A "Cloud Lifestyle": The Diffusion of Cloud Computing Applications and the Effect of Demographic and Lifestyle Clusters

Abstract

Adoption studies have repeatedly analyzed dimensions of novel technologies, including usefulness and ease of use, for understanding people's behavioral intention to use these technologies, yet, we have only limited understanding of the effects of user characteristics and lifestyles. Based on a U.S. national random sample of 402 non-cloud service users, we propose, analyze, and validate a multi-faceted model of adoption that integrates technological, lifestyle, and contextual variables for providing a holistic theoretical understanding of the adoption processes as well as practical insights regarding the target population—i.e., vis-à-vis a proposed Cloud Lifestyle—that is most likely to adopt cloud technologies.

Keywords: cloud, adoption, lifestyle, social influence, knowledge, cluster analysis

1. Introduction

Significant advances in Information and Communication Technologies (ICTs), in general, and the rise of social network sites (SNS) and other Web 2.0 applications, in particular, have given rise to a growing popularity of cloud computing. Through the use of virtualization technologies, cloud computing promises to eliminate the need for maintaining expensive computing hardware and instead offers to serve a larger, more diverse user base using a single shared set of physical resources. Despite its potential advantages of easy data manageability, reliable data recovery, device and location independence, flexibility, as well as potential collaboration support, cloud computing is concurrently associated with significant privacy and security risks. Hence, as a novel technology that is characterized by significant advantages and substantial uncertainty simultaneously, it is important to analyze the adoption and usage of this new medium, not only by referencing characteristics of the technology, but also by considering various user characteristics, including demographic segments, lifestyles, and relevant knowledge that are likely to influence consumer perceptions of the benefits and risks associated with cloud computing.

Three popular models for analyzing and predicting use intention to adopt new technologies include the Technology Acceptance Model or TAM [1], the Diffusion of Innovation theory or DIT [2], and the Expectancy Confirmation Theory or ECT [3-5]. Although all three frameworks have provided many relevant insights into technology adoption and diffusion, they have been criticized repeatedly for ignoring characteristics of the user and his/her social context [6-11]. Hence, building on literature from consumer and media research [12-18], this study posits that—in addition to analyzing characteristics of the technology—understanding intentions to adopt new technologies, like cloud computing—requires us to disentangle how consumers form perceptions of these novel technologies through a variety of individual, social, and contextual factors, including demographic segments, lifestyle, social influence, and past experience with other similar technologies.

In order to analyze characteristics of the cloud computing technology, the user, and his/her social environment, this study analyzed the data from 402 non-cloud note-taking application users from a random U.S.-based national sample of 1721 respondents. First, we used partial-least square (PLS) analysis to study *what contextual factors and innovation attributes of the technology affect adoption intention*? Subsequently, we used cluster analysis for identifying various behavioral lifestyle segments so as to study *what the role is of different contexts, perceptions, and intentions in the adoption process*?

The results from the PLS analysis showed significant effects of innovation attributes on people's behavioral intention to use cloud computing and demonstrated high explanatory power ($R^2 = .53$). Additionally, by adding contextual factors that were shown to impact the innovation's attributes, this study enhanced the predictive power of Diffusion of Innovation theory as well as demonstrated the importance of understanding context for adequately predicting adoption intention. Furthermore, through an additional cluster analysis, this study revealed the existence of three lifestyle clusters—Traditionalists, Hedonic Yuppies, and Intelligent Businessmen—and showed that Hedonic Yuppies most strongly reflect a "Cloud Lifestyle", thereby revealing the importance of disentangling demographic and lifestyle variables for understanding, explaining, and predicting adoption.

2. Theoretical Background and Hypothesis Development: Innovation Adoption

As aforementioned, three popular models for analyzing and predicting user intention to adopt novel technologies include the Technology Acceptance Model or TAM [1], the Diffusion of Innovation theory or DIT [2], and the Expectancy Confirmation Theory or ECT [3-5].

The Technology Acceptance Model (TAM) is an information systems theory that posits that a user's decision to adopt and use a novel technology is affected primarily by two beliefs; *perceived usefulness* (PU)—the degree to which a person believes a technology may enhance his or her job performance—and *perceived ease of use* (PEOU), the degree to which a person believes that using a system will be free from effort [19]. By its focus on these two beliefs, TAM has often been criticized for ignoring prior experience [11], individual differences and consumer characteristics [6,11], as well as social factors, such as social influence and social image [20-25].

Although TAM has been expanded to include additional variables such as emotion [26] or self-efficacy [27], Diffusion of Innovation Theory (DIT) has an even broader scope as a result of its flexibility with respect to (a) its focal *innovation attributes*—relative advantage, compatibility, complexity, observability, and trialability—(b) its *unit of adoption*, which can be any innovation (i.e., idea, technology, service, practice, etc.), and (c), its *unit of analysis*, which can range from the individual to groups and organizations. Despite these differences and their distinct disciplinary origins, the TAM and DIT models have some noticeable resemblances. For example, 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 [28]. Yet, DIT offers a broader set of innovation variables (i.e., technology perceptions) to predict adoption intention and additionally focuses on knowledge as an important determinant of adoption.

Rather than focusing on perceptions of the technology or the innovation, Expectancy-Confirmation Theory (ECT) focuses on the confirmation or disconfirmation of pre-trial expectations as a determinant of a consumer's level of satisfaction. Although the predictive ability of ECT has been demonstrated over a wide range of products, ECT only focuses on existing products, but has largely overlooked how users' experience with existing products affect perceptions of novel products.

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, 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, social, and lifestyle factors as antecedents to user perceptions of innovation attributes, and in turn their effect on the behavioral intention to adopt the innovation. Given that the Diffusion of Innovation Theory offers the broadest range of predictors of adoption and takes into account the role of knowledge, it is best suited for this investigation. Therefore, the next paragraph will elaborate on DIT as the core theoretical foundation for this study.

Table 1. Comparing three prominent theories of technology adoption

	Technology Acceptance Model (TAM)	**Diffusion of Innovation Theory (DIT)**	**Expectancy Confirmation Theory (ECT)**
Source	Davis et al., 1989 [1]	Rogers, 2003 [2]	Oliver, 1980 [5]
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 - Trialability	- 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 - Includes knowledge as antecedent to independent variables	- 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)

2.1 Diffusion of Innovation: Perceived Technology Attributes

Diffusion of Innovations Theory (DIT) explains how an innovation or a new idea propagates in a social system over time, focusing on the knowledge, attitude change, and decision-making process that affect the adoption of an innovation. Existing literature on DIT has provided insights into a broad range of innovation attributes that affects a person's probability of adoption or rejection [29], which have been shown to explain between 49 and 87% of the variance in adoption [2]. These attributes include the relative advantage, compatibility, complexity, observability, and trialability of a technology. Hence, exploring the impact of these five attributes can significantly enhance our understanding of the diffusion process of cloud applications, as follows.

First, *relative advantage* refers to the degree to which an innovation is perceived as better than the idea it supersedes [2]. This measure is closely related to the perceived usefulness (PU) measure in TAM [19]. Existing studies have shown that relative advantage is an important predictor for adoption intention [30,31]. If no clear advantage is perceived, the individual will stick with its current and familiar technology [32,33]. Alternatively, if the user does perceive a relative advantage of the novel tool [34,35], this will provide a motivational force for adoption and may even increase adoption speed [36]. The degree of relative advantage is often described by economic profitability, low initial cost, social prestige, time and effort, satisfaction, that is, decreasing uneasiness or discomfort, as well as immediacy of reward. The superior functionality and time-cost efficiency of cloud note-taking applications when compared to pre-install applications may positively affect their adoption.

