | Web | Email |
|---|---|---|---|---|---|---|
| 1 | 5.15 | 4.23 | 1.92 | 2.96 | 4.31 | 4.02 |
| 2 | 4.91 | 3.81 | 1.66 | 2.85 | 4.57 | 4.10 |
| 3 | 4.84 | 4.18 | 1.69 | 2.58 | 4.69 | 4.13 |
| 4 | 5.16 | 3.72 | 2.13 | 3.15 | 4.67 | 4.16 |
| 5 | 5.04 | 3.70 | 2.06 | 3.12 | 4.94 | 4.18 |
| 6 | 4.78 | 4.28 | 1.63 | 2.55 | 4.65 | 4.11 |
| Average | 4.99 | 3.97 | 1.85 | 2.87 | 4.64 | 4.12 |

Note: Five scale interval measurements were used for all smartphones usage information – (5= Most, 1 = least); SMS: short message service; MMS: Multimedia message service

### *4.3 Treatment*

To manipulate participants' knowledge in the simulator, participants were given an information booklet for the smartphone simulator to be used in the experiments. Incorporating the concepts of knowledge construction through verbal and visual material (Mayer and Sims, 1994), three types of information booklets were developed for experiment (under-subjective), control (over-subjective), and baseline group (objective). According to Mayer and Anderson's study (1992), of the process of knowledge construction about how scientific systems and devices work, visual aids build mental representations that are related to perceived knowledge and confidence in the operation of the systems while verbal information generates actual knowledge about the systems. Thus, for the under-subjective knowledge group, where the objective is to increase only actual knowledge, usage information in text-only format was presented in the booklet. For over-subjective knowledge, where the objective is to increase confidence only, an information booklet was designed with only visual information which represents icons needed to complete a given task. For the objective knowledge group used as a baseline group, to increase both confidence and actual knowledge, both text and graphical information are presented (Figure 3).

Given the difficulty of measuring participants' subjective knowledge, it is manipulated and measured for only manipulation checks in the controlled experiments. To manipulate participants' state of confidence (high vs low) on the simulators, this study adopts Wan and Rucker's method (2013) in that four questions[3] about the simulator were given to all participants. These questions were moderately difficult, so that participants would be able to respond but were not likely to be very confident about the accuracy of their answer. Next, participants in the over-subjective and objective knowledge groups (high confidence) received feedback that they had adequate knowledge about the simulator regardless of the accuracy of their answers. In contrast, those in the under-subjective knowledge group (low confidence) received feedback that their knowledge about the simulator was inadequate and problematic and that they should be careful in using such knowledge. After reviewing the feedback, participants rated their confidence in the simulator on a 5-point scale (1 = not confidence at all; 5 = very confident).

[3] The questions measuring participants' actual knowledge were used.

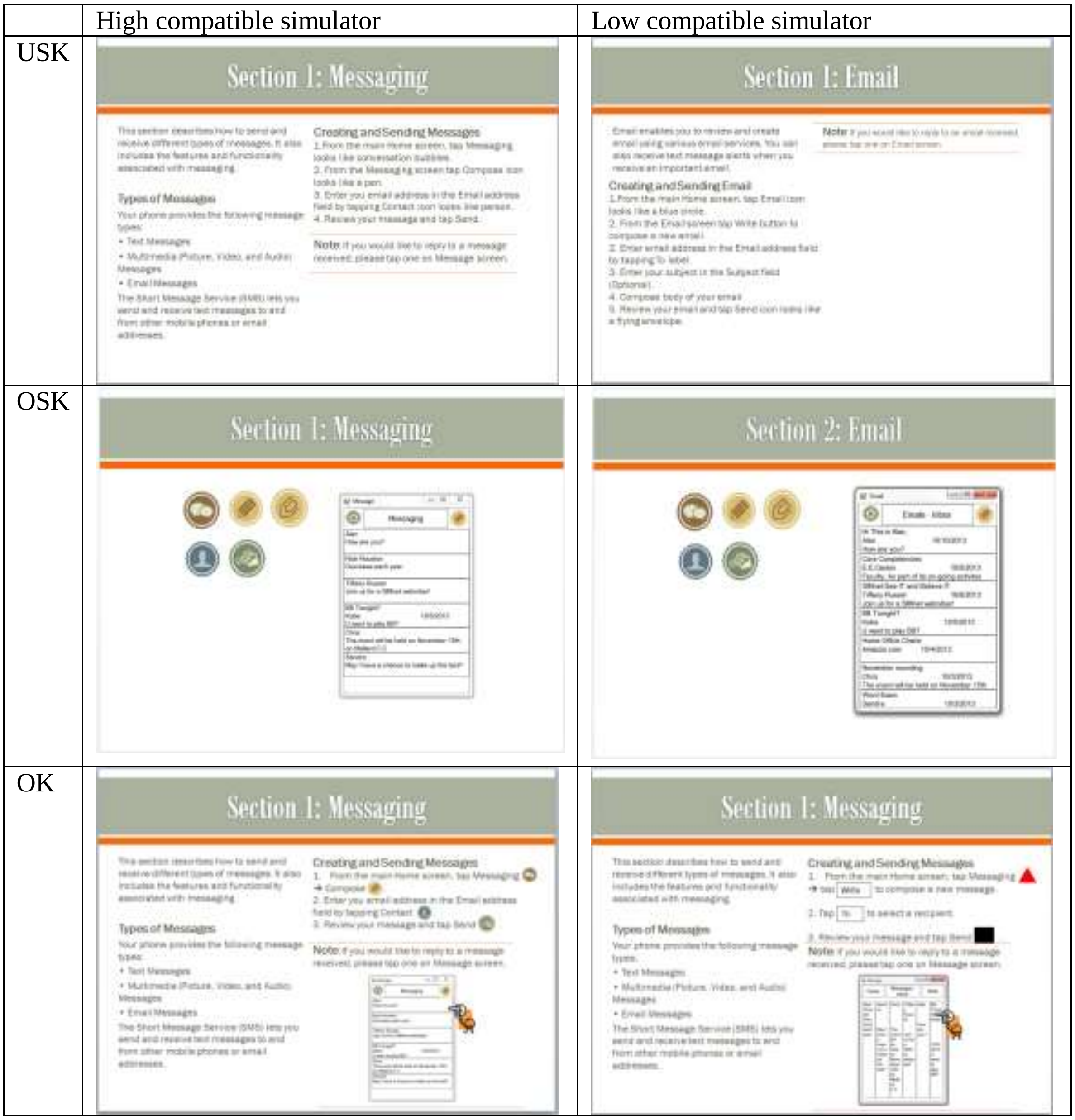



Figure 3 Information booklet

Note: USK: Under subjective knowledge; OSK: Over subjective knowledge; OK: Objective knowledge

### *4.4 Dependent variable*

Intention of adoption: The dependent variable for Hypotheses 1 and 3 is intention to adopt the smartphone simulator. It was measured by a three-item scale adopted from Venkatesh, Thong, and Xu's study (2012) based on Likert-type five-point scales ranging from "strongly disagree" (1) to "strongly agree"(5).

User Performance: One of the dependent variables for Hypotheses 2 and 4 is user performance. There are many measures of performance, each with their own benefits and shortcomings, but the most common approaches to user performance measurement are efficiency and effectiveness (Compeau, Higgins, and Huff., 1999; Cross and Cummings, 2004; Goodhue and Thompson, 1995; Igbaria and Tan, 1997; Webster and Ahuja, 2006). To capture user performance, two different scales were adapted from Webster and Ahuja's (2006) study: efficiency and effectiveness. Implementation efficiency was measured by the time taken to complete the experimental tasks (with a lower time representing higher performance) while effectiveness was assessed through the number of questions answered correctly during the experiment. To determine the number of correct answers, participants were presented with a question sheet which asked them to find the answers to the seven questions while they are using the simulator. There were three types of questions (Table 4).

Table 4 Effectiveness measures

| *Mobile banking questions* | *Weather forecasting questions* | *Sports information searching questions* |
|---|---|---|
| What is the total amount of the bills of this month? | What is the temperature in San Diego, CA tonight? | In soccer, what is the score of the Liverpool game? |
| | Based on Radar, is Cleveland cloudy? | In NCAA, what is the score of LSU game? |
| | What is the temperature in Detroit, MI at Oct 19? | In golf, who is in 9th place? |

### *4.5 Procedure*

Each subject in different knowledge cells will receive an information booklet and have 20 minutes to gain knowledge about the simulator. After this, subjects fill out the perceived and actual knowledge questionnaire. In a few minutes, as stated in treatment section, they received feedback about actual knowledge questions to manipulate their state of confidence and fill out the confidence questionnaire. Then, they were asked to use a simulator to perform the tasks and answer the performance questions. Finally, after completing all the tasks, the intention and the compatibility questionnaire were given.

