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Knowledge Sharing in Social Networking Sites: How Context Impacts Individuals' Social and Intrinsic Motivation to Contribute in Online Communities

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Abstract:

Knowledge-sharing research in online communities has primarily focused on communities of practice and the social factors of knowledge-sharing behavior in organizational contexts. Academic research has not rigorously examined non-business-oriented online communities as venues for facilitating knowledge sharing. Thus, in this paper, we address this research gap by examining the contextual roles of anonymity and community type on an individual's social and individual drivers of knowledge-sharing attitude in social networking sites. Using social capital theory as a theoretical backbone, we propose and empirically validate a relational model through a survey of 329 users of Facebook, LinkedIn, and CNET. From analyzing the data with the partial least squares (PLS) method, we found strong explanatory power of the proposed research model. We discuss our study's implications for both research and practice.

Keywords: Knowledge Sharing, Social Networks, User Anonymity, Community Type, Social Capital Theory.

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1 Introduction

As of June, 2017, approximately four billion people (51.7% of the world's population) had access to the Internet, with the Internet usage penetration being 88.1 percent in North America (Internet World Stats, n.d.). Due to this pervasiveness, social networking sites (SNS) have gained enormous popularity in the last decade or so. SNS refer to online communities in which socialization that transcends geographic and temporal constraints facilitates knowledge sharing between users. With more than two billion active members as at October, 2017 (Statista, 2017a), Facebook alone represents around 53.8 percent of total Internet users.

LinkedIn, the largest social network for professionals, had about 530 million members as of April, 2017, of which 40 percent used it daily and 10 percent spent more than eight hours on it a week (LinkedIn, 2018; Statista, 2017b). For topic-specific social networks, CNET constitutes the largest tech-savvy website and ranked 154 out 500 on the most visited websites list in 2017 (Alexa, 2018a). Such SNS feature a series of collaborative tools such as social bookmarking, commenting, and interacting that enhance participation and collaboration between users. Given the high potential for user collaboration, researchers often refer to SNS as the "social Web".

Knowledge sharing (i.e., one individual's or group's sharing knowledge with another) is a major research theme in knowledge management (Alavi & Leidner, 2001). One of the biggest challenges confronting knowledge sharing in SNS (Hsu, Ju, Yen, & Chang, 2007) is that individuals have a natural tendency to hoard knowledge (Davenport & Prusak, 1998). Gruber (2007) argues that collective intelligence through knowledge sharing is the basic tenet of SNS. Despite the importance of SNS in facilitating a knowledge-sharing revolution, researchers have conducted little empirical research to understand how and why individuals/groups share knowledge in SNS (Fu, Yang, & Huang, 2012; Hsu & Lin, 2008; Yuan, Zhao, Liao, & Chi; 2013).

Various types of SNS exist, such as practice-based/organizational communities, information-exchange communities (e.g., LinkedIn), communities of relationship (e.g., Facebook), and communities of interest (e.g., CNET). However, academic investigations into knowledge sharing tend to focus on practice-based organizational communities (Bock, Zmud, Kim, & Lee, 2005; Chai & Kim, 2010, 2012; Kankanhalli, Tan, & Wei, 2005; Ko, Kirsch, & King, 2005; Lu & Hsiao, 2007; Ma & Agarwal, 2007; Wasko & Faraj, 2005; Yang & Lai, 2011). Researchers have proposed online communities to serve as a powerful foundation to mine data, discover knowledge, and, ultimately, create marketing intelligence for firms' competitive advantage (Chen, Chiang, & Storey, 2012). To date, the few studies that have investigated knowledge sharing in non-organizational online social networks have taken a limited perspective by examining select social constructs and overlooked relevant community contextual characteristics. Considering the vast amount of knowledge shared on SNS, the literature has significantly overlooked the role of non-organizational SNS. Thus, we seem to need research that focuses on understanding the nature of knowledge sharing in non-organizational online social networks (Deltour, Plé, & Roussel, 2014; Belk 2014). This paper addresses this literature gap.

To do so, we address the following research question: "What factors motivate people to share knowledge in social networking sites?". More specifically, we focus on two research objectives (RO):

RO1: To study the impact of social antecedents on knowledge-sharing attitude in social networking sites.

RO2: To investigate what effect relevant contextual factors have on these antecedents of knowledge-sharing attitude in social networking sites.

This paper proceeds as follows: in Section 2, we discuss knowledge sharing in SNS. In Section 3, we apply social capital theory to propose our research model. In Section 4, we empirically validate the model. In Section 5, we discuss our findings. Finally, in Section 6, we discuss the study's theoretical and practical implications and conclude the paper.