Second, *complexity* refers to the degree to which an innovation is perceived as difficult to understand and use [2]. This measure is closely related to the perceived ease of use (PEOU) measure in TAM [19]. The greater the level of complexity—or inversely, the less intuitive its usage—the more negative the perception about the innovation, which subsequently impedes adoption. In the case of cloud note taking applications, their major attraction appears to be the medium's simple and clear user interface, which affords easy and instant use. Therefore, the simple user interface and low complexity of use may positively affect the adoption of such applications.

Third, *compatibility* refers to the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters [2]. According to Rogers [2], the more compatible an innovation is, the lower the uncertainty associated with adoption. Many studies have shown compatibility to be the strongest predictor of the behavioral intention to adopt [2,26,37-39]. Cloud note-taking applications, by being available on both a web- and a mobile-based platform enable anytime / anywhere usage. Furthermore, the use of these applications is as varied as the people who rely on it for note-taking, hence, it can be argued that cloud-based note taking is compatible with its users' existing values, beliefs, and their daily life.

Fourth, *observability* refers to the degree to which the results of an innovation are visible to others [2]. When an adopter can easily observe the result of using an innovation, this perceptual experience is positively related with the innovation's adoption through increased feelings of confidence [28,34,35,40]. Given the widespread availability and thus observability of cloud note-taking applications, positive effects on their adoption may be anticipated.

Fifth, *trialability* refers to the degree to which an innovation may be experimented on a limited basis [2], thus allowing individuals to do a "try and buy". If trialing the innovative idea, practice, or product seems to satisfy individuals' needs, the individual is more likely to adopt the technology [41], whereas unsatisfactory trial experiences may result in rejecting the novel technology. Anecdotally, it may be argued that cloud note-taking applications have high trialability, given their availability at either no or very low cost and the possession of a valid e-mail account as the sole prerequisite for initial use.

In addition to these five innovation attributes, Ostlund [42] has proposed *risk*—that is, the perceived uncertainty in a purchase situation [43]—as an additional predictor of people's behavioral intention to adopt. Risk of the emergence of new and better future products as well as security and privacy negatively affect adoption decisions [44-48]. As aforementioned, cloud computing is associated with security and privacy risks, hence, these may negatively affect adoption.

Building on the above, this study will test the following hypotheses regarding the relationships between these six innovation attributes and people's behavioral intention to adopt cloud note-taking applications.

Hypothesis 1(a-e): *Perceived attributes—i.e., relative advantage, complexity, compatibility, observability, trialability—of the new technology will be positively related to the behavioral intention to adopt the cloud applications.*

Hypothesis 1(f): *Perceived risk of the new technology will be negatively related to the behavioral intention to adopt the cloud applications.*

2.2 Contextual Factors: Past Experience, Knowledge, and Social Influence

Although theories of adoption, such as DIT and TAM have been successful in explaining technology adoption, we argue that behavioral intention for adoption is a multi-faceted construct that is influenced by more than technology-related characteristics alone. For example, previous studies have shown that contextual factors, such as the availability of other means or time pressure mediates effects of usefulness on intention to use [37]. Furthermore, research has shown that personal traits, such as personal innovativeness, can moderate the effect of technology-related characteristics on adoption intention [31]. Hence, including contextual and user-related characteristics may further extend DIT.

Drawing on Coursaris & Kim's [18] contextual usability framework, we suggest that usability and consequences of usability—including adoption—are influenced by four sets of contextual factors, namely characteristics of the User, the Environment, the Technology, and the Task/Activity. In this study, we focus on how characteristics of the User—specifically past experience and knowledge—as well as the Environment—specifically social influence—act as antecedents to perceptions of and subsequent intention to adopt cloud applications (i.e., the Technology) for note-taking (i.e., the Task/Activity) as follows.

First, *past experience*—a user-based characteristic that refers to the level of previous exposure to similar or related technologies—has been found to influence perceptions of the relative advantage [6,49], the complexity [50], the compatibility [51,52], the observability [53], the trialability [54,55] and the perceived risk [56] of novel technologies. As a result, the following hypotheses are proposed:

Hypothesis 2 (a-e): *Past experience will be positively related to the perceived attributes of the new technology (Relative advantage, complexity, compatibility, observability, and trialability).*

Hypothesis 2 (f): *Past experience will be negatively related to the perceived risk of the new technology.*

Second, *knowledge*—a user-based characteristic that refers to a person's awareness of and information about a novel technology [2]—influences people's perception of an innovation's attributes. Rogers [2] identifies three types of knowledge, namely awareness knowledge, how-to knowledge, and principles knowledge (Table 1). Given that principles knowledge is primarily relevant while using the technology and in the decision to be made on its continued use, this study – exploring factors influencing the intention to initially adopt cloud note-taking apps - focuses on awareness knowledge and how-to-knowledge. Existing studies have found evidence for the relationship between knowledge and perceived innovation attributes, including relative advantage [33,57], risk (i.e. uncertainty) [40], as well as observability and trialability [58] of a technology. Thus, the following hypotheses are proposed:

Hypothesis 3 (a-e): *Knowledge will be positively related to the perceived attributes of the new technology (Relative advantage, Complexity, compatibility, observability, and trialability risk).*

Hypothesis 3 (f): *Knowledge will be negatively related to the perceived risk of the new technology.*

Table 2. 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	Use/Continuance
Relevance to this study	Significant (in line with focus on adoption)	Significant (in line with focus on adoption)	Limited (not in line with focus on adoption)

Third, *social influence*—a characteristic of the user's environment, specifically the social pressure exerted by a reference group to perform a particular behavior [38]—has been shown to have an important effect on people's perceptions of an innovation and subsequent adoption decisions [20-22,24,59,60]. Both TAM and DIT have been expanded with the "social norms" [61-63] and "image"[28] constructs respectively to reflect the significance of social influence. Existing studies have shown the importance of using mobile services as a way to maintain membership and support increased interactions within the reference group [23,64], thereby suggesting that social influence may play a significant role in shaping perceptions regarding the innovation attributes of cloud note-taking applications. Also, it is known that social factors such as *community identity* have a positive effect on users' intention to continue using blogs [59]. As a result, the following hypotheses are proposed:

Hypothesis 4 (a-e): *Social influence will be positively related to the perceived attributes of the new technology (Relative advantage, complexity, compatibility, observability, and trialability);*

Hypothesis 4 (f): *Social influence will be negatively related to the perceived risk of the new technology.*

2.3 Research Model

The proposed structural model is shown in Figure 1.

