Uncertainty in cloud service relationships: Uncovering the differential effect of three social influence processes on potential and current users

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1. Introduction

Continuous double-digit growth rates [1] and the expectation of doubling revenues of public cloud services until 2019 [2] have led to an immense competition between cloud providers for new customers. At the same time, cloud services are characterized by low up-front commitment [3], thus leading to longer payoff times for providers [4] and placing special emphasis on maintaining existing users with the service. Thus, motivating new users to join the service and maintaining existing ones are equally critical issues for cloud service providers [5].

The great benefits of novel cloud services for consumers—such as cloud storage, messaging, or other collaboration services—are widely touted. However, despite the potential benefits, consumer cloud services are characterized by a high uncertainty for potential users, for instance, with regard to privacy, security, and availability issues. The nature of cloud services as abstract instantiations of complex technological artifacts makes it difficult to overcome such uncertainties through signals send by the provider. More challenging, even individuals who have adopted the service still face uncertainties because the actual characteristics of the service cannot be fully evaluated by the users. Examples for service characteristics that are subject to continuous uncertainty are providers treatment of the data [6], security issues [7], or uncertainty about the availability of the data [8]. This uncertainty[1] makes many potential and actual consumers reluctant to fully engage in cloud service relationships, especially for personal data-intensive IT services [10]. Without an understanding of individuals' approach to such uncertainties, two orthogonal types of adverse consequences may arise. First, individuals may put their personal data at risk by simply ignoring the potential threats that come along with such services. Second, individuals may overemphasize those risks and hamper the success of innovative digital business models [11].

This study explores how potential and actual users of cloud services handle such uncertainty and when individuals start and continue using those services despite the limited possibilities to examine them. Research on online exchange relationships for products that can be evaluated either before [9] or after purchase [12] has focused primarily on relational factors such as trust and information signals. However, individuals can never fully assess whether cloud providers make information available to third parties without the users' consent, whether security breaches occur, and whether capacities are adequate to ensure availability in peak situations [13]. This aspect limits the effective evaluation of signals [14] and inhibits the formation of trust [15]. Hence, we believe that cloud users seek cues beyond provider signals to reveal the true qualities of the cloud service.

Where reliable information is missing, users value personal information [16,17] and rely on their social environment to form their evaluations [18]. As cloud users and their peers have similar experiences with the same highly standardized service and actively interact with each other (e.g., by sharing files), we argue that individuals facing such continuous uncertainty turn toward their social environment to

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[1] Uncertainty differs from risk. Risk is estimated with a priori calculable probabilities, whereas uncertainty deals with subjective probabilities [9]. 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 [9].

gain additional information to guide their uncertainty evaluation and behavior with regard to cloud services. Accordingly, we draw upon social influence theory [19] as a novel perspective for explaining individuals' uncertainty and their adoption or continuance behaviors. In contrast to many prior studies focusing on subjective norm as a proxy for social influence [e.g.,20,21], we respond to the call to apply social influence processes in their "rich and complex tapestry" [22] and distinguish between three social influence processes from social influence theory (identification, internalization, and compliance). Consequently, we theorize three types of social influence processes and investigate how these processes shape potential and current users' beliefs and behavior. In so doing, we aim to answer the following research question:

How do different social influence processes affect potential and current cloud users' uncertainty evaluation and behavior?

Our study aims to contribute to the literature on IT adoption and continuance by introducing a social influence perspective that takes the continuous uncertainty embedded in cloud services into account. We theoretically and empirically assess the differential influence of three social influence processes (internalization, identification, and compliance) on potential and actual users and thereby advance prior studies that have mostly reduced social influence to only comprise subjective norms (compliance) or focused on one user group. In the light of the high importance of uncertainties and social influence for cloud services, we provide practical guidance to managers of cloud services on which social cues should be facilitated by their service management and design for potential and for current users.

The remainder of this paper is structured as follows. First, we define and explain the core concepts and theoretical boundaries of our study. We then develop a framework for online service relationships for cloud services, which we call the cloud service relationship model. We subsequently empirically validate this model using two large samples of current and potential users of a cloud service and reflect our findings in the light of prior studies. We close by discussing implications for theory and practice.

2. Research foundations

2.1. The nature of consumer cloud services

Cloud computing is an evolution of IT service provisioning with respect to both the underlying technology and the business models for delivering IT-based solutions [23,24]. We define cloud computing as a virtualization-based style of computing where IT resources are offered in a highly scalable way as a cloud service over the Internet [3]. We focus on software-as-a-service solutions, applications running on a cloud infrastructure that is completely managed and controlled by the provider [25], where different customers share a common technical infrastructure and consumers have limited control over data, network, and security [26]. Cloud services are typically accessed through a web browser or a thin client instead of being deployed on the user's computer.

Consumer cloud services are highly standardized services provided to a crowd of cloud users. They can be evaluated on a multitude of attributes. Some of those attributes such as the usefulness or the ease of use of a service can be evaluated either beforehand or at the latest when using the service. However, this does not apply to all attributes of cloud services. As earlier research has shown, cloud users can never fully evaluate the true qualities of the service [13]. The technological abstraction of the service makes it hard (or impossible) for users to monitor the storage and processing of data, and the time lag until users recognize the actual level of service quality can be significant. For instance, the provider could neglect to take preventive security actions to save money or disguise security problems without notice by the user. Further, typical day-to-day use patterns do not push the boundaries of storage, service speed, or availability of supporting resources. Only an emergency would require users to access old versions of their files and to download large amounts of data in a short time frame. Unfortunately, failure in such extreme cases can be a watershed for consumers. Another aspect is user's privacy. The remote storage of the information makes it difficult for individuals to control or enforce access restrictions on their data or on the use of their behavioral data or "telemetry." Further, the provider might change its behavior or service level at any time, contributing to the ongoing uncertainty about those service attributes.

