2013 46th Hawaii International Conference on System Sciences

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

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Abstract

Does a cloud lifestyle exist? If so, are people with a cloud lifestyle more likely to adopt and use cloud technologies? Whereas adoption studies have repeatedly analyzed dimensions of the technology, including usefulness and ease of use, for understanding people's behavioral intention to adopt and use a novel technology, we currently have limited understanding of the effect of user characteristics, in particular various user 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, demographic, 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-a-vis a proposed Cloud Lifestyle—that is most likely to adopt cloud technologies.

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 serve a larger, more diverse user base using the same shared set of physical resources. Despite the potential advantages of easy data manageability, reliability of data recovery, device and location independence, flexibility, and potential collaboration support, cloud computing is also associated with significant privacy and security risks. Hence, as a novel technology that is characterized by advantages, risks, and uncertainty, 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.

In order to analyze both characteristics of the cloud computing technology and user lifestyles simultaneously, this study analyzed the data from 402 non-cloud note-taking application users from a random U.S.-based national sample of 1721 respondents. On the one hand, we used partial-least square (PLS) analysis to study *what contextual factors and innovation attributes of the technology affect adoption intention*? On the other hand, we used cluster analysis for identifying various behavioral lifestyle segments so as to study *what the role of different contexts, perceptions, and intentions is 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. Furthermore, the cluster analysis 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 Hypotheses: Innovation Adoption

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 several characteristics of the technology that affects a person's probability of adoption or rejection [6]. Although other technology adoption theories exist,

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DOI 10.1109/HICSS.2013.2

such as the Technology Acceptance Model (TAM) [18], DIT analyzes a broader set of innovation characteristics—as opposed to only two measures (i.e., perceived usefulness and perceived ease of use)—that have been shown to explain between 49 and 87% of the variance in adoption [52]. These include the relative advantage, compatibility, complexity, observability, and triability of a technology. Hence, exploring the impact of these five innovation 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 [52]. This measure is closely related to the perceived usefulness (PU) measure in TAM [17]. Existing studies have shown that if no clear advantage is perceived, the individual will stick with its current and familiar technology [1, 20]. Alternatively, if the user does perceive a relative advantage of the novel tool [19, 24], this will provide a motivational force for adoption and may even increase adoption speed [55]. 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 [52]. This measure is closely related to the perceived ease of use (PEOU) measure in TAM [17]. 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 [52]. According to Rogers [52], 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 [56, 34, 61]. 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 [52]. 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 [19, 24, 40]. Given the widespread availability and thus observability of cloud note-taking applications, positive effects on their adoption may be anticipated.

Fifth, *triability* refers to the degree to which an innovation may be experimented on a limited basis [52], 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 [32], whereas unsatisfactory trial experiences may result in rejecting the novel technology. Anecdotally, it may be argued that cloud note-taking applications have high triability, 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 [43] has proposed *risk*—that is, the perceived uncertainty in a purchase situation [29]—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 [11,12,27,35,47]. 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-f): *Perceived attributes—i.e., relative advantage, complexity, compatibility, observability, triability, and risk—of the new technology will be positively related to the behavioral intention to adopt the cloud applications.*

2.2 Contextual Factors: Social Influence, Knowledge and Past Experience

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. Drawing on Coursaris & Kim's [15] contextual usability framework, we suggest that usability and consequences of usability—including adoption—are influenced by four sets of contextual factors, User, Environment, Technology, and Task/Activity characteristics. In this study, we explore three contextual factors—namely social influence, past experience, and knowledge—as antecedents to perceptions of and subsequent intention to adopt cloud note-taking applications.

First, *social influence*—that is, social pressure from a reference group to perform a particular behavior [42]—has been shown to have an important effect on people's perceptions of an innovation and subsequent adoption decisions [37,16,54,63]. Both TAM and DIT have been expanded with the "social norms" [58. 59] and "image" [40] 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 [48,10], thereby suggesting that social influence may play a significant role in shaping perceptions regarding the innovation attributes of cloud note-taking applications. As a result, the following hypotheses are proposed:

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

Second, *past experience*—the level of previous exposure to similar or related technologies—has been found to influence perceptions of the relative advantage [2,57], the complexity [63], the compatibility [21,50], the observability [30], the triability [44,25] and the perceived risk [3] of novel technologies. As a result, the following hypotheses are proposed:

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

Third, *knowledge*—people's awareness of and information about a novel technology [52]—influences people's perception of an innovation's attributes. Rogers [52] 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 as well as for the decision for 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 [20,64], risk (i.e. uncertainty) [22], as well as observability and triability [45] of a technology. Thus, the following hypotheses are proposed:

Hypothesis 4 (a-f): *Knowledge will be positively related to the perceived attributes of the new technology (Relative advantage, Complexity, compatibility, observability, triability and risk).*

Table 1. Three Types of Knowledge

	Awareness Knowledge	How-to Knowledge	Principles Knowledge
Def.	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

2.3 Research Model

The proposed structural model is shown in Figure 1.

