The Flock in the Cloud - How Social Influence Processes Shape Cloud Service Relationships

Completed Research Paper

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Abstract

Despite more and more customers relying on cloud services, their unique characteristics hamper individuals' evaluation of privacy, security and availability levels. In contrast to other online exchange relationships, this uncertainty persists even after individuals have adopted the service. We posit that users facing continuous uncertainty lean towards their social environment to form their evaluations about cloud services. Drawing upon social influence theory and a representative data set of 2,011 internet users, we investigate how three social influence processes (compliance, identification, internalization) shape cloud user's uncertainty evaluation and behavior before and after the adoption of the service. Our cloud service relationship model extends previous studies on online exchange relationships by a social influence perspective. The model facilitates an understanding of why and when users rely on services they cannot fully evaluate and provides guidelines how cloud providers and IT managers can exploit social influence processes to successfully manage cloud service relationships.

Keywords: Cloud computing, social influences, IT services, uncertainty, continuance, adoption

Introduction

The great benefits of novel cloud services for consumers - such as cloud storage, messaging or other collaboration services - are widely touted. With 2.4 billion users of cloud services worldwide in 2013 and a projected growth of 50% until 2018 (eMarketer 2014), cloud services become an elementary part of our everyday lives. Revenues of public cloud services are expected to grow between 15% and 19% per year (Forbes 2013), exceeding the $200 billion in revenues in 2016. However, despite the potential benefits, uncertainty still makes many potential consumers reluctant to fully engage in cloud service relationships, especially for personal data-intensive IT services (Bitkom 2014). Cloud services represent a shift from IT-as-a-product to IT-as-a-service (Iyer and Henderson 2010). In contrast to IT product scenarios where consumers are relatively independent from the IT provider once they have deployed the software on their local machine, cloud service users continuously depend on the IT provider and have only limited information about the IT provider's qualities and actions. Thus, cloud service relationships describe a special form of online exchange relationship in which users can never fully evaluate the true qualities of the cloud service at any point of time. For instance, cloud users can never fully assess whether cloud providers make information available to third parties without their consent, whether security breaches occur and whether spare capacities are adequate to ensure availability in peak situations (Trenz et al. 2013). Users' on-going assessment whether or not to rely on a cloud service whose quality is hard to discern puts special emphasis on the importance of understanding user uncertainty in cloud service relationships[1].

Previous research on online exchange relationships has primarily focused on relational factors such as trust and information signals for explaining levels of user uncertainty. Popular examples for signals are service diagnosticity or certifications. This perspective has been effective in explaining user's uncertainty evaluation in online exchange relationships handling search goods (Pavlou et al. 2007), that can be evaluated before the purchase, and experience goods (Dimoka et al. 2012), that can be evaluated after the purchase (Nelson 1970). Cloud services can be best described as credence goods (Darby and Karni 1973), i.e., it is impossible for the user to verify the provider's true qualities even if the individual is already using the service. This characteristic limits an effective evaluation of signals and makes the formation of trust difficult. Hence, we believe that cloud users seek for additional cues (beyond provider signals and trust) to reveal the true qualities of the cloud service in cloud service relationship. In situations where reliable information is missing, users lean toward their social environment to form their evaluations (Duan et al. 2009). As cloud users and their peers make similar experiences with the same highly standardized service, we argue that they have a strong tendency to directly influence each other in their beliefs about the service and their actions. Accordingly, we draw upon social influence theory (Deutsch and Gerard 1955) as a novel perspective for explaining user uncertainty and behavior before and during cloud service relationships. We investigate three types of social influence processes and investigate how these processes shape users' beliefs and behavior before and after the adoption of the service. Thereby, we aim to answer the research question: How do social influence processes affect cloud users' uncertainty evaluation and behavior over time?

The remainder of this paper is structured as follows. First, we define and explain core concepts and theoretical boundaries of our study. We then develop a theory on online service relationships for cloud services, called cloud service relationship model. This theory is subsequently empirically validated using two large samples of current and potential users of a cloud service. We close by discussing implications for theory and practice.

Cloud Service Relationships

Previous studies examined in depth why user uncertainties arise in online exchange relationships, how they are mitigated, and what their behavioral consequences in different contexts are. Consumer concerns and vulnerabilities in online exchange relationships mainly arise due to information asymmetries between the provider and the user (Dimoka et al. 2012; Pavlou et al. 2007). For e-commerce transactions, users' perceived seller- and product-related information asymmetries can be distinguished (Dimoka et al. 2012). For services, the actions of the seller and the quality of the product are inextricably linked. If user uncertainties are prevalent, signaling mechanisms, i.e., cues provided by vendors or providers that reveal their true qualities (Özpolat et al. 2013), can reduce information asymmetries between user and transaction partner. They may originate from three different sources. *First-party information* is provided directly by the transaction partner (e.g., performance reports and trust-assuring arguments on the

[1] Uncertainty is different from risk. Risk is estimated with a priori calculable probabilities, whereas uncertainty deals with subjective probabilities (Dimoka et al. 2012). We focus on user uncertainty because IT services do not provide objective calculable probabilities. User uncertainty is defined as the cloud user's perceived estimate of the variance in cloud service quality based on subjective probabilities about the cloud service's characteristics and whether the cloud service will perform as expected (Dimoka et al. 2012).

website: Kim and Benbasat 2006). *Second-party information* originates from other transaction partners' experiences with the service (e.g., reputation and rating mechanisms: Dewan and Hsu 2004). *Third-party information* provides independent verification of a transaction partner's quality by a quality assurance institution (e.g., third party assurance seals: Özpolat et al. 2013). Several studies have investigated the correspondence between signaling investments and their evaluation by users (Singh and Sirdeshmukh 2000; Trenz et al. 2013). Trusting beliefs with regards to the transaction partner significantly reduce consumers' uncertainty evaluations (Pavlou et al. 2007). Moreover, research has empirically highlighted the behavioral consequences of consumers' uncertainty evaluation to a variety of e-commerce performance indicators including paid price premium (Dimoka et al. 2012), purchasing decisions (Pavlou et al. 2007) or purchase conversion (Özpolat et al. 2013). We build upon this stream of research and extend it to the even more opaque and dynamic field of cloud services.