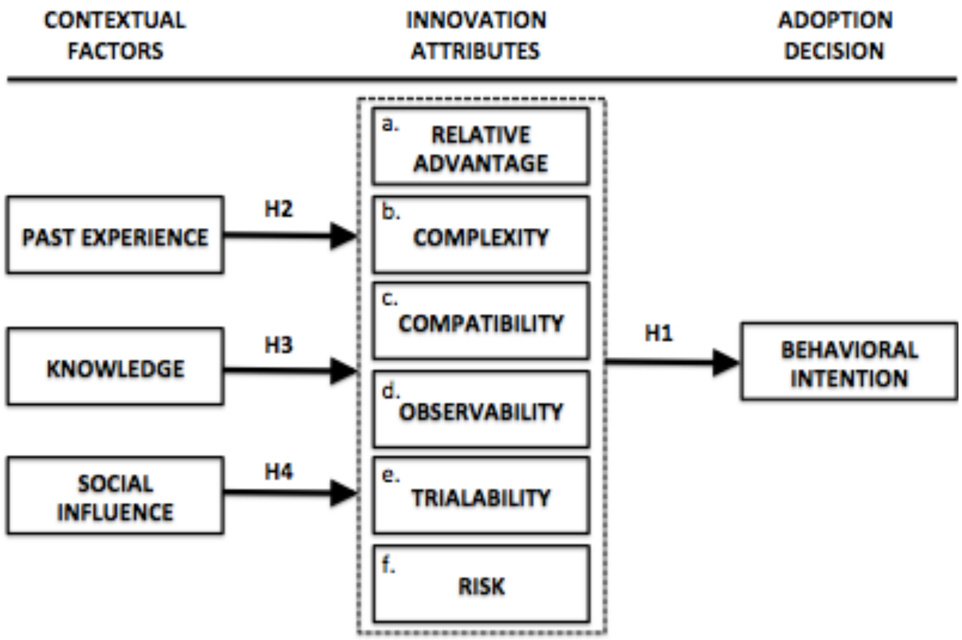


Figure 1. Proposed Research Model

2.4 Consumer Lifestyle Clusters

Based on existing marketing and consumer research, we know that consumer populations are heterogeneous; hence, analyzing only a single set of technological and contextual variables that operate throughout the population is erroneous and myopic. For instance, previous research on technology acceptance has shown that subgroups of users may display varying predictors and different degrees of variance explained by the predictors [65,66]. Therefore, in order to better understand the target population, this study uses lifestyle segmentation in order to allow for a richer and more holistic exploration of market segments than can be achieved through relying on demographic data alone. This in turn can help us explain different adoption behaviors across various societal groups [67,68].

Lifestyle reflects a person's interests, opinions, personality, and needs [69,70]. Although various definitions and models for studying lifestyle exists, this study draws on the Brand

Strategy Research (BSR) model [71-73], since it offers the most holistic multi-dimension operationalization of lifestyle and since it is particularly useful for creating motivation clusters in the light of technology adoption [74]. BSR focuses on five constructs that jointly explain consumer lifestyle, namely character, type of household, professional information, hobbies and interests, and values.

Based on the BSR model, the current study will employ lifestyle segmentation to distinguish between multiple consumer groups based on lifestyle dimensions in addition to demographic, technological, and contextual variables, for providing a more holistic explanation and richer understanding of the adoption process associated with cloud note-taking applications.

3. Research Methodology

3.1 Study Context

In this study, we focus on one type of cloud applications, namely cloud note-taking apps. We define cloud note-taking applications as document editing applications that can be used on a webpage and mobile device and which supports automated sync and updates, a variety of storage options, and sharing (i.e. collaborative) functions. Examples of cloud note-taking applications include Evernote, Springpad, One Note, Simple Note, Google Docs, Google Drive, Catch Note, and Awesome Note.

Cloud note-taking applications thus offer all of the advantages of Cloud Computing, such as custom configuration and automatic sync features, device and location independence, accelerated feature delivery (automatic updates), and collaborative functionality (share function).

Cloud note-taking applications offer superior functionality when compared to pre-install or default notepad or mobile note-taking applications, while preserving the same basic features of note-taking. Adoption decisions of these cloud note-taking applications will therefore likely be impacted by a comparison to pre-install applications as well as familiarity with other cloud services, such as web-based email and SNS.

3.2 Sampling and Research Subjects

A random sample of 1721 respondents, who are aged 18 and older and reside in the U.S. was recruited through Survey Sampling International LLC, "the world's leading provider of sampling solutions for survey research." From the total of 1721 respondents, only 402 respondents, who had not yet used any cloud note-taking applications, were selected in order to study their motivations underlying potential future adoption. The remaining 1319 respondents were disqualified because they were either not active note-takers using traditional media (76%), had prior experience with cloud note-taking applications (19%), or due to missing data (5%). The 402 respondents far exceeded the needed 50 cases for PLS analysis (i.e. ten times the number of items (5) of the most complex construct; [80]).

The 402 respondents encompassed 229 females (57.0%) and 173 males (43.0%). The average age of respondents was 40, ranging from 18 to 79 (*SD*=14.7). The majority of respondents were Caucasian/White (80.8%), followed by African American (9%) and 10.2% fell under the remaining five categories. The majority of participants had some form of college education (79.1%), with the remaining number reporting a high school degree.

In addition to the basic demographic information, data on participants' note-taking practices, as well as prior experience and knowledge of cloud services and was collected. Participants reported a monthly average of 12 notes for professional purposes and 9 notes for personal purposes. The majority reported no experience with cloud services (69.4%), yet, more than half the respondents (56.7%) reported using some form of cloud service, mostly Google calendar, Dropbox, and/or iCloud.

In order to determine respondents' awareness and how-to knowledge of cloud services, the survey encompassed a set of three multiple-choice questions per knowledge category (total of 6 questions for both categories), which will be further discussed below. Low scores (0 or 1 correct answer per category) were obtained by the majority of respondents (65.4% and 69.9% for awareness and how-to knowledge respectively).

3.3 Survey and Instrument Validation

All the scales in the questionnaire, except for the scale for knowledge, were adapted from existing studies. Furthermore, all scales, except for the scale for knowledge, were measured along a five-point Likert scale ranging from "strongly disagree" to "strongly agree".

Knowledge was measured by familiarity with cloud note-taking applications (awareness knowledge) and understanding of the proper usage of the technology (how-to knowledge). In accordance with past studies measuring knowledge regarding novel technologies, this study developed multiple-choice questions containing terminology and examples of cloud note-taking applications for measuring awareness knowledge and multiple-choice questions regarding features and installation for measuring how-to knowledge. All scales and sources are reported in Appendix 1.

The factor loadings for the items used in this study are summarized in Appendix 2. All items had significant factor loadings greater than 0.5 to ensure construct validity [81-83].

The relative advantage, complexity, compatibility, observability, trialability, risk, social influence, and behavioral intention constructs were examined for reliability, as shown in Table 3 below. The results of the reliability analysis showed that all constructs had adequate Cronbach's α above the 0.80 threshold [82], and convergent validity (i.e. AVE) above the 0.5 benchmark [84].

Table 3. 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
COMPAT	3.60 (0.83)	0.767740	0.929643	0.898895
COMPLEX	2.36(0.72)	0.692902	0.900080	0.851548
OBSERV	2.59(0.98)	0.756545	0.903023	0.838409
RISK	2.81(0.83)	0.743204	0.935310	0.913450
ADV	3.54(0.82)	0.752698	0.923789	0.888852
SOCIAL	2.99(0.73)	0.649479	0.902328	0.865981
TRIAL	3.27(0.76)	0.748835	0.899335	0.832154

Furthermore, as shown in Table 4, discriminant validity was supported by confirming that the square root of the variance shared between a construct and its items was greater than the correlations between the construct and any other construct in the model [84].

Table 4. Correlation Matrix and Discriminant Validity Assessment

	BI	COMPAT	COMPLEX	OBSERV	RISK	ADV	SOCIAL	TRIAL
BI	**0.852**							
COMPAT	0.642	**0.876**						
COMPLEX	0.518	0.739	**0.832**					
OBSERV	0.418	0.353	0.422	**0.870**				
RISK	-0.295	-0.275	-0.248	0.095	**0.862**			
ADV	0.605	0.762	0.635	0.313	-0.260	**0.868**		
SOCIAL	0.576	0.518	0.445	0.571	-0.043	0.422	**0.806**	
TRIAL	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).