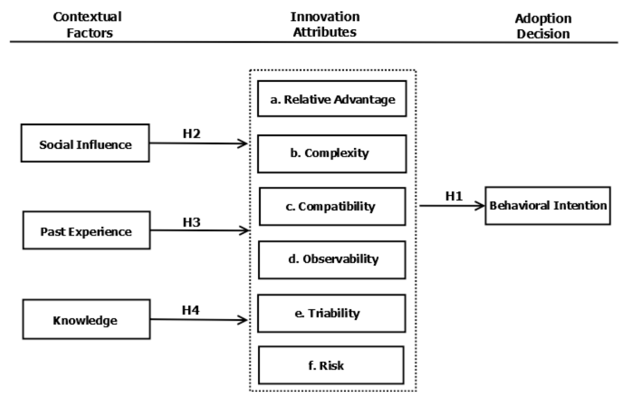

Figure 1. Proposed Research Model

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. Therefore, this study uses lifestyle segmentation, which allows for a richer and more holistic exploration of market segments than can be achieved when relying on demographic data alone; hence, which can help us explain different adoption behaviors across various societal groups [5, 62].

Lifestyle reflects a person's interests, opinions, personality, and needs [31,33]. Although various definitions and models for studying lifestyle exists (see Appendix 1), this study draws on the Brand Strategy Research (BSR) model [7,39,51], 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 [8]. 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, 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 Internal LLC. From the total of 1721 respondents, only 402 respondents, who had not yet used cloud note-taking applications, were selected in order to study their motivations underlying 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; [13]).

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 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 2.

The factor loadings for the items used in this study are summarized in Appendix 3. All items had significant factor loadings greater than 0.5 to ensure construct validity [53,9,28].

The relative advantage, complexity, Compatibility, observability, triabiliy, risk, social influence, and behavioral intention constructs were examined for reliability, as shown in Appendix 4 below. The results of the reliability analysis showed that all constructs had adequate Cronbach's α above the .80 threshold [9], and convergent validity (i.e. AVE) above the 0.5 benchmark [23].

As shown in Appendix 5, 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 [23].

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 [41]. 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 [14]. 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) [4]. 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 model was tested for 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.

This study's structural model, shown earlier in Figure 1, was tested in SmartPLS 2.0 using Bootstrapping, which assesses the significance of PLS parameter estimates in order to evaluate the hypotheses underlying this study [13].

With respect to the relationship between the innovation attributes — relative advantage, compatibility, complexity, observability, triability, 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 (RA) [H1a: $\beta = .26$, $p < .001$]; 2) compatibility (CMP) [H1c: $\beta = .31$, $p < .001$]; 3) observability (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 associated with the use of cloud note-taking applications (PR) people perceived, the higher the intention to use it (H1f: $\beta = -.16$, $p < .01$). Lastly, it was shown that complexity (CMX) did not significantly affect behavioral intention (BI), hence H1b was not supported.

Furthermore, we analyzed the relationships between the contextual factors—*social influence, past experience, and knowledge*—and the innovation attributes—*relative advantage, compatibility, complexity, observability, triability, and perceived risk* (Hypotheses 2 through 4). With respect to the first antecedent, i.e. social influence (Hypothesis 2), 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 (RA) [H2a: $\beta = .26$, $p < .001$]; 2) compatibility (CMP) [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 applications. Also, the lower the level of perceived social influence of the reference group, the higher the level of complexity people perceived [H2b: $\beta = -.43$, $p < .001$]. However, perceived risk (PR) was not found to be significantly influenced by social influence (SI), hence, H2f was not supported.