These arguments make apparent that cloud services exhibit a large number of credence attributes, defined as attributes that cannot be evaluated by a typical customer, as evaluation requires costly additional information that normally cannot be obtained economically [27]. Evaluating the technological capabilities of cloud services is already challenging for enterprises, but almost impossible for individual users [28]. In this regard, cloud services are similar to legal services or a surgical operation [29]. Besides credence attributes, the established classification for products and services also encompasses search and experience attributes [12,29]. Search attributes allow verification during the search process prior to purchase. They include price, appearance, and other physical properties of a product or a service environment. Experience attributes become apparent only after purchase or provision of service. Examples are the taste of food, the look of a new haircut, or the ease of use of an IT solution [12]. Most products or services have some search, experience, and credence attributes and can be classified as search, experience, or credence goods on the basis of the attributes that dominate the overall evaluation process (see Table 1). Due to the strong occurrence of credence attributes, cloud service can be best classified as credence goods. Consequently, uncertainty is not only much more prominent for such cloud services than for other IT products, but, as we argue in the following, typical uncertainty mitigators such as signals are also more difficult to verify—resulting in users leaning toward their social environment to form their decisions.

2.2. An uncertainty perspective on consumer cloud services

Most studies on cloud adoption and continuance focus on an organizational setting in which cloud-oriented decisions are often similar to

Table 1
Differences Between Cloud Services and Other Goods [based on 12,29].

	Search Goods	Experience Goods	Credence Goods
Quality appraisal	Can be evaluated before the transaction	Can be evaluated after the transaction	Can never be fully evaluated
Examples*	Clothing, chairs, computers	Used cars, haircuts, IT products	Medical treatments, cloud services
Uncertainty mitigators	Inspection, signals, belief in transaction partner	Signals, belief in transaction partner	Social influence processes
Examples of studies investigating such online service relationships	[30]	[9]	*This study*

Note: *Most products or services exhibit search, experience, and credence attributes. The classification as search, experience, or credence goods occurs on the basis of the attribute class that stands out.

IT outsourcing and service evaluation decisions [25,31]. Studies on individuals' adoption decisions have confirmed that the drivers in the technology acceptance model also hold in cloud settings [32,33]. Others have focused on very specific problems such as switching from hosted services to cloud solutions [33]. Although studies acknowledge a prominent role of uncertainties for non-users considering adoption [32,33] and also for current users [28], it remains unclear what mitigates individuals' uncertainties in their potential or current relationship with the cloud service.

Studies on uncertainty in IT adoption and use identified a broad number of organizational uncertainties. Studies on market or environmental uncertainties found that it can be an obstacle when adopting particular standards [34] or technologies [35–37]. Uncertainty can also refer to a lack of clarity regarding the benefits of a technology and hamper the adoption of electronic health records [38]. Further, uncertainties shape organizational adoption of e-procurement platforms [39], marketplaces [40–42], or interorganizational systems [43]. While uncertainty in those studies refers to relationships, environment, or technologies, uncertainty can also be embedded in tasks, processes, or project management [44–46]. Regarding cloud computing, one study investigates firms' uncertainty with cloud computing as an obstacle for organizational adoption [47]. Those studies confirm the importance of uncertainty for IT adoption and use in general; however, individuals' uncertainties have not received the same attention. A recent study on uncertainty in e-government adoption provides first insights on the importance of uncertainty for individuals and the challenges of uncertainty mitigation [48]. Considering the high complexity of individuals' technology today in general and the continuous uncertainty induced by cloud services in particular, it is surprising that very little attention has been paid to this area.

In contrast to studies on IT adoption and use, e-commerce literature has put more emphasis on uncertainty mitigation. Previous studies have examined why user uncertainties arise in online exchange relationships, how they are mitigated, and what their behavioral consequences are in different contexts. Consumer concerns and vulnerabilities in online exchange relationships mainly arise from information asymmetries between the provider and the user [9,30]. For e-commerce transactions, users' perceived seller- and product-related information asymmetries can be distinguished [9]. For services, the actions of the seller and the quality of the product are inextricably linked [25]. If user uncertainties are prevalent, vendors or providers offer signaling mechanisms, or cues, that reveal their true qualities [49], which can reduce information asymmetries between user and transaction partner. Cues may originate from three sources. *First-party information* is provided directly by the transaction partner (e.g., performance reports and trust-assuring arguments on the website) [50]. *Second-party information* originates from other transaction partners' experiences with the service (e.g., reputation and rating mechanisms) [51]. *Third-party information* provides independent verification of a transaction partner's quality by a quality assurance institution (e.g., third-party assurance seals) [49]. Several studies have investigated the correspondence between signaling investments and their evaluation by users [13,52]. Trusting beliefs with regard to the transaction partner significantly reduces consumers' uncertainty evaluation [30]. Moreover, research has empirically highlighted the behavioral consequences of consumers' uncertainty evaluation for a variety of e-commerce performance indicators, including paid price premium [9], purchasing decisions [30], and purchase conversion [49]. Interestingly, those studies have all focused on search and experience goods. 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: the cloud provider and the individual cloud user. Because of the emphasized role of credence attributes in cloud services, cloud service relationships can hardly be evaluated for their true quality by non-users [by searching for information,cf.,30] or current users [by experiencing the service, cf., 9]. Thus, a non-dissolvable level of uncertainty continues to shape the relationship between the provider and the user—a characteristic requiring investigation of both current and potential cloud service users. Further, in the evaluation process for credence goods, information provided by first and third parties (e.g., mass media) is well established as less valuable [14] than information from personal sources, which becomes more important as uncertainty increases [16,17]. In addition, a subset of the cloud user's social peers may maintain a cloud service relationship with the same cloud provider. Because cloud users are embedded in a social network, they can employ standardized interfaces to exchange information with their social peers if they use the same or a compatible cloud service [23]. Interaction with social peers is not only limited to the exchange of data using the service, but also shapes other social processes that influence users' beliefs and behavior with regard to a particular service.