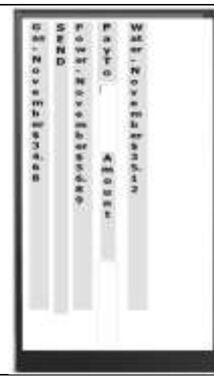
| | Mobile banking | | Mobile ticketing | |
|---|---|---|---|---|
| Low compatibility |  |  |  |  |
| | (a) Main screen of banking | (b) payment page | (c) main screen of ticketing | (d) movie selecting |
| High compatibility |  |  |  |  |

Figure 4 Task procedures

### *4.6 Experimental design*

A 3 x 2 (objective knowledge, over-subjective knowledge and under-subjective knowledge) x (high and low compatibility) between-subject design tests the research hypotheses. The objective knowledge group was included as a baseline group.

### *4.7 Manipulation checks*

A one-way ANOVA showed that experimental group (under-subjective knowledge) considered the treatments with information booklet and with feedback on their answers of the actual knowledge questions as having significantly less subjective knowledge and confidence than the control group and baseline group (over-subjective knowledge group and objective knowledge) and as having significantly more actual knowledge than the control group: subjective knowledge ($F$ (2,138) = 34.516, $p$ = 0.000), actual knowledge ($F$ (2,138) = 29.767, $p$ = 0.000), and confidence ($F$ (2, 138) = 43.627, $p$ = 0.000). Table 5 presents descriptive statistics of treatments. In Table 6 and 7, following *post hoc* tests show that over-subjective knowledge and objective knowledge groups scored significantly higher than under-subjective knowledge group for both subjective knowledge and confidence ($p$ = 0.000, respectively). Under-subjective knowledge and objective knowledge groups scored significantly higher than the over-subjective knowledge group for actual knowledge ($p$ = 0.000). The difference between the objective group and the over-subjective group was not significant for both subjective knowledge and confidence. These results suggest that the over-subjective knowledge group poses a similar level of subjective knowledge and confidence as the reference group (objective knowledge group) and has proved that the subject's knowledge was correctly manipulated.

In addition, the compatibility manipulation of the simulators was tested by the questionnaire on a 5-point scale (1 = strongly disagree; 5 = strongly agree). Items were adapted from the Karahanna *et al*. (2006). A one-way ANOVA showed that the participants who used the low compatible simulator scored significantly lower on the questionnaire than those with the high compatible simulator (Table 6). The results proved that the simulators were properly manipulated.

Table 5. Descriptive statistics

| *Knowledge* | *OK* | | *OSK* | | *USK* | | *Total* | |
|---|---|---|---|---|---|---|---|---|
| Simulator | Low<br>*n*=47 | High<br>*n*=48 | Low<br>*n*=48 | High<br>*n*=45 | Low<br>*n*=46 | High<br>*n*=49 | Low<br>*n*=141 | High<br>*n*=142 |
| SK | 4.15*<br>(0.38) | 4.29<br>(0.43) | 4.00<br>(0.52) | 4.13<br>(0.35) | 2.59<br>(0.78) | 2.61<br>(0.51) | 3.58<br>(0.91) | 3.68<br>(0.88) |
| AK | 2.95<br>(0.43) | 4.10<br>(0.49) | 1.54<br>(0.71) | 2.52<br>(0.59) | 2.86<br>(1.27) | 3.48<br>(0.61) | 2.44<br>(1.17) | 3.39<br>(0.85) |
| Confidence | 4.35<br>(0.53) | 4.29<br>(0.46) | 4.08<br>(0.54) | 4.16<br>(0.52) | 2.55<br>(0.82) | 2.61<br>(0.69) | 3.67<br>(1.02) | 3.67<br>(0.95) |
| Compatibility | 2.48<br>(0.58) | 4.03<br>(0.44) | 2.52<br>(0.55) | 3.89<br>(0.48) | 2.46<br>(0.71) | 4.04<br>(0.35) | 2.49<br>(0.92) | 3.99<br>(1.03) |

Note: OK: Objective knowledge; OSK: Over-subjective knowledge; USK: Under-subjective knowledge; Low: low compatible simulator; High: high compatible simulator SK: subjective knowledge; AK: actual knowledge; *Mean (Standard deviation)

Table 6. Results of manipulation check of compatibility

| *Knowledge* | *OK* | | *OSK* | | *USK* | |
|---|---|---|---|---|---|---|
| Simulator | Low | High | Low | High | Low | High |
| Compatibility | $p < 0.000$ | | $p < 0.000$ | | $p < 0.000$ | |

Note: OK: Objective knowledge; OSK: Over-subjective knowledge; USK: Under-subjective knowledge; Low: low compatible simulator; High: high compatible simulator

Table 7 Results of manipulation check of knowledge and confidence

| *Simulators* | *Manipulations* | *OK* | *OSK* | *USK* | *OK* |
|---|---|---|---|---|---|
| Low | SK | $p < 0.430$ | | $p < 0.000$ | |
| | | | $p < 0.000$ | | |
| | AK | $p < 0.000$ | | $p < 0.452$ | |
| | | | $p < 0.000$ | | |
| | Confidence | $p < 0.112$ | | $p < 0.000$ | |
| | | | $p < 0.000$ | | |
| High | SK | $p < 0.162$ | | $p < 0.000$ | |
| | | | $p < 0.00$ 0 | | |
| | AK | $p < 0.000$ | | $p < 0.000$ | |
| | | | $p < 0.000$ | | |
| | Confidence | $p < 0.479$ | | $p < 0.000$ | |
| | | | $p < 0.000$ | | |

Note: OK: Objective knowledge; OSK: Over-subjective knowledge; USK: Under-subjective knowledge; Low: low compatible simulator; High: high compatible simulator; SK: subjective knowledge; AK: actual knowledge

### *4.8 Hypotheses Testing*

Hypotheses were tested using ANOVA. The between-subjects factors were the manipulated subjective knowledge and objective knowledge. Table 8 displays descriptive statistics for the dependent variable, adoption intention. An examination of the level of intention to adopt the smartphone simulator after manipulating the subjects' knowledge displayed in the *post hoc* test section of Table 6 indicates that, consistent with H1, subjects with under-subjective knowledge are less likely to adopt the simulator than subjects with objective knowledge and over-subjective knowledge.

Table 8 Descriptive statistics and the results of post hoc test for adoption intention

| *Descriptive statistics* | | | |
|---|---|---|---|
| *Measures* | *OK* | *OSK* | *USK* |
| Intention<br>*(Cronbach Alpha* = 0.965) | 3.18<br>(.29) | 3.19<br>(.97) | 1.93<br>(1.05) |
| Intention 1 | 3.32<br>(.47) | 3.40<br>(.96) | 2.00<br>(1.10) |
| Intention 2 | 3.09<br>(.28) | 3.02<br>(1.08) | 0.85<br>(1.05) |
| Intention 3 | 3.13<br>(.38) | 3.15<br>(1.05) | 1.96<br>(1.07) |

| *Post hoc test* - *Between group* | | | | |
|---|---|---|---|---|
| | *OK* | *OSK* | *USK* | *OK* |
| Intention | $p < 0.998$ | | $p < 0.00$ | |
| | | $p < 0.00$ | | |
| Intention 1 | $p < 0.906$ | | $p < 0.00$ | |
| | | $p < 0.00$ | | |
| Intention 2 | $p < 0.934$ | | $p < 0.00$ | |
| | | $p < 0.00$ | | |
| Intention 3 | $p < 0.994$ | | $p < 0.00$ | |
| | | $p < 0.00$ | | |

To test H2, the efficiency and effectiveness of the smartphone simulator use were measured. Consistent with H2, the ANOVA confirmed the completion time of the eight smartphone tasks as being significantly different concerning the type of knowledge: email ($F$ (2, 138) = 264.53, $p$ < 0.000), message ($F$ (2, 138) = 158.08, $p$ < 0.000), tickets ($F$ (2, 138) = 20.41, $p$ < 0.000), banking ($F$ (2, 138) = 84.69, $p$ < 0.000), weather ($F$ (2, 138) = 371.67, $p$ < 0.000), sports ($F$ (2, 138) = 44.08, $p$ < 0.000), wallpaper ($F$ (2, 138) = 33.29, $p$ < 0.000), music ($F$ (2, 138) = 81.42, $p$ < 0.000). Table 9 presents the results of *Post hoc* test and Figure 5 displays the comparisons of the three knowledge types.