With respect to the second contextual variable, past experience (Hypothesis 3), it was found to have a significant effect on three of the six innovation attributes; specifically, the greater the past experience (PE) people have with the cloud, 1) the higher the observability (OBS) [H3d: $\beta = .20$, $p < .001$]; 2) triability (TRI) [H3e: $\beta = .09$, $p < .05$]; and 3) risk (PR) people perceived [H3f: $\beta = .13$, $p < .05$] to be associated with cloud note-taking apps. On the other hand, past experience (PE) did not have a significant effect on the relative advantage (RA), complexity (CMX) and compatibility (CMP) of cloud note-taking applications..

Finally, the third contextual variable, knowledge, 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 (KN), the higher the compatibility (CMP) [H4c: $\beta = .12$, $p < .01$] and triability (TRI) people perceived [H4e: $\beta = .14$, $p < .001$] to be associated with cloud note-taking apps. Also, it was shown that the less knowledge people have, the higher the risk (PR) [H4f: β = - .17, p < .001] and Complexity (CMX) people perceived [H4b: β = - .26, p < .001].

A summary of the hypothesis testing results, as well as a more detailed evaluation is provided in Appendix 6.

In addition to the PLS analysis, we used Hierarchical (Stepwise Linear) Regression in SPSS20.0 for R2 partitioning in order to reveal the amount of unique variance attributed to each predictor. 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, triability, 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 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 <.001), except for the final step (past experience) in the model for triability.

Table 2. Hierarchical Regression Results for R2 Partitioning

DV: CMP	Empirical	Conservative	Average
SI	.223***	.216***	.220***
KN	.010*	.010*	.010*
DV: CPX			
SI	.166***	.153***	.160***
KN	.057***	.057***	.057***
DV: OBS			
SI	.280***	.222***	.251***
PE	.044***	.044***	.044***
DV: TRI			
SI	.251***	.217***	.234***
KN	.011*	.006(n.s)	.009(n.s)
PE	.006(n.s)	.006(n.s)	.006(n.s)
DV: PR			
K	.011*	.018**	.015***
PE	.015*	.008(n.s)	.012*
DV: BI			
CMP	.380***	.036***	.208***
RA	.034***	.023***	.029***
TRI	.043***	.015**	.029***
OBS	.011**	.016**	.014**
PR	.012**	.012**	.012**

*p < .05; **p < .01; ***p <.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 2.

Following the results from Table 2, we can conclude that most innovation attributes—namely compatibility, complexity, observability, and triability—are influenced more by social influence than other contextual factors. Risk, on the other hand, is primarily influenced by knowledge. Furthermore, we found that 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 [52].

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 triability (see Table 3) below.

Table 3. T-Test Results for Differences between Future Adopters and Non-Adopters

	Adopters (N=185)		Non-Ad. (N= 48)		Sig	
	Mean	SD	Mean	SD	T-value	P-value
Perception						
RA	3.97	.70	2.60	.83	-11.54	.000
CMX	2.03	.62	3.01	.90	8.78	.000
CMP	4.06	.61	2.57	.94	-13.34	.000
OBS	2.93	1.02	2.01	.85	-5.72	.000
TRI	3.61	.70	2.74	.88	-7.33	.000
PR	2.63	.95	3.28	.75	4.40	.000
Context						
SI	3.34	.69	2.28	.68	-9.58	.000
KN1	1.22	.95	.88	1.0	-2.19	.030
KN2	1.15	1.10	.50	.90	-3.75	.000

[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).

PE1	.63	1.01	.33	.79	-1.90	.029
PE2	2.94	1.48	3.63	1.1	1.26	.211

Following the t-test results, we analyzed the proposed structural model for the two groups separately to reveal any significant differences in adoption behaviors between the two groups (see Table 4). As the results show, future adopters' behavioral intention was significantly predicted by three innovation attributes—namely observability, triability, and perceived risk—while non-adopters' behavioral intention was not significantly affected by any of the innovation attributes.

Table 4. Path Analysis Results between Future Adopters and Non-Adopters

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

4.2 Cluster Analysis

The auto-clustering algorithm 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 < .000) and clusters 2 and 3 (Mean Difference =-6.605, p < .000), but not between clusters 1 and 3 (Mean Difference = 2.260, p = .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.