We build upon these cloud specificities and extend established models of online service relationships in the context of cloud-based services. Our cloud service relationship model differs from those in previous investigations in two major ways. First, we extend the established view of service relationships by introducing social influence processes that can provide additional cues in situations of uncertainty and thereby shape individuals' beliefs and actions. This extension is motivated by the credence good characteristic of cloud services and the potential emphasis of social influences in handling their uncertainty [14]. To gain an in-depth understanding of social influences, we distinguish three types of social influence processes [53]. Second, our model describes uncertainties in online service relationships for non-users and for users of the service. Because the uncertainty involved in cloud services is not resolved by using the service, investigation of both current and potential consumers is necessary. Thereby, we are able to examine how the processes that shape online service relationships differ depending on the state of the individual.

2.3. Social influence theory

The nature of cloud services as credence goods suggests that cues from the social environment become more important [16,17]. Hence, we extend the established view of online service relationships by a social influence perspective. We build upon social influence theory as an underlying theoretical framework [19,53,54] to explain and predict how social influence processes affect users' uncertainty evaluation and their subsequent behavior.

Social influence theory was developed by Kelman [53] to explain how individuals' emotions, opinions, or behaviors are influenced by others. Two basic needs lead to the fact that people follow the opinions, behavior, or expectations of others [19]: the need to be right (informational social influence) and the need to be liked (normative social influence). *Informational social influence* leads to acceptance of information obtained from peers as evidence about reality. 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. In contrast to informational social influence, *normative social influences* lead to conformity to the expectations and behaviors of peers [19]. Kelman [53] built upon these two types of social influences to distinguish three social influence processes: internalization-, identification-, and compliance-based processes (see Table 2 for an overview).

The process of accepting information received from peers is called *internalization-based social influence* [53]. Positive or negative information that was received from peers is accepted if it is perceived to help solve a problem that the individual faces, for instance, reducing uncertainty about the environment [54]. Then, this information would be internalized and shape individual's beliefs and behavior. Normative social influence can be accomplished through either identification or compliance [54]. *Identification-based social influence* occurs when

Table 2
Underlying Framework: Social Influence Theory .

Type of Social Influence [19]	Social Influence Processes [53]	Goal of Cloud User	Empirically Observable Implications
Informational	Internalization	Gaining knowledge about reality	WOM influences beliefs and behaviors
Normative	Identification	Become similar to social peers	Peer adoption influences beliefs and behaviors
	Compliance	Gaining a favorable reaction from social peers	Subjective norm influences behaviors

individuals adopt beliefs and behavior of social peers because adoption yields a satisfying self-defining relationship to this group [53]. Individuals motivated to enhance their self-concept accept the influence of social peers and consequently identify with them by taking on their judgment and behavior, which they perceive as representative of their reference group [54]. Identification-based social influences mostly operate through non-verbal interaction, as individuals seek to believe and act in a manner similar as their peers [55]. *Compliance-based social influence* occurs if individuals conform to the expectations of others. It develops if individuals accept normative expectations from social peers because they hope to achieve a favorable reaction from them [20]. Thus, identification- and compliance-based social influence processes differ with respect to their goal orientation [54]. While via compliance individuals seek external rewards (i.e., a favorable reaction), via identification, individuals accept the influence because they seek to establish or maintain a positive relationship with their peers [53].

Most studies in information systems research have focused on compliance-based social influence processes that are triggered by subjective norms [e.g.,20,21]. Although subjective norms have been shown to be important in many IT adoption studies using the theory of planned behavior or the unified theory of acceptance and use of technology [e.g.,21,56], social influence can also be exerted by other means than compliance to perceived norms. We believe that distinguishing between different types of social influence can help to better explain and predict how social influences shape users' uncertainty evaluation and subsequent behavior in situations of continuous uncertainty such as cloud service relationships. We thus build upon the social influence theory framework [19,53,54] and apply it to cloud services.

2.4. Social influence processes and their observable implications

As a psychological process, social influence per se is not observable. However, beliefs and behavior may change depending on the individual's consideration or disregard of cues from the social environment. Thus, we discuss the three social influence processes and their observable implications that can be expected *if* a specific social influence process (internalization, identification, or compliance) occurs. Thereby, we outline *how* the occurrence of each social influence process affects uncertainty evaluation and behavior.

2.4.1. Internalization-based social influence

Internalization-based social influence processes refer to the individuals' need to be right [19]. To fulfill this need, individuals tend to accept information from others to facilitate problem solving or to cope with environmental uncertainty [54]. Opinions transmitted from social peers that speak in favor or against a service can be subsumed as word of mouth (WOM)—encompassing all informal communication between the consumer and its social peers concerning the evaluation of a service [57]. Such opinions influence how users evaluate a service [58]. Specifically, if peers have positive attitudes toward a service, an individual is likely to look favorably upon the service, which in turn will impact their own use [59]. In line with prior research [60], we therefore instantiate the influence of WOM on beliefs and behaviors as manifestation of the internalization-based social influence process.

While antecedents of WOM activities have been intensively studied in IS and marketing research [61–66], the consequences of WOM on individuals' evaluation of a product or a service have been widely neglected, especially from a social influence theory perspective [60]. WOM influence on consumers can be both positive and negative. While positive WOM of social peers about the cloud service mitigates users' concerns, negative WOM increases users' uncertainty perception. Because previous research has highlighted that in making evaluations users place different weights on these distinct influence processes [67], 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.