3.4 Analysis and Procedures

Survey data were analyzed using the Partial Least Squares (PLS) method with SmartPLS to test for both the validity of the structural model (shown earlier in Figure 1) and the measurement model.

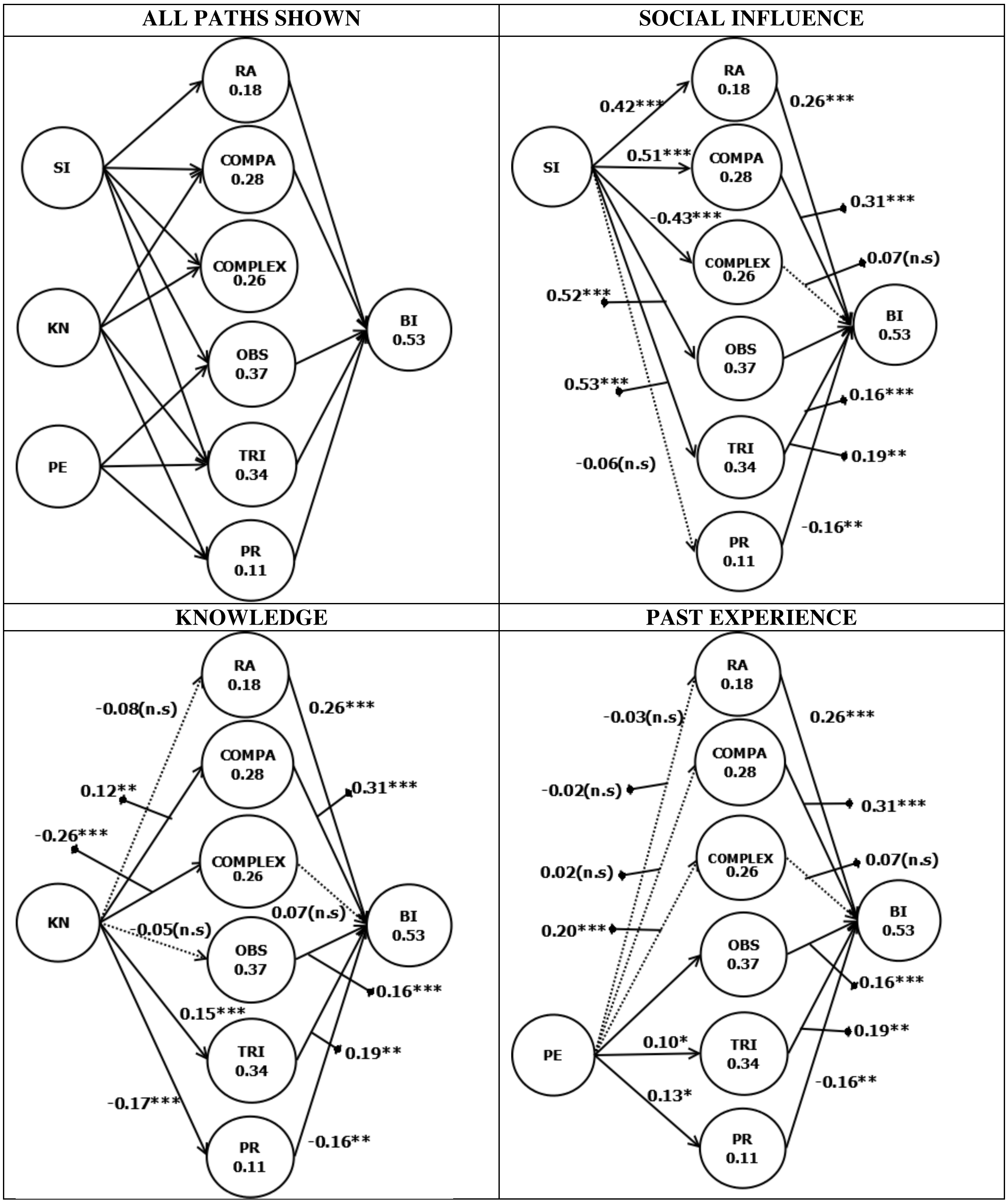
For the comparison of the various consumer lifestyle clusters, this study used TwoStep Cluster in SPSS20.0, which has been suggested as the appropriate method for clustering large data sets with mixed attributes [85]. This approach is based on a probabilistic model in which the distance between two clusters is equivalent to the decrease in log-likelihood function as a result of merging [86]. During the analysis, the original cases are first grouped into preclusters, which are then used for hierarchical clustering. Second, the preclusters are grouped using the standard agglomerative clustering algorithm, producing a range of solutions, which are then reduced to the best number of clusters on the basis of Akaike's information criterion (AIC) [87]. These emergent clusters were then analyzed and compared for determining the different adoption behaviors across the lifestyle clusters.

Results of both the PLS and Cluster analyses are discussed in the next section.

4. Results

4.1 Path Model

Using the survey data, the proposed structural model (Figure 2) was tested in Smart PLS 2.0 using Bootstrapping to evaluate the hypothesized relationships between (1) contextual factors and innovation attributes, as well as between (2) innovation attributes and the behavioral intention to adopt a cloud note-taking application [80].



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

Figure 2. Structural Model Results

A summary of the hypothesis testing results, as well as a more detailed evaluation is provided in Table 5.

Table 5. Hypotheses Validation

Hyp.	Path	Beta	T-Value	Sig.	Hyp. Status
H1	ADV -> BI	0.26	4.37	***	Supported
	COMPLEX -> BI	0.07	0.94	n.s	n.s
	COMPAT -> BI	0.31	4.66	***	Supported
	OBSERV -> BI	0.16	3.43	***	Supported
	TRIAL-> BI	0.19	2.93	**	Supported
	RISK -> BI	-0.16	2.87	**	Supported
H2	EXP -> ADV	-0.03	0.64	n.s	n.s
	EXP -> COMPLEX	-0.20	0.46	n.s	n.s
	EXP -> COMPAT	-0.02	0.51	n.s	n.s
	EXP -> OBSERV	0.20	4.08	***	Supported
	EXP -> TRIAL	0.09	2.07	*	Supported
	EXP -> RISK	0.13	2.05	*	n.s
H3	KNOW -> ADV	0.08	1.70	n.s	n.s
	KNOW -> COMPLEX	-0.26	5.83	***	Supported
	KNOW -> COMPAT	0.12	2.64	**	Supported
	KN0W -> OBSERV	0.05	1.10	n.s	n.s
	KN0W -> TRIAL	0.14	3.14	***	Supported
	KN0W -> RISK	-0.17	3.22	***	Supported
H4	SOCIAL -> ADV	0.42	8.55	***	Supported
	SOCIAL -> COMPLEX	-0.43	8.39	***	Supported
	SOCIAL -> COMPAT	0.51	12.36	***	Supported
	SOCIAL -> OBSERV	0.52	12.51	***	Supported
	SOCIAL -> TRIAL	0.53	12.06	***	Supported
	SOCIAL -> RISK	-0.06	0.72	n.s	n.s

*p < 0.05, **p < 0.01, ***p < 0.001

With respect to the relationship between the innovation attributes — relative advantage, compatibility, complexity, observability, trialability, and perceived risk — and behavioral intention to adopt, we found that all innovation attributes have a significant effect on adoption intentions, except for complexity. More specifically, we found that 1) the higher the level of relative advantage (ADV) [H1a: $\beta = 0.26, p < 0.001$]; 2) compatibility (COMPAT) [H1c: $\beta = 0.31, p < 0.001$]; 3) observability (OBSERV) [H1d: $\beta = 0.16, p < 0.001$]; and 4) trialability (TRIAL) [H1e: $\beta = 0.19, p < 0.01$] perceived from the cloud note-taking app, the higher the intention to use it. Also, the lower the risk associated with the use of cloud note-taking applications (RISK) people perceived, the higher the intention to use it (H1f: $\beta = - 0.16, p < 0.01$). Lastly, it was shown that complexity (COMPLEX) did not significantly affect behavioral intention (BI), hence H1b was not supported.

