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**Online Serendipity:
A Contextual Differentiation of Antecedents and Outcomes**

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Abstract

Critics worry that algorithmic filtering could lead to overly polished, homogeneous web experiences. “Serendipity”, in turn, has been touted as an antidote. Yet, the desirability of serendipity could vary by context, as users may be more or less receptive depending on the services they employ. We propose a nomological model of online serendipity experiences, conceptualizing both cognitive and behavioral antecedents. Based on a survey of 1,173 German Internet users, we conduct structural equation modeling and multi group analyses to differentiate the antecedents and effects of serendipity across three distinct contexts: online shopping, information services and social networking sites. Our findings confirm that antecedents and outcomes of digital serendipity vary by context, with serendipity only being associated with user satisfaction in the context of social network sites.

Keywords: serendipity, social media, online-shopping, social network sites, search, affordances

Online Serendipity:

A Contextual Differentiation of Antecedents and Outcomes

Introduction

In recent years, Internet users could access and consume an ever-increasing wealth of information through news sites, blogs, video platforms, social network sites, search engines, and many other online services. Social media facilitate the creation and sharing of a tremendous variety of content. Through mobile devices, Internet users can access this ever-growing abundance of information anywhere and anytime. As a result, both service providers and researchers are exploring techniques to harness the potential of “big data” while filtering and selecting relevant information to avoid information overload (Mayer-Schönberger & Cukier, 2013).

An interesting paradox emerges: The increasing abundance of potentially available information on the Internet necessitates increasingly restrictive selection mechanisms on the part of users. Thereby, (over)abundance might lead to a net decrease, instead of an actual increase in the variety of Internet users’ information diet (Hoffmann, Lutz, Meckel, & Ranzini, 2015). The volume of global IT traffic is estimated to be 1.1 zettabytes in 2016, which corresponds to 1.1 trillion gigabytes (Cisco Visual Networking Index, 2015); as of early 2016, there were more than 47 billion webpages indexed by Google (Worldwidewebsite, 2016). To navigate this wealth of data, services like social networks and search engines employ algorithms to identify relevant content – and filter out irrelevant content, thereby unavoidably shaping user experiences (Elberse, 2008; He, Patel, Zhang, & Chen-Chuan, 2007; Introna & Nissenbaum, 2000; Lawrence & Giles, 1999).

Many filter algorithms are based on the notion of *homophily*. Users are connected with similar, like-minded users; content is filtered based on users' previous choices (Pariser, 2011). Content selection based on homophily is assumed to reinforce existing opinions, preferences and convictions, gradually removing conflicting views (Baum & Groeling, 2008; Bennett & Iyengar, 2008; Lazarsfeld & Merton, 1954). Therefore, personalized web experiences, based on algorithmic filtering, may increase convenience at the cost of diversity, variety, choice, and surprise. The concept of "serendipity", in turn, has been heralded as an antidote to ever more filtered-down, homogeneous, redundant web experiences.

Serendipity was defined as "*an unexpected experience prompted by an individual's valuable interaction with ideas, information, objects, or phenomena.*" (McCay-Peet, 2013b, p. 11). Serendipity has been heavily associated with information and library science (Erdelez, 2004; Makri & Blandford, 2012), particularly focusing on information acquisition (Foster & Ford, 2003; Martin & Quan-Haase, 2013; Quan-Haase & McCay-Peet, 2014). While algorithmic filtering based on homophily is frequently seen as a threat to online serendipity (Meckel, 2012; Gup, 1997; Pariser, 2011), social networking may also facilitate serendipity by supporting weak ties and extending personal networks (Dantonio, Makri, & Blandford, 2013; Eagle & Pentland, 2004).

Serendipity is, by definition, a beneficial phenomenon. Given that algorithmic filtering based on homophily is held to reduce serendipity experiences, online services may be faced with the difficult challenge of balancing convenience benefits against serendipity benefits. Given this conundrum, authors have called for a contextual differentiation of our understanding of serendipity (McCay-Peet, 2013b). The benefits of serendipity experiences may be more or less salient depending on the online service in question. In other words: Not all online services may be faced with the same imperative to avoid homogeneity and redundancy of content to allow for "unexpected experiences".

As most studies on serendipity have been conceptual in nature (Van Ansel, 1994) or have employed qualitative, small sample approaches (Erdelez, 2004; Makri & Blandford, 2012) or content analyses (Bogers & Björneborn, 2013; Rubin, Burkell, & Quan-Haase, 2011), little is known about users' evaluation of serendipity in different contexts. To fill this research gap, we propose a nomological model of online serendipity. We will test this model and differentiate effects across three distinct contexts: social network sites (SNS), online shopping, and information services. Our analysis is based on a survey of 1,173 Internet users in Germany. It is the first to use a thoroughly developed measure of serendipity experience (McCay-Peet, 2013a) for a large sample outside of North America. The study sheds light on the complex interplay of serendipity, satisfaction with personal web experiences, and a range of antecedent conditions deemed relevant in the online context.

Theoretical Background

Online Serendipity

Largely ignored when first coined by Horace Walpole in 1754, the concept of “serendipity” gained popularity in the mid-1900s when it was applied to various breakthroughs in scientific research (Barber & Fox, 1958). Since then, more and more references to serendipity have appeared in popular culture – it was even voted “UK’s favorite word” in 2000 (Rubin et al., 2011). Public and scholarly interest in serendipity, and the causes and applications of serendipity experiences, has been growing ever since. The importance of serendipity for scientific discoveries has variously been recognized: penicillin, the planet Uranus and, in more recent times, the Rosetta Stone language service were all coincidental byproducts of research projects aimed at very different objectives. They originated from chance encounters resulting in serendipitous outcomes (André, Teevan, & Dumais, 2009; Dantonio, 2010).

Early on, authors recognized that serendipity is contingent upon the readiness of those involved: Horace Walpole used the term “accidental sagacity” (cf. Remer, 1965) to describe a person’s ability to understand the value of a result found by chance. For Erdelez (2004), serendipity requires a specific “forma mentis” for a person to be able to recognize the value of random encounters in the process of information search. Similarly, Makri and Blandford (2012) argue that, aside from unexpectedness, serendipity also requires an element of “insight”; in their sample of interviews on inspirational random encounters, “none were deemed to be entirely due to ‘blind luck’”. In other words, serendipity is unlikely to occur without those involved being open to or ready for it. To date, though, the mental “readiness” of users necessary to experience serendipity has not been operationalized and explored empirically.