2.4.2. Identification-based social influence

Individuals are eager to build social capital, which makes them sensitive not only to what others say but also to what others do [22,68]. Identification-based social influence processes are triggered by nonverbal cues, which stem from the observation of peers' use patterns [22,69]. Identification with others leads to a reflection on the social anchorage of their behavior (e.g., whether to use the service). If identification-based processes occur, users tend to adopt beliefs and behavior of their reference group [54] to enhance a positive relationship with friends and colleagues: by "doing what [the other] does, believing what he believes, the individual maintains this relationship and the satisfying self-definition that it provides him" [53]. The self-defining relationship with peers is therefore enforced not only by adapting behaviors but also by adopting views of the social peers. Individuals can expect that their social peers would not adopt a service that they consider particularly uncertain. As a consequence, if many social peers of individuals have adopted the service, we will observe an adaption of their beliefs (in terms of lower levels of uncertainty) and their behavior (in terms of higher levels of behavioral intentions to adopt the cloud service).

2.4.3. Compliance-based social influence

Compliance-based social influence processes relate to the adherence to group expectations to gain a favorable reaction. They involve social pressures that arise from the urge to comply to peers' expectations. A large number of studies in IS research have investigated compliance-based social influence processes by looking at the influence of subjective norms—defined as an individual's "perception that most people who are important to him think he should or should not perform the behavior" [21]—and have established its influence on the use of IT products [21,59,70,71]. If individuals comply with subjective norms, their own evaluation of a service and the consequent behavior might not be well aligned because individuals act according to social norms rather than their own beliefs. Hence, subjective norms do not influence cloud users' uncertainty evaluation of the cloud service. By contrast, if compliance-based processes occur, individuals may adopt the cloud service because they hope to evoke a favorable reaction from others when they use the service [20].

2.5. Research model

Those empirically observable implications describe the anticipated effects *if* social influence processes are at work. To derive our hypotheses for users and non-users, we combine those implications with

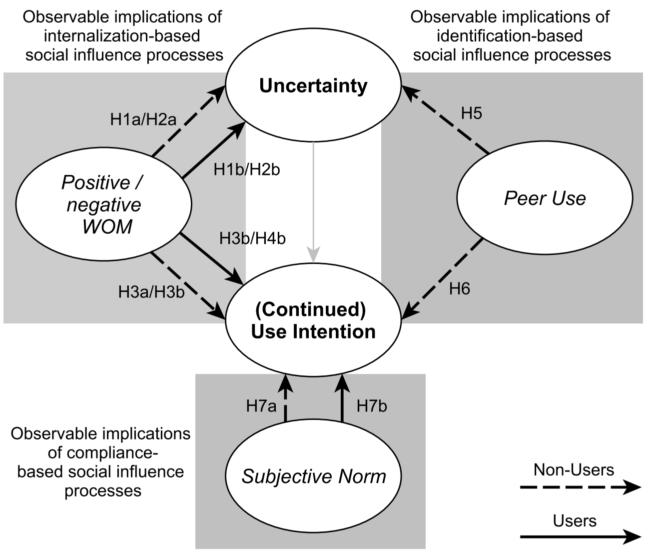

Fig. 1. Empirically Observable Implications of Social Influence Processes for Users and Non-users.

the subsequent analysis *whether* each of the social influence processes occurs for users, non-users or both. Not all social influence processes must occur at all times. Instead, they may be active in some circumstances but inactive in other situations. Previous studies focusing on compliance-based processes highlight that whether social influence processes occur may differ across the phases of the classical IT adoption process. On the one hand, empirical studies provide compelling evidence that subjective norms influence intention to use before individuals adopt an IT product [e.g.,21]. On the other hand, several studies highlight that subjective norms do not predict intention to use after adoption [72]. Consequently, the occurrence of the three social influence processes can depend on whether users have adopted the cloud service.

Internalization-based social influence processes occur for users and non-users of the service alike. In contrast to IT products, cloud services exhibit strong credence characteristics. Thus, the true quality of the service is not only uncertain to non-users, but assessing the storage and processing of the data or even the actual level of service quality in terms of availability and speed is difficult or impossible for current users as well [28]. Such situations cause individuals to accept positive and negative information from others [54] to mitigate their uncertainty and fulfill their need to be right in their decision making [19]. Hence, we hypothesize that non-users and users internalize cues from their social environment to shape their uncertainty evaluation and their behavior:

Hypothesis 1. Positive WOM decreases (a) *non-users'* and (b) *users'* uncertainty about the cloud service.

Hypothesis 2. Negative WOM increases (a) *non-users'* and (b) *users'* uncertainty about the cloud service.

Hypothesis 3. Positive WOM increases (a) *non-users'* and (b) *users'* intention to use the cloud service.

Hypothesis 4. Negative WOM decreases (a) *non-users'* and (b) *users'* intention to use the cloud service.

As discussed before, identification implies that individuals are eager to build a self-defining relationship with their social peers by adopting their beliefs and behavior. This process is triggered by the observation of peers' use patterns [22,69]. If individuals observe their peers to use a specific cloud service, identification would then lead to an adjustment of their uncertainty evaluation and their behavior, eventually leading to the adoption of the cloud service. Once individuals use the cloud service, they become similar to their relevant social groups in this regard, and adjustments could not enhance the positive self-defining relationship with friends and colleagues further. Accordingly, users have already completed the identification process and thus adopted the beliefs and behaviors of referent others. Hence, identification-based processes do only occur for non-users:

Hypothesis 5. Peer use decreases *non-users*' uncertainty about the cloud service.

Hypothesis 6. Peer use increases *non-users*' intention to use the cloud service.

Compliance-based social influence processes trigger behavior that is in line with perceived group norms. Individuals aim at gaining a favorable reaction from their social peers [20]. In contrast to reflections on a self-defining relationship to a group, compliance is the result of social pressures and therefore influences behavior rather than beliefs. Previous studies on experience goods indicate that subjective norms play a diminishing role for predicting use intention after the adoption of an IT product [70,71]. However, as credence goods, cloud services fundamentally differ from experience goods. If individuals can effectively experience and evaluate the product after the adoption, the influence of subjective norms may decrease once users experience the IT product. By contrast, for our scenario, subjective norms continue to influence the user's behavior because the qualities of the service can never be fully assessed by the user. At the same time, if others expect an individual to continue using the cloud service, non-compliance could hamper their interactions and therefore lead to unfavorable reactions. We thus hypothesize that compliance-based social influence processes affect users' and non-users' behavior similarly:

Hypothesis 7. Subjective norms increase (a) *non-users'* and (b) *users'* intention to use the cloud service.