Table 9 The descriptive statistics and the results of Post Hoc test for smartphone task completion time

*Descriptive statistics*

| *Task* | *OK* | *OSK* | *USK* | *Task* | *OK* | *OSK* | *USK* |
|---|---|---|---|---|---|---|---|
| Email | 41.53 (13.53)* | 211.44 (57.09) | 97.61 (23.26) | Weather | 60.04 (19.66) | 216.98 (41.12) | 170.52 (18.48) |
| Message | 44.66 (22.24) | 269.85 (62.76) | 118.54 (86.83) | Sports | 44.91 (20.36) | 90.77 (29.11) | 70.61 (20.86) |
| Tickets | 39.09 (15.77) | 148.27 (27.98) | 94.89 (142.11) | Wallpaper | 8.96 (2.49) | 35.19 (22.97) | 21.46 (14.00) |
| Banking | 51.89 (30.22) | 199.60 (78.01) | 93.89 (51.86) | Music | 8.32 (4.46) | 50.48 (17.99) | 36.04 (21.47) |

*Post hoc test - Between group*

| *Task* | *OK* | *OSK* | *USK* | *OK* |
|---|---|---|---|---|
| Email | *p < 0.00* | (169.91)** | $p$ < 0.00 | (56.08) |
| | | $p$ < 0.00 | 113.83 | |
| Message | *p < 0.00* | (225.19) | $p$ < 0.00 | (73.88) |
| | | $p$ < 0.00 | 151.31 | |
| Tickets | *p < 0.02* | (109.19) | $p$ < 0.004 | (55.81) |
| | | $p$ < 0.006 | 53.38 | |
| Banking | *p < 0.001* | (147.71) | $p$ < 0.002 | (42.00) |
| | | $p$ < 0.00 | 105.71 | |
| Weather | *p < 0.00* | (156.93) | $p$ < 0.00 | (110.48) |
| | | $p$ < 0.00 | 46.46 | |
| Sports | *p < 0.00* | (45.86) | $p$ < 0.00 | (25.69) |
| | | $p$ < 0.00 | 20.16 | |
| Wallpaper | *p < 0.01* | (26.23) | $p$ < 0.001 | (12.50) |
| | | $p$ < 0.00 | 13.73 | |
| Music | *p < 0.00* | (42.16) | $p$ < 0.00 | (27.72) |
| | | $p$ < 0.00 | 14.44 | |
| Total | *p < 0.00* | (899.43) | $p$ < 0.00 | (391.10) |
| | | $p$ < 0.00 | 508.33 | |

Note: * Mean (Standard Deviation); ** Mean difference; Numbers in the parenthesis are negative; OK: Objective knowledge; OSK: Over-subjective knowledge; USK: Under-subjective knowledge.

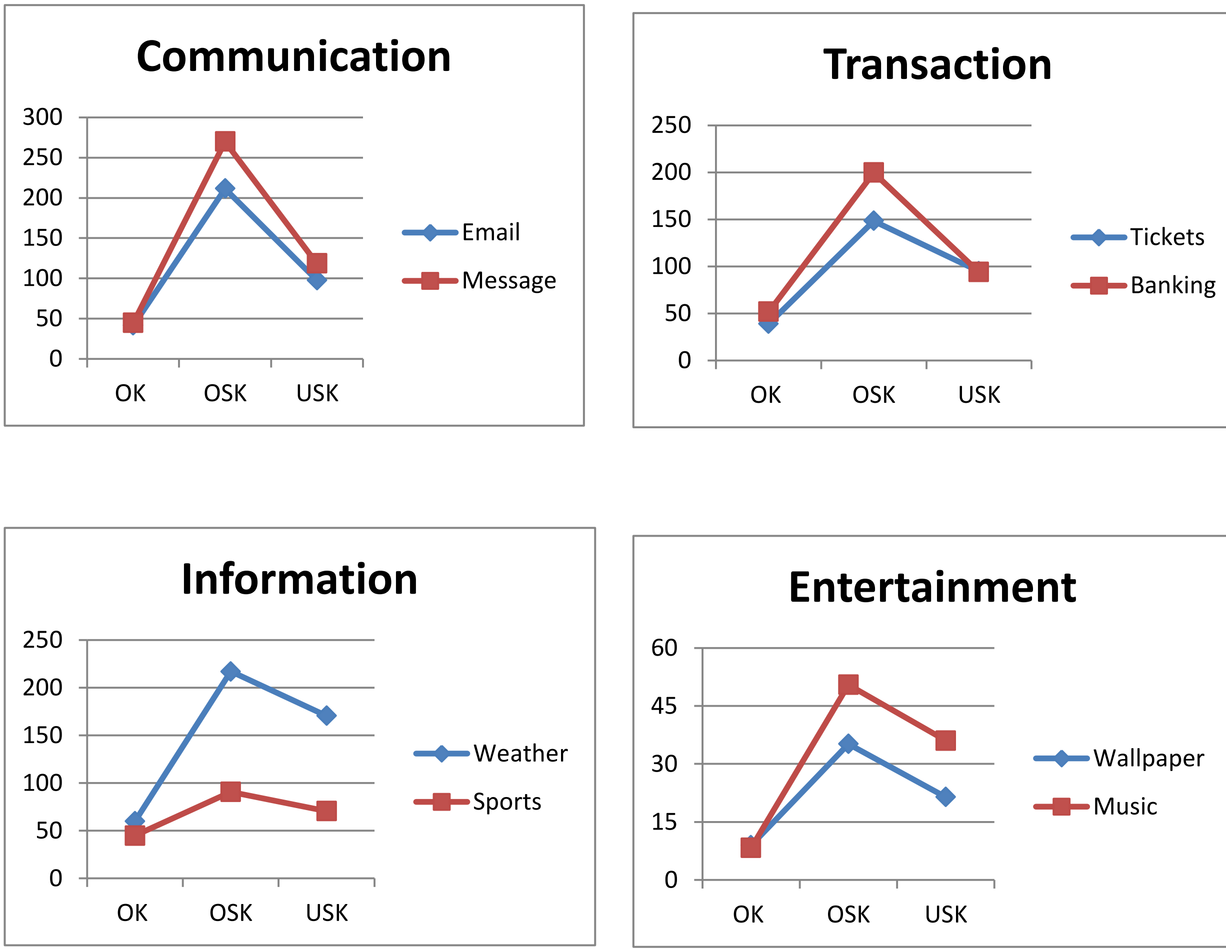



Figure 5 Comparisons of the knowledge types about the completion time of the eight smartphone tasks

Another ANOVA also confirmed H2 showing the number of correct answers as being significantly different concerning the level of subjective knowledge: banking ($F$ (2, 138) = 6.777, $p$ < 0.002), information 1 ($F$ (2, 138) = 8.187, $p$ < 0.000), information 2 ($F$ (2, 138) = 11.673, $p$ < 0.000), information 3($F$ (2, 138) = 12.41, $p$ < 0.000), and sports 2 (F (2, 138) = 4.203, p < 0.017), excepting sport 1 ($F$ (2, 138) = 2.052, $p$ < 0.132) and sports 3 (F (2, 138) = 2.043, p < 0.133). A Post hoc test (Turkey Multiple Comparison) showed significant results between groups (Table 8). Table 10 and Figure 6 depicts the comparison of the number of correct answers.

Table 10 The descriptive statistics and the results of Post Hoc test for the number of correct answers

| *Descriptive statistics* | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Task* | *OK* | *OSK* | *USK* | *Task* | *OK* | *OSK* | *USK* |
| Banking | 0.89 (0.31)* | 0.58 (0.50) | 0.63 (0.49) | Sports 1 | 0.91 (0.28) | 0.77 (0.42) | 0.87 (0.34) |
| Information 1 | 0.94 (0.25) | 0.60 (0.49) | 0.78 (0.42) | Sports 2 | 0.94 (0.25) | 0.77 (0.42) | 0.93 (0.25) |
| Information 2 | 0.94 (0.25) | 0.52 (0.50) | 0.65 (0.48) | Sports 3 | 0.91 (0.27) | 0.81 (0.39) | 0.93 (0.25) |
| Information 3 | 0.96 (0.20) | 0.56 (050) | 0.80 (0.40) | Total | 6.85 (0.47) | 4.63 (1.88) | 5.61 (1.39) |

*Post hoc* test - Between group

| Task | OK | OSK | USK | OK |
|---|---|---|---|---|
| Banking | *p < 0.002* | 0.31** | *p* < 0.013* | 0.31 |
| | | *p* < 0.863 | 0.047 | |
| Information 1 | *p < 0.00** | 0.33 | *p* < 0.158 | 0.15 |
| | | *p* < 0.082 | (0.17) | |
| Information 2 | *p < 0.00** | 0.42 | *p* < 0.005* | 0.28 |
| | | *p* < 0.299 | (0.13) | |
| Information 3 | *p < 0.00** | 0.39 | *p* < 0.144 | 0.15 |
| | | *p* < 0.009 | (0.24) | |
| Sports 1 | *p < 0.121** | 0.14 | *p* < 0.811* | 0.05 |
| | | *p* < 0.371 | (0.10) | |
| Sports 2 | *p < 0.034** | 0.17 | *p* < 1.000 | 0.001 |
| | | *p* < 0.037 | (0.16) | |
| Sports 3 | *p < 0.258** | 0.10 | *p* < 0.951 | (0.02) |
| | | *p* < 0.15 | (0.12) | |
| Total | *p < 0.000** | 2.23 | *p < 0.000** | 1.24 |
| | | *p < 0.02** | (0.98) | |

Note: * Mean (Standard Deviation); ** Mean difference; OK: Objective knowledge; OSK: Over-subjective knowledge; USK: Under-subjective knowledge; 1: correct answer; 0 wrong answer; Numbers in the parenthesis are negative.