Cloud service relationships are defined as bilateral relationships between two transaction partners, namely the cloud provider and the individual cloud user. The cloud user experiences continuous information asymmetries about the true qualities of the cloud service (credence good). In contrast to users of IT products, cloud users can never fully evaluate the true qualities of the service, e.g., with respect to privacy, security, or availability (Trenz et al. 2013). At the same time, there can be a significant time lag until users recognize a reduction in promised service quality. In some case (e.g. disclosing critical information to third parties), the hidden actions of the provider may even never be detected. The cloud provider offers highly standardized services to a crowd of cloud users. A subset of the cloud user's social peers may also maintain a cloud service relationship with the same cloud provider. Embedded in a social network, standardized interfaces allow cloud users to exchange information with their social peers if they use the same or a compatible cloud service (Iyer and Henderson 2010). The interaction with social peers is not limited to the exchange of data using the service, but also shapes other social processes that influence users' beliefs and behavior with regards to a particular service.

In the following, we develop a cloud service relationship model that differs from previous investigations in two major ways. First, cloud services differ widely from other areas such as e-commerce services. As a credence good, the true quality of cloud services cannot be evaluated before (search goods, Pavlou et al. 2007) or after the transaction (experience goods, Dimoka et al. 2012). Instead, a non-dissolvable level of uncertainty continues to shape the relationship between the provider and the (potential) user. To take this into account, we extend the established view on service relationships by introducing social influence processes that can provide additional cues in situations of uncertainty and thereby shape individuals' beliefs and actions. Second, our theory describes uncertainties in online service relationships before and after the adoption of the service. Thereby, we are able to show that the processes that shape online service relationships differ depending on the state of the individual. The integration of our study in the field of online service relationships is illustrated in Figure 1.

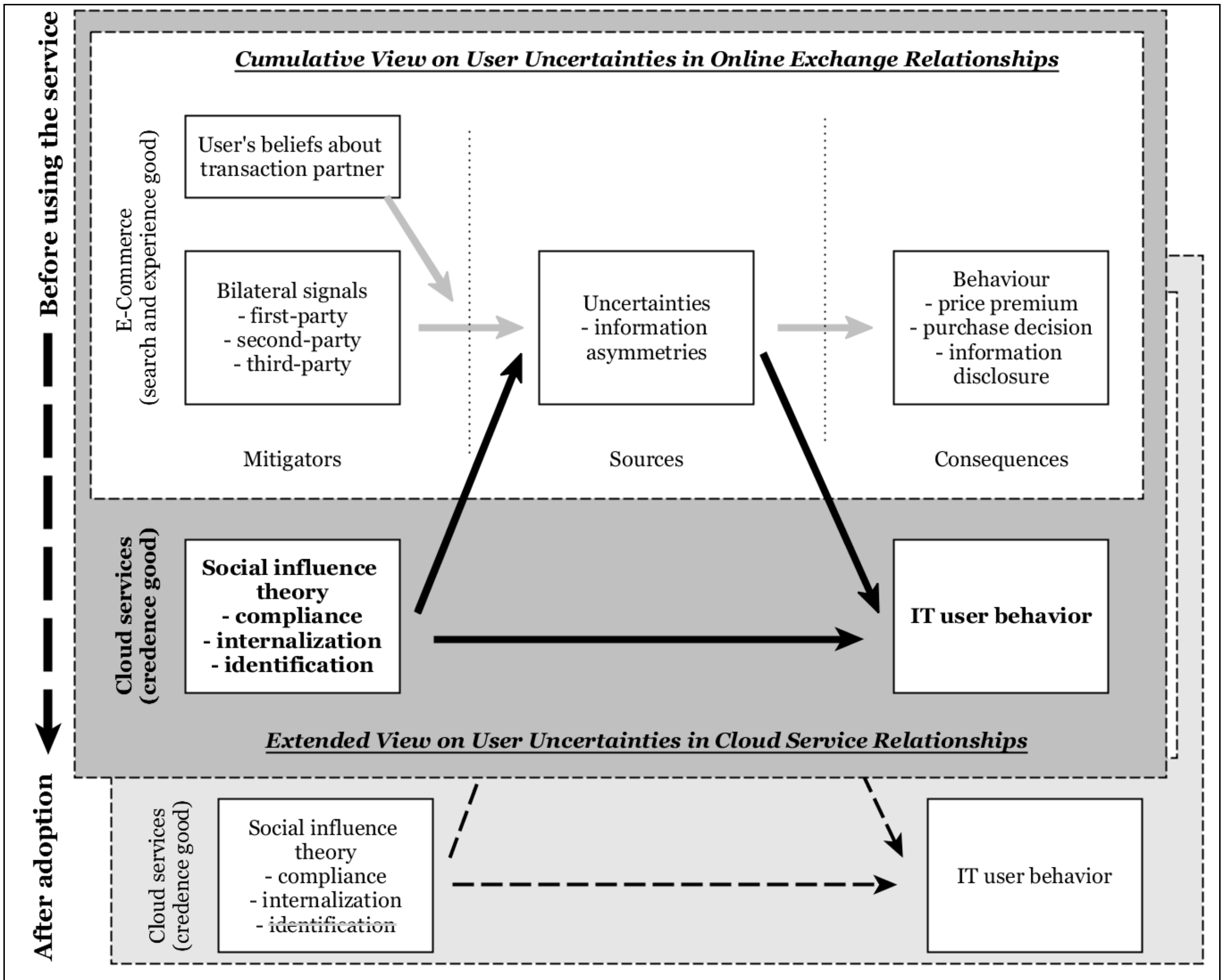


Figure 1. Views on Online Service Relationships

Underlying Framework: Social Influence Theory

In order to explain and predict how social influence processes effect users' uncertainty evaluation and their subsequent behavior, we build upon social influence theory as an underlying theoretical framework (Burnkrant and Cousineau 1975; Deutsch and Gerard 1955; Kelman 1961). Deutsch and Gerard (1955) distinguish between informational and normative social influences. Informational social influence refers to any information obtained from social peers as evidence about reality (Deutsch and Gerard 1955). Thus, this type of influence occurs if individuals seek to enhance their knowledge about the environment and process information provided by their social peers to cope with it. Kelman (1961) terms the process when individuals internalize others' opinions internalization-based social influence processes. In contrast to informational social influence, normative social influences lead to conformity to the believes and behavior of social peers (Deutsch and Gerard 1955). Kelman (1961) has distinguished among two types of normative social influence processes, namely identification- and compliance-based processes (Burnkrant and Cousineau 1975). Identification-based social influence occurs when individuals adopt beliefs and behavior derived from social peers because this is associated with a satisfying self-defining relationship to this group (Kelman 1961). Individuals motivated to enhance their self-concept accept the influence of social peers and thus, identify with them by taking on their judgment and behavior which they perceive as representative of their reference group (Burnkrant and Cousineau 1975). In contrast to internalization-based processes, identification-based social influences mostly operate through non-verbal interaction, i.e., consumers seek to believe and act in a similar manner like those possessing referent power (Lewis et al.