Fig. 1 summarizes the expected observable implications of all three social influence processes for non-users and users and illustrates the resulting hypotheses in a research model.

Lastly, we introduce several control variables that allow us to test the nomological validity of our research model in the empirical evaluation:

Service diagnosticity refers to the degree to which users believe that a website provides them with useful information about the respective cloud service [73,74]. As service diagnosticity is a well-established information signal for safeguarding online exchange relationships [9,30], we control for its effects.

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

User demographics in terms of gender and age play an important role in understanding IT user acceptance [21]. Consequently, we add both as control variables on users' and non-users' uncertainty evaluation and use intention.

3. Research methodology

We tested the hypotheses using survey data collected through an online questionnaire administered to 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 the empirical setting because they share the typical characteristics of cloud services in that 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.

3.1. Measurement development

All measures came from existing measurement scales and were adapted to the context of our study. In light of criticism of the validation of scales [e.g.,75,76], we decided to revalidate our constructs. This process included using two sorting measures to establish the definition and assessment of the domain and dimensionality of the constructs [77] and using a rating method for the assessment of content validity [76,78]. We then pilot-tested the preliminary instrument with 235 participants. After the pretest, we asked the respondents to give an open feedback on the composition of the survey, overall time required, and any issues they experienced. Following the pretest, 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 appears in Appendix A.

3.2. Survey deployment and data collection

The final survey was conducted using a representative dataset of German Internet users. The online survey was well suited to address potential and actual users of cloud storage services because regular online access is a prerequisite for the use of such a service. According to AGOF, a German online research consortium, 53% of German Internet users are male and 47% are female. Moreover, Internet users are younger than the overall German population (9.5% are between 14 and 19, 18.7% between 20 and 29, 17.8% between 30 and 39, 22.6% between 40 and 49, and 16.8% 60 or older) [79]. We used the fine-grained distribution information from AGOF (incorporating different gender distributions within age sets) to deduce the requirements for collecting a representative sample of German Internet users. Following these requirements, a professional online panel sent out individual invitations to its members in the period between November 12, 2012, and December 9, 2012. The first page of the survey stated the definition of cloud storage services and asked participants which cloud storage service they use most. For users of cloud storage services (n = 1113), the survey was then automatically adjusted to address their interactions with this particular cloud storage service. If participants stated that they did not use a cloud storage service (n = 898), they were introduced to Dropbox—Germany's market-leading (as our study confirms) cloud storage provider—and were questioned about this service. Overall, 2011 valid responses were collected.

4. Data analysis and results

We employed covariance-based structural equation modeling (CBSEM using AMOS 22) to validate the structural model and test our hypotheses. We are therefore able to make use of the overall inferential test statistic that CBSEM provides and circumvent discourse about potential validity issues of PLS-based SEM [e.g.,80–84]. We validate the final measurement models for non-users and users separately, before employing a simultaneous estimation of the structural model to ensure comparability of the results.

4.1. Measurement validation

The final measurement models (see Appendix A) exhibited standardized factor loadings above the threshold value of 0.7, except for one item that is just below the threshold in the user sample. However, overall, the values as depicted in Table 3 suggest an adequate level of individual indicator validity and reliability across subsamples [85,86]. For constructs to be reliable, composite reliability must be higher than 0.7 [85,87]. In our model, all constructs reached composite reliability coefficients above 0.8. Validity at the construct level is assured because the latent constructs account for the majority of the variance in its indicators on average [76]. The average variance extracted (AVE) exceeds 0.6 for all constructs in both subsamples.

Discriminant validity of the constructs was confirmed by two methods. Fornell and Larcker [85] suggest that the square root of the average variance extracted for each construct is higher than the variance the construct shares with every other construct in the model. Every construct in both samples met this criterion (Appendix B). Furthermore, we conducted the between-constructs test recommended by Anderson and Gerbing [88]. We computed two chi-square statistics for each pair of constructs and compared one model with a free correlation between the constructs and one model where the correlation between the constructs was set to one (suggesting that the constructs are not distinct). The differences between the two chi-square statistics for each pair of constructs were highly significant ($\alpha < 0.01$), implying that the constructs are empirically distinct.

Because the data collection was based on a single survey, we applied recommended procedural and statistical remedies [89] to minimize and control for common method bias. We used a Harman one-factor test to test that neither one single factor emerged nor one factor accounted for more than 50% of the variance. Overall, six factors with eigenvalues above 1 emerged, explaining 83% of the variance. The most prominent component accounted for 39% of the variance. We also applied a marker variable procedure [90]. We used the smallest correlation in the correlation matrix as a proxy for the common method variance. However, the adjustment of the correlation matrix by this value did not change the statistical significance, indicating the absence of a common method bias. Finally, we included a latent general common method factor that was allowed to load on every item in our model [89]. The results suggested that common method was a very small contributor to variance. Overall, we can therefore rule out common method variance bias of the results of our study.

4.2. Structural model evaluation

The results of the structural model testing are presented in Fig. 2. The chi-square statistic is 1872.640 with 616° of freedom (χ^2/df = 3.040). In line with Hu and Bentler [91,92] and Gefen et al. [93], we used a combination of different goodness-of-fit and badness-of-fit tests to assess the model. Both GFI (0.937) and AGFI (0.917) were above the suggested threshold of 0.9 [94]. We also found that on average residuals were small [SRMR = 0.0267 < 0.05; see 91] and that the fit per degree of freedom was good [RMSEA = 0.032 < 0.05; see 95]. Finally, the normed fit (NFI = 0.964) and the comparative fit index (CFI = 0.975) exceeded even the strict cutoff value of 0.95 [91,96]. From these statistics, we can conclude that the overall model fits the data well. In the following, we present the path estimates and significance levels for non-users and users.