Different *process models of serendipity* have been proposed (McCay-Peet, 2013b). In discussing three such models, Quan-Haase and McCay-Peet (2014) note that “they vary considerably in their focus and key assumptions” (p. 140). Erdelez’ (2004) model focuses on the process elements such as noticing, stopping, examining, capturing, and returning. Rubin et al. (2011) employ a grounded theory approach based on blogs. They propose four facets constituting a serendipity process: prepared mind, noticing, chance, and fortuitous outcome. Finally, Makri and Blandford (2012, p. 697) propose a model that “describes the experience as a mental connection between an informational or non-informational need and a thing with the potential to address the need, which results in an idea that has the potential to lead to a valuable outcome” (Makri & Blandford, 2012, p. 697). In sum, the available process models of serendipity all suppose a form of cognitive or mental readiness to experience serendipity, but do little to clarify elements of characteristics of this readiness.

In the context of Internet use, serendipity has primarily been discussed in relation to personalized search and algorithmic filtering (Pariser, 2011), where serendipity was proposed as an antidote to a narrow, predetermined overly homogeneous or redundant web experience

(André, Schraefel, Teevan, & Dumais, 2009). Accordingly, serendipity could lead to a more diverse and satisfying web experience for users (Hoffmann et al., 2015). Today, we find conflicting views on whether the Internet facilitates or limits serendipity (Cunha, Clegg, & Mendonça, 2010; McBirnie, 2008; Deschamps, 1996; Snowden, 2003). On the one hand, increasing personalization and algorithmic filtering could decrease serendipity and lead to a limited, predictable online experience (Pariser, 2011). On the other hand, social media could act as a driver of serendipitous encounters, because personal bonds can inspire ideas and steer individuals towards new topics (André, Schraefel et al., 2009; André, Teevan et al., 2009; Dantonio et al., 2013; Eagle & Pentland, 2004). That is, unless the composition of personal networks are not themselves determined by homophily-based algorithmic filtering.

Despite recent advances in the study of serendipity, important research gaps remain (McCay-Peet, 2013b; Quan-Haase, 2013): As of today, little is known about the mental or cognitive *antecedents* of serendipity experiences. Rubin et al. (2011) and McCay-Peet (2013b) have proposed several drivers in that regard, for example prior need, background knowledge, personality traits (agreeableness, openness, extraversion), locus of control and creativity. However, few empirical studies on those antecedents exist. Furthermore, the role of the online *context* in creating a serendipitous experience has not been thoroughly investigated. Despite the fact that online serendipity is assumed to be context-specific, little attention has been devoted to differentiating web environments according to how much users appreciate serendipity in that surrounding. As a notable exception, McCay-Peet, Toms and Kelloway (2015) assess the effect of both individual and contextual characteristics on the serendipity experience, using an online survey with 289 participants. They include openness to experience, extraversion and locus of control as individual characteristics and four contextual variables to describe the digital environment (connection-enabling, trigger-highlighting, trigger-rich, and leading to the unexpected). According to their findings, contextual characteristics explain

serendipity experiences more strongly than individual characteristics, which have little explanatory power.

To analyze the contextual nature of online serendipity and its effect on service satisfaction, we first derive a nomological model of serendipity experiences focusing on cognitive antecedents.

Antecedents of Online Serendipity Experiences

This segment will develop a model of online serendipity to address the research gaps identified above. The model includes cognitive antecedents previously described as a required mental readiness to experience serendipity on the Internet (Figure 1). This model will then be tested in the context of different online services.

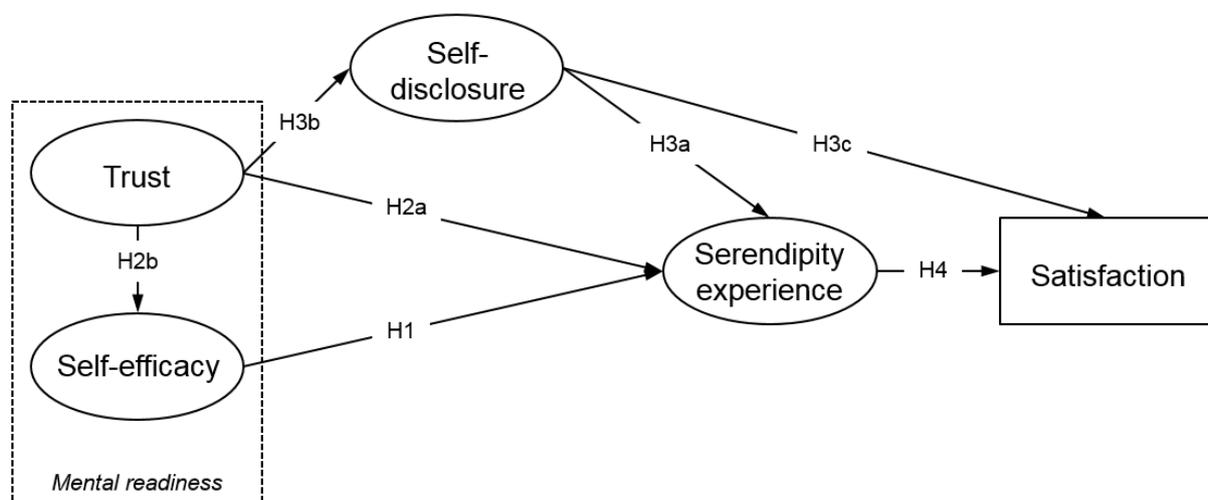


Figure 1: Baseline research model

First, we propose that users' Internet self-efficacy increases their ability to experience serendipity. The concept of self-efficacy is derived from social cognitive theory and describes "the belief in one's capability to organize and execute the courses of action required to manage

prospective situations” (Bandura 1977, p. 2). In the context of online media, self-efficacy encompasses users’ ability to use the medium according to their wishes or preferences (Corbitt, Thanasankit, & Yi, 2003; McKnight, Choudhury, & Kacmar, 2002; Shankar, Urban, & Sultan, 2002). We propose Internet self-efficacy as one element of the “forma mentis” necessary for users to experience serendipity on the Internet (Erdelez, 2004). Self-efficacy describes a form of confidence in one’s ability. Users with high levels of Internet self-efficacy should thereby be expected to feel more capable to find serendipity experiences when desired. Internet self-efficacy has been linked to more directed and successful Internet use (Tsai & Tsai, 2003). Moreover, Internet self-efficacy may lead to more confident, explorative and experimental Internet uses, such as openness for new, unfamiliar services (cf., Eastin & LaRose, 2000; Hsu & Chiu, 2004), which should also increase the likelihood of serendipity experiences.

