CATCH THE CLOUD: USER RESEARCH ON THE CHAOS MARKET

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ABSTRACT

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New products continue to launch quickly but many of them are converged products. The "new product" is not a completely new thing to consumers and the basic features stay the same. As a result, the added functions or fancy design can't explain why consumers adopt the new media. Past studies have examined perceptions of innovations or user experience to understand what factors have impact on the intention. However, most studies failed to explore individual differences or users' context; rather, they investigated consumer perception of innovation independently. In this chaotic market, there is much competition for consumers' attention. In such, it is important to investigate how consumers perceive innovation. The usability field investigates the contextual factors as principal components forming usability and the consequence of usability, which represents the perceptions of the product or service. However, the relationship between contextual factors and innovation attributes has not been widely investigated in the new media adoption studies. There is a growing body of evidence indicating that contextual factors of consumers' impact on communication technology adoption affects their decisions.

In accordance with the importance of the contextual factors with innovation attributes, this study explored factors that led the consumers to adopt a cloud note-taking application as a representative innovation. The study employed 402 respondents comprising three lifestyle clusters of active note-takers and possessing no experience with a cloud note-taking application. The study analyzed how the contextual factors (e.g., social influence, knowledge, and past

experience with similar services) are related with innovation attributes (e.g., relative advantage, complexity, compatibility, observability, triability and risk); furthermore, it explored how innovation attributes are related to adoption intention. The measurement model offered high explanatory power (i.e., 53% of the variance in the behavioral intention to use the innovation was explained by innovation attributes).

The study validated the relationships between innovation attributes and behavioral intention to adopt, and offered support for its applicability in the context of cloud computing. Also, this study demonstrated the utility of adding contextual-specific factors to a well-established theory. By providing insights into the relevant contextual factors impacting innovation attributes, this study has potential of increasing the predictive power of the Diffusion of Innovation theory. Also, the study theoretically and empirically demonstrated that the contextual factors impact intentions indirectly through perceptions of innovation.

In addition, the study investigated various group of people and identified three groups of consumers who live three types of lifestyle (traditionalist, hedonic yuppies, and intelligent businessmen). By exploring the research model with three groups, the study indicated how each group has different contexts, perceptions and intentions in the adoption process. Practically, the study suggested which contextual factors the industry should focus on and invest in to raise perceptions of innovations. Also, the study showed the possible main target group of people for the innovation, and advised how the industry needs to treat their various targets, as well as how to promote their services or products to increase positive perceptions of it.

To my beloved family, friends, Cozy and Dr. Coursaris

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INTRODUCTION

Technology moves fast in these days. People often lose interest when new products keep changing. Sometimes, they are not completely new; products are often converged with other products to give more functionality. Basic features stay the same, and other features are added along with the design to give more convenience and attractiveness. In this competitive and saturated market, people are not convinced by fancy designs and updated features, since they might not be aware of the benefits or even the existence of new products. Moreover, older and existing products can still perform basic features that they want.

Consumer adoption research indicates several predictors of user intention to adopt a new product. The Technology Acceptance Model or TAM (Davis et al., 1989), which has been used tremendously in adoption research area, relies on consumers' perception of usefulness and ease of use toward the new technology to investigate user intention to adopt new technology. However, the TAM has been criticized for ignoring social influence/usage, individual differences, and limited perceptions; as a result, it has been extended in many studies (Agarwal & Prasad, 1999; Al-Somali et al., 2009; Featherman & Pavlou, 2003; Hu et al., 1999; Sung & Yun, 2010; Straub, 2009). Diffusion of Innovation Theory or DIT (Rogers, 2003) has also been used to explore adoption and usage of an innovation. DIT emphasizes the knowledge stage as a precedent stage of persuasion in which consumers form the perception of the characteristics of innovation. Many studies have explored perceptions of innovation without considering knowledge stages (Coursaris et al., 2010; Featherman & Pavlou, 2003; Howcroft et al., 2002; Hsu et al., 2007; Lee et al., 2003; Lin, 2011). Also, even perceptions are not consistently validated to all new technologies; as a result, a few of perceptions were used to study adoption and usage (Leung & Wei, 1999; Low et al., 2011; Tornatzky & Klein, 1982; Wei, 2001).

According to Livingston (1999), understanding the audience and their lives is even more important in media research. Nowadays, the consumer market is full of new and similar products, and they are all competing for the consumer's attention. In this case, consumers take the initiative and reflect the market situation. Therefore, it is important to investigate not only what attributes consumers perceive from innovation but also how they form perceptions, since those perceptions determine how well users will accept a new technology and subsequently how they will be using it. In accordance with the importance of user research, Han et al. (2001; Kwahk & Han, 2002) suggested contextual components as the principal components for forming usability, because they found the usability of a consumer product is formed around the interactions among the user, product, user activity, and environment. Several scholars (Bevan & Macleod, 1994; Shami et al., 2005; Thomas & Macredie, 2002) also attempted to identify additional variables that may impact usability and, subsequently, adoption, leading to the conceptual emergence of context of use. More recently, Coursaris and Kim (2011) proposed a contextual usability framework for a mobile computing environment, and the four contextual factors include User, Technology, Task/Activity, and Environment as impacting usability. What it means is that user, social environment, specific types of technology, and task/activity of the product need to be considered before directly investigating usability dimensions (i.e., effectiveness, efficiency, satisfaction, and playfulness) because contextual factors affect the usability and the consequence of usability (Coursaris & Kim, 2011).

Therefore, when it comes to perception of new technology and adoption, it is essential to explore user-specific factors including consumer backgrounds, experience, or knowledge, to investigate how they form the perception of a new product and how these factors affect the perception of the innovation (Coursaris & Kim, 2011). Past studies have attempted to use

consumer background information to explain intention, but this information was investigated separately or independently from the perception of a new technology and the information was treated as direct factors toward intention without considering the possible relationship with the perceptions (Chan-Olmsted & Chang, 2006; Hsbollah & Idris, 2009; Shin, 2011; Slyke et al., 2007; Sultan & Chan, 2000; Wang & Liao, 2008). Also, past studies even used fragmented information such as only demographic information or only subjective norm (Azouzi, 2009; Hargittai, 2007; Kwon & Chon, 2009; Ratten & Ratten, 2007; Sun & Zhang, 2006; Thurman, 2008; Zainudeen et al., 2010). Expectancy Confirmation Theory (Bhattacherjee, 2001a) considers consumer experience with a single product or service in isolation, but it does not consider the relationship between new and existing services in their adoption; experiences with other similar services and new one being considered adoption.

Therefore, 1) the present research focuses on contextual factors as antecedents to the perception of innovation in order to determine how those factors are related to the perception of innovation, since consumers themselves reflect the market state; their background forms the perception of the innovation. Then, 2) the study explores how perceived innovation attributes are related to adoption intention. The research model can be flexibly validated to various new technologies, because the model starts with the users' background and then addresses how they perceive products. Also, 3) the study investigates how various groups of people with different lifestyles display different processes when adopting an innovation. To investigate the adoption process, the study applied a contextual framework (i.e., User, Technology, and Environment) to explore user characteristics specifically from Coursaris and Kim's study (2011) as antecedents of perception of the new technology. Consumer lifestyle, knowledge of new technology, and past experience are explored as a User component, and surrounding influence is presented as an

Environment component. As a Technology component, the study presents cloud computing. Cloud computing is a representative innovation in this market status. Cloud computing offers easy manageability of data, reliability of data recovery, device and location independence, flexibility, and even supports collaboration and sharing. This implies that cloud computing has relative advantages to other existing technology (e.g., static software and computer). However, at the same time, it has privacy and security issues, which are assumed as a possible risk. Also, existing technology can perform the basic functions without being replaced by cloud computing; therefore, users may not be fully committed to adopt cloud computing just because of convenient and updated features. Moreover, consumers might be unaware of advantages or even of cloud computing, itself, since it is a fairly new service. Likewise, cloud computing is a new technology that has possible advantages, risks, and uncertainty, which reflect new technologies' current state as a good example for the new technology adoption research. Task/Activity component is not adopted since the study will not perform the experiment such as usability testing.

The next chapter (Background & Research Motivation) provides a background of the study including saturated and competitive market state, the importance of audience research, the contextual factors, research questions, theoretical foundation, and the information of cloud computing as targeted new media. The chapter 3 (Hypothesis development) provides extensive literature review of innovation perceptions and the consumer lifestyle cluster studies. Additionally, a review was conducted of the relevant literature pertaining to social influence, knowledge and the past experience examined in this study. Based on this literature review, hypotheses were developed regarding new media adoption. Chapter 4 (Methodology) discusses the research design, data collection, instruments, and measures that formulate the methodology

used in this study. Lastly, chapters 5 (Results) and 6 (Discussion) present the results, implications, and limitation of this study along with recommendations for future research.

BACKGROUND & RESERARCH MOTIVATION

Saturated and Competitive Market

Currently, the diffusion speed of information technology products and services is increasing, and the adoption rate is coming close to 100 percent in developed countries. According to the latest data from the International Telecommunication Union (2011), there were an estimated 5.9 billion mobile phone users at the end of 2011. These estimates are significantly higher than earlier reported numbers of one to two billion users. Also, communication services such as social networking sites (SNS) also show fast and high penetration rates. Facebook, a leading SNS, has a growing audience that exceeded 155 million users in U.S. at March 2012 (Gonzalez, 2012). As a comparably new service, Twitter, which launched in 2006, has gained extensive notability and popularity worldwide (Opstal, 2010). Twitter has 140 million users, and what is remarkable is Twitter's 40 percent growth over the 100 million active users from just few months ago (Wasserman, 2012). This phenomenon shows that customer immigration generated by switching from one service to another is prevalent. Thus, IT suppliers compete in saturated markets.

Consumers compare the utility of previous technology with new alternatives. If the old one was better, then consumers choose to retain it; if not, then they chose the new one. New technology keeps coming out, and the entrance speed is increasing. In this environment, consumers cannot catch up with all of the new technologies and cannot be aware of benefits from new technologies. Past studies regarding consumer adoption did not consider how consumers become aware of a new technology, although the marketing field emphasizes brand awareness and experience.

In addition, technologies are often converged into one product, which means that they combine features from various technologies; thus, some new technology is not totally original (Riemer et al., 2009). Therefore, old technology can still satisfy consumers, although new technology has better utility. New technologies are under competition with older technology. Thus, consumer willingness to adopt new technology is formed from various factors besides product utility. Thus, an improved adoption model is needed to reflect the competitive and saturated market situation and determine what factors impact consumer intention to adopt a new technology.

Understanding New Media Users

Many diffusion models have been employed to analyze new media adoption and usage (Gharavi et al., 2004; Harman & Koohang, 2006; Lee et al., 2006; Liu & Li, 2010). However, the studies used various new media and they are all different. Livingston indicates three characteristics of new media regardless of different contexts, technologies, and user groups. The first is social context use, which blurs the barriers between public and private. Second, media are diversifying in forms and contents; this diversification encourages the multiplication of devices and facilities individualization (Beck, 1992; Chisholm et al., 1990; Reimer, 1995). Therefore, media use is becoming detached from traditional socio-structural determinants and reconstructed within diverse conceptions of lifestyle. In the past, there was only one television at home which was placed in the living room to watch with all family members. However, nowadays, there are multiple televisions at home, and television programs can be watched on various devices, which encourage individualization. The third new factor is democratization. Traditionally, making visible forms of knowledge and opinions was dominant for the higher status or limited group.

However, as media information and telecommunication services become interconnected, people can get rich information from surroundings easily and adoption decisions affected by them.

Fast Internet use, the high mobile phone adoption rate, and the frequent use of social network sites facilitates and encourages social context use of media, individualization, and democratization of information. A key consequence of new media technologies is the transformation of the audience itself (Livingston, 1999). As the audience become less predictable, more fragmented, or more variable in their engagement with media, understanding the audience and their lives is even more important in media research.

Contextual Factors and Innovation Adoption

In accordance with the importance of user research, the concept of varied situational contexts got attention from the usability environment. Usability was originally intended to explain how efficient and effective a product was to use (Bennet, 1984; Shackel, 1984). However, the concept of usability is undergoing a major change as the application area is broadened (Hofmeester et al., 1996; Nielsen, 1996; Jordan, 1997), and usability has been extended to consider a broader range of the subjective aspect such as product image, aesthetics, and appeal. As a result, the concept of context of use emerged out of the work of several scholars (Shami et al., 2005; Thomas & Macredie, 2002) who attempted to identify additional variables that may impact a broader range of usability. Han et al. (2001; Kwahk & Han, 2002) proposed a usability evaluation framework that contains four contextual components (i.e., User, Producer, Activity, and Environment). The four contextual components impact the usability; therefore, they have to be defined and considered to evaluate the usability. More recently, Coursaris and Kim (2011) suggested the contextual usability framework for a mobile computing environment based on Han

et al.'s (2001; Kwahk & Han, 2002) studies, and it includes four contextual factors as impacting usability and consequences of usability (i.e., increasing adoption, retention, and loyalty). The suggested mobile usability framework is presented in figure 1. The first one is the User component which is about human characteristics including demographics/social information, knowledge/experience characteristics, perception/cognition, and emotional/psychological characteristics. User variables are important in defining the target users and determining the logistics of usability evaluation, since user variables indicate users' special needs and challenges (Kwahk & Han, 2002). Second is the Environment component which includes both the physical conditions (i.e., auditory, visual, co-location, experiment type) and psychosocial (or social) conditions. The environment in which a product operates has been considered important, and user performance is known to be affected by it (Kwahk & Han, 2002). The Technology is the third component and it is about the device type or system with which a user may interact. The last component is the Task/Activity given to users at the usability testing to see how users do with the product while they perform the task/activity. It includes the open (outcome defined by user) and closed (pre-defined outcomes or goal) task/activity.

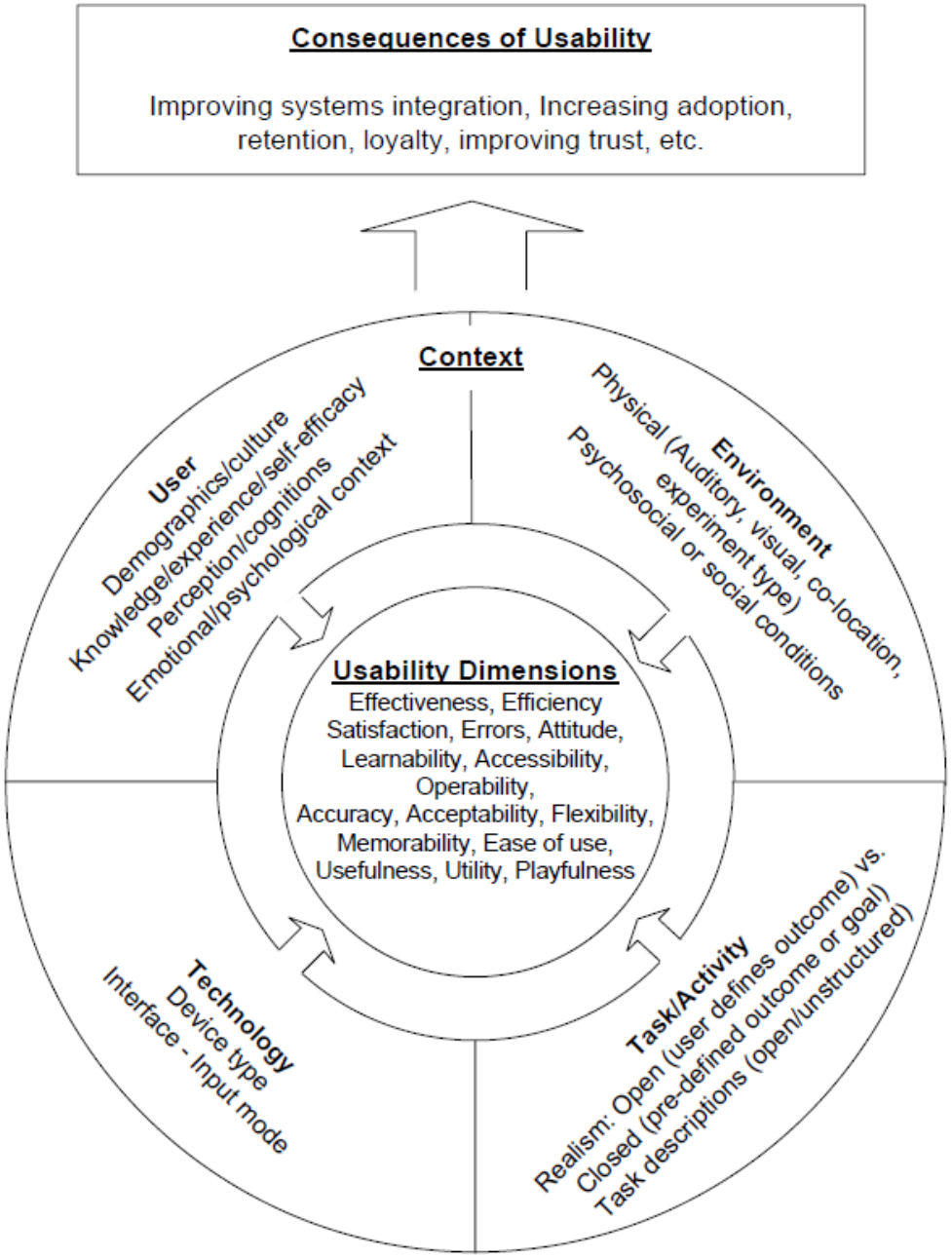


Figure 1. A Contextual Usability Framework for a Mobile Computing Environment (Coursaris & Kim, 2011)

The contextual usability framework was demonstrated through case studies and it was considered important (Coursaris and Kim, 2011). The contextual components at the usability framework were used to define the test situation and it was suggested to evaluators to set each of

the components before performing the usability test. Depending on users' background, the environment in which users are using the product, what technology users are using, and what task/activity users are performing, usability results are varied. In support of the importance of the contextual component, the concept can be applied to explore users' perception of product/service and adoption. Therefore, it is essential to explore contextual factors to investigate how users form the perception of a new product and how these factors affect the perception of the innovation before their investigation, solely.

Research Questions

To identify factors that affect new media technology adoption, in this study a cloud note-taking application, and to gain a broad understanding of issues that influence decision-making process in the adoption, the following research questions are addressed:

1. What are the contextual factors of relevance in the adoption process of an innovation?
2. What are the relevant attributes of an innovation that influence a consumer's intention to adopt it?
3. What differences exist between various lifestyle groups regarding their respective adoption process of an innovation?

Theoretical Foundations

Consumer adoption research indicates several predictors of user intention to adopt innovation. Three dominant theories (i.e. Technology Acceptance Model, Diffusion of Innovation Theory, and Expectancy Confirmation Theory) regarding innovation adoption were

considered for the core theoretical foundation of this study. They are described next, along with a summary discussion and the selection of the core theory used in this study.

Technology Acceptance Model (TAM).

The Technology Acceptance Model (TAM) is originated from the Theory of Reasoned Action (TRA), an intention model from social psychology used as a potential theoretical foundation for research on the determinants of user behavior (Ajzen & Fishbein, 1980; Davis et al., 1989; Fishbein & Ajzen, 1975; Swanson, 1982). The foundation of the TRA conceptual framework is the distinction between beliefs, attitudes, intentions, and behaviors. According to the TRA, a person's performance of a specific behavior is determined by his or her behavioral intention to perform the behavior, and behavioral intention is jointly determined by the person's attitude and subjective norm concerning the behavior in question. Subjective norm refers to an individual's belief that he or she should perform a certain behavior because it is expected by others who are important to the individual (Fishbein & Ajzen, 1975). The TRA has proved successful in predicting and explaining consciously intended behaviors across a wide variety of domains (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975; Schiffman & Kanuk, 2007; Yousafzai et al., 2010). However, it is very general and as such does not specify the beliefs and norms that are effective for a particular behavior (Davis et al., 1989). Hence, Davis (1986) introduced an adaptation of the TRA called the technology acceptance model (TAM).

A key purpose of TAM is to provide a basis for tracking the impact of external factors on internal beliefs, attitudes, and intentions. To achieve this goal, the TAM was formulated by identifying a small number of fundamental variables that deal with the cognitive and affective determinants of computer acceptance (Davis et al., 1989). The TAM (Figure 2) postulates that

two particular beliefs, perceived usefulness (PU) and perceived ease of use (PEOU), are of primary relevance for computer acceptance behaviors. Davis (1989) defined PU as the degree of which a person believes that using a particular system would enhance his or her job performance and PEOU as the degree of which a person believes that using a particular system would be free of effort. Behavioral intentions (BI) to use are determined by PU and PEOU. This is based on the idea that, within organizations, people form intentions towards behaviors, which they believe will increase their job performance overall and the positive or negative feelings evoked toward the behavior (Davis et al., 1989). Also, PU is determined by PEOU, as the lesser the effort required using a system, the more useful it is perceived to be. Finally, BI to use leads to actual system use. Although the TRA indicates that attitude and subject norms affect intentions, the TAM believes that PU and PEOU directly affect a person's attitude. Davis et al. (1989) found that the subjective norm construct did not significantly affect intentions above PU and PEOU and therefore removed it from TRA. In the traditional TAM, PEOU and PU constructs are considered as important criteria in determining the acceptance and use of IT (Keil et al., 1995; Malhotra & Galletta, 1999; Moon & Kim, 2001; Sung & Coursaris, 2011; Sung & Yun, 2010). Its ability to explain intention and attitude towards using IT is better than TRA (Mathieson, 1991).