2003). Other normative influences are compliance-based social influence processes. They develop if individuals accept influence from social peers because they hope to achieve a favorable reaction from the others (Fishbein and Ajzen 1975). Thus, compliance- and identification-based social influence processes differ with respect to their goal orientation (Burnkrant and Cousineau 1975). While via compliance individuals seek for external rewards (i.e., a favorable reaction), via identification individuals accept the influence because they aim for establishing or maintaining a positive relationship with their peers (Kelman 1961). We build upon this social influence theory framework (see a summary in Table 1) to explain and predict how social influences shape users' uncertainty evaluation and subsequent behavior in cloud service relationships.

Table 1. Underlying Framework: Social Influence Theory (Burnkrant and Cousineau 1975)

Type of Social Influence (Deutsch and Gerard 1955)	**Social Influence Processes** (Kelman 1961)	**Goal of Cloud User**
Informational	Internalization	Gaining knowledge about reality
Normative	Identification	Become similar to social peers
	Compliance	Gaining a favorable reaction from social peers

Social Influence on Cloud User's Evaluation and Behavior

If social influence processes (internalization, identification, compliance) occur, we can expect different observable implications for each type of social influence process. These observable implications are discussed in the subsequent section in order to address the question how social influence processes influence uncertainty evaluation and behavior in general. We then explain when social influence processes occur in cloud service relationships and how their occurrence develops over time. Lastly, we introduce several control variables that allow us to test the nomological validity of our research model in the empirical evaluation.

Internalization-based Social Influence Processes

Word-of-Mouth (WOM) - which refers to any informal communication between the consumer and its social peers concerning the evaluation of a service (Anderson 1998) - drives internalization-based social influence processes. I.e., if internalization-based processes occur, opinions of social peers influence how users evaluate the cloud service (Malhotra and Galletta 2005). WOM is an important concept in marketing (Mangold et al. 1999; de Matos and Rossi 2008) and IS research (Kim and Son 2009) because it is assumed that positive and negative sentiments among peers influence consumers' beliefs and behavior. While antecedents of WOM activities have been intensively studied in IS and marketing research (Brady et al. 2012; Chiou et al. 2002; Gittell 2002; Heitmann et al. 2007; Hennig-Thurau et al. 2002; Johnson et al. 2008), the consequences of WOM on individuals' evaluation of a product or service have been widely neglected – especially from a social influence theory perspective. WOM influence on consumers can be both positive and negative. While positive sentiments of social peers regarding the cloud service mitigate users' concerns, negative WOM increases the uncertainty perception of users. Since previous research has highlighted that users place different weights on these distinct influence processes in making evaluations (Richins 1983), we distinguish between positive and negative WOM in our study. Because cloud users process opinions of social peers as information for making evaluations and decisions, we assume that positive and negative WOM influence the evaluation and subsequent behavior of cloud users.

Identification-based Social Influence Processes

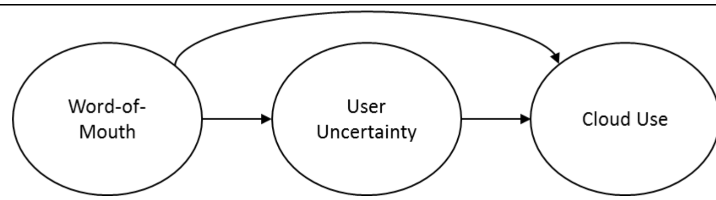
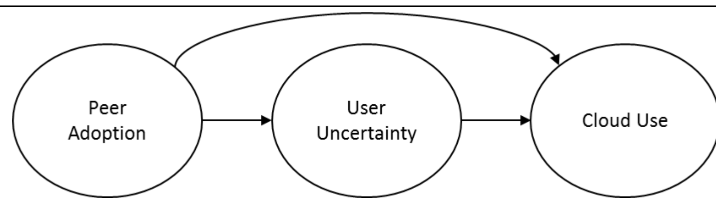
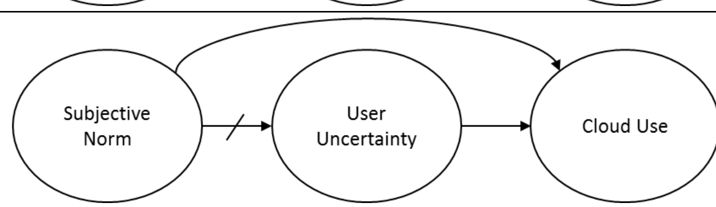
Peer use (PUSE) is a concept studied in social science research as an antecedent of identification-based social influence processes (Schmitz and Fulk 1991; Wang et al. 2013). Individuals are eager to build social capital, which makes them sensitive not only to what others say but also what others do (Eagly and Wood 1982; Wang et al. 2013). If identification-based processes occur, users are concerned with the social anchorage of their behavior (e.g., whether to use the service or not) and therefore adopt beliefs and behavior that enhance a positive relationship with friends and colleagues. As a consequence, if many social peers of an individual have adopted the service, we will observe lower levels of uncertainty and higher levels of behavioral intentions to use the cloud service among users.