Today, filtering mechanisms are deeply ingrained in many online services. Therefore, it requires a certain level of competence to circumvent their selection effects. In the context of Facebook privacy settings, for example, studies have shown that some users experience substantial difficulties in adjusting their settings according to their preferences (Liu, Gummadi, Krishnamurthy, & Mislove, 2011; Madejski, Johnson, & Bellovin, 2012; Netter, Riesner, Weber, & Pernul, 2013). Internet users with higher levels of self-efficacy, instead, take better control of their personal privacy and security settings (Bawden, 2001; Bawden & Robinson, 2008; Bundy, 2004; Eshet-Alkalai, 2004; Gilster, 1997; Lankshear & Knobel, 2008). These findings affirm that self-efficacy should contribute to users’ ability to confidently explore new and surprising experiences on the Internet.

H1: The higher users’ Internet self-efficacy, the more likely they are to experience serendipity.

As a second cognitive antecedent, we propose that users’ online trust increases their likelihood of experiencing serendipity online. To allow for various service contexts, our model will focus

on general Internet trust, or institution-based trust, rather than trust in a specific provider (trusting beliefs). McKnight and colleagues (2002, p. 339) define institution-based trust as users' "belief that needed structural conditions are present (e.g., in the Internet) to enhance the probability of achieving a successful outcome" through their Internet use. Online trust should facilitate a more open-minded, less fearful or restricted use of the Internet. Such an attitude is akin to Walpole's notion of "accidental sagacity", the willingness to be open to new and surprising encounters. Trusting Internet users should be more willing to venture beyond the pre-defined offerings and processes of online services and explore alternatives (Büttner & Göritz, 2008).

H2a: The higher users' online trust, the more likely they are to experience serendipity.

We propose that both elements of users' mental readiness to experience serendipity on the Internet are related. Social cognitive theory suggests that cognitive dispositions are affected by behavior (Bandura, 1977). Accordingly, Internet use experiences are likely to shape attitudes towards the Internet. As more trusting Internet users are more comfortable with the medium, they should (1) more avidly use the Internet, and (2) be more open to diverse use experiences online – both, in turn, facilitating higher levels of Internet self-efficacy (Hsu, Ju, Yen, & Chang, 2007).

H2b: The higher users' online trust, the higher their levels of Internet self-efficacy

So far, we have argued that Internet self-efficacy and trust constitute elements of a mental readiness for online serendipity experiences ("forma mentis") because they allow users to more readily take in, or expose themselves to surprising and challenging online information. Such a view may paint an overly passive picture of Internet users and their influence over serendipity

experiences, though. We therefore complement our research model by incorporating a behavioral mediator that accounts for users' active role in encountering online serendipity: online self-disclosure. A certain level of self-disclosure, the provision of some personal data, is a prerequisite for the use of most online services (Hoffman, Novak, & Peralta, 1999; McKnight et al., 2002; Sheehan & Hoy, 2000). In fact, it would be difficult to use online services without revealing at least some personal information (Rust, Kannan, & Peng, 2002, p. 455).

We propose a positive effect of self-disclosure on online serendipity because providing personal information to online services allows for richer web experiences, thereby enhancing the likelihood of serendipitous encounters. Examinations of serendipity in an offline context have stressed the importance of social interactions for serendipity experiences (e.g., Brown, Efstratiou, Leontiadis, Quercia, & Mascolo, 2014). Applied to the online context, higher levels of online self-disclosure can be assumed to facilitate social connections and exchange on the Internet (e.g., in social media). Such online interactions can trigger serendipity experiences. Accordingly, Internet users do not merely passively peruse information provided by online services. Through their behavior, their active provision or publication of data, they can enhance their chance of experiencing serendipity online.

Given previous research on online trust and privacy concerns, we propose that online trust facilitates online self-disclosure (Joinson, Reips, Buchanan, & Schofield, 2010). Lastly, we propose a positive direct effect of self-disclosure on user satisfaction, as self-disclosure is frequently a precondition for reaping the benefits of online services.

H3a: The higher users' level of online self-disclosure, the more likely they are to experience serendipity.

H3b: The higher users' online trust, the higher their levels of online self-disclosure.

H3b: The higher users' level of online self-disclosure, the higher their satisfaction with the online service.

Finally, we propose a positive effect of serendipity experiences on users' satisfaction with online services. As there is very little research on the matter, it is difficult to substantiate this proposition by previous findings. Yet, the literature on serendipity overall conceptualizes it as a positive, desirable experience (André, Teevan et al., 2009; Budd, 1989; Martin & Quan-Haase, 2014). Therefore, a higher level of serendipity experience should be associated with a positive overall evaluation of the services employed.

H4: The higher users' serendipity experiences, the more satisfied they are with an online service.

Online Contexts: Online Shopping, Social Network Sites and Information Services

Most studies on online serendipity have focused on information acquisition in a search context (Foster & Ford, 2003; Pálsdóttir, 2010; Quan-Haase & McCay-Peet, 2014). However, it has been noted that the effect of serendipity should be differentiated by context (McCay-Peet, 2013b). Aside from information services, such as search engines or news sites, other services also employ algorithmic filtering to select and suggest content. More specifically, in online shopping, services analyze user behavior (individual as well as aggregated) to personalize suggestions. Social network sites filter content streams and suggest profiles to connect to based on algorithmic filtering (Ellison & boyd, 2013). Accordingly, serendipity could have a positive, enriching effect in all of these contexts. In this segment, we derive some propositions for differences in the underlying research model by online service context.

H1 Self-Efficacy: As to the impact of self-efficacy on serendipity, we propose that this effect will be especially pronounced in the case of information services and SNS. In both cases, dominant service providers rely heavily on algorithmic filtering while simultaneously collecting extensive use data and, in some cases, frequently changing their privacy policies (Stutzman, Gross, & Acquisti, 2013). All of these elements make it difficult for users to control both their reliance on and their input into filtering mechanisms. Previous studies have stressed the importance of Internet skills for information purposes, especially (Van Dijk, 2005; Hargittai, 2002; 2010). In the case of online shopping, on the other hand, filtering mechanisms commonly only apply after a user sign-in. In addition, there is a wide selection of suppliers, making it easier to avoid personalized content.

H2 Trust: We propose that the effect of online trust on serendipity is strongest in the online shopping context. First, trust has variously been shown to affect user engagement in online shopping (e.g., Gefen, Karahanna, & Straub, 2003; Lee & Turban, 2001). Second, online shopping is the only context requiring financial transactions. Therefore, users may shy away from actually transacting with diverse, unfamiliar services. Information services require relatively little user trust, as users do not have to engage in significant explicit self-disclosure. There is little risk involved in trying out various different information services. Finally, SNS can be considered a relatively sensitive service context as it requires significant self-disclosure and is associated with high switching costs. Yet, previous studies have found that users tend to focus on “horizontal” interactions among users and pay relatively little attention to the trustworthiness of the service providers themselves (Young & Quan-Haase, 2013).