However, the TAM was designed to understand IT implementation; as such, the variables in the model were framed to predict user behaviors within an organization. In turn, the TAM focuses on only two beliefs and excludes the subjective norm, as mentioned above. These beliefs are meant to be fairy generalizable across systems (Davis et al., 1989). However, nowadays, social usage of media is growing, and new media adoption research has revealed the importance of social influence and social image (Dahlberg et al., 2008; López-Nicolás et. al., 2008; Lucas & Spitler, 1999; Pedersen, 2005; Shin, 2007; Wu et al., 2007). In addition, one of the most

prominent criticisms of the TAM is the lack of acknowledgement of individual differences (Agarwal & Prasad, 1999). Beliefs and attitudes about technology are influenced by more than the PEOU and PU of the product. The original TAM does not take into account prior experience or consumer characteristics, which may influence intention to use an innovation (Straub, 2009). Empirical studies have suggested that TAM be integrated with other acceptance and diffusion theories to improve its predictive and explanatory power (Hu et al., 1999).

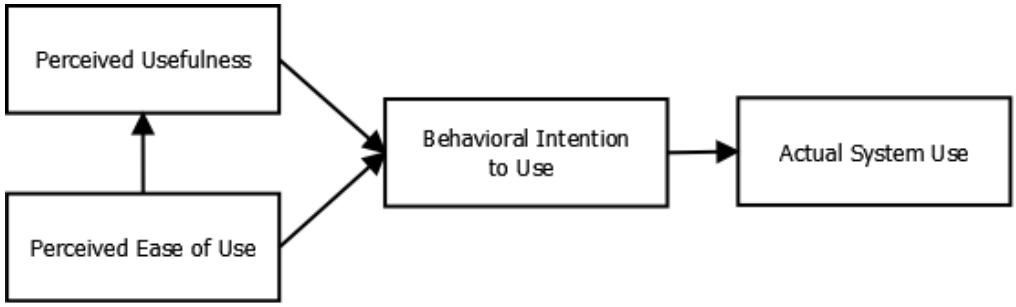


Figure 2. Technology Acceptance Model (Davis et al., 1989)

When compared with the TAM, on the other hand, Diffusion of Innovation Theory (DIT) has a much broader scope, since it includes as an innovation, any idea, practice, technique or object that is perceived as new by a unit of adoption (Rogers, 2003). The unit of adoption ranges from individuals within a social system to groups and organizations. Based on the innovation, the range of beliefs or perceptions about the innovation varies by making the beliefs individual to the innovation and the adopter. The TAM and the DIT have some obvious resemblances, although they originated in different disciplines. The relative advantage factor in DIT is often viewed as the equivalent of PU in TAM, and the complexity factor in DIT closely parallels PEOU in TAM (Moore & Benbasat, 1991). Furthermore, TAM2, an extension of the TAM, suggests several other variables such as result demonstrability (i.e. visibility of the results of using the innovation),

which is similar to observability in DIT (Venkatesh & Davis, 2000). Likewise, compared to DIT, the TAM lacks explanatory power for new media adoption in new markets and audiences.Given the overlap of two prevalent factors from the TAM (PU and PEOU) with factors from DIT (relative advantage and complexity), this study will use DIT rather than TAM.

Diffusion of innovation Theory (DIT).

One well-established theory for user adoption is Diffusion of Innovation Theory (Rogers, 2003). An innovation is an idea, practice or object that is perceived as new by an individual or another unit of adoption, while diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 2003). Innovation diffusion is achieved through users' acceptance and use of new ideas or products/services. The theory explains the process of the innovation decision process, the determinants of rate of adoption, and various categories of adopters. Also, DIT helps predict the likelihood and the rate of an innovation being adopted (Rogers, 2003).

Rogers (2003) proposed that the decision of the adoption process consists of a sequence of actions and decisions. The innovation-decision process comprises a series of stages through which potential adopters pass as they move from seeking information about the innovation to making a decision to adopt or reject and finally to confirming their adoption decision. These stages are shown in Figure 3:

1. Knowledge: learning about the innovation's existence and gaining some understanding of how it functions.
2. Persuasion: forming favorable or unfavorable attitude toward the innovation.

3. Decision: engaging in activities that lead to a choice to adopt and making decision to adopt or reject the innovation.

4. Implementation: using the innovation.

5. Confirmation: seeking reinforcement of an innovation decision.

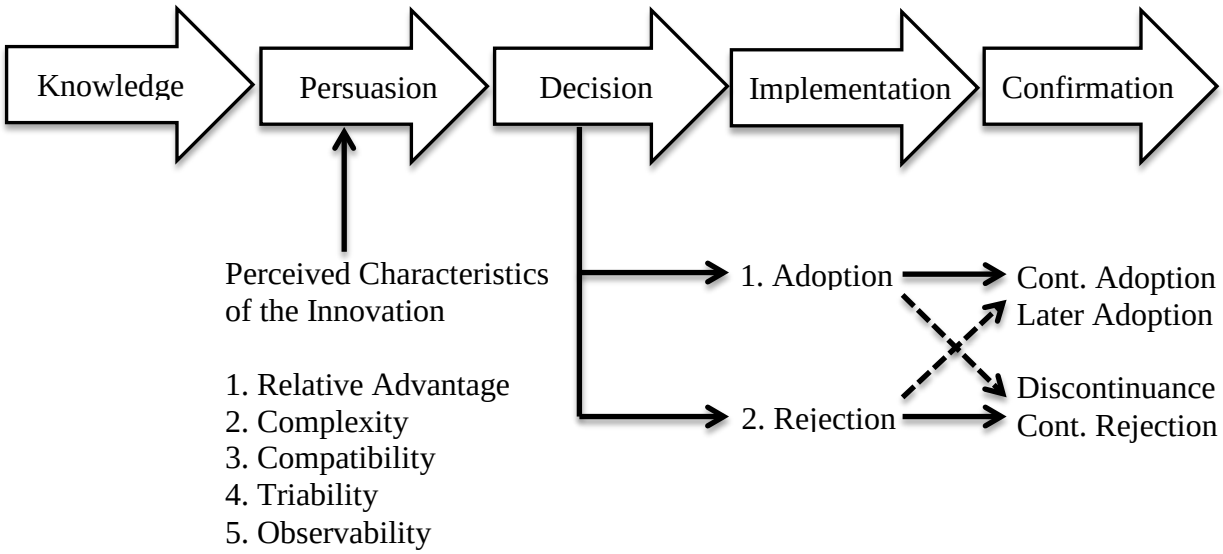


Figure 3. Stages in the Innovation Decision Process (Rogers, 2003)

As summarized in the figure 3, the innovation adoption process begins with an individual becoming aware of an innovation and being interested in understanding how it functions (Rogers, 2003). In the first stage of awareness, the prospective adopter familiarizes him or herself with the innovation and gains some knowledge. During the persuasion stage, attitudes toward the innovation are formed, and the individual seeks to identify the consequences associated with adopting or not adopting the innovation (Rogers, 2003). As the individual becomes familiar with the innovation, the decision process occurs. During the decision stage, the individual engages in various evidence-based decision-making activities in order to arrive at a conclusion to either

adopt or reject the innovation. There are two possible outcomes of the decision stage: An individual may choose to reject the innovation or to adopt the innovation. If the decision to adopt the innovation is made, then the innovation is put into practice, which represents the implementation stage. In the final stage of the framework, the confirmation stage, the individual seeks reinforcement for the decision made. This may include the adopter seeking justification for the decision to adopt the innovation by identifying positive outcomes associated with adoption or negative consequences associated with rejecting the innovation. However, it could also include negative outcomes associated with the adoption (Rogers, 2003).

According to Rogers (2003), the decision to adopt or reject an innovation is subject to a wide variety of factors. These factors can be grouped into four major categories (Leung & Wei, 1999): adopter-related personality traits, socioeconomic influences, interpersonal channels and mass media use, and perceived attributes of an innovation. Specifically, the perceived attributes constitute the individual's subjective perceptions or beliefs about an innovation. Rogers (2003) emphasizes personal or subjective beliefs against expert opinion, even if these perceptions are biased or inaccurate. Similarly, Ostlund (1974) argues that the more positive the individual's perceptions about an innovation are, the greater the probability of its adoption. Rogers (2003) details five characteristics of innovations that significantly influence consumer attitudes: relative advantage, compatibility, complexity, observability, and triability. The perceived attributes of an innovation are particularly influential in leading to an adoption decision; they explain between 49 and 87% of the variance in the rate of adoption (Rogers, 2003). Several researchers have incorporated pieces of Rogers' model in empirical work examining technological innovations. Perceived attributes are valid and significant factors in diffusion (Coursaris et al., 2010; Howcroft et al., 2002; Hsu et al., 2007; Lee et al., 2003). In applying DIT to cloud computing

adoption research, this study adopts the above-perceived attributes of an innovation as the most relevant points to understand the adoption process.

Prior research on the impact of these five belief variables on diffusion has often been inconsistent, although the findings of previous empirical studies have confirmed that the five perceived innovation characteristics are significant predictor variables explaining innovation adoption (Hsu et al., 2007). In a meta-analysis of the relationship between the characteristics of an innovation and its adoption, Tornatzky and Klein (1982) found that only compatibility and relative advantage were usually, but not always consistently, related to the rate of adoption in a positive direction. Similar inconsistencies have been reported in mobile phone research, although Rogers (2003) noted that mobile phones have an almost ideal set of perceived attributes, which was one reason for their rapid adoption. Leung and Wei (1999) compared the impact of the five attributes on the adoption of mobile phones in Hong Kong and reported a significant impact of only compatibility and observability on the likelihood of adoption. Wei (2001) extended this research longitudinally and found that only observability continued to have a significant impact on the likelihood of adoption. Likewise, five attributes are not validated consistently, then, what factor appeared in the knowledge stage and what can be the antecedents of perception on innovation should be considered for the future research, since the perception of innovation formed and affected by knowledge stage. Hence, exploring the impact of antecedents of perception on innovation significantly contributes to our understanding of the diffusion process in this study.

Expectancy Confirmation Theory (ECT).

Regarding post-adoption behavior research with consumers' past experience, the

expectancy-confirmation theory has been studied and extended (Anderson & Sullivan, 1993; Hong et al., 2006; Hossain & Quaddus, 2011; Thong et al., 2006). According to the expectation-confirmation theory, a consumer's level of satisfaction with the product/service is determined by the consumer's initial expectations (pre-purchase expectations) on a product/service and discrepancies between expectations and product/service performance (disconfirmation). Positive disconfirmation occurs when the perceived service/product performance exceeds the expectation; negative disconfirmation occurs when the real performance is lower than the expectation prior to use; and confirmation occurs when the real performance is exactly the same as expectation. Positive disconfirmation and confirmation form satisfaction, or affect (Oliver, 1980). Satisfaction is a judgment that a product or service feature, or the product/service itself, provides a pleasurable level of consumption-related fulfillment.

Empirical evidence supports ECT's hypothesis that satisfaction is a major determinant of continuance intentions or repurchase intentions (Bhattacherjee, 2001a, 2001b). The predictive ability of this theory has been demonstrated over a wide range of product repurchase and service continuance contexts. However, ECT only explains the continuous usage intention of existing services/product, although it considers user expectation based on past experience. It does not consider the relationship between new and existing services in their adoption. The adoption of a new service/product and the retention of an old one are not distinct factors. Therefore, research is needed considering the relationship between users' experience with existing products and perception of new products.

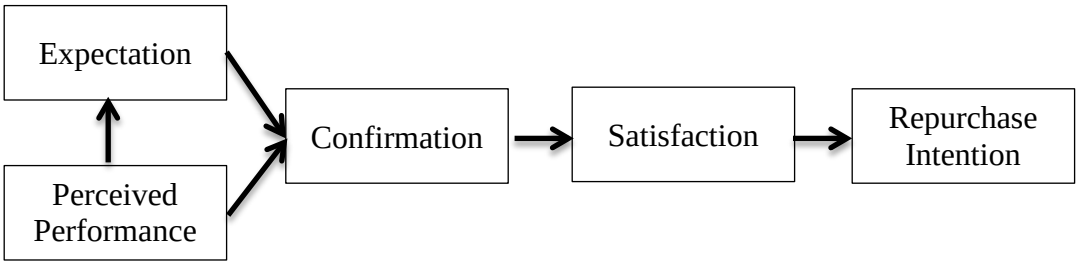


Figure 4. Expectancy Confirmation Theory (Bhattacherjee, 2001a)

As summarized in Table 1, the three most used theories in the study of innovation adoption may be criticized for their ignorance of subjective norms and the importance of prior user experience, their limited consideration of user perceived innovation attributes, and inconsistency regarding which of these attributes are reliable predictors of an innovation's adoption. This study aims to fill these voids by investigating the role of contextual factors (here, social influence, knowledge, and past experience) as antecedents to user perceptions of innovation attributes, and in turn their effect on the behavioral intention to adopt the innovation. Hence, the Diffusion of Innovation Theory is best suited for this investigation and will be serve as the core theoretical foundation for this study.

Table 1. Comparing three prominent theories related to technology adoption

	Technology Acceptance Model (TAM)	Diffusion of Innovation Theory (DIT)	Expectancy Confirmation Theory (ECT)
Source	Davis et al., 1989	Rogers, 2003	Oliver, 1980
Origin	Information Systems	Sociology	Marketing/Communication behavior
Dependent Variable	Behavioral intention to use/Actual system use	Adoption/Rejection	Satisfaction/Repurchase intention
Independent & Mediating Variables	- Perceived Usefulness (PU) - Perceived Ease of Use (PEOU) - Attitude	Innovation attributes - Relative advantage - Compatibility - Complexity - Observability - Triability	- Expectation - Perceived performance - Confirmation
Advantage	- Two reliable self-reported measures (PU and PEOU) in determining the acceptance and use of IT	- Large effect by said innovation attributes on the adoption decision	- Explanatory power on the continuous usage intention of existing service/product
Disadvantage	- Ignores the role of subjective norms, prior experience, and other user differences - Does not consider technology attributes	- Inconsistency among prior studies regarding the innovation attributes relevant in the adoption decision	- Does not consider the relationship between new and existing services (Past Experience construct)

Emergence of Cloud Computing

The evolution of personal computing has occurred in three distinct phases. In Phase 1, computers were separate devices in which software and data were stored, and typical applications were word processing and spreadsheets. Phase 2 came with the emergence of the World Wide Web, which made it possible to access varied and rich data; however, most users still relied on software that ran on individual machines. In the current Phase 3, data as well as software exists on the Internet rather than on a personal computer or a local server, because users

do not need to install software or store data on the computer. Most work is still done using Phase 1 tools. However, as we move from Phase 2 to 3, more and more people, especially the younger generation, are starting to take advantage of the power of Cloud Computing (Nelson, 2009).

The name “cloud computing” is a metaphor for the Internet. A cloud shape is used to represent the Internet in network diagrams in order to hide the flexible topology and to abstract the underlying infrastructure. Cloud computing uses the Internet to deliver different computing services, including hardware, programming environments and software, while keeping users unaware of the underlying infrastructure and location (Wikipedia, 2011a). There are no formal definitions of cloud computing, and the concept still overlaps with grid and cluster computing. Foster et al. (2008) defines cloud computing as a large-scale distributed computing paradigm that is driven by economies of scale, in which a pool of abstracted, virtualized, dynamically- scalable, managed computing power, storage, platforms, and services are delivered on demand to external customers over the Internet. Kaplan views cloud computing as a broad array of web-based services aimed at allowing users to obtain a wide range of functional capabilities on a “pay-as-you-go” basis that previously required tremendous hardware/software investments and professional skills to acquire (Twenty Experts Define Cloud Computing, 2008).

Although the term is new, cloud computing is an extension of the remarkable achievements of virtualization, Web 2.0, Service Oriented Architecture (SOA) technologies, and the convergence of these technologies. Moreover, interest in cloud computing has been driven by many advantages such as the popularity of multi-core processors and the low cost of system hardware, as well as the increasing cost of the energy needed to operate them. As a result, according to the Gartner Group, consumer cloud services for accessing content will be integrated into 90 percent of all connected consumer devices (Gartner, 2012). The number of people

subscribing to mobile cloud apps is also forecasted to rise from 71 million to nearly a billion by 2014 (Cherry, 2009). Cloud computing represented only about 3% of enterprise IT spending in 2010, but totaled $74 billion on public cloud services. It is growing five times faster than overall IT spending and will grow annually by 19% through 2015 (Gartner, 2011). Gartner (2011) also indicated cloud computing as one of top 10 strategic technologies for 2012. In addition, the major cloud computing providers, including Hewlett Packard, Microsoft, Amazon, IBN, Salesforce and Google, all have major initiatives to deliver a broader range of cloud services over the next two years. As more of these big companies continue to expand the market, competition will be heated, and cloud services will be varied (Business Wire, 2011; Gartner, 2011).

There are generally three types of cloud computing: software as a service (SaaS), platform as a service (PaaS) and infrastructure as a service (IaaS) (Arinze, 2010). Among them, SaaS is most relevant to this study, since SaaS provides individual services. The other two types are more related to industry and cloud infrastructure related services (Arinze, 2010; Jin et al., 2010). Software-as-a-Service (SaaS) is based on software use on demand, that is, software installed and running on a cloud platform. The software application can be used via a web browser over the Internet instead of on the user's computer. Services are offered and data shared among users through various computer networks, i.e. the "cloud". In this instance, the service provider offers the network access, security, application software, and data storage from a data center located on the Internet and implemented as a server with the required infrastructure. A service has ubiquitous access through a web browser or mobile device. Therefore, from a users' point of view, individuals can access all of their data from any device as well as applications and services from the cloud. Users see the cloud as personal information carriers following them

wherever they go and easing the flow of information between various devices. In addition, SaaS reduces the users' physical equipment deployment and management costs, because it offers a subscribe or rent model as a price option, which is different from traditional software that requires purchase of the full version (Hilbert & Trevor, 2004; Jin et al., 2010). In general, the cloud computing concept is not limited to single-function applications, such as those available with typical office suites, but can include comprehensive enterprise applications pieced together from components residing in varying Internet locations (Katzan, 2009). Cloud computing, specifically, SaaS, has six representative advantages: manageability, reliability, device and location independence, sharing and collaboration, scalability and flexibility, and cost-effective payment method (see Table 2).

The first advantage of this approach is manageability, since hardware problems are not much of a concern with a large network. Since hard drives fail with some reliability, most people make backup copies of their data; however, this requires some level of effort to maintain. Cloud computing can backup automatically, because it automatically sync data and all the files are backed up on secure server (Aymerich et al., 2008; Jin et al., 2010). For example, SaaS provides tools that are typically used through a program installed on one's own computer (e.g., office program, photo and video gallery, or editing tools). Offered as an Internet-based service and run on the web, the software does not need to be installed on each device, and configuration, updates and bug fixes are deployed in minutes. Thus, it is easier to support and to improve, as the changes reach the clients instantly, and security improves due to centralization of data.

Moreover, performance can be monitored, and it is easy to retrieve the archived data (Katzan, 2009; Strauber, 2010; Wikipedia, 2011b). In addition, the physical computer does not require high specification since data storing and processing occur over the Internet. The fact that

increasing numbers of small, simple computers are being sold is one sign of this trend (Hayes, 2008). This shift, in which our computers are no longer separate units, will make the next generation of cell phones, cameras, music players and consoles all feature “online” as their default setting (Snickars, 2009). In that case, reliability can be improved in cloud computing, since all data and settings are not stored on the device; therefore, possible disasters can be recovered easily (Katzan, 2009).

With the large availability of broadband Internet and wireless access, users are increasingly taking advantage of remote services in their everyday lives as well as at work (Ardissono et al., 2009). As mentioned above, the large availability of broadband and wireless networking is turning the Internet into the ubiquitous computer. In fact, as cloud applications run on remote servers and the complexity of software is placed in the back-end, it can give huge benefits to users, including data accessibility from anywhere that the Internet can be accessed (Weber & Kauffman, 2011). This advantage of device and location independence enables users to access systems using a web browser, regardless of their location or device. At the same time, sharing and collaboration can easily be performed in the cloud computing environment due to the huge accessibility of data. Individuals can upload data to the cloud; others can read and modify it; and data can be shared with more people (Nelson, 2009; Strauber, 2010).

Another advantage is scalability and flexibility. Cloud vendors have vast data centers full of tens of thousands of server computers, offering computing power and storage of a magnitude never before available. Cloud computing promises virtually unlimited resources. Individuals and organizations can store more data in the cloud than on private computer systems. Also, cloud computing offers various options to choose features, storage, costs, and so on. It offers much more flexibility than past computing methods. Thus, it allows users to experience the benefits of

an expandable utility without worrying about storage capacity, compatibility or other matters (Aymerich et al., 2008; Katzan, 2009).

Furthermore, cloud computing uses a pay-per use or subscription payment method (Barnes, 2010). Users do not need to purchase the whole product or service at once like with typical software such as MS Office or Photoshop. Although existing software programs have trial versions, these expire after a limited time. Instead of trial or whole priced service, cloud computing services usually offer a free version with limited features and provide various price options for added features or more storage.

Table 2. Cloud Computing Advantages

Source	Cloud computing advantages
Aymerich et al., 2008	• Device and location independence • Automatic configuration and update • Easy maintenance • Increased Storage
Barnes, 2010	• On demand self service • Broad network access • Rapid elasticity Measured service
Hayes, 2008	• Automatic configuration and update • Low level devices • Mobility Collaboration
Jin et al., 2010	• Less investment in terms of space, time and financial investment • Scale (unlimited resources such as computing power and storage) • Manageability (No configuration and backup)
Katzan, 2009	• Reliability • Device independence • Easy to use Scalability

Table 2 (Cont'd)

Strauber, 2010	• Device and location independence • Automated sync • Easy sharing and collaboration • Easy monitoring of performance (retrieve the history of archived documents) • Automated upgrading
Nelson, 2009	• Limitless flexibility • Better reliability and security • Enhanced collaboration • Portability Simpler devices
Wikipedia, 2011b	• Accessibility from anywhere with an internet connection • Pay per use or subscription based payment methods • Rapid scalability • System maintenance (backup, updates, security, etc) often included in service • Possible security improvements Reliability

With all of these advantages, SaaS businesses are increasingly moving their computing and collaboration applications to the cloud, and their shift in IT spending reflects that change in behavior. A recent market study forecasts that cloud computing and managed hosting spending by U.S. businesses will surpass $13 billion in 2014, which is a 112% increase between 2010 and 2014 (In-Stat, 2011).