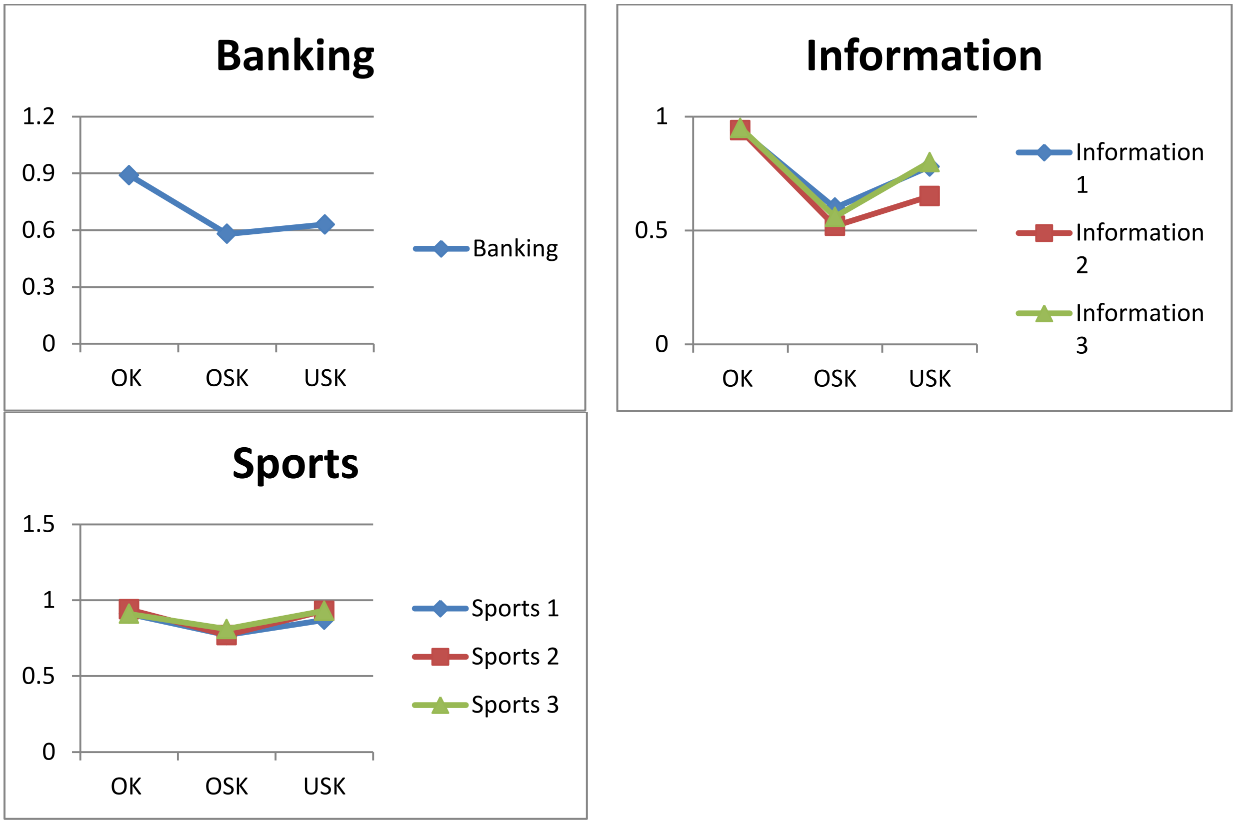



Figure 6 Comparison of the number of correct answers

To test H3, an ANOVA using IBM SPSS Statistics 19 confirmed the intention to adopt technology as being significantly different concerning the level of compatibility. The under-subjective knowledge group using the low compatible simulator rated 1.93 on five-point Likert scale of their intention to adopt the simulator whereas the subjective knowledge group with the high compatible simulator rated 3.27 (($F$ (1,93) = 29.59, $p$ = 0.000) (Table 11). Consequently, the results show that high levels of compatibility strengthen the relationship between under-subjective knowledge and intention to adopt. Figure 7 depicts the interaction effects comparing the impact on objective knowledge and over-subjective knowledge.

Table 11 Descriptive statistics of Intention and ANOVA

| *Measures* | *USK* | | *ANOVA (Compatibility difference)* |
|---|---|---|---|
| | *Low* | *High* | |
| Intention | 1.93 | 3.27 | $F$ (1, 93) = 29.59 |
| (Cronbach Alpha = 0.983) | (1.05) | (1.43) | $p$ = 0.000 |
| Intention 1 | 2.00 | 3.39 | $F$ (1, 93) = 26.37 |
| | (1.09) | (1.37) | $p$ = 0.000 |
| Intention 2 | 1.85 | 3.20 | $F$ (1, 93) = 28.34 |
| | (1.05) | (1.47) | $p$ = 0.000 |
| Intention 3 | 1.96 | 3.31 | $F$ (1, 93) = 26.53 |
| | (1.07) | (1.37) | $p$ = 0.000 |

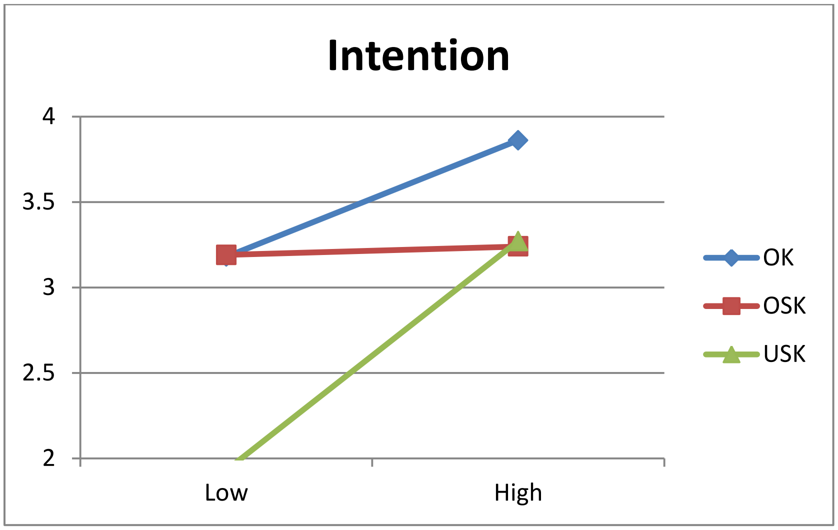


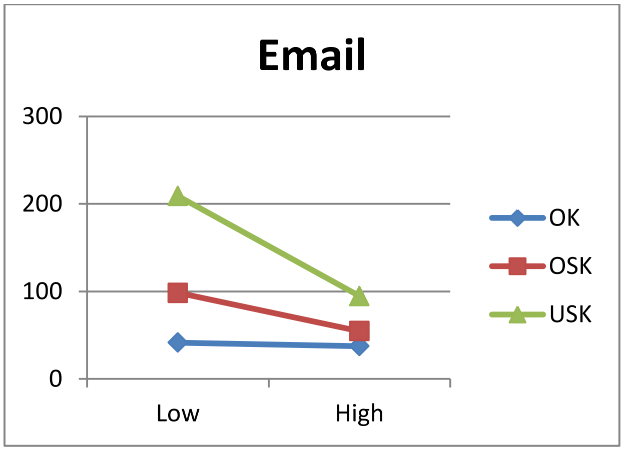

Figure 7 Interaction effect of compatibility on the relationship between knowledge and adoption intention

H4 predicted that compatibility would strengthen the effects of under-subjective knowledge on performance. The high compatibility system demonstrated the highest performance (the lowest time and the highest scores on the quiz), while the low compatibility system demonstrated the lowest performance (Table 12 and 13). Figure 8 and 9 depicts the interaction effects and supports this conclusion.