Compliance-based Social Influence Processes

Individuals' perceived subjective norm (SN) drives compliance-based social influence processes. Subjective norm - defined as an individual's "perception that most people who are important to him think he should or should not perform the behavior" (Venkatesh et al. 2003, p. 452) – is a well-established construct in IS research and has been shown to influence the use of IT products (Thompson et al. 1991; Venkatesh et al. 2003; Venkatesh and Davis 2000; Venkatesh and Morris 2000). If compliance-based processes occur, the evaluation of a service and the consequent behavior might be in conflict because individuals act according to social norms rather than their own beliefs. Thus, via compliance social peers do not adjust their evaluation of a service but their behavior. Therefore, subjective norm does not influence cloud users' uncertainty evaluation of the cloud service. In contrast, if compliance-based processes occur, individuals may adopt the cloud service because they hope to achieve a favorable reaction from others when they use the service (Fishbein and Ajzen 1975).

Table 2 summarizes the empirically observable implications if one of the three social influence processes occurs, before we discuss their occurrences over time in the subsequent paragraphs.

Table 2. How Social Influence Processes affect User Uncertainty and Cloud Use

Process	**Empirically observable implication, if social influence process occurs**
Internalization	
Identification	
Compliance	

Social Influence over Time

Previous studies highlight that whether social influence process occur or not may differ across different phases of the classical IT adoption process. On the one hand, empirical studies provide compelling evidence that subjective norm influences intention to use before individuals adopt an IT product (e.g., Venkatesh et al. 2003). On the other hand, several studies highlight that subjective norm does not predict intention to use after the adoption (Karahanna et al. 1999). Consistently, we believe that whether our three social influence processes occur or not may depend on whether users' have adopted the cloud service or not as we will explain in more detail the following. Based on this analysis on when social influence processes are triggered and the empirically observable implications derived from theory in the previous section that describe what happens if social influence processes are at work, our hypotheses are derived.

Internalization-based social influence processes occur both before and after the adoption of the cloud service. In contrast to IT products, cloud services are credence goods, i.e., cloud users can never fully experience the true qualities of the service (cf. section cloud service relationships). Hence, users continue to seek for additional cues (beyond provider signals) to reveal the true qualities of the cloud service over the whole life-cycle of the relationship:

Hypothesis 1: Positive WOM (PWOM) decreases a user's overall uncertainty evaluation of the cloud service (a) before and (b) after the adoption.

Hypothesis 2: Negative WOM (NWOM) increases user's overall uncertainty evaluation of the cloud service (a) before and (b) after the adoption.

Hypothesis 3: PWOM increases user's intention to use the cloud service (a) before and (b) after the adoption.

Hypothesis 4: NWOM decreases user's intention to use the cloud service (a) before and (b) after the adoption.

In contrast, identification-based social influence processes shape individuals' beliefs only before the adoption of the service. Before adoption, individuals are eager to build a self-defining relationship with their social peers by adopting their beliefs and behavior. This process is completed after the adoption. Once they joined the service, cloud users have become similar to their relevant social group and have adopted their evaluation and behavior. As they have completed the identification process and have adopted the beliefs and behaviors of referent others, identification-based processes do not occur after the adoption of the service:

Hypothesis 5: PUSE mitigates users' uncertainty evaluations of the service <u>before</u> the adoption.

Hypothesis 6: PUSE increases users' willingness to use the service <u>before</u> the adoption.

Because users continue to seek a favorable reaction from their social peers, we propose that compliance-based processes persistently occur before and after the adoption of the service. Previous studies on experience goods show that subjective norm plays a diminishing role for predicting use intention after the adoption of an IT product (Thompson et al. 1991; Venkatesh and Morris 2000). However, cloud services (credence goods) are fundamentally different from experience goods. The use of experience goods involves that individuals by definition can fully experience and evaluate the product after the adoption. Therefore, the influence of subjective norm decreases once users experience the IT product. In contrast, for our scenario subjective norm continues to influence user's usage because the qualities of the service can never be fully experienced by the user at any time:

Hypothesis 7: Subjective norm increases users' intention to use the service (a) before and (b) after the adoption.

Table 3 summarizes the effects of the different social influence processes over time.

Table 3. How Social Influence Processes develop over Time

Social Influence Process	Occurs before Adoption	Occurs after Adoption	Rationale
Internalization	Yes	Yes	Cloud users keep seeking and incorporating knowledge about true qualities of the cloud service
Identification	Yes	No	Through adoption identification processes is completed and cloud users have adopted uncertainty evaluation and behavior from peers
Compliance	Yes	Yes	Cloud users keep trying to get a favorable reaction from social peers

Control Variables

Service Diagnosticity: it refers to the degree to which users believe that a website provides them with useful information about the respective cloud service (Jiang and Benbasat 2007; Kempf and Smith 1998). As a well-established information signal for safeguarding online exchange relationships (Dimoka et al. 2012; Pavlou et al. 2007), we control for its effects.

IT Experience: since a lack of IT experience impedes users from engaging in cloud service relationships, IT experience is proposed as control variable on uncertainty and use intentions.

User demographics: since prior studies show that gender and age play an important role for understanding IT user acceptance (Venkatesh et al. 2003), both are added as control variables on uncertainty evaluation and use intention before and after adoption.

Research Methodology

The hypotheses derived in the previous section were tested using survey data we collected using an online questionnaire among potential and actual users of cloud storage services. Cloud storage services such as Dropbox, Google Drive or Microsoft SkyDrive allow cloud users to back-up, synchronize and share their files over the internet. Cloud storage services were chosen as an empirical setting because they share the typical characteristics of cloud services, i.e., cloud storage users can never fully evaluate the qualities (e.g., privacy, security) of the cloud storage service and these services handle huge amounts of personal data. In the following, we describe our measurement development as well as the survey deployment and data collection procedures.

Measurement Development

All measures used in our study were adopted from existing measurement scales. However, they were adapted to the context of our study. On grounds of the critique raised about the validation of scales in the IS discipline (e.g., Boudreau et al. 2001; MacKenzie et al. 2011), we decided to re-validate our constructs. This process included the definition and assessment of the domain and dimensionality of the constructs using two sorting procedures (Moore and Benbasat 1991) and the assessment of content validity using a rating method (Hinkin and Tracey 1999; MacKenzie et al. 2011). The preliminary instrument was then pilot tested with 235 participants. After the pre-test, the respondents were asked to give open feedback regarding composition of the survey, overall time, and other issues they experienced. Following the pre-test, the instrument was shortened, refined, and validated for its statistical properties. In the final survey, all principal constructs were measured as first-order reflective constructs using three or more indicators. An overview of all measures and their sources is given in Appendix A.