However, there are also challenges related to cloud computing, especially when accessing the cloud from a mobile device. The network may not always be available or may be very slow. There might also be issues related to network configuration, for example, in mobile phone and networks. The always-on connection may consume the battery quickly and incur expenses in mobile networks (e.g., WiFi, 3G or 4G). Also, offline data should be safely and reliably cached to the device to be synched when the network is available (Hayes, 2008; Miller, 2008). In addition, as the data is saved to the cloud, privacy and security issues are crucial. As more data

are distributed over a wider area or a greater number of devices and being shared by unrelated users, the complexity of security is greatly increased. Users might think that they own the data, but the service providers also hold the data. This means when the data are on the cloud, it is no longer private; therefore, trust issues can arise (Katzan, 2009).

Examples of SaaS include online storage and web-based applications, such as email services (e.g., Gmail or Hotmail) and are fairly familiar among IT users. Email servers and user emails are stored on the cloud via the Internet and are managed by companies like Google and Microsoft. Access takes place through the Internet, and users get the benefits of email service without installation and maintenance issues. Social network services such as Twitter, Facebook or LinkedIn are also popular cloud services. Users put their stories, pictures, or information on the Internet and manage them online. Email and social network site have been in service for a long time, so people might perceive them as just websites rather cloud computing services.

Recently, Adobe and Google began providing web-based applications that reflect cloud service's benefits. The Google app provides several Web applications with functionality similar to traditional office software (e.g., MS office program) but also enables users to communicate, create and collaborate easily and efficiently. Since all of the applications are kept online and accessed through a web browser, users can access their accounts from any Internet-connected computer, and there is no need to install anything extra-locally.

Google Apps has several components. The communication components consist of Google Mail and Google Talk, which allow for communication through email, instant messaging, and voice calls. The office components include documents and spreadsheets, through which users can create online documents that also facilitate searching and collaboration. Google Calendar is a flexible calendar application for organizing meetings and events. Google's Web Pages provide a

webpage publishing tool. Also, the Google page can be personalized by adding contents and changing the design of page; the personalized setting can be seen on any device, which can acts as a personal desktop page (Google Apps Products Overview, 2010; Wikipedia, 2011b).

Similarly, Adobe recently launched Photoshop.com, where anyone can upload and store their pictures online. Also, Photoshop Express provides an online image editing program. Users do not need to purchase whole Photoshop program; instead, they can just go to the Photoshop Express page. Aside from documents and photo editing, music services are also on the cloud. Lots of music file downloading service providers are offering the cloud services such as Amazon cloud player, Spotify, mSpot Grooveshark, and so on. Users can listen to downloaded music on any device, or they can listen to music without downloading through streaming services. These music streaming services are usually monthly subscription-based; users do not download the music but rather select what they want to listen (Doerr et al., 2010). In addition, online storages services are offered from many providers as a basic cloud service; examples include iCloud, iDrive, Sugarsync, SkyDrive, Amazon cloud drive, and Dropbox. Online storage gives users a place to store information that is available to them wherever there is an Internet connection and provides a safe and secure place to backup users' important information.

Studied Technology Context: Cloud Note-Taking Application

As mentioned before, SaaS cloud applications are most relevant to the present study. They give a good example of new technology, which is expected to replace old technology, yet for many people their benefits are unknown. Also, although SaaS cloud applications have better utility, it is not a completely new service; old technology can still satisfy consumers in some ways. Therefore, it represents new technology in a competitive and saturated market.

Among SaaS applications, the study will specifically use the cloud note-taking app (i.e., Evernote, Springpad, OneNote, SimpleNote, or GoogleDoc). The note-taking app is not targeted to specific user segments; most of them provide free versions; and they offer all of the advantages of Cloud Computing, such as configuration and auto sync features, device and location independence, accelerated feature delivery (automatic update), and collaborative functionality (share function). Cloud note-taking apps have superior features to pre-install or default notepad or mobile note apps but with the same basic features (see Table 3). Therefore, consumers can compare the existing service and Cloud Computing (SaaS). Also, since the cloud note-taking app is not completely new, users' expectation will be affected by familiarity with similar cloud services, such as email, web calendars, or social network sites.

Table 3. Cloud Note-Taking Application vs. Pre-install Note Taking Application

	Cloud note-taking application	Pre-installed note taking application (mobile phone & personal computer)
Manageability (Sync, data archive)	Automated sync, automated update, and easy retrieve the data (data archive)	No sync, update, and archive
Reliability (recovery)	Easy recovery, but Internet connection is essential	No recovery, Internet connection is not essential
Device and location independence	Device and location independent service (Web based service)	Data saved on each device
Sharing and Collaboration	Sharing feature through SNS (e.g., Facebook, Twitter, email, URL) Or collaborating features that other users can edit the shared documents	No sharing function/mobile app can send the memo by email
Scalability & Flexibility	More storage, various options to choose, additional features [e.g., web clipping (Evernote)]	Limited storage regarding to each device, no option
Security & Privacy	Strong (centralized data) as well as weak (data is stored in online)	Weak (device can be stolen and lost, then all the data's gone with it)

Therefore, this study will use the cloud note-taking app defined as follows: a note-taking including document editing application that can be used on a webpage (personal computer and mobile web browser) and a mobile application; automated sync and updates are available (the most prevalent features of cloud computing); sharing or collaborating features are provided; various options of storage and additional feature are suggested. Examples of cloud note-taking apps include Evernote[1] , Springpad[2], One Note[3], Simple Note[4] , Google Doc[5], Catch Note[6], and Awesome Note[7].

[1] http://www.evernote.com

[2] http://springpadit.com/home/

[3] http://office.microsoft.com/en-us/onenote/

[4] http://simplenoteapp.com/

[5] http://docs.google.com

[6] https://catch.com/

[7] http://www.bridworks.com

HYPOTHESIS DEVEOPMENT

One well-established theory for user adoption is Diffusion of Innovation Theory (Rogers, 2003). The theory explains the process of the innovation decision process, the determinants of rate of adoption, and various categories of adopters. According to Rogers (2003), the decision to adopt or reject an innovation is subject to a wide variety of factors. One of factors is the perceived attributes which constitute the individual's subjective perceptions or beliefs about an innovation. The perceived attributes of an innovation are particularly influential in leading to an adoption decision (Rogers, 2003). In applying DIT to cloud computing adoption research, this study adopts the perceived attributes of an innovation as the most relevant points to understand the adoption process.

Perceived Attributes

Rogers (2003) details five characteristics of innovations that significantly influence consumer attitudes: relative advantage, compatibility, complexity, observability, and triability. These are described next in more detail.

Relative advantage.

Whether a person chooses to upgrade or change their current technology depends on a number of factors. One of the main factors is the comparison between the perceived benefits of upgrading the technology. Rogers (2003) called this the "relative advantage," which he defines as the degree to which consumers perceive a new product or service as different from as (and better than) its substitutes. Kaiming and Enderwick (2000) describe it as the adopter's belief of the likelihood that the technology can improve the economic benefits of the organization and/or

of the person. This relative advantage can be measured and defined individually. For example, it can be measured with economic, social, convenient, or satisfactory to the individual (Sultan & Chan, 2000), or it can be defined as technically superior in terms of cost, functionality, image, etc. (Fichman & Kemerer, 1993).

In researching new technology and building more knowledge about it, productivity and monetary costs are involved, meaning that if there is no clear advantage in adopting new technology, the individual will stick with what is familiar and/or wait until new and better technology is developed (Agarwal & Prasad, 1998; Edmonson et al, 2003). When the new product or service has relative advantages over existing one, this can encourage customers to learn about the new technology, positively influencing both role clarity and ability of the new product. The advantages also provide a motivational force through incentives or perceived rewards, which can lead to intention of use (Eastlick, 1996; Gatignon & Robertson, 1991). Moreover, the relative advantage even increases the speed of adoption (Sultan & Chan, 2000). Relative advantage is one of the perceived attributes that affect adoption of new technologies (Sultan & Chan, 2000, Fichman & Kemerer, 1993, Vishwanath & Goldhaber, 2003; Coursaris et al., 2010).

In addition, in the Information System literature, perceived usefulness (PU) is defined as the prospective user's probability of or the degree of belief that using a specific application system will increase his or her job performance, which closely parallels the concept of relative advantage. Past studies also indicate that PU and relative advantage are similar concepts (Shin, 2011; Slyke et al., 2007). Since PU is an important factor that affects adoption of new technologies, relative advantage receives more support in the adoption process. Therefore, it can be concluded that people will be more likely to adopt a new technology if they perceive any

relative advantage emerging from the new technology. If there is no advantage, then a person will not be likely to adopt a new technology.

Complexity.

One of the attributes that consistently relates to the rate of innovation adoption is complexity (Tornatzky & Klein, 1982). Complexity is the degree to which an innovation is perceived as difficult to understand and use (Rogers, 2003). The greater the level of complexity (or inversely, the less easy it is to use), the more negative the perception about the innovation, which then serves as a barrier to its adoption. New ideas that are simpler to understand are adopted more rapidly than ones that require the development of new skills. Likewise, a complicated, confusing technology will hinder role clarity and ability, because it will be more difficult to operate and understand and may also make the benefits less apparent to the user (Eastlick, 1996). Therefore, if the technology is perceived as more complicated or confusing, a customer will be less likely to try it (Coursaris et al., 2010; Meuter et al., 2005; Vishwananth & Goldhaber, 2003).

The link between perceived ease of use and attitude in TAM theory have been empirically verified in the IS literature. Perceived ease of use (PEOU) refers to the extent to which a person believes that using a system would be free of mental effort (Davis, 1989). This is a major determinant of attitude towards use in the TAM. In the IS literature, it is asserted that PEOU is an important determinant of users' intentions of acceptance and usage behavior. As mentioned previously, the complexity construct in DIT overlaps with the TAM's PEOU concept (Chen, 2008; Liu et al., 2008; Shin, 2011; Slyke et al., 2007). That is, PEOU refers to how easy a person thinks a new technology is; complexity, to how difficult. The two subjects relate to each

other in the sense that if one perceives a new technology to be complex, then it is not easy to use, and vice versa. Since the impact of PEOU on positive behavioral intention (BI) has been validated and investigated in various new media,

Complexity is also supported by its important role in the adoption process (Agarwal & Prasad, 1998; Shin, 2011; Sung & Yun, 2010; Venkatesh, 2008). Therefore, complexity is a huge determinant in the BI to use new technology. The lower the complexity of technologies, the more likely consumers will adopt it.

Compatibility.

Compatibility is defined as the degree to which an innovation is perceived as being consistent with existing values, past experiences, and the needs of potential adopters (Rogers, 2003). Ideas compatible with existing values and norms are adopted more rapidly than ideas that are not. Hernaandez-Encuentra (2009) asked senior citizens to describe what information and communications technology (ICT) they use, how they use it, and what they would like to see offered in the future. The study found that most of the subjects used their technologies to perform basic functions. For example, they used their phones for making calls, their computers for accessing the Internet, and their televisions for watching movies and shows. This means that new technology should be compatible with consumers' existing values and experience. If the new technology is armed with only new and fancy functions, consumers will not give up their comfort zone with existing technology, since they can get all of the functions they value without upgrading.

A good example of this can be seen in the mobile phone industry. Producers struggle to pack all of the cutting-edge technology into a phone without ruining or complicating its basic

functionality. Consumers question the decision to upgrade: are they giving up the comfort and ease of use of their current product for a more advanced yet complicated product that might have many functions they do not need (Jarvenpaa, 2005)? Similarly, Gatignon and Robertson (1991) found that e-banking adoption may require behavior different from consumers' typical routines, which in turn hinders adoption. For instance, e-banking is convenient and cost-effective, but people typically visit a branch bank and receive paper statements. They do not want to completely change their routines by adopting a new service.

Likewise, less compatibility will decrease motivation, because the innovation will not be consistent with values and lifestyle. This may also decrease willingness to learn about the innovation, thus decreasing role clarity (Eastlick, 1996; Gatignon & Robertson, 1991). On the other hand, increased compatibility with personal values and lifestyle increases the willingness of innovation trial and adoption. Past studies have shown that compatibility has the strongest effect on BI among other determinants such as complexity and relative advantage (Tornatzky & Klein, 1982; Leung & Wei, 1999; Wang & Liao, 2008). Therefore, it can be inferred that making a new technology more compatible with potential users' existing values and needs is critical for providers when promoting users' adoption of the new IT.

Observability.

Observability is defined as degree to which the results of an innovation are visible to others (Rogers, 2003). Observability helps clarify the role of the consumer, increase feelings of confidence, and show positive outputs to increase motivation (Eastlick, 1996; Gatignon & Robertson, 1991; Moore & Benbasat, 1991). The ability to observe and communicate with others about the new technology increases the chances that it will be tried. In other words, when an

adopter can see the result of an innovation easily, that experience is positively related with the innovation's adoption. For example, seeing ATMs on the street corners and in grocery stores make this technology more observable than PC banking conducted inside the home. Also, according to Kraut et al. (1994), people will relate more positively to the innovation's adoption if they see others who are important to them also using the system. Therefore, it can be hypothesized that the more frequently the new technology is observed, the more likely consumers will adopt it.

Triability.

Triability, or how easy it is for a consumer to test a product before fully committing to it, is crucial to explaining the current usage for a technology. Triability can be presented as a risk-free exploration of the technology; it allows users to find new things that fit their needs and takes away the risk of getting attached to dysfunctional technology (Agarwal & Prasad, 1998). If potential adopters of a new technology are more comfortable with the technology, then they will be more likely to adopt it (Sinti, 2006). In other words, triability leads to a more positive belief of innovation and therefore a more positive behavior towards IT adoption (Lam et al., 2007).

Past studies have shown the impact of triability in various fields. In the field of online shopping and banking, the trial period for a new service allows the consumer to better understand the service and possible risks and therefore increases the chance of technology adoption (Lee et al., 2003; Ahmad et al., 2010; Sinti, 2006). Hsbollah and Idris (2009) found that observability and triability are two of the most significant predictors of technology adoption in classrooms. If teachers were able to either try out a new technology or observe other teachers using a technology effectively, then they were more likely to commit to the new technology. Similarly,

Pollard (2003) looked at social networking sites and found that 6 out of 7 users who adopted a site trialed it first. These past studies demonstrate that triability is a strong indicator of usage.

In addition, some studies have found that triability can help mitigate certain factors that hinder adoption of new technology, that is, complexity. By allowing users to try the technology, consumers will find that it is not as complex or difficult to use, as they perceived, thus increasing adoption (Hossain & Quaddus, 2011). According to Lee et al. (2003), the more a person is able to try a new technology before fully committing to it, the more they will be able to understand the perceived benefit, which relates to its adoption. They found that only a few businesses allow users to try a new technology in order to limit the producer's risk. Triability enables users to observe how the innovation works, allowing them to recognize the benefits, understand their role, and have confidence in their abilities. In turn, the ability to test the innovation increases chances that it will be adopted.

Risk.

Ostlund (1974) uses an additional perceived characteristic of an innovation variable called "risk." Risk is defined as perceived uncertainty in a purchase situation (Im et al., 2008), and can be identified with economic, personal, service performance or privacy risks (Pavlou, 2003). Since many services require at least a partial release of personal information or exposure to the service, it stands to reason that consumers will wish to stay within their comfort zones with technologies and services that they already trust (Ruyter et al., 2001). Consumers doubt new technology in the rapidly evolving technology market, so the risk is high. The high risk of new technology can delay the adoption of a new product and fear of a better technology emerging to compete with the new technology or improve upon it (Ruyter et al., 2001).

Likewise, risk has been a major driving force in whether or not a consumer intends to use new technology. This has been studied in various fields, especially e-commerce, m-commerce, banking, and digital television (Chan-Olmsted & Chang, 2006; Chen, 2008; Hsu & Chiu, 2004; Liao et al., 2006; Pavlou, 2003). For example, in an e-commerce environment, trust issues can be one of the risks, because consumers find it difficult to assess the reliability of retailers. Therefore, uncertainty reduction, so-called less risk, is imperative in online transactions as a direct antecedent of the consumer's intention to act in an online environment (Pavlou, 2003). Also, the fears inherent in the Internet, like hackers and information being stolen, greatly increase the risks (Liao et al., 2006), which affects the usage of unsecured sites.

As risk increases, the likelihood of trial decreases. Disinterest inhibits changes in behavior and thus results in hesitancy to try new services or media. In other words, as risk increases, motivation to use an innovation decreases, hindering feelings of ability and desire to learn about the innovation. As mentioned previously, cloud computing has issues security and privacy, which may increase the risk. Cloud computing offers potentially great benefits; however, when the risk is greater than the benefits, the benefits will be squandered. For example, most people will not trust cloud computing to store their data if data storage is insecure or unstable depending on the Internet connection (Tuazon, 2010). Therefore, risk is particularly relevant to this study.

Building on past studies that suggest the impact of perceived attributes of innovation on the adoption behavior, this study will test these relationships in the context of a cloud computing service, specifically in the cloud note-taking application. It is plausible that the level of perceived attributes of the new technology is related to the behavioral intention to adopt. Therefore, the following hypotheses are proposed:

Hypothesis 1: Perceived attributes of the new technology will be related to behavioral intention to adopt the cloud applications.

Hypothesis 1a: Relative advantage will be positively related to behavioral intention to adopt the cloud applications.

Hypothesis 1b: Complexity will be negatively related to behavioral intention to adopt the cloud applications.

Hypothesis 1c: Compatibility will be positively related to behavioral intention to adopt the cloud applications.

Hypothesis 1d: Observability will be positively related to behavioral intention to adopt the cloud applications.

Hypothesis 1e: Triability will be positively related to behavioral intention to adopt the cloud applications.

Hypothesis 1f: Risk will be negatively related to behavioral intention to adopt the cloud applications.

Contextual Factors

Coursaris and Kim (2011) proposed a contextual usability framework for a mobile computing environment, and the four contextual factors included User, Technology, Task/Activity, and Environment as impacting usability. The contextual components at the usability framework were used to define the test situation and it was suggested to evaluators to set each of the components before performing the usability test. Depending on a user's background, the environment in which the user is using the IT product, what technology the user was testing, and what task/activity the user was performing, the usability results were likely to

vary. Therefore, when it comes to perceptions regarding a new technology and its potential adoption, it is essential to explore user-specific factors including a consumer's background, experience, or knowledge, to investigate how they perceive a new product and how these factors affect the intention to adopt the innovation (Coursaris & Kim, 2011). The study explores three contextual factors (i.e. social influence, past experience, and knowledge) as antecedents to the perceptions of an innovation to determine their relevance in the shaping of said perceptions.

Social influence.

A number of prior innovation adoption studies were criticized for not having accounted for the role of social influence in the adoption and utilization of new technologies (Agarwal & Prasad, 1999). Social influence refers to the phenomenon that the reference group influences behaviors and experiences in the form of social pressure to perform a particular behavior (Nysveen et al., 2005). Social influence manifests in the individual user acceptance of technology theories and models through its two constituents of subjective norm and image. Subjective norm, a core construct of the TRA, TAM, and TPB, is defined as an individual's perceptions of what significant others think about the individual performing a specific behavior (Fishbein & Ajzen, 1975). Subjective norm reflects an individual's motivation to comply with normative expectations of other people. Therefore, in some cases, individuals may choose to perform behavior in order to comply with others' expectations rather than with their own feelings and beliefs, even if they do not agree with these expectations.

Lucas and Spitler (1999) found that the subjective norm not only affects a user's intention to use technology but is also more important than their perceptions about ease of use and usefulness. Based on their theory and findings, some studies have modified the adoption model to include social norms (Venkatesh & Morris, 2000; Venkatesh & Brown, 2001). Additionally,

Bearden et al. (1989) suggest that such behaviors come from vulnerability to social influence to either comply with group norms or to enhance one's image within a group. Similarly, Venkatesh and Davis (2000) expanded social influence to include subjective norm and image, because use of innovation is perceived as an enhancement of the individual's status in the social system (Lu et. al., 2003). Image, a core construct of IDT, is defined as the degree to which use of an innovation is perceived to enhance one's image or status in one's social system (Moore & Benbasat, 1991).

With these corresponding constructs, social influence is recognized as one of the determinants of behavior, especially for mobile phone or social related services. For instance, mobile multimedia services allow people to be socially connected in anytime and anywhere; therefore, individuals are exposed to informal social networks in which the benefits of mobile technologies are discussed. Being connected with individuals who use mobile multimedia services influences use of the service itself (Pedersen, 2005). As a result, those who do not use mobile technology apparently struggle to maintain their social links (Carroll et al., 2002). Thus, using mobile services may be a way to maintain membership and support through increased interactions within the reference group.

Additionally, mobile phones are predominantly used as symbols of social progress; users may regard them as part of social status in their reference group (López-Nicolás et. al., 2008). When the penetration of an advanced mobile technology is not substantial, users may decide to adopt it to enhance their perceived social status. When members of a person's social group believe that a behavior is correct, it elevates a user's standing within the group. When it comes to the social network services, Guardoila and Diaz-Guilera (2002) found that the surrounding agents that identify the social network are more influential than mass media for adopting a new

service. Even when it comes to products or services with no social function, an individual's outlook can be shaped by those around him or her; individuals appear to act in a manner that is consistent with the social group with which they identify (Dahlberg et al., 2008; Shin, 2007; Wu et al., 2007).