Table 12 Descriptive statistics and the results of ANOVA for task completion time

| *Measures* | *USK* | | *ANOVA* |
|---|---|---|---|
| | *Low* | *High* | *(Compatibility difference)* |
| Email | 209.02 (57.06) | 94.64 (35.94) | $F$ (1, 93) = 138.47 $p$ = 0.000 |
| Message | 267.64 (63.18) | 124.98 (20.61) | $F$ (1, 93) = 224.47 $p$ = 0.000 |
| Tickets | 148.58 (34.13) | 95.47 (52.47) | $F$ (1, 93) = 14.67 $p$ = 0.000 |
| Banking | 199.28 (79.00) | 74.04 (36.32) | $F$ (1, 93) = 127.79 $p$ = 0.000 |
| Weather | 267.82 (57.81) | 142.72 (73.51) | $F$ (1, 93) = 31.59 $p$ = 0.000 |
| Sports | 90.96 (29.44) | 42.24 (31.72) | $F$ (1, 93) = 38.07 $p$ = 0.000 |
| Wallpaper | 35.15 (23.47) | 22.57 (15.66) | $F$ (1, 93) = 9.56 $p$ = 0.000 |
| Music | 45.91 (21.47) | 28.39 (13.18) | $F$ (1, 93) = 43.74 $p$ = 0.000 |
| Total | 1264.36 (168.51) | 625.05 (125.61) | $F$ (1, 93) = 327.52 $p$ = 0.000 |

Note: Mean (Standard deviation); USK: Under-subjective knowledge; Low: Low compatibility simulator; High: high compatibility simulator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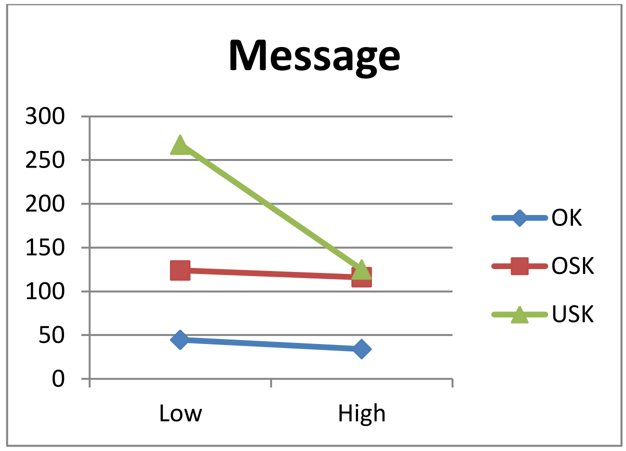
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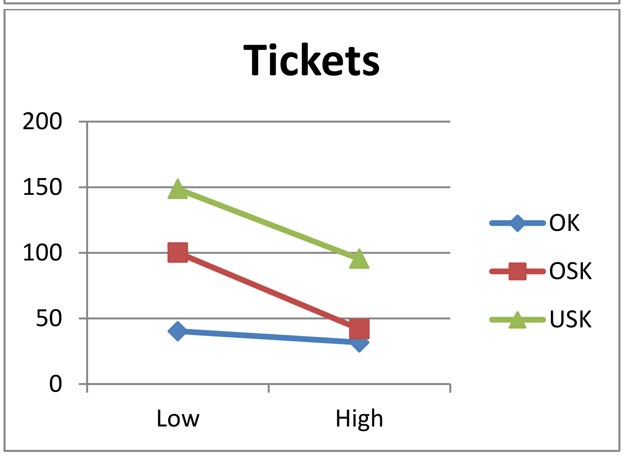
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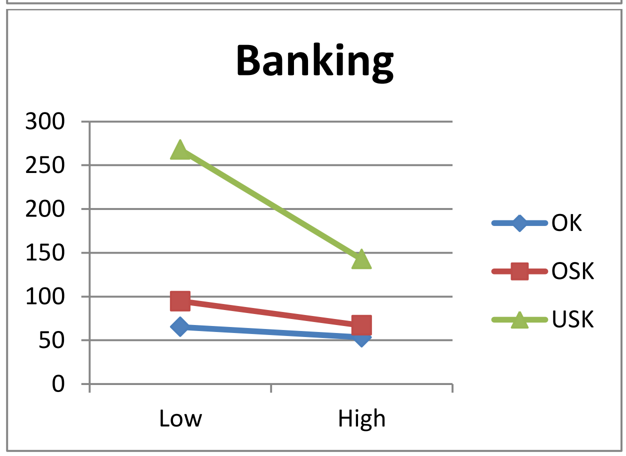
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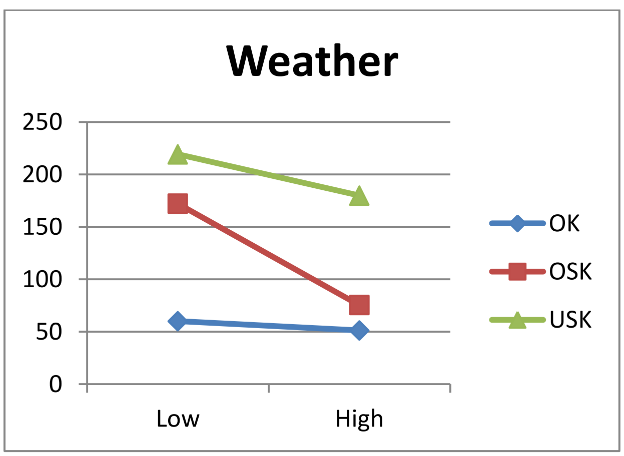
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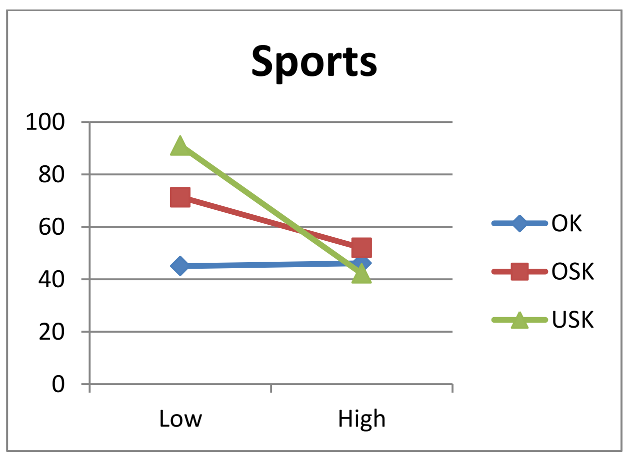
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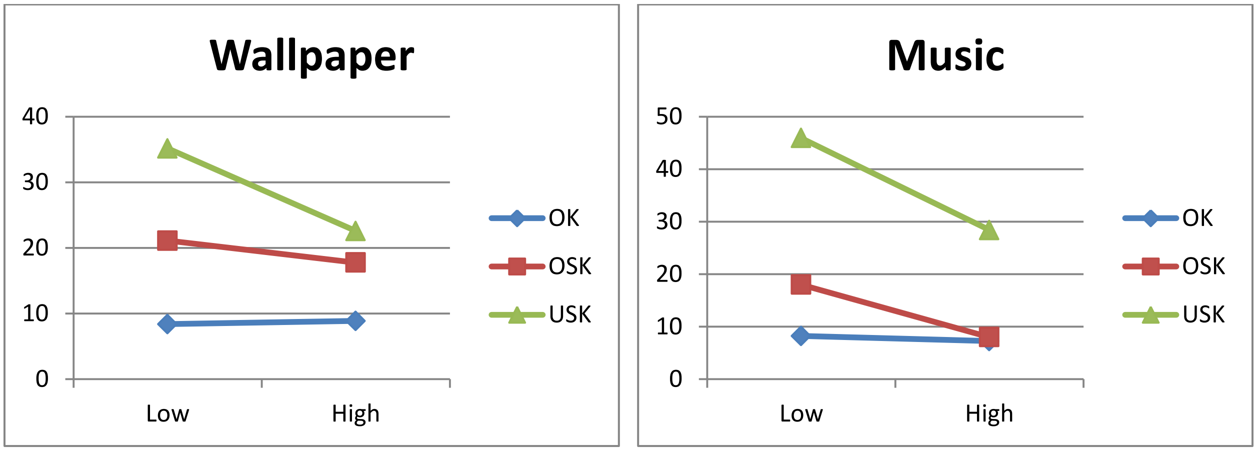
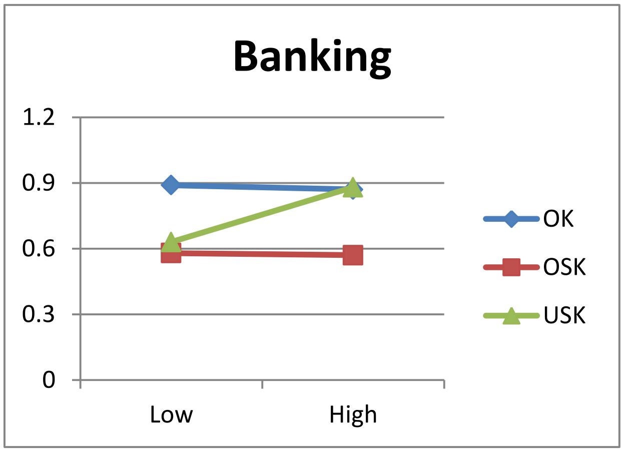



Figure 8 Interaction effect of compatibility on the relationship between knowledge and the task completion time

Table 13 Descriptive statistics and the results of ANOVA for quiz

| Measures | USK | | ANOVA |
|---|---|---|---|
| | Low | High | (Compatibility difference) |
| Banking | 0.63 (0.49) | 0.88 (0.33) | *F* (1, 93) = 8.43 *p* = 0.005 |
| Information 1 | 0.78 (0.42) | 0.96 (0.20) | *F* (1, 93) = 7.06 *p* = 0.009 |
| Information 2 | 0.65 (0.48) | 0.87 (0.37) | *F* (1, 93) = 4.39 *p* = 0.039 |
| Information 3 | 0.80 (0.14) | 0.98 (0.40) | *F* (1, 93) = 8.245 *p* = 0.005 |
| Sports 1 | 0.87 (0.34) | 0.94 (0.24) | *F* (1, 93) = 1.316 *p* = 0.254 |
| Sports 2 | 0.93 (0.25) | 0.98 (0.14) | *F* (1, 93) = 1.171 *p* = 0.282 |
| Sports 3 | 0.93 (0.22) | 0.96 (0.14) | *F* (1, 93) = 0.278 *p* = 0.599 |
| Total | 5.61 (1.39) | 6.55 (0.76) | *F* (1, 93) = 17.026 *p* = 0.000 |