Furthermore, we analyzed the relationships between the contextual factors—*past experience, knowledge, and social influence*—and the innovation attributes—*relative advantage, compatibility, complexity, observability, trialability, and perceived risk* (Hypotheses 2 through 4). With respect to the first contextual variable, past experience (Hypothesis 2), it was found to have a significant effect on three of the six innovation attributes; specifically, the greater the past experience (EXP) people have with the cloud, 1) the higher the observability (OBSERV) [H2d: $\beta = 0.20, p < 0.001$]; 2) trialability (TRIAL) [H2e: $\beta = 0.09, p < 0.05$]; and 3) risk (RISK) people perceived [H2f: $\beta = 0.13, p < 0.05$] to be associated with cloud note-taking apps. On the other hand, past experience (EXP) did not have a significant effect on the relative advantage (ADV), complexity (COMPLEX) and compatibility (COMPAT) of cloud note-taking applications..

The second contextual variable, knowledge (Hypothesis 3), was found to significantly predict four out of the six innovation attributes. The results showed that the more awareness and how-to knowledge people have (KNOW), the higher the compatibility (COMPAT) [H3c: $\beta = 0.12, p < 0.01$] and trialability (TRIAL) people perceived [H3e: $\beta = 0.14, p < 0.001$] to be associated with cloud note-taking apps. Also, it was shown that the less knowledge people have, the higher the risk (RISK) [H3f: $\beta = -0.17$, $p < 0.001$] and complexity (COMPLEX) people perceived [H3b: $\beta = -0.26$, $p < 0.001$].

Finally, with respect to the third antecedent, i.e. social influence (Hypothesis 4), we found that it is significantly related to all of the innovation attributes, except for risk. Thus, the greater the level of perceived social influence of the reference group, 1) the higher the level of relative advantage (ADV) [H4a: $\beta = 0.26$, $p < 0.001$]; 2) compatibility (COMPAT) [H4c: $\beta = 0.31$, $p < 0.001$]; 3) observability (OBSERV) [H4d: $\beta = 0.16$, $p < 0.001$]; and 4) trialability (TRIAL) [H4e: $\beta = 0.19$, $p < 0.01$] people perceived from cloud note-taking applications. Also, the lower the level of perceived social influence of the reference group, the higher the level of complexity people perceived [H4b: $\beta = -0.43$, $p < 0.001$]. However, perceived risk (RISK) was not found to be significantly influenced by social influence (SOCIAL), hence, H4f was not supported.

In addition to the PLS analysis, we used Hierarchical (Stepwise Linear) Regression in SPSS20.0 for R^2 partitioning in order to reveal the amount of unique variance attributed to each predictor (Table 6). Hierarchical regression was conducted for all of the significant endogenous variables[1] in the model, namely five of the six innovation attributes—compatibility, complexity, observability, trialability, and risk—as well as the behavioral intention to adopt a cloud note-taking app..

Hereto, we used two analytical hierarchical regression approaches after importing the latent variable loadings from the PLS output in order to ensure model consistency.

In the first approach, the *empirical* approach, the determinants were added to the model in the order of the statistical significance of the predictor as specified by the results from the PLS analysis. As a result, this model attributes the (majority of the) covariance between determinants

[1]An endogenous variable is a factor in a causal model whose value is determined by the states of other (independent) variables in the model (http://bit.ly/AyU6Gf).

to the first (i.e. the most significant) variable entered in the model. The R^2 change for all steps in the model was significant ($p < 0.001$), except for the final step (past experience) in the model for trialability.

Table 6. Results of Stepwise Linear Regression for R^2 Partitioning

DV: Compatibility	**Empirical**	**Conservative**	**Average**
Social Influence	0.223***	0.216***	**0.220*****
Knowledge	0.010*	0.010*	0.010*
DV: Complexity			
Social Influence	0.166***	0.153***	**0.160*****
Knowledge	0.057***	0.057***	0.057***
DV: Observability			
Social Influence	0.280***	0.222***	**0.251*****
Past Experience	0.044***	0.044***	0.044***
DV: Trialability			
Social Influence	0.251***	0.217***	**0.234*** **
Knowledge	0.011*	0.006(n.s)	0.009(n.s)
Past Experience	0.006(n.s)	0.006(n.s)	0.006(n.s)
DV: Risk			
Knowledge	0.011*	0.018**	**0.015*****
Past Experience	0.015*	0.008(n.s)	0.012*
DV: Behavioral Intention			
Compatibility	0.380***	0.036***	**0.208*****
Relative Advantage	0.034***	0.023***	0.029***
Trialability	0.043***	0.015**	0.029***
Observability	0.011**	0.016**	0.014**
Risk	0.012**	0.012**	0.012**

*p < 0.05; **p < 0.01; ***p < 0.001

In the second approach, the *conservative* approach, multiple iterations of the Stepwise Linear Regression were ran, in order to ensure that each of the determinants would be entered into the model last at least once, in order to obtain only the unique contribution of that predictor. This approach provides the most conservative estimate, since by focusing on the final step, we merely assess the unique contribution of each determinant and disregard any covariance among determinants. Comparison between the two approaches as well as an average across the two approaches is provided in Table 6.

Following the results from Table 6, we can conclude that most innovation attributes—namely compatibility, complexity, observability, and trialability—are influenced more by social influence than other contextual factors. Risk, on the other hand, is primarily influenced by knowledge. Furthermore, we found that the behavioral intention to adopt cloud note-taking applications is primarily influenced by compatibility, i.e., by the degree to which the innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters [2].

In addition to the path analysis and hierarchical regression analysis, we conducted a t-test to study the differences of perceptions and contexts between future adopters and non-adopters. The results from the t-test showed that future adopters perceived significantly lower complexity and risk than non-adopters, while displaying significantly higher relative advantage, compatibility, observability, and trialability (see Table 7) below.

Table 7. Differences in Perceptions and Contextual Factors between Future Adopters and Non-Adopters

	Adopters (N=185)		Non-Adopters (N= 48)		Significance	
	Mean	SD	Mean	SD	T-value	P-value
Perceptions of Innovation Attributes						
Relative Advantage	3.97	.70	2.60	0.83	-11.54	.000
Complexity	2.03	.62	3.01	0.90	8.78	.000
Compatibility	4.06	.61	2.57	0.94	-13.34	.000
Observability	2.93	1.02	2.01	0.85	-5.72	.000
Trialability	3.61	.70	2.74	0.88	-7.33	.000
Risk	2.63	.95	3.28	0.75	4.40	.000
Contextual Factors						
Social Influence	3.34	.69	2.28	0.68	-9.58	.000
Knowledge (Awareness)	1.22	.95	0.88	1.02	-2.19	.030
Knowledge (How-to)	1.15	1.10	0.50	0.90	-3.75	.000
Past Experience (Number)	0.63	1.01	0.33	0.79	-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.