Likewise, people's attitudes and behavior as well as their perceptions of an innovation are affected by social influence. These perceptions are formed by the information that an individual receives from his or her environment, including the social environment. As more friends/families are using a new product or talking about it, individuals become aware of it and compare it with the existing product. In other words, individuals consider the pros and cons of each based on what they see and heard from social networks order to determine the more efficient choice (Guardoila & Diaz-Guilera, 2002). One of social influence constructs was image, which elevates an individual's standing within the group. If adopting the innovation can help achieve expected social image, then benefits or relative advantage of innovation may be perceived. According to Kraut et al. (1994), people gain more benefits from an innovation if others who are important to them also use it; in other words, individuals perceive that the innovation might have benefits. Other past studies also indicate that social influence has a positive effect on perceived usefulness (Hsu & Lu, 2007; Venkatesh & Davis, 2000; Al-Somali *et al*., 2009). Haaker et al. (2007) found that social influence shapes an individual's confidence in or his or her ability to use a technology system. Potential users of advanced mobile services may feel that adopting the service or technology does not require much effort if others in their social environment say that the system is easy to use. Therefore, it can be assumed that social influence shapes how individuals perceive the innovation. As a result, the following hypothesis is made:

Hypothesis 2: Social influence will be related to the perceived attributes of the new technology (Relative advantage, complexity, compatibility, observability, triability and risk).

Hypothesis 2a: Social influence will be positively related to the relative advantage of the cloud applications.

Hypothesis 2b: Social influence will be negatively related to the complexity of the cloud applications.

Hypothesis 2c: Social influence will be positively related to the compatibility of the cloud applications.

Hypothesis 2d: Social influence will be positively related to the observability of the cloud applications.

Hypothesis 2e: Social influence will be positively related to the triability of the cloud applications.

Hypothesis 2f: Social influence will be negatively related to the risk of the cloud applications.

Past experience.

The term "user experience" refers to what an individual experiences while using an information system. User experience can be defined as how individuals use an interactive product, how well they understand how it works, how well it serves their purposes and needs, and how well it fits into the entire context in which they are using it (Alben, 1996). The user's past experiences and future expectations influence their present experience. Current use of these systems creates new experiences and modifies expectations. Larose and Eastin (2004) determine behavior in an analysis of expected outcomes and expectations formed by experience. The model of media attendance measures experience with how frequently an individual is exposed to media.

Past experience with the media affects expected gratification and, in turn, media usage (Larose & Eastin, 2004).

According to path dependence theory, future actions will have similar dependencies on decisions that are made today. This suggests that technology adoption choices are likely to be affected by past actions due to knowledge and managerial experience with specific technologies (Weber & Kauffman, 2011). Often when users upgrade their technology, they are replacing a product with a newer version. People who use the certain product more often are more likely to upgrade that product to a newer version (Young, 2008). This means that users become accustomed to the functions of a specific brand or type of technology. To this extent, those with previous knowledge of similar technologies are also more likely to be able to use new technologies efficiently (Agarwal & Prasad, 1999). In general, individuals tend to wait and see which product fits with their prior knowledge and experiences. Their experiences with similar products makes knowledge more accessible and reliable (Fazio & Zanna, 1978; Reagan & Fazio, 1977) and may make lower the possible risks of adopting the new product (Ajzen & Fishbein, 1980).

This implies that IT usage may be more effectively modeled for experienced users. In other words, prior experience provides people with relevant information about the outcomes of performing a behavior and hence allows them to use that information again when deciding to engage in that behavior (Ozer, 2011). According to Hackbarth et al. (2003), users might perceive an information system to be easier to use if they gain more knowledge and confidence through direct experience of using the system. Thus, consumers who have had experiences with similar products might be more inclined to new innovation. Wu and Kuo (2008) found that habitual usage and past usage may influence how easily the product works. Similarly, it has been shown

that pre-existing knowledge and behavior with computers and technology influences whether an individual perceives new technology to be useful (Venkatesh, 2000). Costa-Font and Mossialos (2006) note that knowledge from past experience reduces possible risks and uncertainty of innovation, hence, influences the likelihood of adoption.

The impact of past experience is proven with the concept of the technology cluster. Rogers (2003) argues that when an individual adopts a new product, he or she will easily adopt another new product that has similar features or functions. In past years, experiences with other computer-related products and services played a major role in the purchase of PCs (Dickerson & Gentry, 1983), and computer adoption was related to Internet adoption intention (Lin, 1998). Recently, Jung et al. (2011) found that people who own more new media are more aware of and have more interest in e-book readers. Also, their intention to adopt the e-book reader was correlated with new media ownership. In brief, adoption of an innovation might be stimulated by the experience of a trigger innovation, which refers to past experience with innovation.

Likewise, previous use of related technology will shape perceptions of innovation and even increase self-confidence and ability to use it. Also, it may allow for the recognition of motivation and guide behavior. Therefore, the study hypothesizes the following:

Hypothesis 3: Past experience will be related to the perceived attributes of the new technology (Relative advantage, complexity, compatibility, observability, triability and risk).

Hypothesis 3a: Past experience will be positively related to the relative advantage of the cloud applications.

Hypothesis 3b: Past experience will be negatively related to the complexity of the cloud applications.

Hypothesis 3c: Past experience will be positively related to the compatibility of the cloud

applications.

Hypothesis 3d: Past experience will be positively related to the observability of the cloud applications.

Hypothesis 3e: Past experience will be positively related to the triability of the cloud applications.

Hypothesis 3f: Past experience will be negatively related to the risk of the cloud applications.

Knowledge.

According to Rogers (2003), individuals collect and synthesize information about the innovation or at least are aware of it, which is a first step in the innovation diffusion process. Knowledge is the first stage in Rogers' model; without it, none of the subsequent stages can occur. While past experience involves user experience with products/services that individuals have used or have been using, knowledge addresses the new product/service that users have not adopted. Rogers identifies three types of knowledge relevant to the adoption of innovations: a*wareness knowledge,* which relates to the existence and basic properties of an innovation; *how-to knowledge, which* is needed to use the innovation properly; and *principles knowledge,* which concerns the functional principles underlying how the innovation works. Of the three types, awareness knowledge is necessary for the adoption process to proceed. An adequate level of how-to knowledge is important to both the decision to adopt and to avoid frustration and discontinuance later on. Principles knowledge is less crucial to the adoption decision but can reduce the likelihood of misuse and eventual discontinuance of an innovation (Rogers, 2003). Therefore, two types of knowledge (awareness and how-to knowledge) are treated in this study as constituents of a single knowledge construct.

Table 4. Three Types of Knowledge

	Awareness Knowledge	How-to Knowledge	Principles Knowledge
Definition	Existence or basic properties of innovation	How to install and use the innovation	Functional principles underlying how the innovation works
Phase	Adoption	Adoption/Use	Adoption/Continuance
Importance	High	High	Medium

Knowledge is one of the main dynamic elements of innovation adoption and an important factor of the adoption of innovations in various fields (Caselli & Coleman, 2001; Goldfarb & Prince, 2008; Kraut et al., 1998; McIntosh et al., 2000). To explore why new technology in higher education is still not widely adopted, Bondarky (1998) helped teachers and students learn how to use it and showed the benefits and efficiency of the new technology; this influenced them to have positive perceptions of the new technology. Also, Kraut et al. (1998) found that well educated people who were aware of new technology adopted the Internet more than others. This was consistent with Goldfarb and Prince's research (2008) of Internet adoption and usage patterns, which found that the percentage of Internet adoption was affected by consumers' knowledge.

Such awareness/knowledge of the innovation forces potential adopters to seek further information, which can be referred as characteristics of innovation, such as relative advantage, complexity, compatibility, triability, observability, or possible risks. This view is consistent with prior research which finds that awareness precedes other processes in innovation adoption; this information process leads to the formation of perceptions about the innovation (Agarwal & Prasad, 1998; Rogers, 2003). For example, in order for individuals to move from one product to a new, technologically-advanced alternative, individuals must find a clear advantage to switching

to it and, at the same time, perceive that the new technology improves on the old technology's ease of use. In order to determine whether there is an advantage in switching, individuals allow a period of adjustment while the new product is trialed and compared. As more knowledge is gained about how the product works and how efficient and advantageous it is, consumers decide whether to reject or retain use of their existing product (Edmonson et al., 2003; Young, 2008).

Focusing on the role of uncertainty and risk aversion, Feder and O'Mara (1981) introduced knowledge as a factor which reduced uncertainty and thereby induced adoption by risk-averse individuals. In addition, Pagani (2004) interviewed people the mobile multimedia service adoption and usage. He found that the degree of interest is directly related to the degree of knowledge of the service. Specifically, people who showed a low level of interest in services knew the least about the main features and potential outcomes of these services, even though they offered an in-depth explanation of the meaning of each service. It can infer that the low level of knowledge, which can show low interests, could overlook the possible triability of the innovation or even observability of it. You can see as much as you know.

Thus, knowledge is a crucial prerequisite in the development of perceptions of new technology, which, in turn, can lead to adoption. Thus, the hypotheses examined here are:

Hypothesis 4: Knowledge of the cloud note-taking application will be related to the perceived attributes of the cloud note-taking application (Relative advantage, complexity, compatibility, observability, triability and risk).

Hypothesis 4a: Knowledge of the cloud applications will be positively related to the relative advantage of the cloud applications.

Hypothesis 4b: Knowledge of the cloud applications will be negatively related to the complexity of the cloud applications.

Hypothesis 4c: Knowledge of the cloud applications will be positively related to the compatibility of the cloud applications.

Hypothesis 4d: Knowledge of the cloud applications will be positively related to the observability of the cloud applications.

Hypothesis 4e: Knowledge of the cloud applications will be positively related to the triability of the cloud applications.

Hypothesis 4f: Knowledge of the cloud applications will be negatively related to the risk of the cloud applications.

Summarizing the aforementioned hypotheses, the proposed research model is presented in Figure 5.

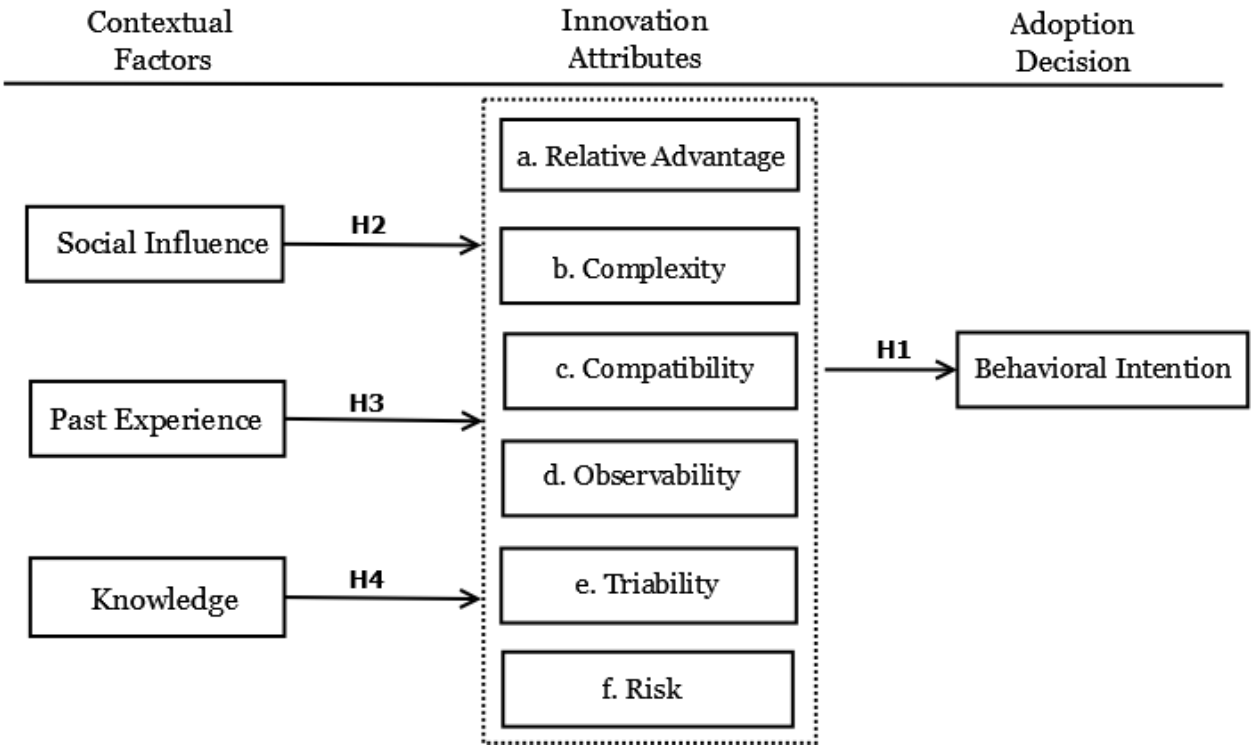


Figure 5. Proposed Research Model

Consumer Lifestyle Clusters

Unlike telecommunication research, marketing and consumer research addresses market segmentation. The key point of market segmentation is that there is no single homogeneous population. People are different in various criteria and points of view. Therefore, differences need to be identified in order to better understand the target population. Segmentation groups people by their differences. For example, if a designated concept received an overall rating of 2.0 on a 5-point scale, the concept might be dropped. However, if the sample were segmented into light, medium, and heavy users, and the ratings were 3.0 among light users, 1.7 among medium users, and 5.0 among heavy users, then the evaluation of this concept would be different (Plumer, 1974). In this approach, segmentation can explore important understandings that averages cannot reveal. Likewise, segmentation can identify more detailed groups of people and can yield greater understanding of them.

Among various market segmentations, lifestyle segmentation is most closely related to the present research. Lifestyle segmentation provides a redefinition of the key target. Instead of defining the consumers in demographic terms (e.g., gender, age, or income), lifestyle segmentation demonstrates the diversity of those definitions and provides new definitions. In addition to old white woman or young Asian students, lifestyle provides definitions like “active geek citizen” or “shy but religious housewife.” Lifestyle relates to how people live and what values they consider in terms of consumer group traits or behaviors in their everyday life. Also, lifestyle can reflect interests and opinions, personality, and even needs (Kotler, 1991; Lazer, 1963). Hence, the lifestyle segment is different from fragmental demographical information. Lifestyle segmentation provides a richer redefinition of the audience.

Lifestyle can be defined by various concepts such as personality, hobbies, values, household, activities, and demographics. Plummer (1974) proposed four components to define lifestyle: activities (e.g., hobbies, sports, and club membership), interests (e.g., family, community, and achievements), opinions (e.g., social issues, politics and culture), and demographics. Huneke (2005) discussed a voluntary simplistic lifestyle that includes aspects such as running a home, childrearing, making a living, and/or seeking community in combination with the consumption choices made. Doyle and Youn (2000) described lifestyle segments based on personality traits and profiled individuals. More recently, Ganglmair-Wooliscroft and Lawson (2011) used attitudes, interests, and opinions on a large range of topics—including social and political issues, consumption and media habits, self-identity, product ownership, and travel behavior as well as values—to define the lifestyle segments. Brand Strategy Research (BSR) is a psychographic segmentation model that has been used in national and international research since 1985 (Brethouwer et al., 1995). BSR is used by The SmartAgent Company[8] a market research company whose core business is to identify motivational groups or clusters (Callebaut et al., 1999). These motivational clusters are groups of persons who have (more or less) the same views, motivations, and attitudes. The BSR lifestyle segments consist of five categories: character, type of household, professional information, hobbies and interests, and values. A summary of lifestyle studies is provided in table 5.

[8] www.smartagent.nl

Table 5. Summary of Lifestyle Studies

Resources	Plummer (1974)	Huneke (2005)	Doyle & Youn (2000)	Ganglmair-Wooliscroft & Lawson (2011)	Brand Strategy Research (Brethouwer et al., 1995) Bouwman et al., 2008; Molina-Castillo et al., 2010; Reuver & Bouwman, 2010
Lifestyle Components	- Activities - Interests - Opinions - Demographics	- Running a home - Childbearing - Making a living - Seeking community	- Personality traits - Profile	- Attitudes - Interests - Opinions - Values	- Character - Type of household - Professional information - Hobbies & Interests - Values
Research Purpose	Marketing	Marketing	Social indicator (Happiness)	Subjective wellbeing	New media adoption

The BSR segments are specifically related to this study, since they have been used to investigate the adoption of various media by exploring the influence of different user types and lifestyles (Bouwman et al., 2008; Molina-Castillo et al., 2010; Reuver & Bouwman, 2010). These studies found four consumer clusters and explored for differences between them in terms of the constructs in the proposed research model. Each consumer cluster was found to act differently on a number of relevant factors, including social influence, attitude, PEOU, PU, and media use.

As mentioned above, lifestyle segments can be defined by various concepts, from consumer characteristics to demographics. They can be used to examine how well innovation is

meeting the needs of consumer types, since lifestyle segmentation provides a great deal of information on the different needs of types of people. Several past studies found links between lifestyle and the adoption of consumer products. Investigating adoption and use of new wireless communication technologies in China, Wei (2006) found that people whose approach to life emphasizes the new, informative, and sociable were heavy users of new media (Wei, 2006). In addition, Akinci et al. (2004) developed an understanding of consumers' attitudes and adoption of Internet banking based on sophisticated consumers in a well-developed country. They investigated a random sampling of academicians, demographic, and behavioral characteristics. People who are skeptical, positive towards, or more experienced for technology showed positive attitudes toward Internet banking. Also, household members' knowledge and use of technology were important factors that affected the adoption of and familiarity with the technology (Azouzi 2009; Miniaci & Parisi, 2005; Ratten & Ratten, 2007; Thurman, 2008). In addition, consumer background and demographics such as age, gender, education or income also influence attitudes and use of innovations.

Representatively, gender is an important factor that shows the differences in acceptance of new technology based on the confidence of learning innovation (Hargittai, 2007; Kwon & Chon, 2009; Sun & Zhang, 2006; Zainudeen et al., 2010). Younger people are more interested in using new technologies and tend to be less fearful of change, whereas older consumers have less awareness (Meyer, 2007; Monsuwé et al., 2004; Wei, 2006). People who well educated, which means they know more about the new technology, are more likely to adopt it and more quickly (Kipsat, 2007; Wetengere, 2009). Depending on occupation, more exposure to innovation and more conversation within the community can yield more knowledge (Johnson & Lybecker, 2008). Moreover, occupation connects with opportunity cost of leisure time and differences in

usefulness of innovation activities (Goldfarb, 2008). In addition to the demographics, Taylor et al. (2011) found that smart phone users are more interested in the mobile cloud activity than the non-smart phone users, which is more specific to the Cloud Computing adoption than the general new media adoption. They conducted a mobile cloud survey of 11,016 U.S. mobile users to investigate the future mobile cloud service market. Over half of all Smartphone users expect to access email, update social network, and shop on their mobile devices within next two years. Also, another half of all Smartphone users expect to perform activities on their smart phone that usually performed on their PC such as storing/sharing photos, editing documents, and attending web conferences. On the other hand, non-Smartphone users have little or no interest in these mobile cloud activities. Also, they found that there was a high level of interest in a service that would allow users to store and manage content across multiple devices among smart phone users. Therefore, consumers who own a Smartphone and have multiple devices have more interests to adopt mobile cloud services.

Likewise, lifestyles are specific patterns of individual behaviors which result from those individuals' values. Furthermore, lifestyle can be identified as distinctive characteristics or an individual's typical way of life which includes the products they purchase, how they consume, what they think, and how they feel toward them. Also, the demographic information and technology-specific user background can influence an individual's interest and behavioral pattern regarding the adoption and use of a technology. A number of past studies have examined demographics and personal traits to understand the behavior of the consumers. However, a fragmental approach that explores each trait lacks richness. Lifestyle segmentation can be useful to distinguish one group of people from another when fragmental demographic characteristics are not enough to make distinctions. Therefore, the current study will divide people to several

groups by their demographic information (e.g., age, gender, and education), technology specific background (new media ownership), and lifestyle components (e.g., Character, type of household, professional information, hobbies & interests, and values) as extracted from Brand Strategy Research, to investigate how different groups may act differently in the decision process to adopt an innovation, here a cloud-note taking application.

METHODOLOGY

Subjects

The context of this research is not limited to a specific group of people. Therefore, the sample comprised of adults who are aged 18 and older residing in the U.S. The sample was recruited and included only participants who are active note-takers (i.e. taking notes more than 4 times a month), and have not yet used cloud note-taking applications such as Evernote, OneNote, Simplenote, Plaintext, Springpad, because the research asks about their intentions to adopt the cloud note-taking application. To get the various groups, sample was purchased from Survey Sampling International LLC[9], a leading sampling company. Based on the data analysis method selected (i.e. Partial Least Squares or PLS), the minimum sample size should be the larger of (a) 10 times the number of items for the most complex construct or (b) 10 times the largest number of independent variables impacting a dependent variable. In our model, the most complex construct contains five items. The first condition yields a minimum sample size required of 50, which was satisfied by the solicited sample of 402 responses.

The subjects were recruited by making announcements in various groups of people who registered to participate in the survey to Survey Sampling Internal LLC. A total of 1721 responses were received, however, 1319 (77%) of them were disqualified because they are not the active note-takers (76%), have experience with the cloud note-taking applications (19%), or did incomplete the survey (5%). Therefore, the remaining usable sample for analysis was 402 and encompassing 74 (56.9%) females and 56

[9] http://www.surveysampling.com/en

(43.1%) males. The average age was 40 ranging from 18 to 79 (*SD*=14.70). Most respondents were Caucasian/White (80.8%) and African American (9%). More than half of responses have some college education (35.1%) or college degree (24.1%). More detailed demographic information is listed on the Table 6.