4.2.1. Non-users

For non-users, we find that the impact of perceived uncertainty (b = −0.165; $p < 0.001$) on intention to use the cloud service is significant. Both positive WOM (b = −0.158; $p < 0.001$; Hypothesis 1a) and negative WOM (b = 0.283; $p < 0.001$; Hypothesis 2a) significantly influence a user's uncertainty evaluation. As hypothesized, positive WOM influences intention to use the cloud service (b = 0.153; $p < 0.001$; Hypothesis 3a), but negative WOM does not (b = 0.001; $p > 0.05$; Hypothesis 4a). Peer use influences users' uncertainty evaluation (b = −0.082; $p < 0.05$; Hypothesis 5), but does not directly influence intention to use (b = −0.040; $p > 0.5$; Hypothesis 6), whereas subjective norm does (b = 0.196; $p < 0.001$; Hypothesis 7a). Service diagnosticity had a direct influence on both the evaluation (b = −0.122; $p < 0.001$) and the intention to use (b = 0.328; $p < 0.001$) 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.

Table 3
Measurement Model Results.

Constructs	Variable Name	Non-user			User		
		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)
	USE2	0.892		3.27 (2.02)	0.944		5.77 (1.40)
	USE3	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)
Positive 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)
Negative 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)

4.4.2. Users

For users, we find a significant impact of perceived uncertainty (b = −0.151; $p < 0.001$) on continuance intention. Moreover, both positive WOM (b = −0.113; $p < 0.05$; Hypothesis 1b) and negative WOM (b = 0.383; $p < 0.001$; Hypothesis 2b) have a significant influence on a user's uncertainty evaluation. As hypothesized, both also influence users' intention to continue using the cloud service (positive WOM: b = 0.115; $p < 0.01$; Hypothesis 3b, negative WOM: b = −0.209; $p < 0.001$; Hypothesis 4b). Peer use influences users' continuance intention (b = 0.095; $p < 0.01$). The same pattern can be observed for subjective norms. Subjective norms do not influence users' uncertainty evaluation (b = −0.036; $p > 0.05$) but affect users' intention to use the service (b = 0.125; $p < 0.05$; Hypothesis 7b). Service diagnosticity had a direct influence on both evaluation (b = −0.179; $p < 0.001$) and intention to continue using the cloud service (b = 0.138; $p < 0.001$). The other control variables (age, gender, Internet experience) had no significant influence on the dependent variables. Overall, our findings provide strong support for our

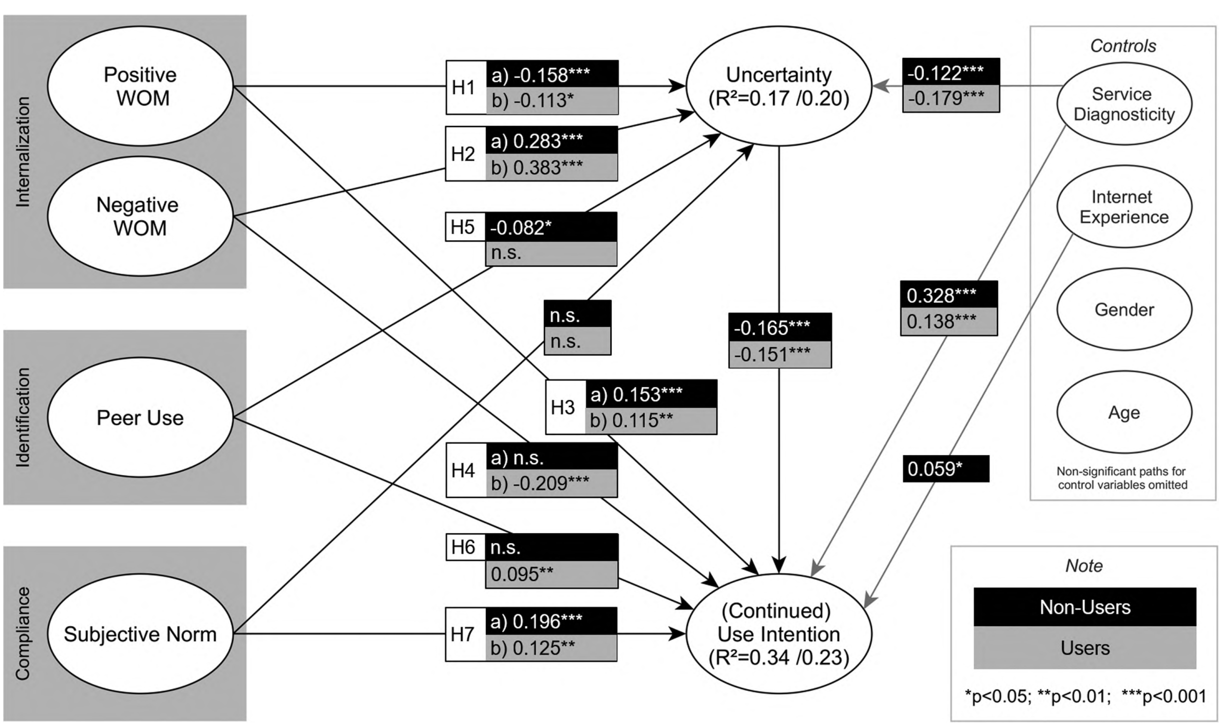

Fig. 2. Structural Model Evaluation.

Table 4
Overview of Tested Hypotheses.