Table 5. Lifestyle Cluster Information

Label	Traditionalists	Hedonic Yuppies	Intelligent Businessmen
Cluster	1	2	3
Size	114 (28.4%)	159 (39.7%)	128 (31.9%)
Edu	Some college (36%) High school (32.5%)	Some college (41.5%) College (18.2%)	College (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	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%)
Occ.	No occ. (14%) Housewife (10.5%) Husband (7.9%) Volunteer (6.1%)	Business man/woman (13.8%) Housewife (11.3%) Publ.servant (6.9%) Manager (5%)	Business man/woman (14.1%) Scientist (7.8%) Manager (6.3%) Entrepreneur (5.5%)
Hobby	Home quietly (19.3%) Watch TV (15.8%) Jobs around house (10.5%) Surf Internet (7.9%)	Sociable evening (17%) Home quietly (10.7%) Make dreams come through (8.2%) Shopping (8.2%)	Surf Internet (11.7%) Sociable evening (10.2%) Camping (8.6%) Active sports (7.0%)
Value	Respect (18.4%) Tranquility (17.5%) Enjoyable life (13.2%)	Enjoyable life (20.8%) Independence (10.7%) Respect (8.2%)	Privacy (17.2%) Enjoyable life (12.5%) Independence (12.5%)
Family	Cozy old-fashion (28.9%) Stable (15.8%)	Happy (25.8) Warm (15.1%) Stable (9.4%)	Happy (15.6%) Bachelor (12.5%) Harmonious (9.4%)
Char.	Honest (13.2%) Down-to-earth (13.2%) Capable (10.5%) 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 (6.3%)

Based on these self-reported demographic and lifestyle variables, we labeled the clusters in line with common terminology from existing lifestyle research [7,39] 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 5 contains more detailed frequency distributions for the lifestyle variables within clusters.

Following the cluster analysis, we conducted a PLS analysis based on our initial structural model to investigate potential differences between the three clusters. Table 6 below only shows those variables for which we found significant differences, namely for nine paths.

Table 6. Path Analysis Results Among Clusters (only significant differences)

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

With respect to the relations between the innovation attributes and behavioral intention, we found significant differences for observability and triability. Whereas observability and triability 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 (PE) was found to have no impact on triability (TRI) for Hedonic Yuppies and Intelligent Businessmen; on observability (OBS) for Hedonic Yuppies; and perceived risk for Traditionalists and Hedonic Yuppies. Knowledge did not impact perceived risk for Hedonic Yuppies; and triability (TRI) or observability (OBS) for Traditionalists and Intelligent Businessmen.

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), contextual, demographic 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 [52]—namely relative advantage, compatibility, observability, and triability. It was confirmed that innovation attributes have a significant impact on people's behavioral intention to use the innovation. These findings are consistent with previous studies [52,55,60]. 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. [36]) and potentially due to its immature state.

In line with previous research [11,12,35], 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 [26,38].

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 [56, 49]. 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 triability—except for risk. This illustrates that people's perceptions of innovations are strongly influenced by important people around them.

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.

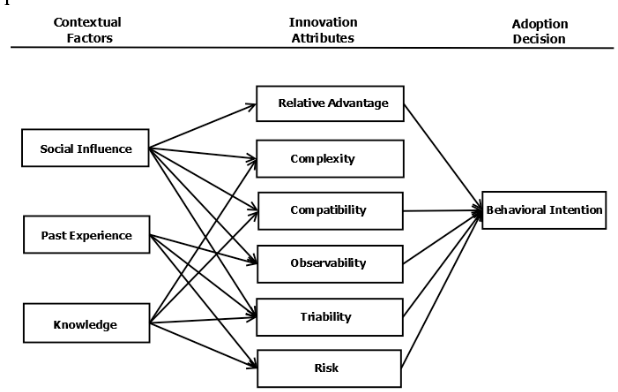

Figure 2. Validated Model

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

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 innovation's values, features, and 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 their stable position and avoiding any uncertainty associated with novel technologies. The adoption intention of Hedonic Yuppies was affected by observability, triability, 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 would 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 more influenced 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 contextual, demographic, and lifestyle variables.

Based on the findings that consumers' adoption intention is primarily affected by anticipated benefits 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 innovation attributes into account when formulating design features. Also given the importance of social influence, marketing managers can further leverage the power of social media marketing to enhance the popularity of cloud services. 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 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 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; [52]); providing a longitudinal perspective of adoption rates and behaviors across adopter types over time; collecting behavioral [46] rather than self-reported data; investigating other types or a broader range of cloud services beyond note-taking applications; exploring other contextual variables or additional lifestyle parameters.

6. Appendices

Provided online at http://bit.ly/LbwoJZ.

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