Table 6. Participant Demographic Information (n=402)

Age	18-26	89 (22.1%)
	27-33	78 (19.4%)
	34-42	74 (18.4%)
	43-55	86 (21.4%)
	56-79	75 (18.7%)
Gender	Male	188 (46.8%)
	Female	214 (53.2%)
Education	High school	83 (20.6%)
	Some college	141 (35.1%)
	College degree	97 (24.1%)
	Some graduate school	21 (5.2%)
	Graduate degree	59 (14.7%)
Ethnicity	Caucasian/White	325 (80.8%)
	African American	36 (9.0%)
	Indigenous or Aboriginal Person	1 (0.2%)
	Asian/Pacific Islander	13 (3.2%)
	Hispanic	16 (4.0%)
	Latino	1 (0.2%)
	Multiracial	7 (1.7%)
	Would rather not say	3 (0.7%)

In addition to the demographic information, this study also collected data regarding the participants' prior experience and knowledge of cloud services, note-taking usage, and various devices ownership. Participants took on average 12 notes for professional purposes and 9 notes for personal purposes per month. Most of them believed to have no experience with cloud services (69.4%), yet more than half of

experienced participants used a cloud service a year or more (56.7%). The most used cloud service is Google calendar followed by Dropbox and iCloud (See figure 6).

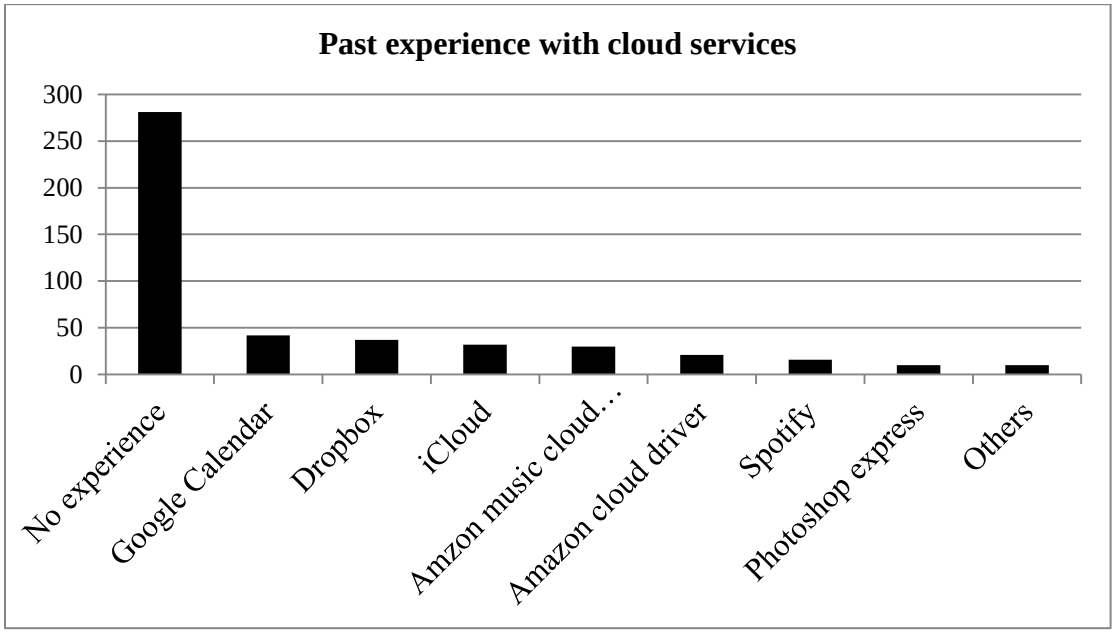


Figure 6. Frequency Graph for Past Experience with Cloud Services

Also, more than half of participants owned 2 (35.3%) or 3 (22.9%) devices. Laptop (80%), Desktop (68%), and smartphone (50%) are the most owned devices. In addition, the study asked questions to check the level of knowledge regarding to awareness and how-to use the cloud note-taking application. More than half of participants did not know the answer (0 correct answers) or correct only one answer for both awareness and how-to knowledge questions (See table 7).

Table 7. Participants' Experience and Knowledge with Cloud Service (n=402)

Note-taking purpose (how often taking notes in the past month)	Professional purpose	12 times (mean)
	Personal purpose	9 times (mean)
Past experience with cloud service (The number of cloud services experienced)	0 (No experience)	279 (69.4%)
	1	73 (18.2%)
	2	33 (8.2%)
	3	11 (2.7%)
	4	4 (1.0%)
	5	2 (0.5%)
Period of cloud service use (Month)	1-3	26 (23.4%)
	4-8	22 (19.8%)
	9-13	19 (17.1%)
	14-24	22 (19.8%)
	25-74	22 (19.8%)
Device ownership (The number of device owned)	1	106 (26.4%)
	2	142 (35.3%)
	3	92 (22.9%)
	4	47 (11.7%)
	5	14 (3.5%)
	6	1 (0.2%)
Knowledge (awareness)	0 (No correct answer)	141 (35.1%)
	1	122 (30.3%)
	2	107 (26.6%)
	3	32 (8.0%)
Knowledge (How-to)	0	188 (46.8%)
	1	97 (24.1%)
	2	60 (14.9%)
	3	57 (14.2%)

Procedures

The survey was created using SurveyGizmo (http://www.surveygizmo.com), and participants required approximately fifteen minutes to complete this web-based survey. The structural model shown in Figure 5 was analyzed using the Partial Least Square (PLS) method by the SmartPLS package. This method features advantages over other methodologies. The PLS is not only used to identify relationships between constructs but

also between items and corresponding constructs (Chin & Gopal, 1995). Variance-based PLS supports confirmatory and exploratory research and are robust to deviation from a multivariate distribution (Gefen et al., 2000). These features are important, because it allows for the specification of both the structural and measurement models.

For the comparison of consumer lifestyle cluster, this study used TwoStep Cluster in SPSS 20.0; this has been suggested appropriate in clustering large data sets with mixed attributes (Nourusis, 2003). The method is based on a distance measure that enables data with both continuous and categorical attributes to be clustered. This is derived from a probabilistic model in which the distance between two clusters is equivalent to the decrease in log-likelihood function as a result of merging (Chiu et al., 2001). In the first step, original cases are grouped into preclusters that are then used in place of the raw data in the hierarchical clustering. Based upon its similarity to existing preclusters, each successive case is added to form a new precluster, using a likelihood distance measure as the similarity criterion. Cases are assigned to the precluster that maximizes a log-likelihood function. In the second step, the preclusters are grouped using the standard agglomerative clustering algorithm, producing a range of solutions, which is then reduced to the best number of clusters on the basis of Akaike's information criterion (AIC). In addition, both background noise and outliers can be identified and screened out.

Based on a cluster analysis, consumer clusters were distinguished. Every respondent was assigned a probability of belonging to a specific cluster. Corresponding groups of sample (cluster) were analyzed separately and compared to determine how different groups of people act differently in the adoption process.

Measure/Instruments

All measures except knowledge were adapted from prior studies (Table 8), and minor changes in the wordings were made to fit them into the current investigation context. A 5-point scale, ranging from 1 (strongly disagree) to 5 (strongly agree), is used to measure other statements in the questionnaire. Past experience is measured by how many media are used by respondents; and how long it had been since the respondents first started using it. The media selected for reflecting past experience are other cloud computing services. The lifestyle clusters are organized by BSR lifestyle questionnaires, demographic info (gender, age, and education), and device ownership (smartphone, PC, laptop, tablet, and AppleTV).

Knowledge measures are constructed by familiarity with cloud note-taking application (awareness knowledge) and how to use the cloud note-taking app (how-to knowledge). Principle knowledge is excluded, because it does not affect to the adoption rather continuance usage (Rogers, 2003). Other studies that investigated knowledge were considered to develop the measurement. Rebane and Barham (2011) investigated Solar Home System (SHS) knowledge based on familiarity of SHS and how-to knowledge of SHS. They showed SHS related pictures and checked whether respondents could recognize it. Also, they asked questions about SHS components (e.g., charge controller) and classified respondents as *familiar with SHS* or *not familiar with SHS*. For the how-to knowledge, they asked questions about best battery type and correct battery fluid and classified respondents as *knows SHS* or *does not know SHS*. Similarly, a study that examined the knowledge of digital television (Chanolmsted & Chang, 2006) also asked the digital television related questions (e.g., DTV is the same as HDTV or not; Converter

needed to received DTV signals or not) and classified respondents accordingly. In accordance with past studies of knowledge measurement, the study developed questions about cloud note-taking applications to determine the level of knowledge. The questionnaires are based on the definitions and features of cloud computing, SaaS, and Synch (Wikipedia, 2011a, 2011b, 2011c). The questions for awareness knowledge contain terminology and examples of cloud note-taking applications, while how-to knowledge questions involve features and installation related issues.

Table 8. Survey Items

Resources	Items
Relative advantage (Vishwanath & Goldhaber, 2003)	Using a cloud note-taking app would enable me to be more efficient.
	Using a cloud note-taking app will decrease the number of things I have to do.
	I believe a cloud note-taking app would be useful for me.
	Using a cloud note-taking app will make my life easier.
Complexity (Moore & Benbasat, 1991)	I believe it would be easy to use a cloud note-taking app for whatever I want to do
	My interaction with a cloud note-taking app is clear and understandable
	Learning to use a cloud note-taking app would be easy for me
	Overall, I believe a cloud note-taking app would be easy for me
Compatibility (Moore & Benbasat, 1991)	Using a cloud note-taking app is consistent with my daily lifestyle
	Using a cloud note-taking app would be compatible with all aspects of my life
	Using a cloud note-taking app would fit into my work style
	I think that using a cloud note-taking app would fit well with the way I like to work
Observability (Moore & Benbasat, 1991; Agarwal & Prasad, 1997)	I have acquaintances that use a cloud note-taking app.
	I have seen what others can do using a cloud note-taking app.
	I have seen cloud note-taking app demonstrations.
Triability (Moore & Benbasat, 1991; Agarwal & Prasad, 1998)	A cloud note-taking app is available for a trial whenever I would like to use it
	A cloud note-taking app provides enough freedom that lets me test its various functions
	I can use a cloud note-taking app as a free member and test its relevant functions

Table 8 (Cont'd)

Risk (Chen, 2008)	In general, I believe that it would be riskier to use a cloud note-taking app.
	Compared to pre-installed note application on my computer or mobile phone, I believe that using cloud note-taking app is riskier.
	I believe that there will be high potential for loss associated with using cloud note-taking app.
	I believe that there will be too much uncertainty associated with using cloud note-taking app.
	I believe that using cloud note-taking app will involve many unexpected problems.
Social Influence (Bagozzi & Lee, 2002; Moore & Benbasat, 1991)	Most people who are important to me think that I should use cloud note-taking app for team collaboration.
	Most people who are important to me would approve of me cloud note-taking app for team collaboration.
	People in my organization who use the cloud note-taking app have more prestige than those who do not.
	People in my organization who use the cloud note-taking app have a high profile.
	Having the cloud note-taking app is a status symbol in my organization.
Behavioral intention (Moore & Benbasat, 1991)	I have intention to use a cloud note-taking app.
	I want to experience a cloud note-taking app.
	I prefer to use a cloud note-taking app than pre-installed note application on my computer or mobile phone.
Lifestyle (BSR Questionnaires: Brethouwer, et al., 1995; Oppenhuisen, 2000)	Which character traits fit the best for the person that has the same opinion about housing as you do? _a little bit shy _a little impatient _easygoing _adventurous _assertive _balanced _capable _cheerful _classy _cozy _critical _deliberate _energetic _enthusiastic _leader _a little bit imprudent _gentle _helpful _honest _intelligent _interested in others _jovial _sympathetic _neat _opinionated _ordinary _passionate _self-assured _self-confident _serene _serious _down-to-earth _commercial _spontaneous _strong character
	Which family or household types fit the best for the person that has the same opinion about housing as you do? _a family where everyone goes their own way _artistic household _bachelor _broad-minded family _busy dynamical family _cozy old-fashioned family _happy family _harmonious family _ideal family _isolated family _not suited for family life _perfect family _quiet family _rigid family _single _sportive family _stable family _aristocratic household _striving for a family _warm family

Table 8 (Cont'd)

Lifestyle (BSR Questionnaires: Brethouwer, et al., 1995; Oppenhuisen, 2000)	Which occupations fit the best for the person that has the same opinion about housing as you do? Occupations can be done both by males or females. _account manager _activity guide _beauty specialist _member of the board _business-man/-woman _social worker _commercial assistant _commissioner _designer _e-business _entrepreneur _financial planner _free-lancer _full time house wife _house-husband _journalist _male nurse _manager _no occupation _nurse _part time house-wife _photographer _artist _anchor man _programmer _project manager _public servant _receptionist _scientist _secretary _shop assistant _shopkeeper _social worker _sports teacher _student _stylist _temporary employee _truck driver _unemployed _vets assistant _volunteer
	Which hobbies, interests and/or leisure activities fit the best for the person that has the same opinion about housing as you do? _a sociable evening with friends _active sports _adventurous holidays _top-notch achievement _astrology _being at home quietly _build a successful career _camping _cars / motor bikes _classy parties _a day out _dine out together _do odd jobs around the house _gardening _going out together _going to a discotheque _golf _investing in stocks _make dreams come through! _religious matters _swimming _playing chess _reading magazines _shopping _snow-boarding _working out _surfing the Internet _visiting friends and relatives _team sports _visiting a pub _watching TV
	Which values fit the best for the person that has the same opinion about housing as you do? anonymity _challenge, stimulation _enjoyable life _enthusiasm _expression, uniqueness friendship _heroism, glory _independence _intimacy _passion _privacy, tranquility _rationalism _recognition of performances _respect _security _self-belief _self-expression, growth _social alliance _social harmony _solidarity _status _success in life
Past experience (Larose & Eastin, 2004)	How many of the following media have you ever used? _Dropbox _ iCloud (apple) _iDrive _Spotify _SugarSync _ Amazon cloud drive _Amazon music cloud player _Google Calendar _Photoshop Express (website or mobile app) _Other cloud services
	Please choose one service you used first. How long have you been using the service? _Years _ Month

Table 8 (Cont'd)

Knowledge (Wikipedia, 2011a, 2011b, 2011c)	Awareness Knowledge
	The cloud note-taking application is an example of cloud computing. What does the term "cloud" mean? _Don't know _Internet _Light weight device _Easiness of use _Eco-friendly
	Which of the following is not a cloud note taking-application? _Don't know _Evernote _OneNote _Dropbox _GoogleDoc
	What does "sync" refer to in the cloud note-taking application? _Don't know _Synchronization of directories or files on computers _Synchronization, the coordination of events to keep them in time _Sync (Unix), a command for Unix-like operating systems _Sync, a single used in composite video systems to coordinate the timing of lines, fields and frames
	How-to knowledge
	Which one is **NOT** the installation method for the cloud note-taking application? _Don't know _Through the mobile web browser _Through the web browser _Through the mobile application _Through the software CD
	Which one is **NOT** a feature of cloud note-taking app compared to the pre-installed or default note taking app? _Don't know _Automated update and sync _Easy sharing _Archiving files _Synching in offline
	How do you synchronize your notes between devices in cloud note-taking application? _Don't know _Automatically when you connect to Internet _Copy and Paste _Emailing from one device to another _Automatically sync when offline

Reliability and Validity of Measurements

The relative advantage, complexity, compatibility, observability, triability, risk, social influence, and behavioral intention constructs were examined for reliability, as shown in Table 9. Internal consistency is evaluated by Cronbach's alpha value and the composite reliability of each construct, and all scales exceeded the recommended rule of thumb of .80. Convergent validity and discriminant validity for each construct were demonstrated. Convergent validity (see Table 9) was assessed through the average variance extracted (AVE) to ensure constructs differed from each other, and all constructs exceeded the recommended rule of thumb of .50 (Fornell and Larcker, 1981). Discriminant validity (See Table 10) was reviewed by the PLS CFA method, and the measurement items loaded more on the latent variables than their loadings on other variables, which satisfy the requirement for discriminant validity (Gefen and Straub, 2005). Face validity for the measurement of knowledge level was performed by asking a panel of five subject matter experts in human-computer interaction/cloud computing experts whether the measurements were appropriate to check the level of knowledge about the cloud note taking application. The result was a 100% agreement between them, or a content validity ratio of 1. Given the above statistical test results, it is confirmed that the scales and constructs demonstrate sufficient reliability and validity.

Table 9. Construct Validity and Reliability

Constructs	Mean (SD)	Convergent validity (AVE)	Composite Reliability (Internal Consistency)	Cronbach's Alpha
BI	3.41 (0.82)	0.726609	0.888385	0.811410
COMPATA	3.60 (0.83)	0.767740	0.929643	0.898895
COMPLEX	2.36(0.72)	0.692902	0.900080	0.851548
OBS	2.59(0.98)	0.756545	0.903023	0.838409
PR	2.81(0.83)	0.743204	0.935310	0.913450
RA	3.54(0.82)	0.752698	0.923789	0.888852
SI	2.99(0.73)	0.649479	0.902328	0.865981
TRI	3.27(0.76)	0.748835	0.899335	0.832154

Table 10. CFA Loadings Matrix (Item statistics)

	BI	COMPATA	COMPLEX	KN	OBS	PE	PR	RA	SI	TRI
BI1	**0.875**	0.556	0.446	0.159	0.411	0.136	-0.267	0.533	0.516	0.472
BI2	**0.879**	0.582	0.467	0.254	0.283	0.116	-0.340	0.556	0.444	0.372
BI3	**0.801**	0.503	0.411	0.155	0.378	0.213	-0.133	0.453	0.519	0.413
COMPATA1	0.597	**0.862**	0.694	0.175	0.282	0.085	-0.248	0.689	0.435	0.390
COMPATA2	0.544	**0.846**	0.604	0.077	0.297	0.109	-0.226	0.659	0.454	0.374
COMPATA3	0.530	**0.894**	0.636	0.133	0.337	0.105	-0.230	0.649	0.472	0.425
COMPATA4	0.577	**0.901**	0.652	0.153	0.322	0.126	-0.260	0.672	0.454	0.406
COMPLEX1	0.486	0.715	**0.801**	0.108	0.323	0.029	-0.233	0.646	0.382	0.369
COMPLEX2	0.395	0.542	**0.793**	0.266	0.497	0.221	-0.128	0.454	0.465	0.474
COMPLEX3	0.388	0.570	**0.849**	0.338	0.282	0.105	-0.245	0.456	0.271	0.353
COMPLEX4	0.451	0.629	**0.883**	0.269	0.286	0.120	-0.224	0.552	0.347	0.356
KN_AWA	0.175	0.118	0.233	**0.807**	0.137	0.237	-0.073	0.105	0.050	0.179
KN_HOW	0.203	0.143	0.265	**0.897**	0.117	0.227	-0.149	0.082	0.085	0.180
OBS1	0.378	0.343	0.377	0.144	**0.830**	0.267	0.045	0.296	0.466	0.528
OBS2	0.384	0.345	0.433	0.122	**0.902**	0.286	0.039	0.309	0.515	0.523
OBS3	0.328	0.232	0.287	0.116	**0.876**	0.295	0.166	0.209	0.508	0.497
PE	0.175	0.088	0.131	0.301	0.238	**0.765**	0.011	0.071	0.206	0.201
PE_TIME	0.176	0.121	0.144	0.263	0.325	**0.999**	0.075	0.085	0.215	0.241
PR1	-0.244	-0.232	-0.214	-0.152	0.126	0.054	**0.833**	-0.194	0.004	-0.082
PR2	-0.236	-0.193	-0.187	-0.102	0.104	0.062	**0.837**	-0.183	-0.013	-0.088

Table 10 (Cont'd)

PR3	-0.263	-0.232	-0.211	-0.096	0.107	0.086	**0.876**	-0.250	-0.051	-0.024
PR4	-0.277	-0.260	-0.232	-0.138	0.045	0.054	**0.901**	-0.258	-0.071	-0.117
PR5	-0.248	-0.266	-0.221	-0.093	0.031	0.053	**0.862**	-0.232	-0.051	-0.106
RA1	0.495	0.625	0.570	0.104	0.280	0.069	-0.251	**0.856**	0.340	0.300
RA2	0.434	0.552	0.416	0.065	0.283	0.025	-0.138	**0.777**	0.391	0.250
RA3	0.593	0.730	0.599	0.108	0.243	0.091	-0.265	**0.907**	0.342	0.306
RA4	0.564	0.724	0.605	0.091	0.283	0.103	-0.242	**0.924**	0.394	0.289
SI1	0.523	0.490	0.445	0.104	0.577	0.196	-0.047	0.429	**0.801**	0.479
SI2	0.525	0.532	0.458	0.142	0.374	0.194	-0.279	0.411	**0.726**	0.470
SI3	0.405	0.342	0.293	0.034	0.436	0.137	0.073	0.255	**0.848**	0.435
SI4	0.397	0.340	0.284	0.016	0.450	0.169	0.091	0.230	**0.838**	0.453
SI5	0.416	0.302	0.234	-0.010	0.424	0.160	0.064	0.310	**0.810**	0.370
TRI1	0.373	0.342	0.332	0.111	0.517	0.197	-0.004	0.253	0.453	**0.824**
TRI2	0.443	0.456	0.482	0.215	0.529	0.233	-0.113	0.316	0.484	**0.876**
TRI3	0.455	0.380	0.397	0.207	0.498	0.199	-0.122	0.286	0.506	**0.894**

Discriminant validity was also tested through the approach proposed by Fornell and Larcker (1981) and Hulland (1999). Fornell and Larcker (1981) suggest that the correlation between any two constructs should be less than the square root of the variance extracted by the individual constructs separately. In other words, values along the diagonal of the correlation matrix in Table 11 must be greater than the corresponding values in each row or column. Since this is the case for all constructs, discriminant validity can be safely assumed.