Hypothesis	Postulated Relationship	Sample	Support	Path Coefficient
H1a	Positive WOM $\rightarrow^{-}$ Uncertainty	Non-users	YES	-0.158^{***}
H1b	Positive WOM $\rightarrow^{-}$ Uncertainty	Users	YES	-0.113^{*}
H2a	Negative WOM $\rightarrow^{+}$ Uncertainty	Non-users	YES	0.293^{***}
H2b	Negative WOM $\rightarrow^{+}$ Uncertainty	Users	YES	0.383^{***}
H3a	Positive WOM $\rightarrow^{+}$ Use intention	Non-users	YES	0.153^{***}
H3b	Positive WOM $\rightarrow^{+}$ Use intention	Users	YES	0.115^{**}
H4a	Negative WOM $\rightarrow^{-}$ Use intention	Non-users	NO	0.001(ns)
H4b	Negative WOM $\rightarrow^{-}$ Use intention	Users	YES	-0.209^{***}
H5	Peer use $\rightarrow^{-}$ Uncertainty	Non-users	YES	-0.082^{*}
H6	Peer use $\rightarrow^{+}$ Use intention	Non-users	NO	-0.040(ns)
H7a	Subjective norm $\rightarrow^{+}$ Use intention	Non-users	YES	0.196^{***}
H7b	Subjective norm $\rightarrow^{+}$ Use intention	Users	YES	0.125^{*}

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

cloud service relationship model for users. An overview on the results for the different hypotheses tests is given in Table 4.

5. Discussion

In line with past studies on search goods [30] and experience goods [9], first-party signals are effective to mitigate the continuous uncertainties occurring in service relationships for cloud services. We characterize cloud services as credence goods because they can hardly be evaluated at any time. In this context, we argue that such signals are not the most effective mitigators of uncertainty, and instead, personal information cues become more prominent. We find empirical support for our theoretical argument for social influence theory as a perspective for studying cloud service relationships. Results confirm most of the hypotheses beyond the established measure of signals used in previous studies. Further, by applying social influence theory, we distinguished three types of social influence processes, and our results suggest that all three process types play an important role in the perception of the service. Social influence also affects prospective users' intention to use and current users' intention to continue use. The fact that the occurrence of the three social influence processes varies between potential and actual users underscores the importance of (a) moving beyond a single dimension for social influence and (b) distinguishing between individuals in different states when studying the induced uncertainty.

Of the three social influence processes, compliance processes have been frequently studied and characterized as the influence of subjective norms. Those studies suggest that subjective norms play an important role before the start of using an IT product, but less so afterwards [70,71]. However, in contrast to the IT products investigated in the literature, individuals cannot evaluate and experience all characteristics of the cloud service even after adoption. In accordance with our theoretical model, we find that compliance-based social influence persists with the use of cloud services. Our study also provides empirical evidence for the way that compliance processes work. Social influence theory suggests that compliance processes do not alter inner beliefs about the service but directly change behavior for the purpose of receiving a favorable reaction from peers [54]. Our results resonate with these theoretical considerations: subjective norms do not influence users' uncertainty beliefs, but only their behavior. As a result, we find support for the general mechanics of compliance-based social influence processes, but for cloud services, compliance-based processes not only take place before adoption but also shape users' interactions with the service.

The other two social influence processes—internalization and identification—have received less research attention. Internalization processes are driven by the urge to gain knowledge about the cloud service [57]. In line with previous studies, we find that opinions of social peers influence users' evaluation of the service [58], particularly when potential users form beliefs about cloud service uncertainty. To gain a more fine-grained understanding of the informal influence of those opinions, we distinguished between peers' positive and negative cues. Interestingly, behavioral intentions are influenced only by positive information cues, while negative information is not fully internalized and does not directly influence intended behavior. This interesting finding is in line with other studies that find users discounting potential future losses [97]. For instance, the privacy literature largely struggles to explain why users' awareness of potential future losses influences their attitude but not their actual behavior [98,99]. Potential explanations for this puzzle, such as bounded rationality or the privacy calculus [100], may also be applicable to cloud services, opening the way for further research. Owing to cloud services' nature as credence goods and ongoing requirements for cues about the true quality of the service, internalization processes strongly shape the evaluation and behavior of current users of the service—as predicted by our theory.

Finally, identification processes are in place when users try to become similar to their social peers. Identification is driven by non-verbal cues that stem from the observation of others' use patterns [22,69]. As expected, we find that the strong influence of these processes for uncertainty beliefs diminishes when individuals are already using the service. Once internalized, a belief is separated from the original source, and uncertainty beliefs are no longer affected by the behavior of peers. In this regard, our results deviate from recent findings in the work context and support the notion that patterns of social influence differ between contexts [22]. In the case of services with continuous uncertainty, we find that users' levels of uncertainty are significantly lower than those of non-users—suggesting that the behavior of social peers has shaped individuals' beliefs. 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.

The 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 [13]. Second, our analysis reveals that continuance intention is influenced by the number of peers using the service. This result is in line with network effect theory, which may be another promising perspective to study user behavior in cloud service relationships [101]. Third, we find support that IT experience drives the adoption and use of innovative technologies, as more experienced users are early adopters of cloud services [102]. Fourth, our results are consistent with previous studies of online service relationships, finding that signals are important predictors of uncertainty evaluation and subsequent behavior [9,30]. These relationships persist for cloud services, although social influence plays a more prominent role.

5.1. Theoretical contribution

The cloud service relationship model aims at contributing to theoretical knowledge in three ways. First, we contribute to IT adoption and use literature by introducing a social influence perspective on those phenomena. While the drivers of existing technology acceptance models and continuance models have been validated in the context of cloud services [e.g.,25,32,33], those models are mostly based on evaluative criteria of the product or the service. With technological details and the provider's behavior hidden from the consumer over the life cycle of the cloud service relationship, such evaluations are characterized by an increased uncertainty. Because information acquisition from personal sources becomes more important as uncertainty increases [16,17], we theorized about the importance of social influence in the evaluation process for cloud services. In contrast to e-commerce scenarios where buyers share their experiences almost anonymously over the providers' or third-party websites [9,30], users are strongly personally connected through collaboration activities and 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. We therefore build upon prior studies on online service relationships [9,30] and develop a cloud service relationship model of cloud service adoption and continuance. The tested cloud service relationship model suggests that individuals' adoption or continuance decisions in the context of cloud services are characterized by a continuous uncertainty and that those uncertainty evaluations are largely socially constructed.