H3 Self-Disclosure: We propose that the impact of self-disclosure should be especially pronounced in the case of SNS. Here, self-disclosure facilitates not only a selection of content, but also the establishment of connections (Zhao, Grasmuck, & Martin, 2008). Erdelez (1995) stresses the importance of social networks for the encounter of information. Personal

connections are sources of potentially serendipitous information (McCay-Peet, 2013b, p. 33). Since self-disclosure in SNS impacts both the filtering of content and of connections, its effect on serendipity should be especially strong. We propose that self-disclosure has the weakest impact in the context of information services, as these services frequently do not rely on explicit self-disclosure, but rather employ analyses of users' trace data. In the case of online shopping, we expect a moderately sized effect since self-disclosure does occasionally take place, for example in the refinement of recommendations or in the form of ratings and comments, but is not required to a significant degree for the use of most services (Quan-Haase & McCay-Peet, 2014, p. 151; Shani & Gunawardana, 2011;).

H4: Satisfaction: We expect serendipity to exert the strongest positive effect on user satisfaction in the context of SNS. SNS are hedonic information systems that are primarily used in voluntary settings and in the context of leisure (Van der Heijden, 2004). Thus, browsing and exploration are important elements of SNS use: "Environments known for exploration, browsing, and discovery are often associated with serendipity" (McCay-Peet, 2013b, p. 33). In the case of information services, use behavior is more task-oriented and directed. Serendipity experiences in this context could be perceived as interesting and enriching, but could just as well be seen as disrupting and distracting. Overall, the effect of serendipity should therefore be more ambiguous (Meckel, 2012; André, Teevan et al., 2009; Pariser, 2011). In the case of online shopping, we expect the weakest positive effect of serendipity on satisfaction as online shoppers are frequently looking for a specific item to purchase. Content widely deviating from the intended purpose may therefore be considered more cumbersome than enlightening. Of course, that may be less the case for shoppers simply browsing the online store, looking for inspiration or distraction (McCay-Peet, 2013b). Figure 2 summarizes the proposed differences in the underlying research model.

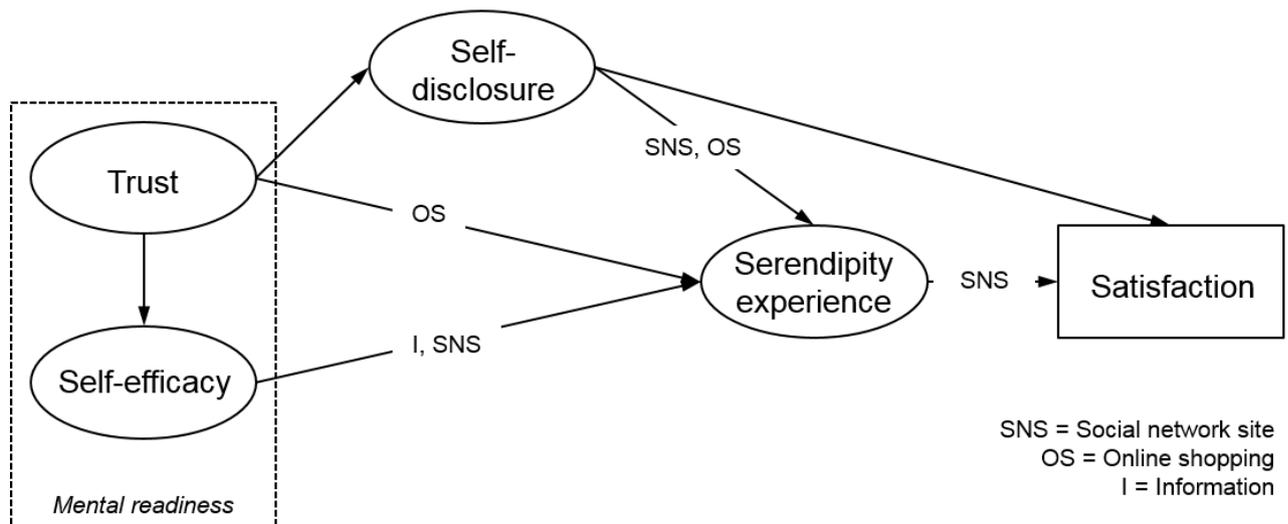


Figure 2: Contextual differentiation of hypothesized effects

Methods

Sample

Our analysis is based on an online survey among German Internet users, conducted in September 2013. The survey sample was recruited from a pool of German Internet users, provided by a certified German market research institute. Participants were offered a small monetary incentive and contacted via email. The sample was ensured to be representative of the German population in terms of gender and age composition by defining quotas on these attributes.

The questionnaire asked respondents to select an online service they most recently employed, name the chosen provider and assign it to a choice of online services (SNS, information services, online shopping, online banking, other). Of all 1,666 participants, 752 directed their answers at an online shopping provider, 294 at a SNS service, and 201 towards information services (e.g., Google or online-newspapers). The remaining respondents (419) chose a variety of other services that could not be assigned to the three service categories of interest (249

referred to online banking services) or were missing values (135). Thus, the net sample is composed of 1,247 users. The profiles and demographics of the respondents are summarized in Table 1.

The identified sub-samples exhibit some differences in socio-demographic characteristics. In the online shopping sample, with 53.2% women and 46.8% men, gender is more equally distributed than in the SNS sample with 60.5% women and 39.5% men. By contrast, in the information services category men (57.2%) outnumber women (42.8%). In terms of age, one third of the participants referring to an online shopping provider are between 26 and 45 years old, another third between 46 and 65. In contrast, the participants referring to a SNS service are younger, with 35% under 16 years, 17% between 16 and 25, and 23% between 26 and 45. As for education, most respondents of the online shopping sample either hold a high school diploma (62.9%) or a college/university degree (26.4%). In the SNS sample, however, most respondents are still in school (39.2%) or have completed an apprenticeship (18.4%). Finally, in the information services context respondents fall in between the other two sub-samples: 21.0% are still in school and 20.5% hold a college/university degree.