Note: Mean (Standard deviation); USK: Under-subjective knowledge; Low: Low compatibility simulator; High: high compatibility simulator; 1: correct answer; 0 wrong answer.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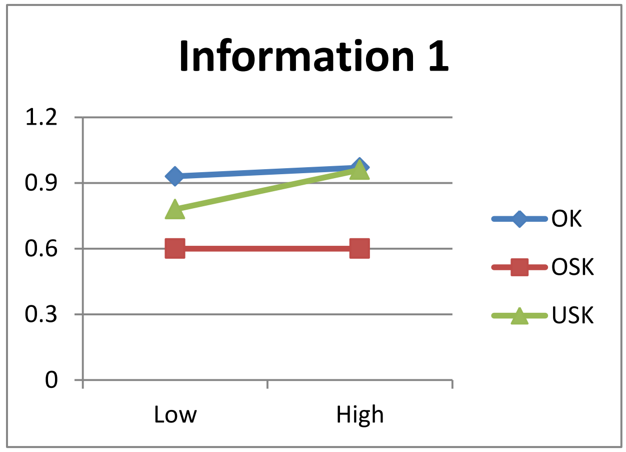
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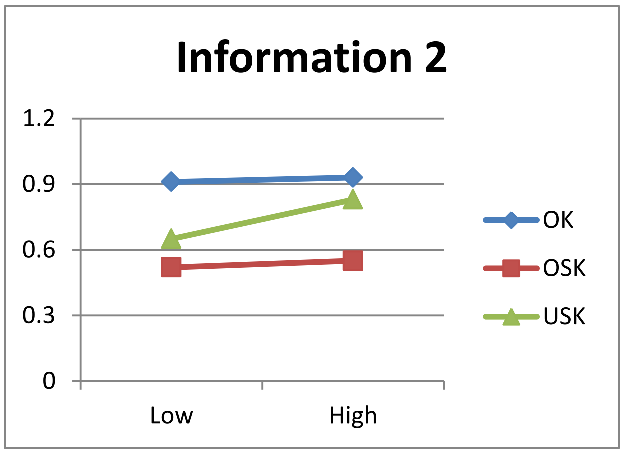
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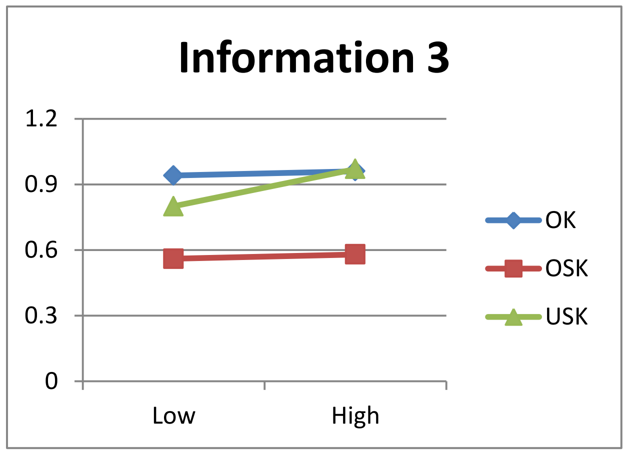
Information 3
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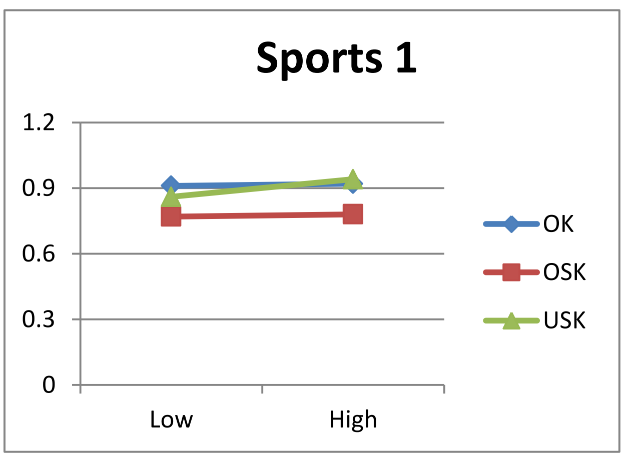
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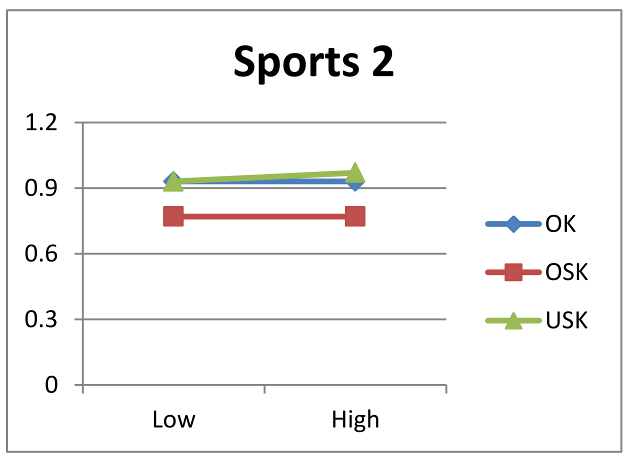
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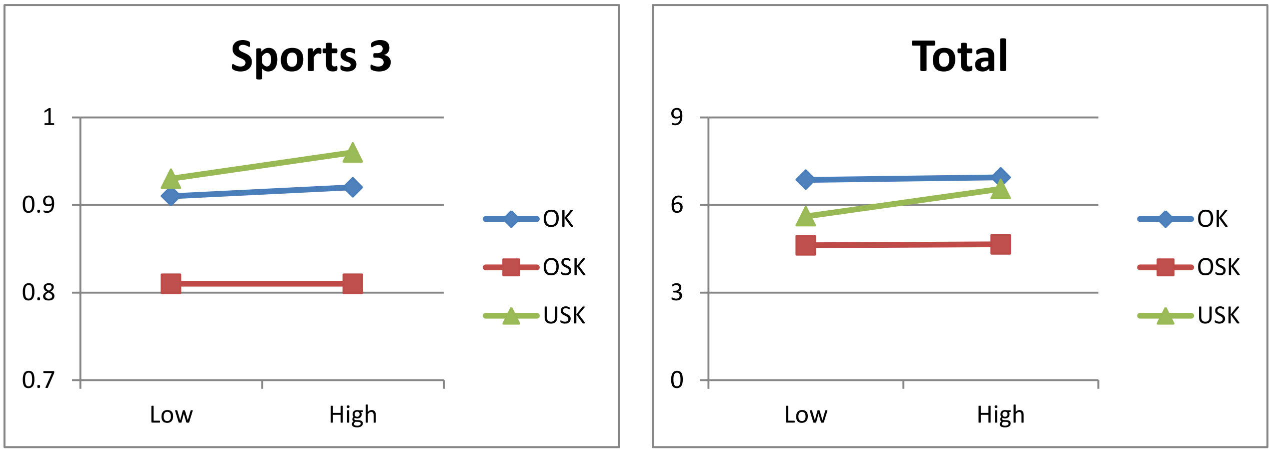


Figure 9 Interaction effect of compatibility on the relationship between knowledge and the task completion time

## 5. Discussion

One major goal of this study is to add a new theoretical perspective to the existing knowledge literature. Taking into account the mounting evidence on knowledge differences in information technology innovations adoption and use, the current study set up a laboratory experiment to explore whether or not these differences are accompanied by different knowledge types that can be formed by users' prior experiences. In fact, this study found a considerable number of the impact of knowledge type on IT innovations adoption and use. The following discussion summarizes the results and outlines important implications.

The results of the study indicate that the impact of under-subjective knowledge on intention to adopt IT innovations and performance is different from over-subjective knowledge. Consistent with H1, users with under-subjective knowledge are less likely to adopt a new technology than users with over-subjective knowledge are. In contrast, users with under-subjective knowledge demonstrate higher performance executing the tasks related with smartphones than over-subjective knowledge users. Perhaps the most significant contribution of the current work is to develop a new construct and explore its unique effect on IT adoption and user performance.

Second, our study effectively applies theories related to compatibility such as the innovation of diffusion theory to user knowledge research field and extends IT innovations adoption theory by demonstrating the moderating effect of compatibility on the relationships between under-subjective knowledge and intention to adopt IT innovations and performance. In general, our results show support for the distinction between under- and over- subjective knowledge. This study identifies conditions, under-subjective knowledge, under which compatibility would apply. Specifically, for users with under-subjective knowledge, compatibility is an important determining factor of intention to adopt technology.