Following the t-test results, we conducted a second PLS analysis to investigate the proposed structural model for the two groups separately to reveal any significant differences in adoption behaviors between the two groups (see Table 8). As the results show, future adopters' behavioral intention was significantly predicted by three innovation attributes—namely observability, trialability, and perceived risk— while non-adopters' behavioral intention was not significantly affected by any of the innovation attributes.

Table 8. Results of Path Analysis Between Future Adopters and Non-Adopters

Hyp		Path	Group	Beta	T-Value	Sig.	Status
H1	a	ADV -> 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	COMPAT -> BI	Adopter	0.12	1.15	n.s.	n.s.
			Non-Adopter	-0.07	0.22	n.s.	n.s.
	d	**OBSERV -> BI**	Adopter	0.40	4.18	***	Supported
			Non-Adopter	-0.03	0.10	n.s.	n.s.
	e	**TRIAL -> BI**	Adopter	0.21	2.21	*	Supported
			Non-Adopter	0.14	0.73	n.s.	n.s.
	f	**RISK -> BI**	Adopter	-0.25	2.49	*	Supported
			Non-Adopter	-0.21	1.40	n.s.	n.s.
H2	a	**SOCIAL -> ADV**	Adopter	0.22	2.50	*	Supported
			Non-Adopter	0.16	1.00	n.s.	n.s.
	b	SOCIAL -> COMPLEX	Adopter	-0.33	4.48	***	Supported
			Non-Adopter	-0.55	5.45	***	Supported
	c	SOCIAL -> COMPAT	Adopter	0.25	2.85	**	Supported
			Non-Adopter	0.47	3.31	**	Supported
	d	**SOCIAL -> OBS**	Adopter	0.58	8.94	***	Supported
			Non-Adopter	0.22	2.00	n.s.	n.s.
	e	**SOCIAL -> TRIAL**	Adopter	0.51	7.89	***	Supported
			Non-Adopter	0.50	4.54	***	Supported
	f	**SOCIAL -> RISK**	Adopter	0.19	2.00	*	n.s.
			Non-Adopter	0.01	0.06	n.s.	n.s.
H3	a	EXP -> ADV	Adopter	-0.07	0.68	n.s.	n.s.
			Non-Adopter	0.15	0.70	n.s.	n.s.
	b	EXP -> COMPLEX	Adopter	0.02	0.17	n.s.	n.s.
			Non-Adopter	-0.09	0.73	n.s.	n.s.
	c	EXP -> COMPAT	Adopter	0.01	0.05	n.s.	n.s.
			Non-Adopter	0.04	0.24	n.s.	n.s.
	d	EXP -> OBSERV	Adopter	0.21	1.76	n.s.	n.s.
			Non-Adopter	0.26	1.12	n.s.	n.s.
	e	EXP -> TRIAL	Adopter	0.06	0.72	n.s.	n.s.

			Non-Adopter	0.26	1.84	n.s.	n.s.
	f	EXP -> RISK	Adopter	0.18	1.55	n.s.	n.s.
			Non-Adopter	-0.12	0.38	n.s.	n.s.
H4	a	KNOW -> ADV	Adopter	-0.01	0.09	n.s.	n.s.
			Non-Adopter	-0.07	0.22	n.s.	n.s.
	b	**KNOW -> COMPLEX**	Adopter	-0.12	1.04	n.s.	n.s.
			Non-Adopter	-0.04	3.36	*	Supported
	c	KNOW -> COMPAT	Adopter	0.02	0.22	n.s.	n.s.
			Non-Adopter	0.10	0.64	n.s.	n.s.
	d	KNOW -> OBSERV	Adopter	0.05	0.73	n.s.	n.s.
			Non-Adopter	0.25	1.11	n.s.	n.s.
	e	**KNOW -> TRIAL**	Adopter	0.19	2.17	*	Supported
			Non-Adopter	0.24	1.59	n.s.	n.s.
	f	KNOW -> RISK	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

4.2 Cluster Analysis

The auto-clustering algorithm—as explained in section 3.4—indicated that a three-cluster solution was the most appropriate model, as confirmed by the lowest AIC value. The resulting clusters contained 114 (28.4%), 159 (39.7%), and 128 (31.9%) cases respectively. It is important to note that these clusters emerged a posteriori (i.e., from the data), rather than a priori (i.e., imposed by theory).

In order to establish the lifestyle profiles, we looked at four demographic variables—gender, age, education, occupation—, device ownership, and lifestyle variables i.e. character, professional information, household type, hobbies and interests, and values.

With respect to the demographic variables, we found that cluster 2 consisted primarily of females (98.1%), whereas cluster 3 consisted primarily of males (99.2%), with cluster 1 displaying gender balance (50.8% males; 49.2% females). The majority of respondents across all three clusters reported some form of college degree, although cluster 1 had the largest number of participants (32.5%) who reported high school education as their highest degree.

Post-hoc tests for age and device ownership showed that there were significant differences for age between clusters 1 and 2 (Mean Difference = 8.865, $p < 0.000$) and clusters 2 and 3 (Mean Difference =-6.605, $p < 0.000$), but not between clusters 1 and 3 (Mean Difference = 2.260, $p = 0.435$). No significant differences were found between the three clusters with respect to device ownership.

With respect to the lifestyle variables, we found that the three groups reported different characters. Whereas cluster 1 reported to be honest (13.2%), down-to-earth (13.2%), or shy (9.6%), cluster 3 reported intelligent (11.7%), balanced (8.6%), and strong character (6.3%). Cluster 2 displayed some characteristics that were in accordance with clusters 1 and 3, namely easy going (14.5%), down-to-earth (11.9%), honest (6.9%), and intelligent (6.9%).

For professional information, clusters 2 and 3 reported more specialized jobs than cluster 1, such as business man/woman (13.8%), public servant (6.9%), or manager (5%)—found in cluster 2—and business man/woman (14.1%), scientist (7.8%), manager (6.3%) or entrepreneur (5.5%)—found in cluster 3. Cluster 1 consisted largely of people with unpaid work, such as no job (14%), housewife or husband (10.5% and 7.9% respectively), or volunteer (6.1%).

Regarding hobbies, we found that cluster 1—in line with their professional identity—preferred being at home quietly (19.3%), watching TV (15.8%), doing odd jobs around the house (10.5%), or surfing the internet (7.9%). Cluster 2 and 3 preferred more active and social activities, such as social evening with friends (17% and 10.2% respectively). Cluster 2 also preferred enacting their dreams and shopping, whereas cluster 3 reported camping, active sports and surfing the Internet as important hobbies.

The three clusters displayed noticeable differences with respect to values and household types. Cluster 1 reported respect (18.4%) as the highest value; enjoyable life (20.8%) was highest in cluster 2, and privacy (17.2%) in cluster 3. Cluster 1 was dominated by cozy old-fashioned family life (28.9%); happy family (25.8%) was the most common household type for cluster 2; and bachelor as well as happy family (12.5% and 15.6%) were common for cluster 3.

Based on these self-reported demographic and lifestyle variables, we labeled the clusters in line with common terminology from existing lifestyle research [71,72] as follows. Respondents in cluster 1 are best characterized as "*Traditionalists,*" given the dominance of housewife-husband, middle-aged, high-school educated people, with a laid-back attitude, conservative values, and old-fashioned household types. Respondents in cluster 2, which consisted predominantly of females, are best described as "Hedonic Yuppies" given their focus on social and entertaining activities, their easy-going nature, and their self-reported happy family life. They consider themselves to be intelligent and trendsetters. Finally, respondents in cluster 3, which consisted predominantly of males, are best characterized as "Intelligent businessmen", given their higher-educated, independent, ambitious, and control-oriented nature. Table 9 contains more detailed frequency distributions for the lifestyle variables within clusters.