Table 1: Sample Profile

Variables	Distribution	n	Percent	Missings
Online Context	Online shopping	752	60.3	0
	Social network sites	294	23.6	
	Information	201	16.1	
	<i>Total</i>	<i>1,247</i>	<i>100</i>	
Gender	male	583	46.8	0
	female	664	53.2	
	<i>Total</i>	<i>1,247</i>	<i>100</i>	
Age	under 16	197	17.1	94
	16 - 25	146	12.7	
	26 - 45	302	26.2	
	46 - 65	312	27.1	
	above 65	196	17.0	
	<i>Total</i>	<i>1,153</i>	<i>100</i>	
	still in school	228	18.3	3

Education (Highest degree achieved)	high school without access to college/university (equals Real- and Hauptschule in the German system)	457	23.6
	high school with access to college/university (equals Gymnasium in the German system)	208	16.7
	Apprenticeship (according to the German system equals finished vocational training with degree)	233	18.7
	college/university	267	21.5
	others	14	1.1
	<i>Total</i>	<i>1,244</i>	<i>100</i>

Method

We relied on a multiple group analysis based on structural equation modeling (SEM) to address the research questions. SEM combines confirmatory factor analysis (CFA) and regression models, and allows the testing of hypothesis systems. In contrast to normal regression analysis (linear – OLS, or multinomial logistic), SEM can take account of indirect effects and latent variables as well as measurement errors in the specification of latent constructs. We used MPlus (Version 6) to carry out the analyses, relying on robust Maximum Likelihood Estimation (MLR), to account for non-normality and other sources of distortion, such as heteroscedasticity and non-normal distribution of error terms (Byrne, 2012). Out of the 1,247 respondents in the sample, 1,173 filled out the entire questionnaire and entered the SEM.

Measurement

We employed the online serendipity measure proposed by McCay-Peet (2013a) which was translated into German. It featured four items (see Appendix A for the Questionnaire and the operationalization of all constructs applied in this study). Considering that it is a new scale developed for a complex phenomenon, the scale proved very good reliability (Cronbach's

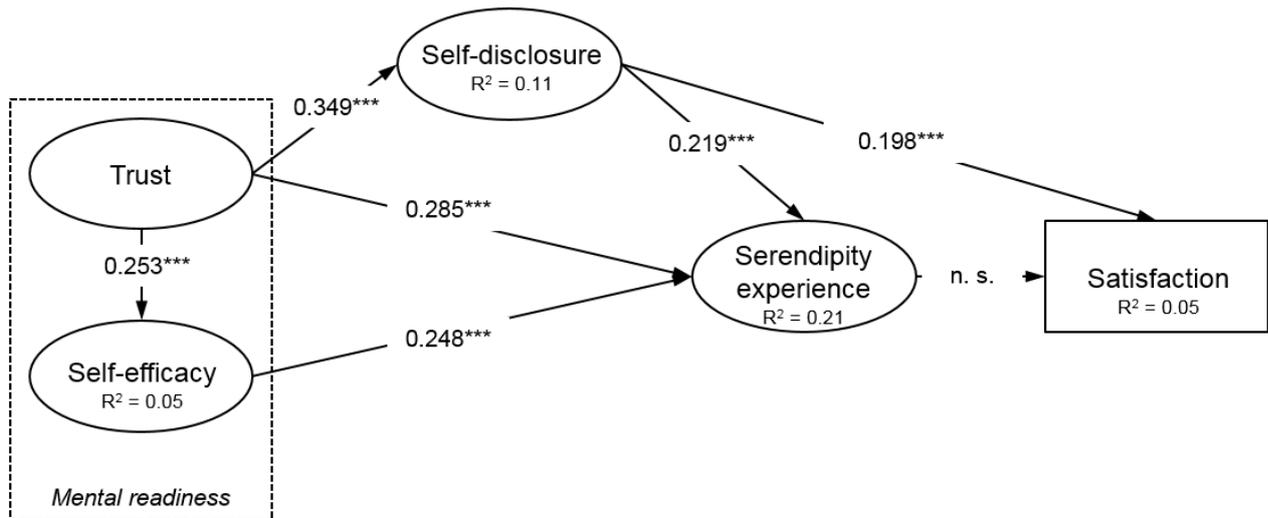
Alpha = 0.88). For online trust we employed the measure for institution-based trust developed by McKnight et al. (2002). The measure for self-disclosure was adopted from Krasnova, Spiekermann, Koroleva and Hildebrand (2010). We used a scale with three items to measure self-efficacy. The scale was used in previous research by the authors (Hoffmann, Lutz & Meckel, 2015) and shows good measurement properties. For the sake of conciseness and since we consider self-disclosure in our analysis, the measure focuses on the use of interactive online services. Each item was rated by the survey participants based on a five-point Likert scale (1=strongly agree; 2=agree; 3=neither agree nor disagree; 4=disagree; 5=strongly disagree).

Finally, user satisfaction was measured with one item (“All together, how satisfied are you with the service you chose?”), rated on a five-point Likert scale (1=very satisfied; 2=somewhat satisfied; 3=neither satisfied nor dissatisfied; 4=somewhat dissatisfied; 5=very dissatisfied). Different multi-item measures had been taken into consideration, yet ultimately a measure broad enough to be applied to all surveyed service contexts was chosen (cf., Kim, Ferrin, & Rao, 2009). The respondents answered the self-efficacy and trust questions before being assigned to a specific service context. The serendipity, self-disclosure and satisfaction measures referred to the service chosen by the participants. The complete measurement model of all latent constructs is reported in Appendix B. It satisfies the necessary conditions (Bollen 1989; Netemeyer, Bearden, & Sharma, 2003), i.e., has convergent and discriminant validity (Fornell & Larcker, 1981; see Appendix C).

Results

Overall Model

Figure 3 presents the model results across all three online services.



* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (N=1173)

Figure 3: Results of the overall model

We find that Internet self-efficacy does indeed positively affect users' serendipity experience (H1). Hypothesis 2a is also confirmed, as online trust has a significant positive effect on serendipity. As hypothesized, trust also positively affects users' self-efficacy (H2b). Moreover, we find a significant effect of self-disclosure on serendipity (H3a), confirming our hypothesis. Self-disclosure is positively affected by online trust, confirming H3b. As proposed, self-disclosure has a positive direct effect on users' satisfaction with the chosen service (H3c). Finally, across all online service contexts, we do not find a significant effect of serendipity experience on user satisfaction, so we have to reject H4. Thus, all hypotheses were confirmed for the overall model, except for H4.

Online Contexts: Online Shopping, SNS, Information Services

In a first descriptive step, we conducted a t-test to analyze for significant differences in the experience of serendipity across the three service contexts. We found that users in the online-

shopping context revealed the lowest overall serendipity scores, while information services was slightly higher than SNS. The identified differences between the three online settings are significant at the 5% level.

In order to evaluate the research model in the three service contexts and to conduct the multiple group analysis, we first had to check for configural and metric invariance. To do so, we followed the procedure suggested in the literature (Bollen, 1989; Cheung & Rensvold, 2002; Mullen, 1995). In a first step, we tested the model for configural invariance. In this model, only the factor structure is constrained to be equal across groups, whereas all other parameters can be estimated freely (Bollen, 1989). Thus, the configural model uses identical items to measure identical constructs in all groups. As shown in Table 2, the configural model (M1) fits well.