Table 11. Correlation Matrix and Discriminant Validity Assessment

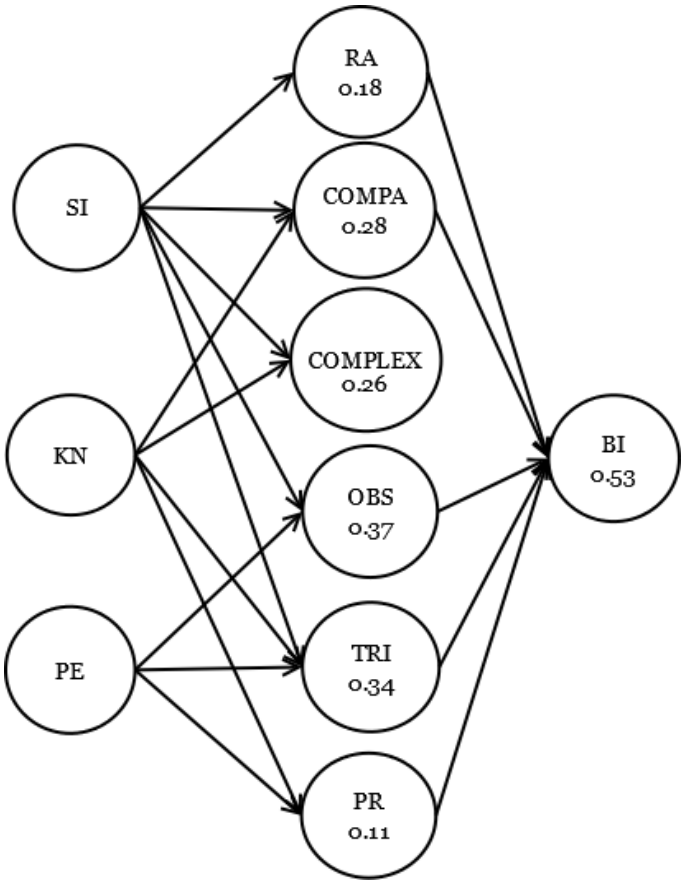
	BI	COMPATA	COMPLEX	OBS	PR	RA	SI	TRI
BI	**0.852**							
COMPATA	0.642	**0.876**						
COMPLEX	0.518	0.739	**0.832**					
OBS	0.418	0.353	0.422	**0.870**				
PR	-0.295	-0.275	-0.248	0.095	**0.862**			
RA	0.605	0.762	0.635	0.313	-0.260	**0.868**		
SI	0.576	0.518	0.445	0.571	-0.043	0.422	**0.806**	
TRI	0.492	0.455	0.469	0.593	-0.096	0.331	0.557	**0.865**

* Off-diagonal values are correlations. All correlation values are significant at 0.01 level (2-tailed).

RESULTS

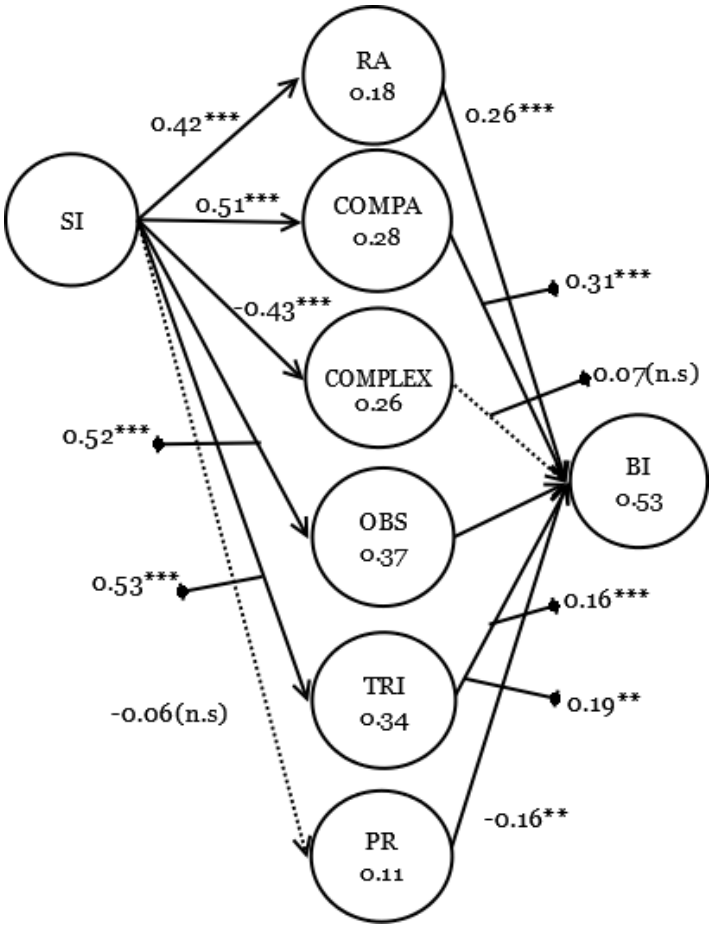
Path Model

The structural model shown in Figure 7 to 10 were analyzed using the Partial Least Square (PLS) method through the SmartPLS package. Overall, the model demonstrated high explanatory power. The R-square of the behavioral intention construct was .53, or 53% of the variance in user intention to use the cloud note-taking application was explained by the model. The R-square values for the rest of the endogenous variables exceeded the 10% benchmark recommended by Falk and Miller (Falk and Miller, 1992). The variance explained is large enough to accept relative advantage (RA), compatibility (COMPATA), observability (OBS), triability (TRI), risk (PR), social influence (SI), knowledge (KN), and past experience (PE) as significant antecedents of users' behavioral intention to use a cloud note-taking application. Table 12 presents the validation of hypotheses in more detail.



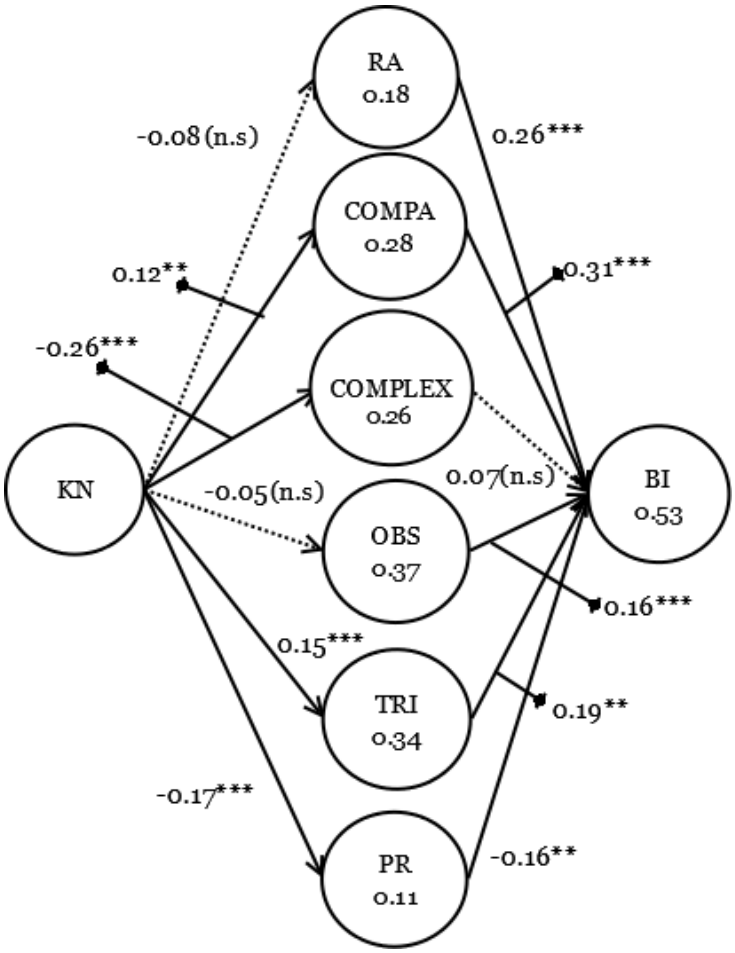
KEY: RA- Relative Advantage; COMPA- Compatibility; COMPLEX- Complexity; OBS- Observability; TRI- Triability; PR- Risk; SI- Social Influence; KN: Knowledge; PE: Past Experience; BI: Behavioral Intention

Figure 7. Structural Model Results



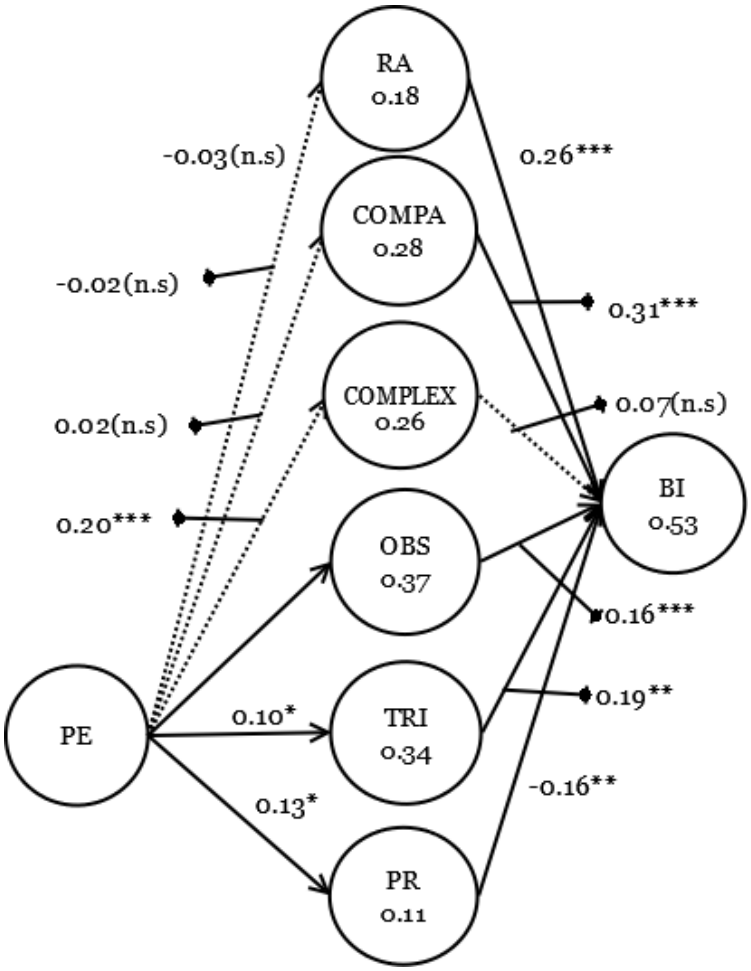
KEY: RA- Relative Advantage; COMPA- Compatibility; COMPLEX- Complexity; OBS- Observability; TRI- Triability; PR- Risk; SI- Social Influence; KN: Knowledge; PE: Past Experience; BI: Behavioral Intention
*p < .05, **p < .01, ***p < .001

Figure 8. Structural Model Results (Only Social Influence)



KEY: RA- Relative Advantage; COMPA- Compatibility; COMPLEX- Complexity; OBS- Observability; TRI- Triability; PR- Risk; SI- Social Influence; KN: Knowledge; PE: Past Experience; BI: Behavioral Intention
*p < .05, **p < .01, ***p < .001

Figure 9. Structural Model Results (Only Knowledge)



KEY: RA- Relative Advantage; COMPA- Compatibility; COMPLEX- Complexity; OBS- Observability; TRI- Triability; PR- Risk; SI- Social Influence; KN: Knowledge; PE: Past Experience; BI: Behavioral Intention
*p < .05, **p < .01, ***p < .001

Figure 10. Structural Model Results (Only Past Experience)

Table 12. Hypotheses Validation

Hypo	Path	Beta	T	Sig	Status
H1	RA -> BI	0.26	4.37	***	Supported
	COMPLEX -> BI	0.07	0.94	n.s	n.s
	COMPATA -> BI	0.31	4.66	***	Supported
	OBS -> BI	0.16	3.43	***	Supported
	TRI -> BI	0.19	2.93	**	Supported
	PR -> BI	-0.16	2.87	**	Supported
H2	SI -> RA	0.42	8.55	***	Supported
	SI -> COMPLEX	-0.43	8.39	***	Supported
	SI -> COMPATA	0.51	12.36	***	Supported
	SI -> OBS	0.52	12.51	***	Supported
	SI -> TRI	0.53	12.06	***	Supported
	SI -> PR	-0.06	0.72	n.s	n.s
H3	PE -> RA	-0.03	0.64	n.s	n.s
	PE -> COMPLEX	-0.20	0.46	n.s	n.s
	PE -> COMPATA	-0.02	0.51	n.s	n.s
	PE -> OBS	0.20	4.08	***	Supported
	PE -> TRI	0.09	2.07	*	Supported
	PE -> PR	0.13	2.05	*	n.s
H4	KN -> RA	0.08	1.70	n.s	n.s
	KN -> COMPLEX	-0.26	5.83	***	Supported
	KN -> COMPATA	0.12	2.64	**	Supported
	KN -> OBS	0.05	1.10	n.s	n.s
	KN -> TRI	0.14	3.14	***	Supported
	KN -> PR	-0.17	3.22	***	Supported

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

Reviewing the above results, the following conclusions may be drawn. First, regarding to the effect of innovation attributes toward behavioral intention to use the cloud note-taking app, 1) the higher the level of relative advantage (RA) [H1a: $\beta = .26$, $p < .001$]; 2) compatibility (COMPATA) [H1c: $\beta = .31$, $p < .001$]; 3) obersability (OBS) [H1d: $\beta = .16$, $p < .001$]; and 4) triability (TRI) [H1e: $\beta = .19$, $p < .01$] perceived from the cloud note-taking app, the higher the intention to use it. Also, the lower the risk of

cloud note-taking app (PR) people perceived, the higher the intention to use it (H1: $\beta = -.16$, $p < .01$). Complexity (COMPLEX) showed that it is not significantly related to behavioral intention (BI).

Second, on the topic of contextual factors, hypothesis 2 predicted that social influence would be significantly related to innovation attributes. While social influence is not significantly related with the risk, other attributes showed significant relationships. The greater the level of perceived social influence of the reference group, 1) the higher the level of relative advantage (RA) [H2a: $\beta = .26$, $p < .001$]; 2) compatibility (COMPATA) [H2c: $\beta = .31$, $p < .001$]; 3) observability (OBS) [H2d: $\beta = .16$, $p < .001$]; and 4) triability (TRI) [H2e: $\beta = .19$, $p < .01$] people perceived from cloud note-taking app. Also, the lower the level of perceive social influence of the reference group, the higher the level of complexity people perceived [H2b: $\beta = -.43$, $p < .001$]. However, the risk (PR) is not related with the social influence (SI).

Hypothesis 3, which predicted that past experience with similar cloud service have significant relationships with innovation attributes, are only supported half of them. The greater the past experience (PE) people have, 1) the higher the observability (OBS) [H3d: $\beta = .20$, $p < .001$]; and 2) triability (TRI) [H3e: $\beta = .09$, $p < .05$]. However, the greater the past experience (PE) people have, the higher the risk (PR) people perceived [H3f: $\beta = .13$, $p < .05$]. The relative advantage (RA), complexity (COMPLEX) and compatibility (COMPATA) of cloud note-taking app has no significant relationship with the past experience (PE).

Hypothesis 4 investigated the relationship between knowledge of cloud note-taking app (KN) and innovation attributes. The results showed that the more the

knowledge people have (KN), the higher the compatability (COMPATA) [H4c: $\beta = .12$, $p < .01$] and triability (TRI) people perceived [H4e: $\beta = .14$, $p < .001$]. Also, the less the knowledge people have, the higher the risk (PR) [H4f: $\beta = -.17$, $p < .001$] and complexity (COMPLEX) people perceived [H4b: $\beta = -.26$, $p < .001$].

In addition, to explore the amount of unique variance explained by each predictor, three analytical approaches to Stepwise Hierarchical Regression are conducted in SPSS20.0 using the latent variable loadings from the PLS output in order to ensure model consistency (see Table 13). In the first approach Stepwise Linear Regression, the determinants in the order of the statistical significance of the predictor as specified by the structural model were added and it was referred to as the empirical approach. For instance, from social influence to knowledge to past experience were added for checking R^2 change of observability. In the second approach, we iterations of the Stepwise Linear Regression were ran, in order to ensure that each of the predictors would be last once, in order to obtain the unique contribution of that predictor. This approach provides the most conservative estimate, since by focusing on the final step only; we merely assess the unique contribution of each predictor and disregard any covariance among determinants. Comparison between the two approaches as well as an average across the two approaches is provided in Table 13 below.

Table 13. Results of Stepwise Linear Regression for R^2 Partitioning

DV: Compatibility	**Empirical**	**Conservative**	**Average**
Social Influence	.223***	.216***	**.220***
Knowledge	.010*	.010*	.010*
DV: Complexity			
Social Influence	.166***	.153***	**.160***
Knowledge	.057***	.057***	.057***
DV: Observability			
Social Influence	.280***	.222***	**.251***
Past Experience	.044***	.044***	.044***
DV: Triability			
Social Influence	.251***	.217***	**.234***
Knowledge	.011*	.006(n.s)	.009(n.s)
Past Experience	.006(n.s)	.006(n.s)	.006(n.s)
DV: Risk			
Knowledge	.011*	.018**	**.015***
Past Experience	.015*	.008(n.s)	.012*
DV: Behavioral Intention			
Compatibility	.380***	.036***	**.208***
Relative Advantage	.034***	.023***	.029***
Triability	.043***	.015**	.029***
Observability	.011**	.016**	.014**
Risk	.012**	.012**	.012**

*p < .05; **p < .01; ***p <.001

Following the result presented in Table 13, it is concluded that, regarding the impact of each contextual factors on perceptions: 1) Compatibility, complexity, observability and triability were significantly more influenced by social influence than other contextual factors; and 2) risk was significantly more influenced by knowledge than past experience. Also, behavioral intention was significantly more influenced by compatibility. In addition to path analysis for all subjects, the study divided subjects into two groups by their behavior intention to adopt the service—adopter and non-adopter—to see where the cut-off might exist between two significantly different groups in terms of subjects' perceptions and contexts. The T-test was performed to compare the two groups

(see Table 14), and it was found that future adopters perceived complexity and risk significantly less than non-adopters. Also, future adopters perceived relative advantage, compatibility, observability, and triability significantly more than non-adopters. Regarding contextual factors, future adopters have significantly more knowledge and past experience except during period of cloud computing use. Also, future adopters are significantly more influenced by reference groups than non-adopters.

Table 14. Results of T-Test in Differences of Perceptions and Contexts Between Future Adopters and Non-Adopters

	Adopters (N=185)		Non-Adopters (N= 48)		Sig	
	Mean	SD	Mean	SD	T-value	P-value
Perception						
Relative Advantage	3.97	.70	2.60	.83	-11.54	.000
Complexity	2.03	.62	3.01	.90	8.78	.000
Compatibility	4.06	.61	2.57	.94	-13.34	.000
Observability	2.93	1.02	2.01	.85	-5.72	.000
Triability	3.61	.70	2.74	.88	-7.33	.000
Risk	2.63	.95	3.28	.75	4.40	.000
Context						
Social Influence	3.34	.69	2.28	.68	-9.58	.000
Knowledge (Awareness)	1.22	.95	.88	1.02	-2.19	.030
Knowledge (How-to)	1.15	1.10	.50	.90	-3.75	.000
Past Experience (Number)	.63	1.01	.33	.79	-1.90	.029
Past Experience (Period)	2.94	1.48	3.63	1.19	1.26	.211

* The mean difference is significant at the 0.05 level.

The proposed structural model was also analyzed by two groups to see whether there are any differences between two groups regarding to the cloud note-taking app adoption (See Table 15). It was found that non-adopters were not affected by any perceptions the research model proposed, on the other hand, observability, triability and

risk were related to future adopters' intention. Regarding to contextual factors related to those three perceptions, social influence was related to observability and risk only for future adopters; and knowledge was related to triability only for future adopters.