Table 9. Within Lifestyle Clusters Information

Label/Cluster	Traditionalists (1)	Hedonic Yuppies (2)	Intelligent Businessmen (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%)
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%)

Following the cluster analysis, we conducted a third PLS analysis based on our initial structural model to investigate the proposed structural model for the three clusters separately in order to reveal potential differences between the three lifestyles. Before doing so, we first confirmed that significant differences existed between the three clusters with respect to relative advantage, complexity, compatibility, trialability and behavioral intention to adopt cloud note-taking applications through ANOVA. In general, we found that hedonistic yuppies (cluster 2) or Intelligent Businessmen (cluster 3) perceived stronger (or higher) innovation attributes (e.g., relative advantage, compatibility, observability, trialability, and risk). Also, the behavioral intention of hedonistic yuppies (cluster 2) [*M*= 3.52, *SD*= 0.87] was found to be significantly higher than Traditionalists (cluster 1) [*M*= 3.22, *SD*= 0.84], and Intelligent Businessmen (cluster 3) [*M*= 3.44, *SD*= 0.73]. Following the ANOVA, the PLS analysis (Table 10) enabled us to further disentangle the differences between the three clusters by showing those variables for which we found significant differences, namely for nine paths.

Table 10. Results of Path Analysis Among Clusters

Hyp.		Path	Cluster	Beta	T-Value	Sig.	Hyp. Status
H1	a	ADV -> 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	COMPAT -> BI	1	0.27	2.12	*	Supported
			2	0.25	2.20	*	Supported
			3	0.41	3.27	**	Supported
	d	OBSERV -> 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	TRIAL -> 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	RISK -> BI	1	-0.24	2.52	*	Supported
			2	-0.13	2.20	*	Supported
			3	-0.09	1.29	n.s.	n.s.
H2	a	EXP -> 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	EXP -> 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	EXP -> COMPAT	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	EXP -> OBSERV	1	0.34	2.58	*	Supported
			2	0.06	0.65	n.s	n.s.
			3	0.23	3.19	**	Supported
	e	EXP -> TRIAL	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	EXP -> RISK	1	0.00	0.03	n.s.	n.s.
			2	0.00	0.00	n.s.	n.s.
			3	0.30	3.00	**	Supported
H3	a	KNOW -> ADV	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	KNOW -> 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	KNOW -> COMPAT	1	0.10	1.54	**	Supported
			2	0.11	1.44	***	Supported
			3	0.11	1.16	**	Supported
	d	KNOW -> OBSERV	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	KNOW -> TRIAL	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	KNOW -> RISK	1	-0.20	2.41	*	Supported
			2	0.03	0.25	n.s.	n.s.
			3	-0.32	3.30	***	Supported
H4	a	SOCIAL -> ADV	1	0.41	5.91	***	Supported
			2	0.45	5.18	***	Supported
			3	0.42	4.80	***	Supported
	b	SOCIAL -> COMPLEX	1	-0.42	6.04	***	Supported
			2	-0.47	5.73	***	Supported
			3	-0.38	2.98	***	Supported
	c	SOCIAL -> COMPAT	1	0.55	8.34	***	Supported
			2	0.50	6.97	***	Supported
			3	0.53	7.22	**	Supported
	d	SOCIAL -> OBSERV	1	0.36	4.80	***	Supported
			2	0.59	9.80	***	Supported
			3	0.53	7.97	***	Supported
	e	SOCIAL -> TRIAL	1	0.44	5.10	***	Supported
			2	0.56	7.25	***	Supported
			3	0.55	7.43	***	Supported
	f	SOCIAL -> RISK	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.

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

With respect to the relations between the innovation attributes and behavioral intention, we found significant differences for observability and trialability. Whereas observability and trialability did significantly affect Hedonic Yuppies' behavioral intention, it did not affect Traditionalists and Intelligent Businessmen. Furthermore, perceived risk did significantly affect the behavioral intention of Hedonic Yuppies and Traditionalists, but not for Intelligent Businessmen.

Regarding the effect of contextual factors on innovation attributes, we found some significant differences for past experience and knowledge. Past experience with similar services (EXP) was found to have no impact on trialability (TRIAL) for Hedonic Yuppies and Intelligent Businessmen; on observability (OBSERV) for Hedonic Yuppies; and perceived risk for Traditionalists and Hedonic Yuppies. Knowledge did not impact perceived risk for Hedonic Yuppies; and trialability (TRIAL) or observability (OBSERV) for Traditionalists and Intelligent Businessmen. Thus the combined results of the cluster analysis and the path analysis of the three lifestyle groups reveals key differences in their respective process of adopting cloud note-taking applications.

5. Discussion

In this study we explain the formation of the behavioral intention to adopt a cloud note-taking application through a holistic examination of technological (innovation), user-specific, social/contextual, and lifestyle attributes by combining results from a PLS, hierarchical regression, and lifestyle cluster analysis in order to understand both *what contextual factors and innovation attributes of the technology affect adoption intention* as well as *what the role is of different contexts, perceptions, and intentions in the adoption process*.

Our first set of findings from the path analysis pertains to the innovation attributes—derived from DIT [2]—namely relative advantage, compatibility, observability, and trialability. It was confirmed that innovation attributes have a significant impact on people's behavioral intention to use cloud note-taking applications. These findings are consistent with previous studies [2,36,88]. In contrast, we found no significant relationship between the complexity of the innovation and adoption intention, which is in line with previous studies (e.g. [89]) and potentially due to the technology's immature state.

In line with previous research [44,46,47], we found a significant effect of risk on the behavioral intention to adopt cloud note-taking applications. In the context of cloud computing this is no surprise, given the extensive criticism over its lack of security and privacy [90,91].

Based on the results from the hierarchical regression analysis for R^2 partitioning, we can conclude that risk, relative advantage, and compatibility had the highest predictive power in relation to behavioral intention among the innovation attributes. This is consistent with existing research that had emphasized the strong predictive power of relative advantage and compatibility [92,93]. Thus consumers' appreciation for cloud services is primarily based on its relative benefits and its compatibility with existing values and needs.

Our second set of findings pertains to three contextual factors that influence the abovementioned innovation attributes, namely social influence, past experience with, and knowledge of cloud services. We found that social influence is the strongest factor for all innovation attributes—relative advantage, compatibility, complexity, observability, and trialability—except for risk. This illustrates that people's perceptions of innovations are strongly influenced by the people around them who they consider important.

Risk, on the other hand, was primarily affected by the level of knowledge and past experience. Interestingly, whereas higher knowledge levels decrease perceived risk, more past experience increases perceived risk. This seems to illustrate that whereas increasing knowledge levels result in confidence about the ability to mitigate risks, past experience—perhaps through bad experiences—increases concerns of possible risks.

The third set of findings pertains to the difference between future adopters and non-adopters. Whereas adopters were significantly influenced by observability, trialability and risk; non-adopters were not affected by any of the investigated innovation attributes. Also, future adopters perceived significantly higher observability and trialability and lower risk of innovation than non-adopters. Social influence and knowledge were found to be significant contextual antecedents of these three innovation attributes (see Figure 3).