Table 2: Invariance Test to Compare the Structural Model

		M₁	M₂	Criterion
	<i>Constraints</i>	<i>Unconstrained (Configural)</i>	<i>Factor Loading (Metric)</i>	-
Chi-squared Test of Model Fit	Value (Chi-squared)	619.24	653.75	-
	Degrees of Freedom (df)	294	316	-
	P-Value	0.000	0.000	-
	Chi-squared/ df	2.10	2.07	≤ 3
RMSEA	Estimate	0.053	0.052	<0.08
CFI/TLI	CFI	0.956	0.954	≥ 0.90
	TLI	0.946	0.948	≥ 0.90
SRMR	Value	0.051	0.054	≤0.08

In a second step, we tested the model for metric invariance, in which both the factor structure and the factor loadings are held equal between the groups. This is a necessary condition when comparing the structural paths between the groups and implies equal measurements for all groups. The M2 model fit indices are very similar to those of M1. We used the CFI difference test to carry out a formal assessment of measurement invariance (Cheung & Rensvold, 2002).

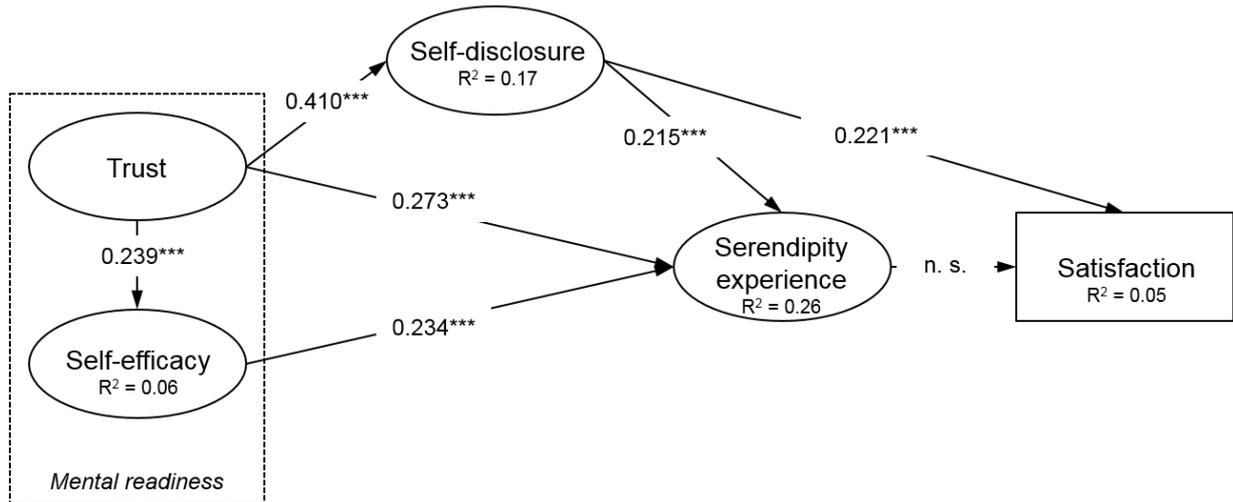
The CFI difference test is superior to the chi-square difference test for studies with large sample sizes, where the chi-square value is frequently significant regardless of model fit (Yuan and Bentler 2004). Cheung and Rensvold (2002) propose that a difference in $CFI \leq 0.01$ between the models supports measurement invariance. In our case, this condition is satisfied and we can therefore assume metric invariance and proceed to compare the structural models.

To take account of the demographic differences in the three subsamples (see section 3.1), we included age, gender and education as control variables for the analysis of the online shopping, SNS and information services context. We added these variables as independent variables influencing the serendipity experience construct. Comparing the models with and without the control variables, we found that all paths maintained both their direction and significance (i.e., significant paths in the uncontrolled model stayed significant in the controlled model). The effect sizes decreased slightly in the control model but none of the demographic predictors showed a significant effect on serendipity experience. However, since the inclusion of the control variables led to substantially lower case numbers¹ and fit values, we focus our analysis and discussion on the uncontrolled models only.

Figures 4-6 display the structural models for the three online service contexts. Looking at the antecedents of online serendipity, we find some interesting differences between the three contexts: In the case of self-efficacy (H1), we find the strongest effect in the information services context, followed by online shopping. The latter finding is counter our expectation, as we had expected a stronger effect in the SNS context when compared to the online shopping context. In the SNS context, though, self-efficacy does not significantly affect serendipity experiences. As expected, the effect of online trust on serendipity (H2) is strongest in the online shopping context. We also find a significant, relatively strong effect in the information services

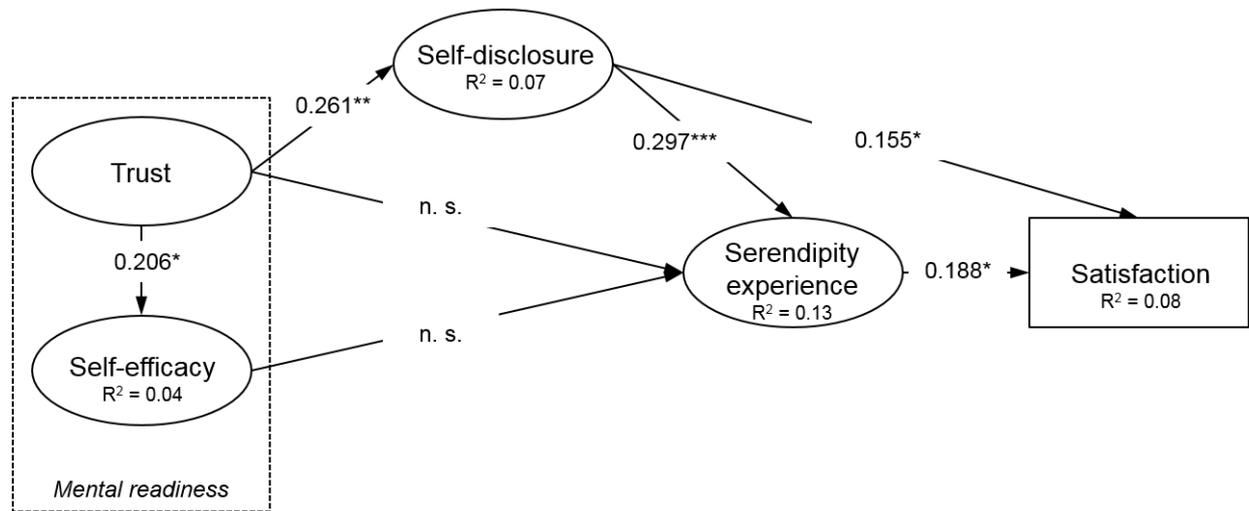
¹ Some users did not indicate their age and education, so that, for example, in the online shopping the control model comprises only 657 cases, compared with 709 cases for the uncontrolled model.

context, while there is no significant effect in the SNS context. The effect of self-disclosure on serendipity (H3) is in line with our expectations: we find the strongest effect for SNS, followed by online shopping. The effect is insignificant in the information services context (as is the effect of self-disclosure on satisfaction).