### *5.1 Theoretical implications*

Although previous research has acknowledged the unique impact of subjective knowledge on the decision making process, little of this research distinguished under-subjective knowledge from over-subjective knowledge and its distinct effect. From this perspective, this study's theoretical contributions are twofold: contributions to information technology innovations adoption research and to consumer knowledge research. Compatibility is crucial in IT innovations adoption, a finding already known from previous research (Moore and Benbasat, 1991; Lopez-Nicolas, Molina-Castillo, and Bouwman, 2008; Nevo and Wade, 2010). Empirical evidence on how it makes an impact on adoption of IT innovations, however, has largely been an open question. This study sheds light on this issue by providing empirical support for a new approach to understanding the mechanism where how compatibility relates to IT innovations adoption and use through users' knowledge. The major implication of successfully applying compatibility is that it demonstrates that under-subjective knowledge users' negative attitude toward a new technology is attenuated by compatibility, which has been overlooked in past research. This study gives evidence to suggest that the negative attitude which is formed due to the lack of assessment of their actual knowledge is reduced by compatibility. In highlighting the role of compatibility as a moderator between under-subjective knowledge and IT innovations adoption and user performance, this study helps extend current theoretical perspectives associated with IT innovations adoption and use.

In addition to the IS discipline, this study significantly contributes to the consumer knowledge research field by introducing a new construct. It responds to calls in the research literature for theoretical frameworks and research examining the different types of knowledge and their unique role on consumers' decision making process (Carlson *et al.*, 2009, Alba and Hutchinson, 2000). Prior researches are struggling with substantial variations across studies regarding the relationships between objective knowledge and subjective knowledge. Due to the mixed results, researchers continue to call for further research to better understand the knowledge types and their role in decision making process. Unlike previous research that concludes that consumers frequently think they know more than they actually do (Alba and Hutchinson, 2000), potential adopters of IT innovations are more likely to think the opposite way due to the high level of complexity and fear to use a new technology, and to a low level of self-confidence. From this perspective, the current study extends the theoretical paradigm related to consumer knowledge by exploring a new construct, under-subjective knowledge, and demonstrating its negative impact on IT innovations adoption and user performance.

### *5.2 Practical implications*

Technologies are rapidly developed and equipped with features that are complex to perform. People are being overwhelmed by technologies in struggling with acquiring knowledge. Thus, understanding a new concept, under-subjective knowledge, and its impact on IT innovations adoption behavior and user performance is especially noteworthy because most IT innovations adoption decisions are made under uncertainty; that is, they are made without complete knowledge about a new technology. Such uncertainty is manifested not only in users' levels of objective knowledge but also in their levels of subjective knowledge. Brucks (1985) found that independent of objective knowledge, subjective knowledge influences the selection of product (Brucks, 1985). Especially, lower self-assessed knowledge is associated with higher perceived importance of new information (Park et al, 1988). Information seeking increases feeling of effort and of difficulty (Weary and Jacobson, 1997). Increases in feeling of effort and of difficulty are associated with increases in the perception of a hindrance in completing a task, which in turn decreases confidence (Tsai and McGill, 2011). Given the expensive and complex nature of consumer IT innovations such as smartphones, this phenomenon is evident on the process of adoption and use (Billeter, Kalra, Loewenstein, 2011). The results of this study indicate that if users know more about an IT innovation ( i.e., objective knowledge) but feels that they are not sufficiently knowledgeable about it (i.e., under-subjective knowledge), they are less likely to adopt the innovation due to the lack of confidence and a high level of fear to use it. Finally, by demonstrating a unique IT adoption behavior associated with under-subjective knowledge, the current study encourages managers and marketers to pay attention to how increase not only users' actual knowledge but also their feeling of confidence.

Although previous research has studied the unique impact of subjective knowledge on product judgement and choice, little is known about the effect of under – subjective knowledge on IT innovation adoption and user performance and how it interacts with compatibility. In addition, in an attempt to help users to wisely use their IT innovations such as smartphones, smartphone manufacturers have tried to enhance user smartphone knowledge through various forms of technology education. Unfortunately, such attempts to educate have not always succeeded in improving users' smartphone usage or performance. As stated earlier in this research, people don't fully use cutting-edge features of their smartphones but utilize only basic features such as game, music, and social networking. This research has revealed that compatibility may trigger a transformation from under-subjective knowledge to a condition of objective knowledge (and possibly, and less ideally, to a condition of over-subjective knowledge) which increases the users' intention to adopt IT innovations and their performance. Our study will hopefully educate practitioners in terms of the importance of focusing on not only how to educate users about their multi-featured device but also how to reduce users' efforts to learn how to use the devices.

Moreover, the three different knowledge types may have different relationships with confidence and actual knowledge (Figure 10). Previous research has acknowledged that confidence and self-efficacy is positively related to IT innovations adoption rate (Moores and Chang, 2009; Thatcher and Perrewe, 2002). Users in an under-subjective knowledge condition may have a lower level of confidence (area A in Figure 10), compared to users in an objective knowledge condition and those in an over-subjective knowledge condition (B+ C in figure 10). In other words, consumers (and marketers) may have lost the "A" or "A+B+C" chance for people in an under-subjective knowledge condition to take advantage of new technology. This may help practitioners set up strategies to increase adoption of IT innovations by users who have the knowledge to successfully use such innovations.

Therefore, managers or developers need first of all to ensure that an IT innovation is technically and cognitively compatible with user's previous belief and experience about IT innovations to improve their confidence.

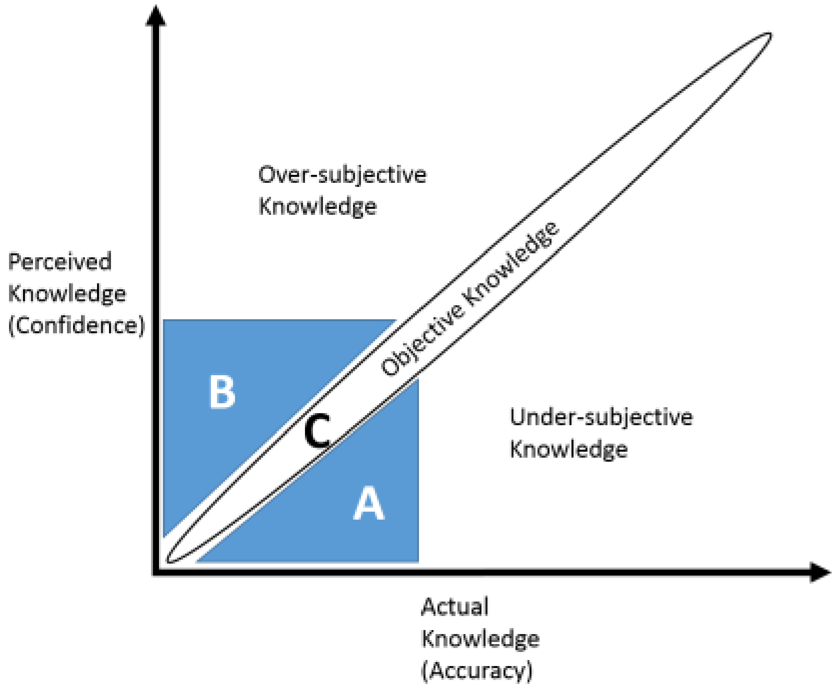


Figure 10 Relationship between confidence and Actual Knowledge

### *5.3 Limitations and Future Research*

Even though this study has offered some insights into users' knowledge on IT innovation adoption and performance, several limitations to our research must be acknowledged. First, the manipulation for the compatibility may limit the validity and generalizability of our findings. Two simulators that were developed for this study have a different level of compatibility to investigate the moderating effect of compatibility on the relationships between under-subjective knowledge and IT adoption and performance. The simulator is designed by controlling unexpected mixed effect such as usability and quality of design. The manipulation of interface, especially low-compatibility simulator, could lower other design factors such as usability and interface quality. This could make subjects difficult to operate the simulator and affect the results of the experiments.

However, we expect this problem to be minimal since compatibility could be one of the antecedents of usability and interface quality. According to Adipat et al. (2011) and Hoehle & Venkatesh (2015), mobile device usability is defined as the extent to which the operating system is user friendly. One of the factors affecting user friendly interface is users' expectation to interact with device (Satzinger and Olfman, 1998). Users expect to interact with mobile devices based on their previous working experience, preferred work style, and values (Karahanna, Agarwal, and Angst, 2006). In other words, compatibility is positively associated with usability (Ishi et al, 1988). Thus, if a mobile application is not compatible with potential users' expectation and needs, usability will be also decreased.

In addition, poor design quality of interface could be the incongruence of users' expectation since 'good' design is forms of users' sensibility rather than objective properties of things (Ann and Bianchin, 2012). Therefore, the reason why people think the interface of the smartphone is not good and easy to use is the interface is not compatible with their previous working experience or expectations (Karahanna, Agarwal, and Angst, 2006). This suggests several avenues for future research. First, more research is needed to delineate the role of compatibility in how usability affects IT innovation adoption and user performance. Second, it is possible that the design factors included have interaction effects that were neither theorized nor tested.