Survey Deployment and Data Collection

The final survey was conducted using a representative data set of German internet users. The online survey was very well suited to address potential and actual users of cloud storage services because the regular online access is a prerequisite for usage of such a service. According to a recent study of the German online research consortium ("Arbeitsgemeinschaft Online Forschung e.V.", short AGOF), 53% of all German internet users are male and 47% female. Moreover, internet adopters are younger compared to the entire German population (9.5% in the ages between 14 and 19, 18.7% in the ages between 20 and 29, 17.8% in the ages between 30 and 39, 22.6 % in the ages between 40 and 49, 16.8% in the ages of 60 or older; cf. AGOF 2013). We used the fine-grained distribution information from AGOF (incorporating also different gender distributions within age-sets) to deduce the requirements for collecting a representative sample of German internet users. Using these requirements, a professional online panel has sent out individual invitations to its members in the period between 12th of November 2012 and 9th of December 2012. On the first page of the survey, the definition of cloud storage services was given and participants were asked which cloud storage service they use most. If participants declared not to use a cloud storage service, they were introduced to *Dropbox* – Germany's market leading (as our study confirms) cloud storage provider. All questions were then automatically adapted to refer to the particular cloud storage service. Overall, 2,011 valid responses were collected.

Data Analysis and Results

We used covariance-based structural equation modelling (CBSEM using AMOS 22) to validate the structural model and test our hypotheses. Thereby, we are able to make use of the overall inferential test statistic that CBSEM provides and circumvent the discourse about potential validity issues of PLS based SEM in our (Aguirre-Urreta and Marakas 2014; e.g., Goodhue et al. 2012; Marcoulides et al. 2012) and in other disciplines (McIntosh et al. 2014; e.g., Rönkkö and Evermann 2013). We validate the final measurement models for non-users and users separately, before using a simultaneous estimation of the structural model to ensure comparability of the results.

Measurement Validation

The final measurement models (see Appendix A) exhibited standardized factor loadings above the threshold value of 0.7, except one item which is just below the threshold in the user sample. However, overall the values as depicted in Table 4 suggest an adequate level of individual indicator validity and reliability across subsamples (Bollen 1989; Fornell and Larcker 1981). For constructs to be reliable, composite reliability must be higher than 0.7 (Fornell and Larcker 1981; Nunnally and Bernstein 1994). In our model, all constructs reached composite reliability coefficients above 0.8. The validity at the construct level is assured because the latent constructs account for the majority of the variance in its indicators on average (MacKenzie et al. 2011). The average variance extracted (AVE) even exceeds 0.6 for all constructs in both subsamples. Discriminant validity of the constructs was evaluated based on the Fornell and Larcker (1981) criterion. Appendix B shows that, for both samples, the square root of the AVE for each construct is higher than the variance that the construct shares with every other construct in the model. We also conducted a standard common method bias analysis based on the recommendations of Podsakoff et al. (2003). Our analysis suggests that a common method error does not substantially bias our results.

Table 4. Measurement Model Results

		Non User			User		
Constructs	**Variable Name**	**Factor Loadings**	**CR**	**Mean (STD)**	**Factor Loadings**	**CR**	**Mean (STD)**
Use / Continuance Intention	USE1	0.924	0.943	2.69 (1.63)	0.948	0.930	5.82 (1.33)
	USE 2	0.892		3.27 (2.02)	0.944		5.77 (1.40)
	USE 3	0.943		2.65 (1.66)	0.812		5.74 (1.43)
Uncertainty	UNC1	0.884	0.958	5.06 (1.81)	0.816	0.934	3.71 (1.79)
	UNC2	0.904		4.67 (1.82)	0.825		3.28 (1.65)
	UNC3	0.958		4.74 (1.82)	0.95		3.15 (1.64)
	UNC4	0.942		4.72 (1.87)	0.934		3.05 (1.67)
Pos WOM	PWOM1	0.876	0.916	2.19 (1.73)	0.787	0.837	4.30 (1.97)
	PWOM2	0.868		1.83 (1.41)	0.748		3.36 (2.02)
	PWOM3	0.914		1.92 (1.57)	0.845		3.91 (2.16)
Neg WOM	NWOM1	0.893	0.910	1.61 (1.30)	0.892	0.893	1.58 (1.13)
	NWOM2	0.782		1.48 (1.09)	0.819		1.60 (1.13)
	NWOM3	0.851		1.67 (1.40	0.783		1.69 (1.29)
	NWOM4	0.856		1.73 (1.42)	0.793		1.78 (1.32)
Peer Use	PUSE1	0.950	0.969	2.33 (1.33)	0.942	0.951	4.12 (1.66)
	PUSE2	0.964		2.27 (1.31)	0.956		3.99 (1.68)
	PUSE3	0.915		2.40 (1.41)	0.870		4.05 (1.66)
	PUSE4	0.939		2.34 (1.37)	0.872		3.92 (1.64)
Subjective Norm	SN1	0.858	0.954	2.11 (1.49)	0.654	0.874	3.74 (1.96)
	SN2	0.962		2.07 (1.49)	0.913		3.55 (1.94)
	SN3	0.979		1.95 (1.40)	0.919		3.26 (1.98)
Service Diagnosticity	DIA1	0.934	0.966	4.21 (1.74)	0.851	0.935	4.65 (1.47)
	DIA2	0.974		4.38 (1.74)	0.910		4.88 (1.36)
	DIA3	0.964		4.39 (1.72)	0.917		4.84 (1.36)
	DIA4	0.873		4.05 (1.74)	0.859		4.82 (1.40)

Testing the Structural Model

The results of the structural model testing are presented in Figure 2. The chi-square statistic is 1872.640 with 616 degrees of freedom ($\chi^2/df = 3.040$). The other goodness-of-fit and badness-of-fit tests that are suggested by Gefen *et al* (2011) delivered decent values and confirm the overall good fit of the model (SRMR=.0267; RMSEA=0.032; GFI=0.937; AGFI=0.917; NFI=0.964; CFI=0.975). In the following, we present the path estimates and significance levels for non-users and users.