Table 15. Results of Path Analysis Between Future Adopters and Non-Adopters

Hypo		Path	Group	Beta	T	Sig	Status
H1	a	RA -> BI	Adopter	0.04	0.43	n.s	n.s
			Non-Adopter	0.47	1.90	n.s	n.s
	b	COMPLEX -> BI	Adopter	0.09	0.65	n.s	n.s
			Non-Adopter	-0.06	0.24	n.s	n.s
	c	COMPATA -> BI	Adopter	0.12	1.15	n.s	n.s
			Non-Adopter	-0.07	0.22	n.s	n.s
	d	**OBS -> BI**	Adopter	0.40	4.18	***	Supported
			Non-Adopter	-0.03	0.10	n.s	n.s
	e	**TRI -> BI**	Adopter	0.21	2.21	*	Supported
			Non-Adopter	0.14	0.73	n.s	n.s
	f	**PR -> BI**	Adopter	-0.25	2.49	*	Supported
			Non-Adopter	-0.21	1.40	n.s	n.s
H2	a	**SI -> RA**	Adopter	0.22	2.50	*	Supported
			Non-Adopter	0.16	1.00	n.s	n.s
	b	SI -> COMPLEX	Adopter	-0.33	4.48	***	Supported
			Non-Adopter	-0.55	5.45	***	Supported
	c	SI -> COMPATA	Adopter	0.25	2.85	**	Supported
			Non-Adopter	0.47	3.31	**	Supported
	d	**SI -> OBS**	Adopter	0.58	8.94	***	Supported
			Non-Adopter	0.22	2.00	n.s	n.s
	e	SI -> TRI	Adopter	0.51	7.89	***	Supported
			Non-Adopter	0.50	4.54	***	Supported
	f	**SI -> PR**	Adopter	0.19	2.00	*	n.s
			Non-Adopter	0.01	0.06	n.s	n.s

Table 15 (Cont'd)

H3	a	PE -> RA	Adopter	-0.07	0.68	n.s	n.s
			Non-Adopter	0.15	0.70	n.s	n.s
	b	PE -> COMPLEX	Adopter	0.02	0.17	n.s	n.s
			Non-Adopter	-0.09	0.73	n.s	n.s
	c	PE -> COMPATA	Adopter	0.01	0.05	n.s	n.s
			Non-Adopter	0.04	0.24	n.s	n.s
	d	PE -> OBS	Adopter	0.21	1.76	n.s	n.s
			Non-Adopter	0.26	1.12	n.s	n.s
	e	PE -> TRI	Adopter	0.06	0.72	n.s	n.s
			Non-Adopter	0.26	1.84	n.s	n.s
	f	PE -> PR	Adopter	0.18	1.55	n.s	n.s
			Non-Adopter	-0.12	0.38	n.s	n.s
H4	a	KN -> RA	Adopter	-0.01	0.09	n.s	n.s
			Non-Adopter	-0.07	0.22	n.s	n.s
	b	**KN -> COMPLEX**	Adopter	-0.12	1.04	n.s	n.s
			Non-Adopter	-0.04	3.36	*	Supported
	c	KN -> COMPATA	Adopter	0.02	0.22	n.s	n.s
			Non-Adopter	0.10	0.64	n.s	n.s
	d	KN -> OBS	Adopter	0.05	0.73	n.s	n.s
			Non-Adopter	0.25	1.11	n.s	n.s
	e	**KN -> TRI**	Adopter	0.19	2.17	*	Supported
			Non-Adopter	0.24	1.59	n.s	n.s
	f	KN -> PR	Adopter	-0.02	0.11	n.s	n.s
			Non-Adopter	-0.17	0.62	n.s	n.s

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

Cluster Analysis

The auto-clustering algorithm indicated that a three cluster solution was the best model, because it minimized the AIC value and the change in them between adjacent numbers of clusters. The resulting clusters 1, 2, and 3 contained 114, 159, and 128 cases, which corresponded to 28.4%, 39.7%, and 31.9%, respectively. These three clusters emerged from a posterior data rather than being theoretically imposed.

Lifestyle profiling.

Within cluster analysis indicates that female individuals make up a larger percentage (98.1%) of cluster 2 than any other clusters, on the other hand, cluster 3 is dominated by male individuals (99.2%). The cluster 1 is evenly distributed with male (50.8%) and female (49.1%) individuals. As a matter of education, the majority of respondents have some college or college degree, although the cluster 1 contains a large percentage of participants who has high school education (32.5%). Additionally, ANOVA and Post-Hoc test were performed to check for differences among clusters in terms of age and device ownership (See table 16 and 17). The results showed that age is significantly different among three groups (F=1.682, $p < .001$), except between cluster 1 and 3 (Mean difference=2.26, $p > .05$). The cluster 1 (M= 43.88, SD=16.02) contains older participants than other clusters, and half of them are aged from 43 to 79 (53.5%). Similarly, half of participants in the cluster 3 are also aged from 43 to 79 (46.1%) and average age is 42 (SD=13.74). The cluster 2 has younger participants (M= 35.01, SD=13.24), and half of them are aged from 18 to 33 (55.3%). Device ownership has no difference among clusters (F= .77, $p > .05$), but the cluster 2 showed highest percentage of two or three device ownership (63.7%).

Table 16. Results of ANOVA in Differences of Age and Device Ownership Among Clusters

	Cluster 1		Cluster 2		Cluster 3		Sig	
	Mean	SD	Mean	SD	Mean	SD	F-value	P-value
Age	43.88	16.02	35.01	13.24	41.62	13.74	14.68	.000
Device ownership	2.26	1.23	2.40	1.01	2.25	1.10	.77	.462

Table 17. Results of Post-Hoc Test of Age and Device Ownership Among Clusters

Multiple Comparisons							
Tukey HSD							
Dependent Variable	(I) Cluster3	(J) Cluster3	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Age	1	2	8.865*	1.747	.000	4.75	12.97
		3	2.260	1.833	.435	-2.05	6.57
	2	1	-8.865*	1.747	.000	-12.97	-4.75
		3	-6.605*	1.691	.000	-10.58	-2.63
	3	1	-2.260	1.833	.435	-6.57	2.05
		2	6.605*	1.691	.000	2.63	10.58
Device ownership	1	2	-.133	.136	.589	-.45	.19
		3	.013	.142	.995	-.32	.35
	2	1	.133	.136	.589	-.19	.45
		3	.146	.131	.506	-.16	.45
	3	1	-.013	.142	.995	-.35	.32
		2	-.146	.131	.506	-.45	.16

* The mean difference is significant at the 0.05 level.

In regarding to occupation, higher percentage of participants in the cluster 1 has no job (14%), or they are the full-time housewife (10.5%) or husband (7.9%), free-lancer (6.1%) and volunteer (6.1%). In accordance with the occupation, the participants in the cluster 1 chose being at home quietly (19.3%), watching TV (15.8%), doing odd job around the house (10.5%) or surfing the Internet (7.9%) as hobby, interest and/or leisure activity. On the other hand, participants in the cluster 2 and 3 showed that they do more

active and social activity. The participants in the cluster 2 enjoy their sociable evening with friends (17%), do things to make dreams come through (8.2%), or do shopping (8.2%). The participants in the cluster 3 also showed high percentage of social evening with friends (10.2%) as a leisure activity. Camping (8.6%), active sports (7.0%) and surfing the Internet (11.7%) are also chosen as a hobby or interest for the participants in the cluster 3. Moreover, the cluster 2 and 3 contains participants who have more specialized jobs than the cluster 1. The cluster 2 has people who are business man/woman (13.8%), public servant (6.9%), manager (5%) and student (15.1%). The cluster 3 is comprised of business man/woman (14.1%), scientist (7.8%), manager (6.3%), or entrepreneur (5.5%).

As a matter of value participants think best, enjoyable life is chosen by all three clusters, and additionally privacy, independence or respect is chosen. Respect (18.4%) is the highest value in the cluster 1; enjoyable life (20.8%) is the highest in the cluster 2; and privacy (17.2%) is the one for the cluster 3. In regarding to household or family type, the cluster 1 said cozy old fashioned family (28.9%), stable (15.8%) or quiet family (8.8%) fit the best for them. Also, they described their characteristics as honest (13.2%), down to earth (13.2%) or little bit shy (9.6%). On the other hand, the cluster 3 includes bachelor (12.5%) as a household type including happy (15.6%) and harmonious family (9.4%). The most chosen characteristics for the cluster 3 are intelligent (11.7%), balanced (8.6%), and strong character (6.3%). For the cluster 2, happy family (25.8%) was chosen the most; warm (15.1%) and stable family (9.4%) are followed. Also, easy going (14.5%), down to earth (11.9%), honest (6.9%), and intelligent (6.9%) presented as their characteristics.

Based on the self-reported demographic and lifestyle, the three clusters are labeled and summarized as follow. The cluster 1 is labeled to the "*Traditionalists*." Members of this group are mostly a housewife/husband, or a volunteer, middle-aged, and have some college or high school education. They have lay back attitude and a serious view on the world. They are conservative, traditional, and not interested in the change. Not opinionated, however, fundamental in their opinion. The cluster 2 is labeled to the "*Hedonic yuppies*." Easy going, sociable, independent, higher educated and relatively young women are included in this group. They are intelligent and trendsetters. The cluster 3 is labeled the "*Intelligent businessmen*." People are ambitious, dynamic, and control oriented. Higher educated, independent, and middle-aged men with strong character are included in this group. The three labels used above (i.e. traditionalists, hedonic yuppies, and intelligent businessmen) emerged from the data, but are also in line with existing lifestyle researches, and will be discussed further in the next section (Bouwman et al., 2008; Molina-Castillo et al., 2010)

Table 18 contains more detailed frequency distributions for the lifestyle variables within clusters.

Table 18. Within Clusters Information

Label	Traditionalists	Hedonic Yuppies	Intelligent Businessmen
Cluster	1	2	3
Size	114 (28.4%)	159 (39.7%)	128 (31.9%)
Education	Some college (36%) High school (32.5%)	Some college (41.5%) College degree (18.2%)	College degree (28.9%) Some college (26.6%)
Gender	Male (50.9%) Female (49.1%)	Female (98.1%)	Male (99.2%)
Age	43.88 (mean) 43-55 (28.9%) 56-79 (24.6%)	35.01 (mean) 18-26(30.8%) 27-33 (24.5%)	41.62 (mean) 43-55 (24.2%) 56-79 (21.9%)
Device ownership	2.26 (mean) 1 (33.3%) 2 (29.8%) 3 (21.9%)	2.40 (mean) 2 (39.6%) 3 (23.9%) 1 (19.5%)	2.25 (mean) 2 (35.2%) 1 (28.9%) 3 (21.9%)
Occupation	No occupation (14%) Fulltime housewife (10.5%) House husband (7.9%) Free-lancer (6.1%) Volunteer (6.1%)	Student (15.1%) Business man/woman (13.8%) Fulltime housewife (11.3%) Public servant (6.9%) Manager (5%)	Business man/woman (14.1%) Scientist (7.8%) Free-lancer (6.3%) Manager (6.3%) Entrepreneur (5.5%)
Hobby, interest and/or leisure activity	Being at home quietly (19.3%) Watching TV (15.8%) Do odd job around the house (10.5%) Surfing the Internet (7.9%)	A sociable evening with friends (17%) Being at home quietly (10.7%) Make dreams come through (8.2%) Shopping (8.2%)	Surfing the Internet (11.7%) A sociable evening with friends (10.2%) Camping (8.6%) Active sports (7.0%)
Value	Respect (18.4%) Privacy, Tranquility (17.5%) Enjoyable life (13.2%)	Enjoyable life (20.8%) Independence (10.7%) Respect (8.2%)	Privacy, Tranquility (17.2%) Enjoyable life (12.5%) Independence (12.5%)

Table 18 (Cont'd)

Family or household	Cozy old fashioned family (28.9%) Stable family (15.8%) Quiet family (8.8%)	Happy family (25.8) Warm family (15.1%) Stable family (9.4%)	Happy family (15.6%) Bachelor (12.5%) Harmonious family (9.4%)
Characteristic	Honest (13.2%) Down to earth (13.2%) Capable (10.5%) A little bit shy (9.6%)	Easygoing (14.5%) Down to earth (11.9%) Honest (6.9%) Intelligent (6.9%)	Intelligent (11.7%) Easygoing (11.7%) Balanced (8.6%) Strong character (6.3%)

Contextual factors and innovation attributes.

The innovation attributes and contextual factors are also compared among three clusters by ANOVA test (See table 19). The results showed that the perceived level of relative advantage, complexity, compatibility, triability and behavioral intention to use the cloud note taking app are significantly different among three clusters. In general, hedonistic yuppies (cluster 2) or Intelligent Businessmen (cluster 3) perceived stronger (or higher) innovation attributes (e.g., relative advantage, compatibility, observability, triability, and risk). Also, behavioral intention of hedonistic yuppies (cluster 2) [*M*= 3.52, *SD*= .87] is significantly higher than Traditionalists (cluster 1) [*M*= 3.22, *SD*= .84], and Intelligent Businessmen (cluster 3) [*M*= 3.44, *SD*= .73]. In more detail, hedonistic yuppies (cluster 2) perceived significantly higher relative advantage (*M*= 3.70, *SD*= .86) and compatibility (*M*= 3.70, *SD*= .86) than other clusters. The triability is perceived significantly more to Intelligent Businessmen (cluster 3) [*M*= 3.39, *SD*= .76]. Also, participants in Traditionalists (cluster 1) perceived significantly more complexity from the cloud note-taking app (*M*= 2.53, *SD*= .68). In addition, social influence, past experience, observability and risk are perceived more to the participants in Intelligent

Businessmen (cluster 3), although they are not significantly different among three clusters.

Table 19. Results of ANOVA in Differences of Contextual Factors and Innovation Attributes Among Clusters

	Traditionalists		Hedonic Yuppies		Intelligent Businessmen		Sig	
	Cluster 1		Cluster 2		Cluster 3			
	Mean	SD	Mean	SD	Mean	SD	F-value	P-value
Social influence	2.89	.69	2.99	.77	**3.05**	.71	1.47	.231
Knowledge								
- Awareness	.93	.97	**1.09**	1.00	1.08	.97	2.20	.112
- How to	.81	1.07	.99	1.05	**1.08**	1.14	1.95	.143
Past experience								
- Number of service	.40	.87	.45	.79	**.63**	1.03	2.14	.120
- Period of usage	13.71	12.94	11.41	11.09	**18.05**	15.70	2.71	.071
Relative Advantage	3.34	.79	**3.70**	.86	3.53	.76	6.80	.001
Complexity	**2.53**	.68	2.26	.79	2.33	.65	4.90	.008
Compatability	3.43	.79	**3.70**	.86	3.53	.76	3.90	.021
Observability	2.46	.94	2.63	1.00	**2.67**	.98	1.55	.213
Triability	3.14	.65	3.27	.81	**3.39**	.76	3.35	.036
Risk	2.81	.81	2.71	.87	**2.93**	.78	2.44	.088
Behavioral intention	3.22	.84	**3.52**	.87	3.44	.73	4.84	.008

Path model for different clusters.

The proposed structural model was analyzed by three clusters using the Partial Least Square (PLS) method through the SmartPLS package, to see whether there are any differences among three groups regarding to the cloud note-taking app adoption (See table 20).

Table 20. Results of Path Analysis Among Clusters

Hypo		Path	Cluster	Beta	T	Sig	Status
H1	a	RA -> BI	1	0.24	2.07	*	Supported
			2	0.25	2.40	*	Supported
			3	0.28	3.12	**	Supported
	b	COMPLEX -> BI	1	0.19	1.53	n.s	n.s
			2	0.03	0.22	n.s	n.s
			3	0.04	0.33	n.s	n.s
	c	COMPATA -> BI	1	0.27	2.12	*	Supported
			2	0.25	2.20	*	Supported
			3	0.41	3.27	**	Supported
	d	OBS -> BI	1	0.13	1.43	n.s	n.s
			2	0.21	3.46	***	Supported
			3	0.13	1.41	n.s	n.s
	e	TRI -> BI	1	0.19	1.79	n.s	n.s
			2	0.27	2.41	*	Supported
			3	0.05	0.41	n.s	n.s
	f	PR -> BI	1	-0.24	2.52	*	Supported
			2	-0.13	2.20	*	Supported
			3	-0.09	1.29	n.s	n.s
H2	a	SI -> RA	1	0.41	5.91	***	Supported
			2	0.45	5.18	***	Supported
			3	0.42	4.80	***	Supported
	b	SI -> COMPLEX	1	-0.42	6.04	***	Supported
			2	-0.47	5.73	***	Supported
			3	-0.38	2.98	***	Supported
	c	SI -> COMPATA	1	0.55	8.34	***	Supported
			2	0.50	6.97	***	Supported
			3	0.53	7.22	**	Supported
	d	SI -> OBS	1	0.36	4.80	***	Supported
			2	0.59	9.80	***	Supported
			3	0.53	7.97	***	Supported
	e	SI -> TRI	1	0.44	5.10	***	Supported
			2	0.56	7.25	***	Supported
			3	0.55	7.43	***	Supported
	f	SI -> PR	1	-0.17	1.51	n.s	n.s
			2	-0.08	0.57	n.s	n.s
			3	-0.01	0.09	n.s	n.s

Table 20 (Cont'd)

H3	a	PE -> RA	1	0.03	0.30	n.s	n.s
			2	0.00	0.09	n.s	n.s
			3	-0.09	0.93	n.s	n.s
	b	PE -> COMPLEX	1	0.02	0.19	n.s	n.s
			2	-0.02	0.28	n.s	n.s
			3	0.02	0.20	n.s	n.s
	c	PE -> COMPATA	1	0.00	0.04	n.s	n.s
			2	0.00	0.00	n.s	n.s
			3	-0.06	0.66	n.s	n.s
	d	PE -> OBS	1	0.34	2.58	*	Supported
			2	0.06	0.65	n.s	n.s
			3	0.23	3.19	**	Supported
	e	PE -> TRI	1	0.19	2.04	*	Supported
			2	0.03	0.37	n.s	n.s
			3	0.10	1.18	n.s	n.s
	f	PE -> PR	1	0.00	0.03	n.s	n.s
			2	0.00	0.00	n.s	n.s
			3	0.30	3.00	**	Supported
H4	a	KN -> RA	1	0.04	0.50	n.s	n.s
			2	0.11	1.26	n.s	n.s
			3	0.06	0.54	n.s	n.s
	b	KN -> COMPLEX	1	-0.24	3.29	n.s	n.s
			2	-0.24	3.54	n.s	n.s
			3	-0.30	2.97	n.s	n.s
	c	KN -> COMPATA	1	0.10	1.54	**	Supported
			2	0.11	1.44	***	Supported
			3	0.11	1.16	**	Supported
	d	KN -> OBS	1	0.04	0.54	n.s	n.s
			2	0.17	2.27	*	Supported
			3	-0.12	1.13	n.s	n.s
	e	KN -> TRI	1	0.12	1.59	n.s	n.s
			2	0.20	2.30	*	Supported
			3	0.06	0.66	n.s	n.s
	f	KN -> PR	1	-0.20	2.41	*	Supported
			2	0.03	0.25	n.s	n.s
			3	-0.32	3.30	***	Supported

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

In addition, the three clusters showed differences on to nine paths (See table 21). The main differences, regarding to the relationships between innovation attributes and behavioral intention to use the cloud note-taking app, are 1) observability (OBS) and triability (TRI) did not impact on behavioral intention for Traditionalists (cluster 1) and Intelligent Businessmen (cluster 3); and 2) the effect of the risk (PR) toward behavioral intention (BI) was not validated for Intelligent Businessmen (cluster 3). Regarding to the effect of contextual factors on the innovation attributes, the past experience and knowledge showed differences for each clusters. It was found that 1) past experience with similar services (PE) has no impact on triability (TRI) for hedonistic yuppies (cluster 2) and Intelligent Businessmen (cluster 3); 2) the observability (OBS) is not affected by past experience (PE) for hedonistic yuppies (cluster 2); 3) the relationship between the past experience (PE) and the risk (PR) is not validated for Traditionalists (cluster 1) and hedonistic yuppies (cluster 2); 4) the level of knowledge (KN) doesn't impact on the risk (PR) for hedonistic yuppies (cluster 2); and 5) triability (TRI) and observability (OBS) have no significantly relationship with the knowledge (KN) for Traditionalists (cluster 1) and Intelligent Businessmen (cluster 3).

Table 21. Results of Path Analysis Among Clusters (only different results)

Path	Cluster	Beta	T	Sig
OBS-> BI	1	0.13	1.43	n.s
	2	0.21	3.46	***
	3	0.13	1.41	n.s
TRI -> BI	1	0.19	1.79	n.s
	2	0.27	2.41	*
	3	0.05	0.41	n.s
PR -> BI	1	-0.24	2.52	*
	2	-0.13	2.20	*
	3	-0.09	1.29	n.s
PE -> TRI	**1**	0.19	2.04	*
	2	0.03	0.37	n.s
	3	0.10	1.18	n.s
PE -> OBS	1	0.34	2.58	*
	2	0.06	0.65	n.s
	3	0.23	3.19	**
PE -> PR	1	0.00	0.03	n.s
	2	0.00	0.00	n.s
	3	0.30	3.00	**
KN -> PR	1	-0.20	2.41	*
	2	0.03	0.25	n.s
	3	-0.32	3.30	***
KN -> TRI	1	0.12	1.59	n.s
	2	0.20	2.30	*
	3	-0.09	1.29	n.s
KN -> OBS	1	0.04	0.54	n.s
	2	0.17	2.27	*
	3	-0.12	1.13	n.s

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

All in all, the path analysis showed which contextual factors impact perceptions regarding the innovation's attributes, and in turn their effect on behavioral intention to adopt the innovation. Also, the cluster analysis identified three lifestyle groups, and the path analysis for each group revealed key differences in their respective process of

adopting an innovation. A summary of results along with implications will be discussed in the next section.

DISCUSSION

New products are launched quickly, but many are converged products. Therefore, the new product is not completely new to consumers, and the basic features stay the same. As a result, the added functions or fancy designs can't explain why consumers adopt the new media. Past studies have examined perceptions of innovations or user experience to understand what factors have an impact on the intention. However, most studies did not explore individual differences or users' context, but investigated their perception of innovation independently. In this chaotic market, everyone is competing for consumers' attention. It is important to investigate how consumers develop perceptions of innovation. The usability field investigates the contextual factors as principal components that form usability and the consequence of usability, which represents the perceptions of the product or service. In accordance with the importance of contextual factors, investigating the relationships between users' contextual information and their perception of innovation attributes and then asking what attributes impact their intention could provide valuable information about the new media adoption process.

Summary of Results

The study examined factors that led various groups of people to adopt the cloud note-taking application as a representative innovation. The study proved that most innovation attributes, such as relative advantage, compatibility, observability, and triability, have an impact on the intention to use the innovation. These findings are consistent with previous studies (Rogers, 2003; Sultan & Chan, 2000; Vishwanath & Goldhaber, 2003), where adopters generally require an innovation to have relative

advantages; be compatible with their needs and values; be observable from surroundings; and allow for testing before fully owning the innovation.

However, the complexity of the innovation, which has been validated in past studies as an important factor toward the intention, had no significant relationship with intention. Low et al. (2011) also found the insignificant effect of complexity on the intention in the context of cloud computing, and they concluded that it could be because of the immaturity of cloud computing technology and unclear mechanism. If people have no idea whether the innovation is going to be hard to understand or easy to use, complexity can be insignificant as it relates to intention. There is a possibility that people might not care or care less about the easiness of the innovation, or that some innovations are readily understood by most consumers. Although the new media and services continue to be introduced quickly, there is nothing original or new. As previously stated, many are converged products or updated versions. Therefore, intimidation from new media might not be as strong and or effective as in past days as the average value for the complexity was low (mean = 2.36) and more than half of participants (57.6%) perceived the cloud service is less complex.