The second limitation of the current study is that we are not able to measure an actual adoption processes. As well, we have a "virtual test of task performance" with our simulator. While this is a limitation, based on previous studies people who have high task performance are also more likely to adopt new technology (Roger, 2003; Gatignon and Robertson, 1985; Tornatzky and Klein, 1982; Moore and Benbasat, 1991; Premkumar, Ramamurthy, and Nilakanta, 1994), so we have some confidence in a relationship between compatibility and IT innovation adoption and performance, at least for the under-subjective knowledge condition. While longitudinal experimental research is recommended to best observe IT innovations adoption processes, our laboratory setting does allow us to measure adoption behavior under rigorously controlled conditions.

Another important limitation of the current study stems from selection of a specific category product. This study only focuses on wireless handheld devices and evaluates the effect of under-subjective knowledge on the technology adoption. To understand more fully the effect of under-subjective knowledge, the study of other new technology categories is necessary.

The scope of the study was restricted to the impact of knowledge on use and performance, excluding the relationship between use and performance. The experiment conducted in this study took a necessarily narrow focus on the relationships between the distinct knowledge types and outcomes such as use and performance so as to achieve a high degree of control over the variables. Thus, the relationship between use and performance have not been investigated here and may not lend themselves to experiments. Future research could attempt to have a more holistic view of the impact of knowledge on use and the relationship between use and performance to incorporate a longitudinal study.

### *5.4 Conclusions*

To our knowledge, this is the first empirical study to propose the concept of under-subjective knowledge and test its effect on technology adoption and performance, thus providing a comparison with objective knowledge and over-subjective knowledge. The results will contribute to the understanding of the effect of knowledge on IT innovations adoption processes. It is also important to demonstrate how to transform under-subjective knowledge to objective knowledge and realize a positive effect on IT innovations adoption processes. We believe that the unique characteristics of under-subjective knowledge may result in different effects on adoption decision making processes and that the study of under-subjective knowledge helps us better understand end user behavior. A strength of this study's design was the consistent content, task, and structure of the experimental smartphone simulator. Nevertheless, we manipulated its compatibility with a relatively unstructured method, because this best represents low compatible innovations. Therefore, future study should develop a structured technique to develop an experimental simulator for compatibility and knowledge research.

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Appendix A: PLS test of the impact of prior smartphone experience on intention to adopt the experimental simulators and performance

A PLS test was conducted to test the impact of prior experience on intention to adoption and performance. The results found that the relationships with prior smartphone experience and intention of adoption the simulators and performance is not significant (Figure 1).

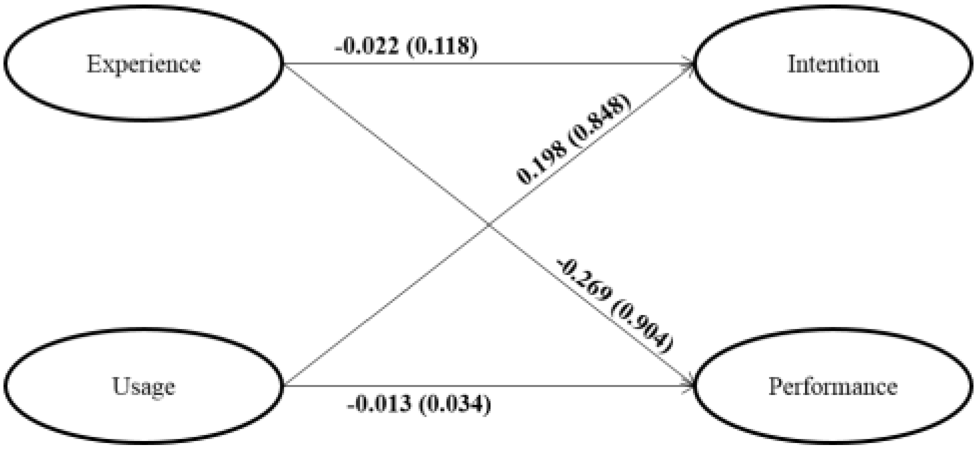


Figure 1. PLS model test

The model was tested using the partial least squares (PLS) method of structural equation modeling (SmartPLS V2.0) due to PLS method's ability to handle formative constructs models. In the model, the measures of the latent variables are not interchangeable, as each captures a distinct aspect of the latent variables. Thus, all indicators determine the latent variables instead of each item reflecting the construct, suggesting a formative nature. Table 1 shows the summary of the measurement model.

| | Experience | Operation | Intention | Performance |
|---|---|---|---|---|
| Year | 0.1782 | 0.0000 | 0.0000 | 0.0000 |
| Devices | 0.6393 | 0.0000 | 0.0000 | 0.0000 |
| Minutes | 0.3157 | 0.0000 | 0.0000 | 0.0000 |
| Often | -0.1332 | 0.0000 | 0.0000 | 0.0000 |
| SMS | 0.0000 | 0.0265 | 0.0000 | 0.0000 |
| MMS | 0.0000 | -0.2493 | 0.0000 | 0.0000 |
| Ringtones | 0.0000 | 0.6980 | 0.0000 | 0.0000 |
| Web | 0.0000 | -0.0135 | 0.0000 | 0.0000 |
| Games | 0.0000 | -0.2296 | 0.0000 | 0.0000 |
| email | 0.0000 | 0.7680 | 0.0000 | 0.0000 |
| INT1 | 0.0000 | 0.0000 | 0.1690 | 0.0000 |
| INT2 | 0.0000 | 0.0000 | 0.1652 | 0.0000 |
| INT3 | 0.0000 | 0.0000 | 0.3395 | 0.0000 |
| INT4 | 0.0000 | 0.0000 | 0.3263 | 0.0000 |
| Banking | 0.0000 | 0.0000 | 0.0000 | 1.1827 |
| Sport 1 | 0.0000 | 0.0000 | 0.0000 | -2.5180 |
| Sport 2 | 0.0000 | 0.0000 | 0.0000 | -1.0683 |
| Sport 3 | 0.0000 | 0.0000 | 0.0000 | -3.3441 |
| Weather 1 | 0.0000 | 0.0000 | 0.0000 | 1.2157 |
| Weather 2 | 0.0000 | 0.0000 | 0.0000 | 3.7502 |
| Weather 3 | 0.0000 | 0.0000 | 0.0000 | 1.7817 |
| Email time | 0.0000 | 0.0000 | 0.0000 | 2.5988 |
| Message time | 0.0000 | 0.0000 | 0.0000 | 1.5683 |
| Tickets time | 0.0000 | 0.0000 | 0.0000 | 2.0157 |
| Banking time | 0.0000 | 0.0000 | 0.0000 | 1.2361 |
| Weather time | 0.0000 | 0.0000 | 0.0000 | 1.8494 |
| Sports time | 0.0000 | 0.0000 | 0.0000 | 1.1232 |
| Wallpaper time | 0.0000 | 0.0000 | 0.0000 | 1.2489 |
| Music time | 0.0000 | 0.0000 | 0.0000 | 1.8654 |

Table 1. The summary of the measurement model.

Note: Experience, operation, and performance is a formative construct while intention is a reflective construct. Since high internal consistency of items is undesirable for formative constructs, reliability of formative constructs is evaluated by examining the nonexistence of excessive multicollineaity because common factor analysis is useless for formative constructs. The variance inflation factor (VIF) statistics, an indicator of multicollinearity, for the formative measures of the constructs were between 1.004 and 1.788, which are lower than 3.3 (the suggested maximum value for reliability of formative measures), indicating satisfactory reliability for the scale.

Appendix B: Measures of subjective knowledge, actual knowledge, confidence, and compatibility

**Intention**
I intend to continue using the smartphone in the future.
I will always try to use the smartphone in my daily life.
I plan to continue to use the smartphone frequently.
Source: Venkatesh *et al*., 2012
**Subjective knowledge**
I think I know how to use the smartphone simulator used in this experiment.
I think I can use the smartphone simulator to perform a task.
I think I understand the features of the simulator.
Source: Raju, Lonial, and Mangold, 1995
**Actual knowledge**
Please fill the blank.
If you would like to reply to a message received, you should tap ___________________.
If you would like to purchase movie tickets, you should click _____________________.
If you would like to pay a bill, you should select ________________________________.
If you would like to see hourly forecast, you should click ________________________.
Source: Moorman *et al*., 2004
**Compatibility**
Using the smartphone simulator fits my preferred routine for conducting my work.
Using the smartphone simulator is compatible with most aspects of the way I typically conduct my work.
Using the smartphone simulator is compatible with my past smartphone experience.
Using the smartphone simulator is consistent with the way I view the world.
Source: Karahanna *et al*., 2006
**Confidence**
I feel confident about my ability to perform a task with the smartphone.
I have the skills required to perform a task with the smartphone.
I have no trouble performing a task with the smartphone.
I am not afraid to perform a task with the smartphone.
Source: Bearden *et al*., 2001
Note: all measurement items were adopted from existing measures, but they were adapted for this study