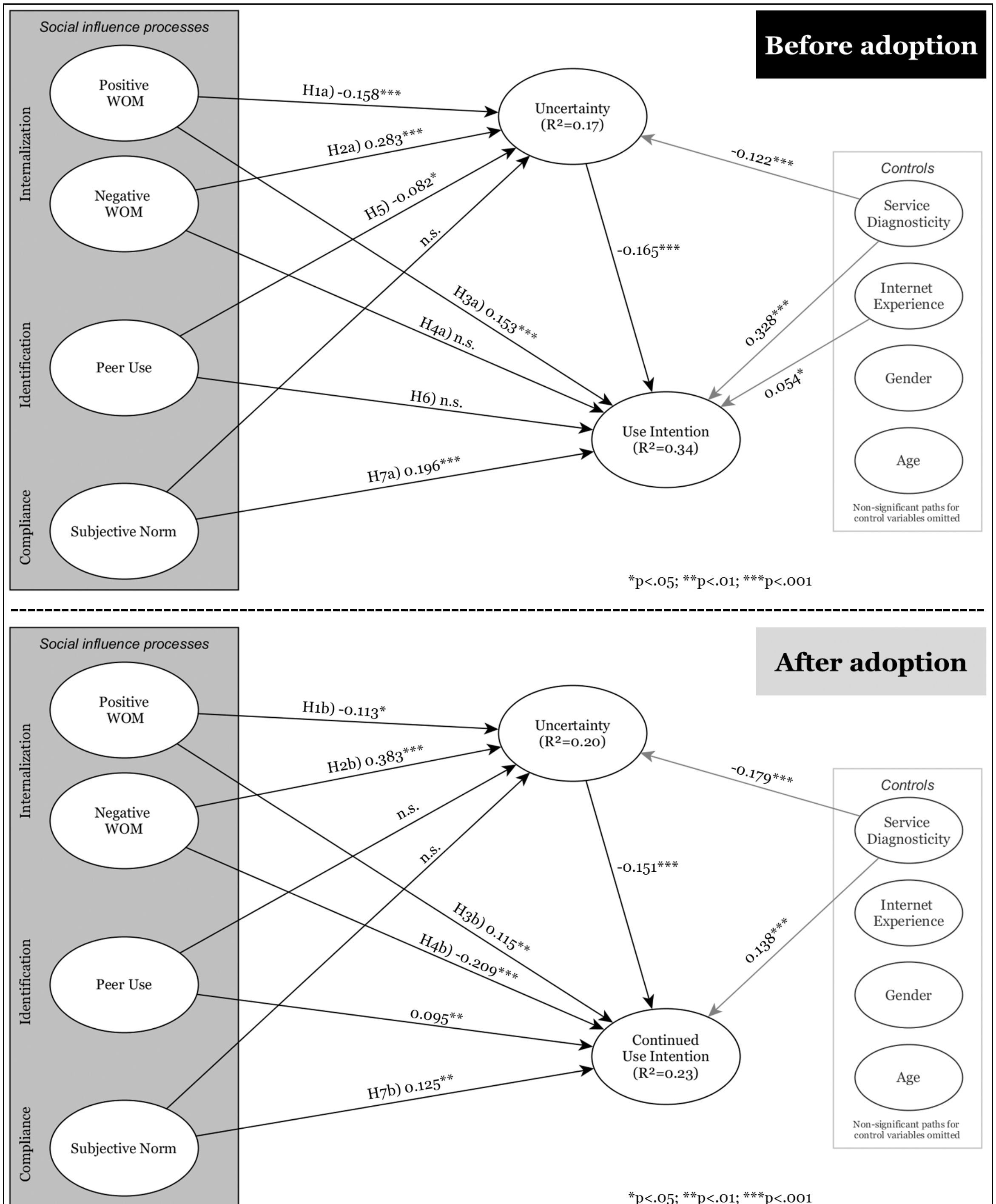


Figure 2. Structural Model Evaluation

Before Adoption

For non-users we find that the impact of perceived uncertainty (b=-.165; p<.001) on intention to use the cloud service is significant. Both PWOM (b=-.158; p<.001; H1a) and NWOM (b=.283; p<.001; H2a) have a significant influence on a user's uncertainty evaluation. As hypothesized, PWOM influences users' intention to use the cloud service (b=.153; p<.001; H3a) but NWOM does not (b=.001; p>.05; H4a). PUSE influences users' uncertainty evaluation (b=-.082; p<.05; H5). In turn, PUSE does not directly influence intention to use (b=-.040; p>0.5; H6), while SN does (b=.196; p<0.001; H7a). Service diagnosticity had a direct influence on both the evaluation (b=-.122; p<.001) and intention to use (b=.328; p<.001) of the cloud service. The other control variables (age, gender, internet experience) had no significant influence on the dependent variables apart from IT experience on use intention (b=0.054; p<0.05). Overall, our findings provide strong support for our cloud service relationship model for non-users.

After Adoption

For users we find that the impact of perceived uncertainty (b=-.151; p<.001) on continuance intention is significant. Moreover, both PWOM (b=-.113; p<.05; H1b) and NWOM (b=.383; p<.001; H2b) have a significant influence on a user's uncertainty evaluation. As hypothesized, both also influence users' intention to continue using the cloud service (PWOM: b=.115; p<.01; H3b, NWOM: b=-.209; p<.001; H4b). PUSE influences users' continuance intention for users (b=.095; p<.01). The same pattern can be observed for SN. SN does not influence users' uncertainty evaluation (b=-.036; p>.05) but effects users' intention to use the service (b=.125; p<0.05; H7b). Service diagnosticity had a direct influence on both the evaluation (b=-.179; p<.001) and intention to continue using the cloud service (b=.138; p<.001). The other control variables (age, gender, internet experience) had no significant influence on the dependent variables. Overall, our findings provide strong support for our cloud service relationship model for users.