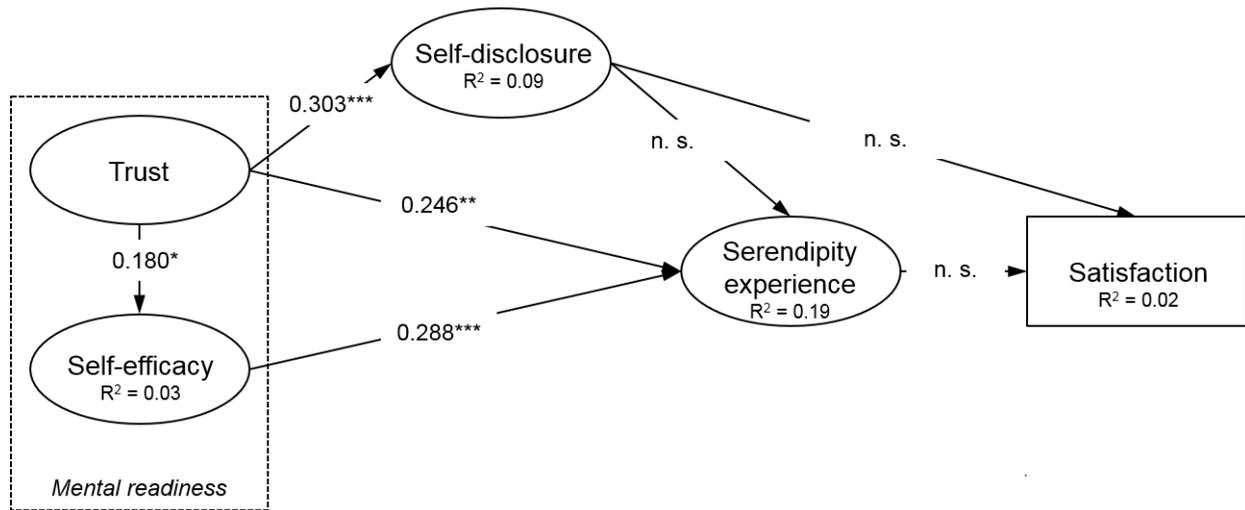
* p < 0.05 ** p < 0.01 *** p < 0.001 (N=709)

Figure 4: Serendipity model for the online shopping context



* p < 0.05 ** p < 0.01 *** p < 0.001 (N=272)

Figure 5: Serendipity model for the SNS context



* p < 0.05 ** p < 0.01 *** p < 0.001 (N=192)

Figure 6: Serendipity model for the information services context

Finally, we find that serendipity only positively affects user satisfaction (H4) in the SNS context. This finding is somewhat in line with our proposition that this effect should be strongest in the SNS context, as it, in fact, is only statistically significant in this context. Overall, our analysis reveals some noteworthy differences in the antecedents and evaluation of online serendipity between the three analyzed service contexts. We will discuss the implications of these findings in the following segment.

The model fit comparison of the three online contexts (Table 3) shows that the model fit values are lowest in the online shopping context. By contrast, the SNS and information services models fit better than the overall model and the online shopping model (except for the SRMR value, which is best in the overall model). At the same time, the R² values indicate that most variance in online serendipity is explained in the online shopping context, followed by information services and SNS. Thus, while we are able to explain serendipity in the online shopping context better than in the SNS and information services context, we seem to miss relevant model parameters in the online shopping context.

Table 3: Fit Index Comparison of the Models

	Overall Model	Online-Shopping	SNS	Information	Criterion
<i>Value Chi-squared</i>	394.015	341.807	138.016	136.788	-
<i>Degrees of Freedom (df)</i>	98	98	98	98	-
<i>P-Value</i>	0.000	0.000	0.000	0.000	-
<i>Chi-squared/ df</i>	4.02	3.49	1.41	1.40	≤ 5
<i>RMSEA</i>	0.051	0.059	0.039	0.045	<0.08
<i>CFI</i>	0.959	0.948	0.971	0.970	≥ 0.90
<i>TLI</i>	0.950	0.936	0.964	0.963	≥ 0.90
<i>SRMR</i>	0.044	0.052	0.048	0.048	≤0.08

Discussion and Conclusion

Summary and Implications

Our findings contribute to the current debate on serendipity by analyzing antecedents of the serendipity experience on the Internet and by differentiating these effects by three distinct online service contexts. A number of previous studies had stressed that individual attitudes or characteristics would affect serendipity – in the vein of accidental sagacity (Rubin et al., 2011; Erdelez, 2004; Makri & Blandford, 2012). Our research model identifies two cognitive antecedents of users' online serendipity in the vein of a mental readiness: Internet self-efficacy and (general) online trust. To account for users' active contribution to serendipity experiences, we include self-disclosure as a behavioral mediator in the model.

Based on this nomological model, we confirm that users require a kind of mental readiness to experience serendipity on the Internet: Self-efficacy could be required to autonomously explore the net, possibly also to circumvent overly selective filtering and personalization effects, for example, by adjusting privacy settings or switching between different services. Trust not only increases users' self-efficacy, it also directly drives serendipity – presumably because it allows

for a more explorative, open, experimental Internet use. Trust also positively affects user self-disclosure on the Internet. Finally, self-disclosure does indeed facilitate serendipity experiences. Kane, Alavi, Labianca, and Borgatti (2014) stress that self-disclosure is an important precondition for establishing new connections and fostering a more diverse personal network.

Despite most theoretical work framing serendipity as a beneficial phenomenon, in the overall sample, we do not find evidence that serendipity experiences are positively (or negatively) related to user satisfaction with online services. This would indicate that online services need not worry about a loss of serendipity due to algorithmic filtering or homogeneous interactions. Yet, a differentiation of the research model by online service context sheds some further light on these relationships:

We find that in the case of information services, self-efficacy has an especially strong effect on serendipity. This may be due to challenges in circumventing filtering mechanisms in this context (André, Schraefel et al., 2009; André, Teevan et al., 2009; Pariser, 2011). Self-disclosure, on the other hand, does not play a significant role – presumably because most information services do not require the disclosure of substantial personal data. Filtering and personalization of information services is based primarily on the analysis of use data. Accordingly, self-disclosure also does not significantly affect service satisfaction. The insignificant effect of serendipity on satisfaction may be due to the directed, purpose-driven use of such services, where unexpected, surprising and diverging content may be experienced as distracting and unhelpful.