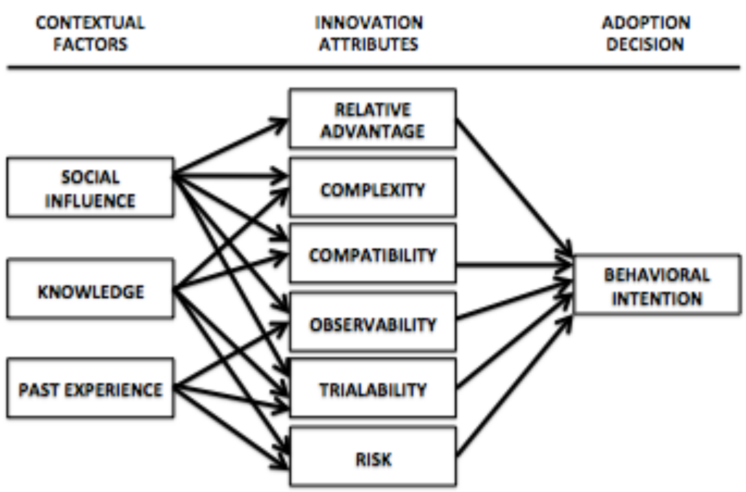


Figure 3. Validated Model

The final set of findings pertain to the three different lifestyle clusters that emerged from our data, Traditionalists (cluster 1), Hedonic Yuppies (cluster 2), and Intelligent Businessmen (cluster 3). Our findings from the path analysis of differences between the three clusters revealed that Intelligent Businessmen only care about the *compatibility* and *relative advantage* of the innovation, which were significant for people from all three clusters. In other words, the sole antecedents of their intention were the values and features of the cloud technology and the alignment hereof with their individual needs.

In addition to *compatibility* and *relative advantage*, Traditionalists' were also affected by perceived *risk*, which is in line with their lifestyle and preference for maintaining a stable position and uncertainty avoidance. The adoption intention of Hedonic Yuppies was affected by *observability*, *trialability*, and *risk*, in addition to the common predictors of *compatibility* and *relative advantage*. Since Hedonic Yuppies are trendsetters and highly sociable people, they value other people's usage behaviors and risk perceptions, traits that further support the finding regarding *observability*.

Finally, *social influence* was found to be the strongest predictor of perceptions associated with the innovation's attributes across the three clusters. Furthermore, whereas *past experience* was important for Intelligent Businessmen and Traditionalists, Hedonic Yuppies were influenced more by *knowledge* about the innovation.

Based on the above findings, this study provides some important contributions for both theory and practice. With respect to theory, not only did this study validate the significance of understanding attributes of the technology (i.e., the innovation) for predicting adoption, it also revealed the importance of developing more holistic models of adoption that additionally account for user-specific, social/contextual, and lifestyle variables.

Based on the findings that users' adoption intention is primarily affected by anticipated benefits (i.e., relative advantage) and compatibility with existing values and needs, specific recommendations can be made for practice. Whereas marketing managers should emphasize these dimensions of cloud services in their advertisements, designers of cloud applications should take these innovation attributes into account when formulating design features.

Furthermore given the importance of social influence for people's cloud technology perception, marketing managers can further leverage the power of social media marketing to enhance the popularity of cloud services and designers can emphasize the strong social and collaborative features that cloud services provide. Finally, based on the findings from our cluster analysis, we can argue that Hedonic Yuppies have the highest intention to adopt, hence, are the optimal market to target for cloud applications and thus best reflect a "*Cloud Lifestyle*". Hedonic Yuppies are trendsetters and highly sociable, hence, the new media industry can influence and enhance their perceptions by emphasizing the social features and services that are facilitated through the use of cloud applications.

Although this study has aimed to provide a holistic model and understanding of the adoption of cloud services, several challenges and open questions remain, such as: analyzing differences in behavioral intention among various types of adopters (e.g., early vs. late adopters; [2]); providing a longitudinal perspective of adoption rates and behaviors across adopter types and lifestyle clusters over time; collecting behavioral [94] rather than self-reported data; investigating other types or a broader range of cloud services beyond note-taking applications; as well as exploring additional contextual variables or lifestyle parameters in order to obtain an even more comprehensive understanding of technology perception.

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Appendices

Appendix 1. Survey Scales and 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.
Trialability (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
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

	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
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

Appendix 2. CFA Loadings Matrix (Item statistics)

	BI	COMPAT	COMPLEX	KNOW	OBSERV	EXP	RISK	ADV	SOCIAL	TRIAL
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
COMPAT1	0.597	**0.862**	0.694	0.175	0.282	0.085	-0.248	0.689	0.435	0.390
COMPAT2	0.544	**0.846**	0.604	0.077	0.297	0.109	-0.226	0.659	0.454	0.374
COMPAT3	0.530	**0.894**	0.636	0.133	0.337	0.105	-0.230	0.649	0.472	0.425
COMPAT4	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
KNOW_AWA	0.175	0.118	0.233	**0.807**	0.137	0.237	-0.073	0.105	0.050	0.179
KNOW_HOW	0.203	0.143	0.265	**0.897**	0.117	0.227	-0.149	0.082	0.085	0.180
OBSERV1	0.378	0.343	0.377	0.144	**0.830**	0.267	0.045	0.296	0.466	0.528
OBSERV2	0.384	0.345	0.433	0.122	**0.902**	0.286	0.039	0.309	0.515	0.523
OBSERV3	0.328	0.232	0.287	0.116	**0.876**	0.295	0.166	0.209	0.508	0.497
EXP	0.175	0.088	0.131	0.301	0.238	**0.765**	0.011	0.071	0.206	0.201
EXP_TIME	0.176	0.121	0.144	0.263	0.325	**0.999**	0.075	0.085	0.215	0.241
RISK1	-0.244	-0.232	-0.214	-0.152	0.126	0.054	**0.833**	-0.194	0.004	-0.082
RISK2	-0.236	-0.193	-0.187	-0.102	0.104	0.062	**0.837**	-0.183	-0.013	-0.088

RISK3	-0.263	-0.232	-0.211	-0.096	0.107	0.086	**0.876**	-0.250	-0.051	-0.024
RISK4	-0.277	-0.260	-0.232	-0.138	0.045	0.054	**0.901**	-0.258	-0.071	-0.117
RISK5	-0.248	-0.266	-0.221	-0.093	0.031	0.053	**0.862**	-0.232	-0.051	-0.106
ADV1	0.495	0.625	0.570	0.104	0.280	0.069	-0.251	**0.856**	0.340	0.300
ADV2	0.434	0.552	0.416	0.065	0.283	0.025	-0.138	**0.777**	0.391	0.250
ADV3	0.593	0.730	0.599	0.108	0.243	0.091	-0.265	**0.907**	0.342	0.306
ADV4	0.564	0.724	0.605	0.091	0.283	0.103	-0.242	**0.924**	0.394	0.289
SOCIAL1	0.523	0.490	0.445	0.104	0.577	0.196	-0.047	0.429	**0.801**	0.479
SOCIAL2	0.525	0.532	0.458	0.142	0.374	0.194	-0.279	0.411	**0.726**	0.470
SOCIAL3	0.405	0.342	0.293	0.034	0.436	0.137	0.073	0.255	**0.848**	0.435
SOCIAL4	0.397	0.340	0.284	0.016	0.450	0.169	0.091	0.230	**0.838**	0.453
SOCIAL5	0.416	0.302	0.234	-0.010	0.424	0.160	0.064	0.310	**0.810**	0.370
TRIAL1	0.373	0.342	0.332	0.111	0.517	0.197	-0.004	0.253	0.453	**0.824**
TRIAL2	0.443	0.456	0.482	0.215	0.529	0.233	-0.113	0.316	0.484	**0.876**
TRIAL3	0.455	0.380	0.397	0.207	0.498	0.199	-0.122	0.286	0.506	**0.894**