2 Theoretical Background and Hypothesis Development

2.1 Knowledge Sharing in SNS

Based on the network model of knowledge management (KM) (Alavi, 2000), we define a SNS as a digital social network that comprises a group of geographically and temporally dispersed individuals with similar interests and in which Internet technologies and Web 2.0 artifacts such as social bookmarking, commenting, and really simple syndication (RSS) facilitate knowledge sharing. Knowledge sharing occurs via communication through networking with others or through documenting, organizing, and capturing knowledge for others (Pulakos, Dorsey, & Borman, 2003). It depends on individuals' willingness to share their knowledge with one another (Nonaka, Toyama, & Konno, 2000). While researchers have investigated knowledge sharing's antecedents and barriers in online communities of practice (Ardichvili, Page, & Wentling, 2003; Chiu, Hsu, & Wang, 2006; Hsu et al., 2007), they have mainly focused on enhancing knowledge flow to solve organizational problems.

Studying actual knowledge-sharing behavior in many contexts is a complex endeavor, which explains why researchers across various domains have studied knowledge-sharing attitude and its antecedents (Hau, Kim, Lee, & Kim, 2013; Wang & Noe, 2010) including SNS contexts (Pi, Chou, & Liao, 2013). Attitude toward knowledge sharing refers to the degree to which users possess positive or negative feeling about knowledge sharing. Researchers widely believe attitude, which has its roots in the theory of reasoned action, to strongly predict intention or willingness to behave in voluntary settings (Ajzen, 1991), which, in turn, affects knowledge-sharing behavior (Bock et al., 2005). KM research has extensively used attitude. Additionally, Wasko and Faraj (2005) suggest that a stream of research that applies perceptual endogenous variables instead of actual knowledge-sharing behavior exists. Thus, we selected attitude in this study as the endogenous dependent variable. Next, we examine the social antecedents of knowledge-sharing attitude in SNS from a social capital theory lens.

2.2 Social Capital Theory

Online communities such as Facebook and LinkedIn are SNS with actors (members) and ties (relationships). Such SNS adapt to the network model of social capital. We apply Wasko and Faraj's (2005) model of social capital theory as a foundation to explain the social factors that motivate an individual to share knowledge in online communities.

Social capital theory posits that interactive relationships among individuals in social networks could be productive resources to create and exchange intellectual capital such as knowledge. Nahapiet and Ghoshal (1998) define social capital as the "sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (p. 243). We draw on two relevant types of social antecedents of knowledge contribution that Wasko and Faraj's (2005) framework for social capital proposes: relational capital and individual motivation.

2.2.1 Relational Capital

The relational dimension of social capital refers to affective components in the relationships between the nodes of a social network. Relational capital is stronger when members of a social network trust each other, establish and follow norms, see themselves as one with the network (i.e., identification), and perceive an obligation to participate in a collective. Wasko and Faraj (2005) suggest that individuals who identify more with the network and individuals guided by a norm of reciprocity are more likely to contribute their knowledge to an online network.

Identification refers to the willingness of individuals to maintain a relationship with others in a community (Dholakia, Baggozi, & Pearo, 2004) and occurs when individuals' interests merge with the community's interests. In other words, people identify themselves with a community when they have a high degree of mutual understanding and even personal attachment. Nahapiet and Ghoshal (1998) discuss that identification as a relational social capital would lead to resource exchange among individuals. Feeling accepted and part of the community enhances knowledge creation and sharing in online forums (Sheng & Hartono, 2015). Hsu and Lin (2008) argue that identification with a community has a significant positive relationship with users' willingness to share knowledge in online communities. We expect that identification is an important motivational factor in SNS information-exchange communities (specifically communities of relationship).Thus, we hypothesize:

H1: Identification positively impacts attitude toward knowledge sharing in SNS.

Reciprocity refers to the degree of fairness and perceived mutual benefits of relationships among individuals. In its simplest form, reciprocity refers to a mutual indebtedness in a sense that individuals "reciprocate the benefits they receive from others" (Wasko & Faraj, 2005, p. 43). Social capital theory explicates the role of reciprocity as a relational capital in resource exchange among individuals in social networks (Nahapient & Ghoshal, 1998). Wasko and Faraj (2005) explain that people who contribute to online communities believe in reciprocity. In their study, they found that one-to-one reciprocity did not affect knowledge contribution helpfulness, but they proposed that generalized reciprocity existed in the network they examined (i.e., current help received may result in future help giving but not necessarily to the same user) (Wasko & Faraj, 2005). Norms of reciprocity lead people to cooperate, understand, and empathize with each other and may affect knowledge sharing (Yao, Tsai, & Fang, 2015). Thus, we hypothesize that:

H2: Reciprocity positively impacts attitude toward sharing knowledge in SNS.