Discussion

Our empirical results provide strong support for the appropriateness of using social influence theory as a perspective for studying cloud service relationships. Most of the hypotheses have been confirmed over and above the established measure of signals used in previous studies on goods that can be evaluated before (search goods, Pavlou et al. 2007) or at least after the transaction (experience goods; Dimoka et al. 2012). For the scenario of cloud services, that we characterize as credence goods because they can hardly be evaluated at any time, all three types of social influence processes play an important role in the perception of the service. The processes furthermore also influence the intention to use the service for prospect users and the continuance intentions for current users. However, our proposed cloud service relationship model and our empirical results indicate that the occurrence of the different social influence processes varies between potential and actual users.

Compliance processes do work on the shallowest level of all social influence processes. These processes do not alter the inner beliefs about the service but directly change the behavior aiming to receive a favorable reaction from peers. We find strong support for the impact of these processes on consumers' use of the service while the subjective norm does not influence users' uncertainty beliefs. This finding supports our argument that cloud services (credence goods) are fundamentally different from IT products (experience goods). For cloud services, individuals continue to rely on their peers because they cannot fully experience the quality of the service although they are already using it.

Internalization processes are driven by the urge to gaining knowledge about the cloud service. We find that these internalization processes are at work when potential users form beliefs about the uncertainty of the cloud service. Interestingly, their behavioral intentions are only influenced by positive information cues provided by peers while negative information is not fully internalized and does not directly influence their intended behavior. This is an interesting finding that is in line with other studies that find users discounting potential future losses (Acquisti and Grossklags 2005). For instance the privacy literature largely struggles to explain why users' awareness of potential future losses does influence their attitude but not their actual behavior (Jensen et al. 2005; Norberg et al. 2007). Potential explanations for this puzzle such as bounded rationality or the privacy calculus (Dinev and Hart 2006) may also be applicable to cloud services and thus, this interesting finding opens the stage for further research. Due to their nature as credence goods and the ongoing requirements for cues about the true quality of the service, internalization processes strongly shape the evaluation and behavior after the adoption of the service – as predicted by our theory.

Identification processes are in place when users try to become similar to their social peers. As expected, we find the strong influence of these processes for uncertainty beliefs to be diminished when individuals are already using the service. After the adoption has taken place, the identification process is completed and uncertainty beliefs are no longer affected by the behavior of peers. At the same time, levels of uncertainty are significantly lower among users compared to non-users confirming that beliefs of social peers have been adopted. Surprisingly, identification processes only indirectly influence behavioral intentions for people who are not yet using the cloud service. While identification processes reduce uncertainty beliefs, they are not strong enough to change consumers' decisions other than through the indirect process of influencing their beliefs.

Our control variables and paths provide evidence for the nomological validity of our study. First, our results confirm that users' perceived uncertainty is an important predictor of cloud use (Trenz et al. 2013). Second, our analysis reveals that continuance intention is influenced by the number of peers using the service. This is in line with network effect theory which may be another promising perspective to study user behavior in cloud service relationships (Shapiro and Varian 1999). Third, we find support that IT experience drives the adoption and use of innovative technologies. In line with Rogers' early adopter theory (Rogers 1962), more experienced users are early adopters of cloud services. Fourth, our results are consistent with previous studies on online service relationships (Dimoka et al. 2012; Pavlou et al. 2007) finding that signals are important predictors of uncertainty evaluation and subsequent behavior. We find that these relationships persist for cloud services, although social influence plays a more prominent role.

Theoretical Contribution

The cloud service relationship model aims at contributing to theoretical knowledge in three ways. First, we extend the understanding of online relationships between consumers and firms by being the first to study online relationships for credence goods. Cloud services can never be fully evaluated because the technological details and the provider's behavior are hidden from the consumer over the whole life-cycle of the cloud service relationship. We thereby extent previous online exchange relationship frameworks for search goods (Pavlou et al. 2007) and experience goods (Dimoka et al. 2012) to the most complex type of goods (Darby and Karni 1973). We show that uncertainty evaluations for these situations of continuous uncertainty are largely socially constructed and therefore require studying credence goods using different theories than the evaluation of other types of goods.

Second, we explain how social influence processes shape users' perceptions of cloud services and their behavior. Users of cloud services enjoy instantiations of exactly the same service. In contrast to e-commerce scenarios where buyers share their experiences almost anonymously over the providers' or third-party websites (Dimoka et al. 2012; Pavlou et al. 2007), users are strongly personally connected (through collaboration activities as well as social networks). Thus, cloud users are exposed to norms, behaviors and opinions of their social peers who may be using no, the same or a different cloud service. As we draw upon social influence theory (Kelman 1961)(Kelman 1961b), we are able to explain and predict how three types of social influence processes shape users' uncertainty evaluation of cloud services. The results indicate that social influence processes are strong predictors of users' beliefs and behaviors over and above the established concept of signals.

Third, we extent previous insights on social influence processes by investigating the occurrence of social influence processes at different stages of the lifecycle of the provider-user relationship. While previous studies have focused on the perceived locus of causality of social influence processes (Malhotra and Galletta 2005) or have solely looked into determining current use (Gallivan et al. 2005; Wang et al. 2013), we explicitly investigate the different social influence processes driving adoption and continuance decisions. In the case of cloud services, our theory indicates that identification processes only influence beliefs and behavior for the adoption, but not for the continuance decision. Thereby, we show that the occurrence of social influence processes varies conditional on the state of the consumer. As the importance of consumer retention increases and interactive exchange processes become more prevalent in many areas (Nitzan and Libai 2011), we expect that the perspective of stage-dependent social influence processes will also be of high value for other online exchange relationships, for instance in electronic or mobile commerce, or social networks.

Practical Contribution

Due to their growth potential, cloud markets are highly competitive. Accordingly, cloud computing providers need to understand why consumers start using cloud services. As cloud services require little up-front commitment, it is of even higher importance to understand why users would stay with their service. Our results have indicated that social influence processes largely shape users' uncertainty evaluation which, in turn, is crucial for their (continued) use of cloud services. This understanding of consumer's uncertainty evaluations is not only relevant for consumer-focused clouds services but reaches far into the enterprise sphere. Enterprise buyers have been found to be more and more mimicking consumers in their purchasing behavior (Avanade 2013). Further, many enterprise IT users start using their self-deployed IT services for solving business problems which they find more useful than the IT products provided by the company's IT function (Accenture 2011). This trend of consumerization and individualization of IT shifts the focus from institutional towards individual decisions (Baskerville 2011).