The situation is similar in the case of online shopping, where serendipity does not affect user satisfaction either. Again, users shopping for specific items may find unexpected, surprising or even challenging content more cumbersome or distracting than helpful. We find that trust is an especially important driver of serendipity in the online shopping context, which may be

because these services involve financial transactions. Self-disclosure positively affects serendipity. Possibly, sharing information on shopping sites does lead to surprising new discoveries or recommendations by other users.

We do find evidence for the notion that serendipity is perceived as beneficial when users are in a more playful, explorative mindset – as in the case of SNS (McCay-Peet, 2013b). Here, the analysis reveals a significant positive effect of serendipity on satisfaction. Interestingly, in the context of SNS, neither trust nor self-efficacy is a driver of serendipity, but self-disclosure is (as discussed above). This leaves the question of how to conceptualize the appropriate mental readiness to experience serendipity in SNS. Trust does seem to play a role, but only in that it facilitates self-disclosure. It would be worthwhile to further explore these relationships in the context of privacy concerns and to differentiate the extent and quality of self-disclosure necessary to experience serendipity in SNS.

By identifying, quantifying and differentiating antecedents of serendipity, this study significantly contributes to a young, emerging research area. We gain a better understanding of what attributes constitute the right “forma mentis” (Erdelez, 2004) for users to actually experience serendipity. We show that both the antecedents and effects of serendipity differ according to the context in which users explore the Internet. Finally, we find that serendipity may contribute to user satisfaction primarily in contexts where users are in a more hedonic rather than purpose-driven mindset (Van der Heijden, 2004). The latter finding should be of particular interest to online service providers.

Limitations and Avenues for Future Research

Unavoidably, our study bears a number of limitations. *First*, our typology of online contexts is by no means exhaustive. Certain online services, such as online-dating or entertainment via

video platforms, like YouTube, were left out for the sake of simplicity. Neither is our typology of online settings very fine-grained. The affordances of platforms subsumed in the SNS category differ vastly. Future research should connect the technological affordances of specific platforms with users' experience of serendipity (cf. Bogers & Björneborn, 2013; Sun, Zhang, & Mei, 2013, for analyses based on Twitter data). *Second*, we used quantitative and cross-sectional data to test our model and thus neglected a process view of serendipity. Previous research has strongly stressed the individual steps that make up serendipitous experiences, thus implying a temporal dimension (Erdelez, 2004; Makri & Blandford, 2012). Using longitudinal data, such as panel analyses, and mixed-methods approaches would be fruitful steps in exploring this dimension.

Third, the measurement of satisfaction with the service could be more refined. In particular, assessing satisfaction with only one item may not be sufficiently robust. Future studies may wish to employ a validated multi-item scale to measure user satisfaction applicable to distinct use contexts. Moreover, additional outcomes of serendipity should be considered, such as positive hedonic experiences in the form of enjoyment or cognitive learning effects. *Fourth*, while our model allows for a differentiated analysis of antecedents of serendipity experiences, we do not fully explore the expectations users form towards distinct services, which may affect their mental preparedness for serendipity experiences. Future studies could delve deeper into how users' mental approaches to distinct services, their expectations and use purposes, differ – and how this affects their experience and evaluation of serendipity. *Finally*, our study is limited to a single Western European country. Since the identified antecedents of serendipity may vary by cultural context, we could assume that serendipity and its outcomes are also culture-specific to a certain degree (Brown et al., 2014). Comparative studies could shed light on the cultural contingency of serendipity.

Overall, the study of online serendipity is still in its infancy and provides ample opportunities for further research. By applying a recent measure of serendipity and analyzing antecedents and outcomes of serendipity in different online contexts based on a large-scale quantitative survey, this study may provide some important contributions to an emerging research stream – while leaving numerous important questions unanswered, and discovering some additional questions to be tackled in future studies.

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Appendix A Measures

Construct	Item	Wording ^{1,2}
Online serendipity (OS)	OS1	<i>I have made an accidental fortunate discovery that was useful for me in my everyday life</i>
	OS2	<i>I have made an unexpected fortunate discovery that was useful for me in my work</i>
	OS3	<i>I encountered useful information, ideas, or resources that I am not looking for when I use digital environments.</i>
	OS4	<i>I have gained unexpected insights that were valuable for me.</i>
Online Trust (T)	T1	<i>The Internet has enough safeguards to make me feel comfortable using it to transact personal business.</i>
	T2	<i>I feel assured that legal structures adequately protect me from problems on the Internet.</i>
	T3	<i>I feel confident that technical structures, such as encryption applications, adequately protect me from problems on the Internet.</i>
	T4	<i>In general, the Internet is a robust and safe environment in which to transact personal business.</i>
Self-Disclosure (SD)	SD1	<i>My user profile contains all data requested by the service.</i>
	SD2	<i>My user profile is comprehensive.</i>
	SD3	<i>My user profile is up-to-date.</i>
	SD4	<i>My user profile says a lot about me.</i>
Internet Self-efficacy (SE)		<i>I am confident in my ability to...</i>
	SE1	<i>...create a profile on a social network site.</i>
	SE2	<i>...publish a video on the Internet (e.g. on YouTube).</i>
	SE3	<i>...publish information on a blog or Twitter.</i>

¹ Each item battery was preceded by the instruction "Please rate the following statements".

² All items were rated on a 5-point Likert scale: 1 - strongly agree, 2 - rather agree, 3 - neutral, 4 - rather disagree, 5 - strongly disagree.

Appendix B Measurement Model of the Latent Constructs

Construct	Item	Standardized loading	t-values	R ²	α	C.R.	AVE
Online serendipity (OS)	OS1	.81	47.39***	.66	.88	.88	.65
	OS2	.74	39.44***	.55			
	OS3	.82	51.81***	.68			
	OS4	.85	57.81***	.72			
Online Trust (T)	T1	.79	45.22***	.62	.88	.88	.65
	T2	.82	53.46***	.67			
	T3	.86	67.22***	.74			
	T4	.75	37.47***	.57			
Self-Disclosure (SD)	SD1	.78	47.19***	.60	.82	.83	.56
	SD2	.90	93.54***	.81			
	SD3	.73	64.09***	.53			
	SD4	.55	46.54***	.30			
Internet Self-efficacy (SE)	OSE1	.76	44.77***	.57	.87	.87	.69
	OSE2	.89	62.89***	.80			
	OSE3	.85	50.51***	.71			
Criterion		≥ 0.5	min*	≥ 0.4	≥ 0.7	≥ 0.6	≥ 0.5

Appendix C Fornell Larcker Criteria of the Latent Constructs (Discriminant Validity)

	<i>Nr. of items</i>	<i>AVE</i>	<i>DS</i>	<i>T</i>	<i>SD</i>
DS	4	.65			
T	4	.65	.13		
SD	4	.56	.08	.11	
SE	3	.69	.09	.05	.00

Squared correlations between constructs