On the other hand, the risk is found as important innovation attributes affecting the intention, which is not included in the diffusion of innovation theory. This result is consistent with past studies (Chan-Olmsted & Chang, 2006; Chen, 2008; Liao et al., 2006), and it reflects current concerns about the possible risk or uncertainty of the new media. New media is being connected and shared, and therefore, privacy and security have become an issue. Cloud computing in particular has been criticized for its lack of

security and privacy issues, since all data is saved to the cloud, and the Internet connection is essential to the process (Hayes, 2008; Miller, 2008).

In addition to risk, relative advantage and compatibility had the highest impact on behavioral intention. Especially, compatibility showed the highest explanatory power on behavioral intention among innovation attributes. It has been found and validated that relative advantage and compatibility are the most relevant constructs to adoption research, and they have been consistently related to various innovation adoptions (Tornatzky & Klein, 1982; Plouffe et al., 2001). Also, the study showed consumers' appreciation for cloud service's relative benefits (relative advantage), at the same time it consistently satisfies consumers' existing values and needs (i.e. compatibility).

Given that various innovation attributes are important in understanding behavioral intention, the study also examined the factors that led to the innovation attributes, so called 'contextual factors' such as social influence, knowledge and past experience with similar services. By exploring the effect of contextual factors, the study showed how the impact of innovation attributes can be increased. First of all, social influence was found to be the strongest factor and it offered the greatest explanatory power toward innovation attributes, such as relative advantage, compatibility, complexity, observability and triability, with the exception of risk. It showed that perceptions of innovation are influenced by consumers' surroundings that they consider important, or people who are in the same organization, which means people want to comply with others' expectations. Also, according to Dwivedi and Irani (2009), after launching an innovation to market, the period of uncertainty about its relative advantage becomes less as consumers become more aware of its benefits, impact and usefulness. It is possible that the information about

relative advantage of innovation can be diffused through social networks. Relative advantage and compatibility can be acquired through social surroundings. Similarly, Nonaka (1994) and Burt (2000) provide a meso-view to an organizational activity and information creation. They found that redundantly shared information in organizations can organize personal knowledge. Also, according to Rogers (2003), the diffusion process is conceived fundamentally as a process of information exchange facilitated by mass media and interpersonal channels within the social system. The social network is the perfect place for information to be diffused and redundantly provided. Therefore, people who are more influenced by their social network are more exposed to informal social networks in which the benefits are discussed. Also, information from social networks help people notice the innovations in their surroundings and realize these innovations can be tested before the purchase them.

It is interesting to note that social influence was the only factor that affected relative advantage, which was one of the strongest antecedents of behavioral intention. The relative advantage has no significant relationship with past experience and knowledge. It could reflect the importance of social values as a relative advantage since relative advantage includes not only functionality, costs or convenience but also social images (Fichman & Kemerer, 1993). Also, according to the Uses and Gratification theory, individuals interact with each other to achieve a sense of belonging (Rubin, 1986). Several scholars have uncovered possible relationships between socializing gratification and media consumption. For instance, past research on the Internet has elaborated about social gratifications such as the enjoyment of forging social ties that Internet users derive from using the Internet (LaRose & Eastin, 2004). Also, in terms of social media use, past

studies noted that socializing and maintaining relationships were regarded as one of the gratifications that motivate people to use social networking sites (Dunne et al., 2010; Park et al., 2009). The popularity of social networking sites and social related features proves that the importance of social values in the new media is strengthening. Therefore, people who are highly influenced by social networks could perceive more relative advantage when the innovation has a strong social impact.

In addition to the important role of social influence, risk was affected by the level of knowledge and past experience. It was interesting to note that the more knowledge people have, the less the risk is perceived. On the other hand, the more past experience people have, the more the risk is perceived. The knowledge includes awareness and how-to knowledge; therefore, this type of knowledge could give people the self- confidence to know that they can handle the innovation (Park et al., 1994). However, with regard to past experience, the study asked how many other cloud services participants have used, and how long they used it. It did not include whether they had positive or negative experiences with other cloud services. Also, according to past studies, consumers' perception of risks is inherent in product adoption in general (Bauer, 1967; Dowling & Staelin, 1994; Featherman & Pavlou, 2003). Therefore, users of cloud services have concerns about possible privacy or security, although nothing has happened to them. Uncertainty and possible security issues has been a barrier to adoption of cloud computing (Katzan, 2009). Therefore, experienced users might feel that usual cloud services carry risk, although they did not experience real risk with their cloud services. In other words, past experience could include their bad memory or general insecurity with services they used, and they therefore expect the risk. Likewise, knowledge can give

confidence to ignore the risk of innovation, while past experience can bring concerns of possible risk.

Aside from risk, among the innovation attributes from diffusion of innovation theory, relative advantage, complexity and compatibility can be decided by more subjective interpretation when compared to observability and triability. In other words, the level of relative advantage, complexity and compatibility can be the result of subjective evaluation by comparing a subject's own ability, value, or needs with the innovation. On the other hand, observability and triability are not the result of subjective evaluation, but the result of what people saw and heard. The result showed that the past experience did not have an impact on the relative advantage, complexity or compatibility, although the social influence and the knowledge have an impact on them. The past experience might not give enough information (e.g., benefits, easiness or values) to evaluate the inexperienced and similar innovation. Also, the past experience was not about the same featured/purposed services (e.g., note-taking tool), but the same technology type (e.g., cloud service). Therefore, past experience might not give information related to its functionality or values. It could be because of the insignificant relationship with relative advantage, complexity and compatibility. However, past experience was the significant antecedent for the observability and triability. It showed that familiarity and information from the past experience could make people notice the innovation and its triability. Even though the innovation has high observability in general, observability can be low if a subject doesn't recognize or notice its presence. Also, according to Jung et al (2011), people who own more new media are more aware of and have more interest in new services. If the subject does not experience with the specific

innovation (e.g., cloud note taking app) but he has experiences with similar innovation (e.g., cloud services), he might be more exposed to similar innovations than inexperienced subjects. Therefore, it can be concluded that past experience might not provide sufficient information to estimate the innovation's values, benefits or easiness but does provide objective information or experience to see the presence of innovation or whether they can try it before owning it. Through the findings, we can see people who have more experience with similar services perceived more observability and triability, which are the important antecedents of intention.

If the past experience provides less subjective information, knowledge can provide both subjective and objective information about innovation, since it has an impact on compatibility, complexity, and triability. It is consistent with the past studies that knowledge can help establish an innovation's functionality and efficiency (Bondarky, 1998; Hackbarth et al., 2003). The study also showed that knowledge can provide information about whether the innovation can be consistent with existing values, past experience and the needs; is easy to use or understand; or can be tested. However, knowledge is not related to observability. The observability can be acquired when the subject notice the innovation demonstrated by surroundings. Therefore, subject's awareness of innovation is important but also exposure of social network or new innovation market is needed as shown by impact of social influence and past experience to observability. In addition, knowledge was not strong as social influence and had no impact on relative advantage. It could be because knowledge is static information. On the other hand, social influence can affect people to see or hear how friends or acquaintances use the innovation effectively, easily, or interestingly, since socially influenced people

are more exposed to their surroundings (Goldenberg et al., 2009). However, knowledge might not give insight about how upgraded or fancy features can be used and improve benefits, compared to existing features. Although the knowledge is not as strong a factor as social influence, it still provides information to people to determine compatibility and triability.

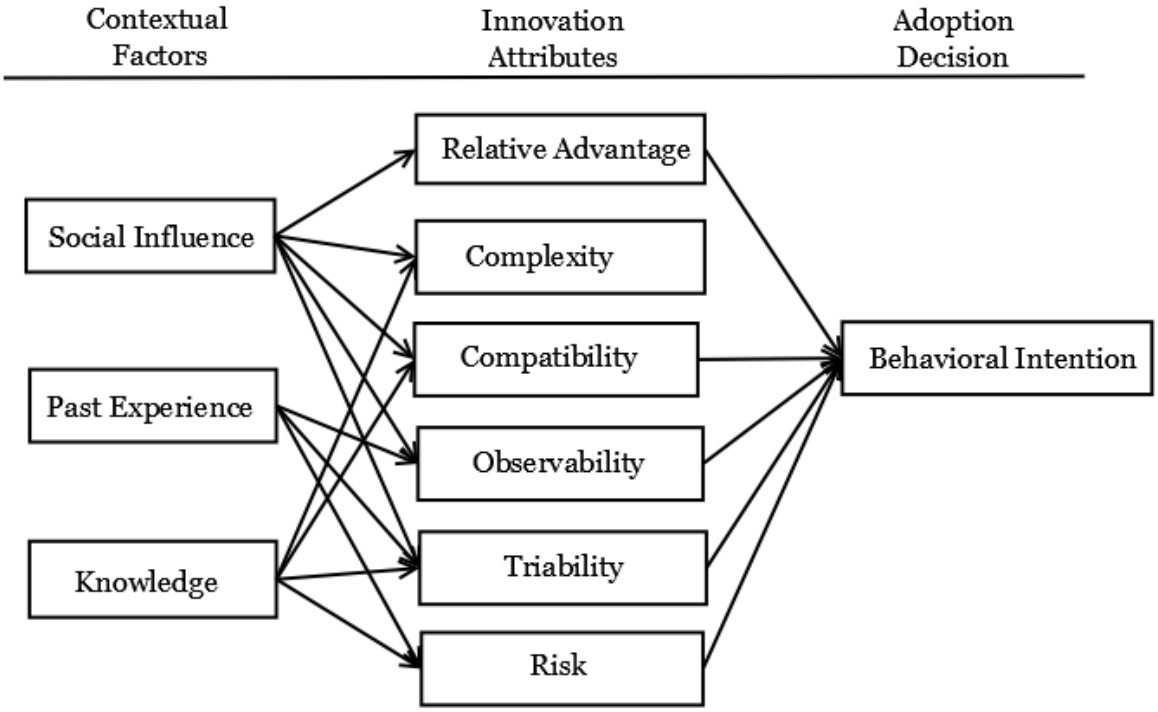


Figure 11. Validated Model

Additionally, the study investigated difference between future adopters and non-adopters regarding the adoption process. It was found that adopters were significantly influenced by observability, triability and risk; on the other hand, non-adopters were not affected by any innovation attributes. Also, future adopters perceived significantly higher observability and triability and lower risk of innovation than non-adopters. It is telling

that future adopters are more influenced by innovation's visibility and risk rather than its functionality or efficiency. Also, future adopters want to try innovation before they fully own it. Social influence and knowledge were found to be antecedents of those three innovation attributes.

In addition, the study explored various groups of people to see how they behaved in the adoption process as an exploratory study. The cluster analysis revealed three distinct groups of people: Traditionalists (cluster 1), Hedonic Yuppies (cluster 2), and Intelligent Businessmen (cluster 3). In regard to the antecedents of behavioral intention, Intelligent Businessmen only care about the compatibility and relative advantage of innovation. In other words, the important antecedents of their intention were innovation's values, features, and needs. Their intention was not affected by the complexity, observability, triability, and even the risk. Similarly, the intention of Traditionalists was not affected by most of the innovation attributes. The difference between Traditionalists and Intelligent Businessmen was that Traditionalists are affected by risk, in addition to relative advantage and compatibility. Traditionalists want to stay in their stable position and are not interested in change. The insecurity of the innovation might be related with their intention. On the other hand, Hedonic Yuppies were influenced by various attributes of innovation. Their intention was affected by observability, triability and risk in addition to relative advantage and compatibility. They are the trendsetters and sociable people, and they might consider how other people use the innovation, what they heard about it, and what the possible risks are, and they might want to test it before they fully commit to buying it.

When it comes to contextual factors, generally, social influence was the strongest antecedent of innovation attributes for all clusters. Aside from social influence, past experience is a more important factor to Intelligent Businessmen and Traditionalists than Hedonic Yuppies. Past experience has no impact on any innovation attributes for Hedonic Yuppies. On the other hand, past experience affected observability and triability for Traditionalists. For Intelligent Businessmen, past experience was related to observability and risk. These results showed that past experience could provide objective information to both Traditionalists and Intelligent Businessmen, but may cause concern to Intelligent Businessmen.

For Hedonic Yuppies, knowledge was a more important factor than past experience. Observability or triability was affected by past experience or social influence for Traditionalists and Intelligent Businessmen. However, knowledge had an impact on observabiltiy and triability for Hedonic Yuppies, in addition to social influence. It might be because they do not obtain sufficient information from their past experience, which is about similar services, not the same purposed/featured services. Therefore, they might be more influenced by their current knowledge about the innovation, not by their unrelated and dated information from past experience, since they are the trendsetters and sociable people.

In addition, since it was not that every attribute were related to behavioral intention for all three groups, impacting contextual factors for three groups were different. Relative advantage and compatibility were the common innovation attributes impacting behavioral intention of all three groups. Also, those innovation attributes were affected by social influence of all three groups. Since relative advantage and compatibility were the

only innovation attributes for intention of Intelligent Businessmen, social influence is the only contextual factor to be considered. Traditionalists and Hedonic Yuppies, however, risk was another innovation attribute impacting intention, in addition to relative advantage and compatibility. Knowledge was found as the contextual factor that was negatively related to risk for Traditionalists. Therefore, knowledge is another contextual factor to be considered for Traditionalists, as well as social influence. In addition to relative advantage, compatibility, and risk, behavioral intention of Hedonic Yuppies is affected by observability and triability, and those attributes were positively related to knowledge and social influence. In accordance with Traditionalists, social influence and knowledge are the impacting contextual factors on innovation attributes that are related to behavioral intention for Hedonic Yuppies.

Implication for Research

This study validated the relationships between innovation attributes and behavioral intention to adopt. Also, the study showed the importance of risk as an additional innovation attribute which reflects current concerns about innovation. Complexity has been treated as the only negative factor toward intention, but the study showed that it is better to consider risk as an important innovation attribute, since consumers are getting accustomed to the new media. Consumers might not be overwhelmed by the complexity of the innovation, but the possible risk is getting attention and can't be ignored. In addition, this study validated the importance of two factors, relative advantage and compatibility, which have been found and validated that two factors are the most relevant constructs to adoption research.

Also, this study demonstrated the utility of adding contextual-specific factors to a well-established theory. By exploring the relevant contextual factors, the study found the importance of social influence, knowledge and past experience on the decision process, especially for new media, by identifying them as antecedents of perceptions of innovation. Thus, this study provides insight into the relevant contextual factors impacting innovation attributes, and showed predictive power of Diffusion of Innovation Theory.

Implication for Practice

The study validated the relationships between innovation attributes and behavioral intention to adopt theoretically, but also offered support for its applicability in the context of cloud computing. The study showed consumers' appreciation for cloud service's relative benefits (relative advantage), at the same time it consistently satisfies consumers' existing values and needs (compatibility). Therefore, marketing managers can promote the cloud service by showing that it has upgraded features but is still compatible with their existing values, norms or even routines. Also, the study showed the importance of social influence on the decision process, which can translate into social marketing. Since social influence is related to relative advantage, compatibility, observability and triability, marketing managers could sell the services' merits by relating to people's social value or social image. Also, promoting the service in the community or organization may appeal to people in the same circle. Regarding the impact of knowledge and past experience, it is advised that raising consumers' knowledge of the innovation can reduce its perceived risk. Therefore, industry should understand what concerns consumers and try to minimize bad memories from past experience and general concern by helping clarify their uncertainty

and the possible risk. Furthermore, we can see people who have more experience with similar services perceive more observability and triability, which are the important antecedents of intention. Therefore, experienced people are likely a good target for industry. Also, although knowledge is not as strong a factor as social influence, it still provides information to people to determine compatibility and triability; therefore, educating people about new services and knowing how to use them can result in a positive perception of the service.

Lastly, the cluster analysis and comparison showed that Hedonic Yuppies are the optimal target to focus on, as they showed the highest intention to adopt the innovation. Also, relative advantage and compatibility of the innovation, which are the strongest antecedents of intention, were significantly more important for Hedonic Yuppies than for Intelligent Businessmen and Traditionalists. Moreover, Hedonic Yuppies are influenced by other factors, such as observability, triability and risk, unlike other clusters. The contextual factors that affect these attributes are social influence and knowledge for Hedonic Yuppies. Therefore, new media industry needs to provide social features or services to people in the same circle to generate more positive perceptions of innovation, especially for Hedonic Yuppies, since they can be the main target. Also, educating them to raise awareness and general knowledge can be helpful in raising innovation's presence and triability. In addition, if the target is Intelligent Businessmen or Traditionalists, marketing managers need to focus on promoting the innovation's benefits, features, or values; try to understand the general concerns of innovation; and help consumers clarify the uncertainty or possible risk by improving their level of knowledge or using social network.

Limitations and Future Research

A number of lessons emerged from the results of this research. Even though this research made meaningful contributions, it still had several limitations. First of all, the study excluded 19% of disqualified subjects (or 15% of potential users) because they have already been using the cloud note-taking application. However, Rogers (2003) defined an adopter category as a classification of individuals within a social system on the basis of innovativeness. He suggested a total of five categories of adopters in order to standardize the usage of adopter categories in diffusion research: Innovators, early adopters, early majority, late majority and laggards. Therefore, Diffusion of Innovation Theory would correspond to Innovators and Early Adopters, who were excluded frmo this study. Since the study only used subjects that can be the early majority, late majority and laggards, the predictive power of explaining behavioral intention to adopt the innovation can only be applied to those groups. The model does not explain innovators' and early adopters' perceptions of innovation, or impacting factors in their decision to adopt the innovation. Although three groups that were examined in this study are occupied by 84% of the population (Roger, 2003), it is advised to include excluded groups to lend more predictive power toward the Diffusion of Innovation Theory. In accordance with exploring five adopter categories, it will be interesting to investigate the perceived innovation attributes in a longitudinal setting to explore what innovation attributes are more salient and which ones are more temporal regarding to the rate of adoption.

Second, the study adapted the constructs of past experience from past studies and it did not capture the full flavor of the construct. This study only checked the number and

the period of similar service consumers have experienced, so we couldn't ascertain whether they had a positive or negative past experience. Also, the past experience of this study only included similar services that have different purposes, but they are under the same technology type. Therefore, past experience with similar services might not give consumers as much information as obtaining the perception of innovation. Thus, for future research, it is advised to extend the concept of past experience with similar-featured or valued services and their satisfaction level. In that case, past experience can better explain perceptions of innovations.

Third, the self-reported recall measures may be a limitation of the present study, especially for the the contextual factors of knowledge and past experience. According to Papper et al. (2004), direct observations can be more accurate measures than self-reports because people tend to underestimate their usage or ability.

Forth, the cloud note-taking application represents the cloud services, and in a bigger picture, the innovation. However, exploring one type of technology lacks generalizability. The cloud note-taking application is an example of SaaS cloud service, which is also one of types of cloud computing. Consumer needs and perceptions could be different among various proposed functions of SaaS cloud services and even among different types of cloud computing. Therefore, future research should explore various types of SaaS cloud services (e.g., music, movie, storage, or virtual desktop cloud services), and different types of cloud services (e.g., PaaS and IaaS) to give more validity and generalizability to the research model.

Finally, exploring more contextual factors or more detailed lifestyles may lead to a more thorough understanding of what influences users' intention of adoption.

Particularly, observability was related to social influence and past experience, since it can be acquired within the environment to observe innovation and awareness to notice it. Subjects that are more exposed to social network and environment to observe innovation can perceive more observability of innovation. However, social influence refers to the phenomenon that the reference group influence behaviors and experiences in the form of social pressure to perform a particular behavior (Nysveen et al., 2005). Observability and social influence share social environment or social value, but social influence focuses on the reference group and observability is related to visibility from everyone. Also, the impact of social influence was high on observability, but observability was only 37% explained by contextual factors. Therefore, future research needs to explore more contextual factors that give a more comprehensive understanding toward perception of innovation.

Research Conclusion

This study makes a number of unique contributions to the existing body of knowledge regarding theories and practices related to the adoption of new media technologies. Contributions to theory center on the relationship between contextual factors and innovation attributes. These relationships have not been widely investigated in the new media adoption studies. However, there is a growing body of evidence indicating that contextual factors of consumers impact on communication technology adoption decisions. This study adds to this body of knowledge. Also, the study use the context of cloud computing, an innovation technology that has grown rapidly in importance and has a lot in common with recent media.

This study demonstrates the utility of adding contextual specific factors to a well-established theory. The results of this research indicate that adding contextual factors to the diffusion of innovation theory provide the predictive power to the innovation attributes. Exploring the contextual factors with innovation attributes, the study can investigate how consumers form the perceptions of innovation. This allows making a contribution to the existing knowledge of emerging contextual factors. The study theoretically demonstrates that the contextual factors impact intentions indirectly through perceptions of innovation.

In detail, social influence was found to be the strongest factor related to perceptions by increasing the exposure to the strong informational channel and social values. The knowledge and past experience were also influential to perceptions by giving subjective or objective information, confidence, and concerns. Aside to the importance of contextual factors risk is validated as an important attribute for the new media, in addition to the existing attributes from diffusion of innovation theory.

In addition, the study investigated various groups of people and showed how each group had different contexts, perceptions and intentions in the adoption process. In accordance, practically, the study suggested which contextual factors the industry should focus on and invest in to raise perceptions of innovations. Also, the study showed the possible main target group of people for the innovation and advised how the industry needs to treat its various targets and how to promote its services or products to increase positive perceptions of it.

The study was limited by the narrow concept and self-reported measure, and one type of target technology. However, the study helps fill the gap in existing new media

research by providing understanding of how users' contextual information interact with perceptions of innovation and how various groups of people act differently in adoption process.

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