Second, we explain how social influence processes shape users' perceptions of cloud services and their behavior. The strong focus on subjective norms as conceptualization and operationalization of social influence in information systems research [20,21] may lead to an emphasis of compliance-based social influence while not capturing identification and internalization processes [22,58]. Our study relies on the original conceptualizations of social influence [19,53,54] and thereby uncovers a more distinguished picture of social influence processes in the context of cloud services. Results indicate that all the three social influence processes are strong predictors of individuals' beliefs and behaviors over and above the established concept of signals. The analysis reveals the complexity of social influence processes that comprise more than just subjective norms.

Third, we extend previous insights on social influence processes by investigating the occurrence of social influence processes for potential and actual users. While previous studies have focused on the perceived locus of causality of social influence processes [58] or have solely looked into determining current use [22,103], we explicitly investigate the different social influence processes driving adoption and continuance decisions. In the case of cloud services, our study indicates that identification processes influence beliefs and behavior for the adoption decision but not for the continuance decision. Thereby, we show that the occurrence of social influence processes varies depending on the stage of the consumer. As the importance of consumer retention increases and interactive exchange processes become more prevalent in many areas [104], we expect that differentiating between social influence processes for adoption and continuance decisions will also be of high value for other online exchange relationships, for instance, in electronic or mobile commerce or social networks.

5.2. Practical contribution

The continuous uncertainties embedded in cloud services may lead to adverse consequences for cloud providers because individuals may overemphasize those risks and hamper their success. Our study provides insights into the social influence processes that largely shape individuals' uncertainty evaluation and into when individuals start and continue using those services despite their inability to examine them. Thus, cloud providers should try to facilitate social influence processes that are most effective in mitigating this uncertainty and influencing their decisions to start or continue using the service.

In the competitive cloud markets, understanding and managing individuals' reluctance to employ cloud services can present a competitive advantage. Potential customers were found to react particularly strongly to subjective norms. Thus, the service design should aim to make the transmission of such normative cues easy, e.g., by incentivizing users' sharing invitations with non-users to convey the unspoken expectation that the service should be used. In addition to sharing and inducting norms, positive recommendations should be incentivized. Some cloud providers already implicitly use internalization processes by offering bonus storage space for direct recommendations. These positive messages from peers not only increase the likelihood of adoption but also mitigate potential uncertainty beliefs that prospective customers may have. Managers particularly concerned with uncertainty surrounding their service offering can also exploit identification-based processes by providing information on the number of users in an individuals' peer group, either on a more general level (e.g., "95% of [your social group] use our service") or more directly by matching social network or address book data (with permission).

As cloud services require little up-front commitment, understanding why users would stay with their current service is of even higher importance. Standardized consumer cloud services are often reluctant to offer communication channels for direct contact. However, our results indicate that negative communication from peers can trigger social influence processes that reduce continuance intentions. In the light of their strong influence, managers should consider changing this policy and try to incentivize a direct feedback on negative experiences to be able to mitigate them before they are shared with peers via social media, personal recommendations, electronic WOM, and product reviews. If the uncertainty perceptions cannot be mitigated, managers can also try to stimulate the perception of subjective norms to enforce continuance.

The understanding of consumers' uncertainty evaluations is not only relevant for consumer-focused cloud services but reaches far into the enterprise sphere. Many enterprise IT users have begun to use their self-deployed IT services to solve business problems, as they find self-deployed services to be more useful than the IT products provided by the company's IT function [105]. IT managers can actively exploit social influence processes as a way of maintaining control over their IT landscape and preventing behavior that puts data at risk.

5.3. Limitations and future research

Like all empirical research, our study has limitations. First, we chose cloud storage services 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 consisting of more than just selected early adopters. Further, cloud storage services share the typical characteristics of cloud services 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, who may have a different disposition to privacy and security than individuals in other cultural settings. Therefore, investigating cultural differences in cloud service relationships is an interesting opportunity for future research. Third, we observe lower uncertainty levels for users than for non-users. This indicates that—as expected—some characteristics of cloud services such as their ease of use can be evaluated during usage. At the same time, our cloud service relationship model explains less variance for users of the service than for non-users. One explanation is the absence of identification-based social influence processes among users. However, it could also be that performative characteristics of the cloud service become more prominent in continuance decisions.[2] Future studies could therefore compare the importance of different evaluation criteria between users and

[2] We thank an anonymous reviewer for this interesting idea.

non-users. Finally, we investigate signals and social influences as two dynamics that drive individuals' perceptions and behaviors. Incorporating the reinforcing or extenuating effects of social influences on the perception and processing of signals could be a fruitful path to build upon and extend our cloud service relationship model.

6. Conclusion

The relationship between cloud services and their current and prospective users is characterized by high 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 for users and non-users of the service. Drawing on a large representative sample, this 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.

Appendix A

See Table A1.

Table A1
Measurement Model.

Use Intention (USE) [72,106]
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) [107]
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) [30]
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) [108]
Others have said positive things about [cloud service] to me. (PWOM1)
People whose advice I seek 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) [109]
My friends and colleagues have cautioned against [cloud service]. (NWOM1)
My friends and colleagues have complained about [cloud service]. (NWOM2)
My friends and colleagues told me not to use [cloud service]. (NWOM3)
Others have said negative things about [cloud service]. (NWOM4)
Peer Use (PUSE) [110]
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, then 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) [111]
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) [73]
[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 was dropped owing to low factor loadings.

Appendix B

See Table B1.

Table B1
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	.15 / .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.

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