Our theoretical results can be translated into guidelines for managers being confronted with consumerization as well as managers of cloud services. Firms need to make use of social influence processes as means to keep the control over their IT landscape. Creating norms has been found to one effective mean to achieve that (Hu et al. 2012). Our results suggest that positive cues from peers regarding the firm infrastructure or communication of high levels of compliance as additional preventive measures. Regarding the former, individuals may for instance be enabled to share their positive experiences or approaches for solving business problems using the available infrastructure. These cues trigger internalization processes that evoke behaviors that are aligned with firm policies. After consumerization has taken place, primarily negative communication from peers can be used to trigger social influence processes that reduce continuance intentions. Managers of cloud services and entrepreneurs need to actively exploit social influence processes and incorporate their effects into their engagements with regards to social media, personal recommendation, electronic WOM and product reviews. Some cloud providers already implicitly use internalization processes by offering bonus storage space for direct recommendations. These positive messages from peers do not only increase the likelihood of adoption, they also mitigate potential uncertainty beliefs the prospect customer may have. In times where virtual social interactions are commonplace, the importance of controlling social influence processes cannot be overemphasized.

Limitations and Future Research

As every empirical study, our study suffers from a series of limitations that shall be disclosed. First, we chose cloud storage services as the empirical instantiation for testing our model. The major reason for this choice is the large number of users that enabled us to study a set of users that does not only consist of "early adopters". Further, cloud storage services share the typical characteristics of cloud services described above and are therefore an excellent representative of the class of cloud services we investigate. Nevertheless, cross-validation using different types of cloud services would be welcomed. Second, our sample consists of German internet users. As Germans may have a different disposition to privacy and security than other individuals, the results should not be generalized to other cultural settings. Instead, investigating cultural differences in cloud service relationships is an interesting opportunity for future research. Lastly, we investigate signals and social influences as two dynamics that both drive individuals' perceptions and behaviors. Incorporating the reinforcing or extenuating effects of social influences on the perception and processing of signals could be fruitful path to build upon and extent our cloud service relationship model.

Conclusion

The relationship between cloud services and their (prospective) users are characterized by a high level uncertainty. We develop and validate a cloud service relationship model that describes the impact of three social influence processes on the evaluation of cloud services and on individuals' behavior. As we theoretically evaluate in which phases of the provider-user relationship these social influence processes are triggered, we are able to characterize the impact of social influences on cloud service relationships before and after the initial adoption of the service. Based on a large representative sample, the empirical study provides strong evidence for the validity of the model and its explanatory power over and above signals provided by the transaction partner. Our theory offers researchers and practitioners new avenues for understanding and managing this emergent class of IT-based services.

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Appendix A: Measurement model

Use Intention (Hong et al. 2006; Karahanna et al. 1999)
I intend to use %cloud service% in the future. (USE1) I expect that I experiment with %cloud service% in the future. (USE2) I expect to use %cloud service% often in the future. (USE3) During the next six months, I plan to experiment with %cloud service%.*
Continued Use Intention (Use) (Bhattacherjee 2001)
I intend to continue rather than discontinue using [cloud service]. (USE1) My intentions are to continue rather than discontinue using [cloud service]. (USE2) If I could, I would like to continue my use of [cloud service] (USE3) I plan to discontinue using [cloud service] [reversed]*
Uncertainty (UNC) (Pavlou et al. 2007)
I feel that using [cloud service] involves uncertainty. (UNC1) I feel the uncertainty associated with using [cloud service] is high. (UNC2) I am exposed to many uncertainties if I am using [cloud service]. (UNC3) There is a high degree of uncertainty when using [cloud service]. (UNC4)
Positive Word-of-Mouth (PWOM) (Kim and Son 2009)
Others have said positive things about [cloud service] to me. (PWOM1) People whose I seek for advices have recommended [cloud service] to me. (PWOM2) My friends have referred me to [cloud service].* My friends and colleagues have encouraged me to use [cloud service]. (PWOM3)
Negative Word-of-Mouth (NWOM) (Blodgett et al. 1997)
My friends and relatives have cautioned against [cloud service]. (NWOM1) My friends and relatives have complained about [cloud service]. (NWOM2) My friends and relatives told me not to use [cloud service]. (NWOM3) Others have said negative things about [cloud service]. (NWOM4)
Peer Use (PUSE)
Many of my friends and colleagues use [cloud service]. (PUSE1) [Cloud service] is widely distributed among my friends and colleagues. (PUSE2) If friends and colleagues use a cloud storage service, than most of the time it is [cloud service]. (PUSE3) [Cloud service] is often used by my friends and colleagues for storing and exchanging data. (PUSE4)
Subjective Norm (SN)
My colleagues appreciate when I use [cloud service]. (SN1) My colleagues think that I should use [cloud service]. (SN2) My friends appreciate when I use [cloud service].* My superiors appreciate when I use [cloud service]. (SN3)
IT Service Diagnosticity (DIA) (Jiang and Benbasat 2007)
[Cloud service]'s website is helpful for me to evaluate the quality of the service. (DIA1) [Cloud service]'s website is helpful in familiarizing me with the service. (DIA2) [Cloud service]'s website is helpful for me to understand the performance of the service. (DIA3) I expect [cloud service]'s website to help me get a real feel for how the service operates. (DIA4)
Note: * Item has been dropped due to low factor loadings

Appendix B: Correlation Matrix and AVE

	USE	UNC	NWOM	PWOM	PUSE	SN	DIA
USE	**.92 / .90**						
UNC	-.17 / .15	**.92 / .88**					
NWOM	.001 / -.21	.28 / .38	**.85 / .82**				
PWOM	.153 / .12	-.16 / .-11	.36 /.08	**.89 / .79**			
PUSE	-.04 / .10	-.08 /.01	.14 / .07	.53 / .50	**.94 / .91**		
SN	.20 /.13	-.08 / .04	.15 / .03	.67 / .62	.57 / .55	**.93 / .91**	
DIA	.33 / -.14	-.12 / -.18	-.13 / -.15	.22 / .18	.20 / .19	.34 / .26	**.94 /.84**

Note: The diagonal elements (in bold) represent the square root of AVE;
Notation: Non-User Sample / User Sample.