2.2.2 Individual Motivation

In addition to the relational dimension of social capital, Wasko and Faraj (2005) explored the influence of individual rewards from contributing to a network that motivates individuals to exert effort and share knowledge in SNS. They examined the impact of individuals' reputation expectation and enjoyment in helping others in an online network on the quality and quantity of participants' knowledge-sharing contributions to that network.

With regards to reputation, Bandura (1986) posits that social acceptance can be a source of motivation for social activities. Note that, in this context, by reputation, we mean perceived reputation by individuals and not reputation of the system or the SNS. In SNS, users participate in the contribution, generation, and flow of information. Whether a SNS is a community of relationship (e.g., Facebook) or an information-exchange community (e.g., LinkedIn, CNET), the more users contribute knowledge, the stronger reputation they gain from others as being reliable, respectful, and high-status members. Since sharing knowledge does not involve any competition in the context of non-organizational/non-business-oriented SNS, users may have a high tendency to participate. Wasko and Faraj (2005) present reputation as an individual motivating factor that affects knowledge contribution helpfulness and volume in electronic networks of practice. They provide evidence that forming reputation in online environments strongly motivates individuals to actively participate. Wang and Lai (2006) also provide evidence that reputation enhances knowledge sharing in technology-related virtual communities. Thus, we hypothesize that:

H3: Reputation positively impacts attitude toward sharing knowledge in SNS.

Enjoyment in helping, a motivator in which one seeks to enhance the welfare of others, also represents another intrinsic motivating factor for why individuals share knowledge (Hars & Ou, 2002). Krebs (1975) defines the term altruism as gaining intrinsic pleasure from helping others without anticipating anything in return. Wasko and Faraj (2005) report that the enjoyment of helping others does not affect whether users contribute knowledge in electronic communities of practice. They explain that the aforementioned relationship might differ for other types of communities such as communities of interest and communities of relationship where extrinsic rewards do not exist and individual motivations are more salient to users. We expect that enjoyment in helping others will serve as an important motivational factor of knowledge sharing in information-exchange communities and specifically communities of relationship (e.g., Facebook) where users expect implicit knowledge sharing (i.e., sharing of experience) more than explicit knowledge sharing. Thus, we hypothesize:

H4: Enjoyment in helping others positively impacts attitude toward sharing knowledge in SNS.

Engagement is another intrinsic motivator that particularly influences individuals' intention to and whether they actually use systems such as SNS, which include a mix of utilitarian and hedonic components (Wu & Lu, 2013). Research considers technology users as engaged when an activity holds their attention and they pursue it for intrinsic purposes (Webster & Ho, 1997). In the context of information systems (IS) research, several studies affirm the impact of fun or pleasure on technology acceptance and use (Brown & Venkatesh, 2005; Thong, Hong, & Tam, 2006; Van der Heijden, 2004). Venkatesh, Thong, and Xu (2012) conclude that perceived enjoyment, as an intrinsic hedonic motivation, is a critical determinant of behavioral intention (particularly in non-organizational contexts). Empirical studies have shown that various intrinsic motivators including engagement and playfulness contribute to usage intentions (Davis, Bagozzi, & Warshaw, 1992; Webster & Ahuja, 2006). Moon and Kim (2001) found that enjoyment affected Internet usage; thus, one can apply it to understand how individuals judge virtual community usage. Venkatesh and Bala (2008) also explain the indirect effect of playfulness on behavioral intention. We believe that engagement in SNS and online communities affects users' attitude towards participation in such communities. We propose that the more users engage with SNS communities, the more they experience positive feelings about sharing knowledge. Thus, we hypothesize:

H5: Engagement is positively associated with attitude toward sharing knowledge in SNS.

2.3 Context in SNS

Cappelli and Sherer (1991) describes context as "the surroundings associated with phenomena which help to illuminate that phenomena, typically factors associated with units of analysis above those expressly under investigation" (p. 56). Johns (2006) stresses that context can have both subtle and powerful effects on research results. He stresses two important reasons for studying and reporting context. First, if one does not understand context, then one cannot understand person-situation interactions. Second, context can help to make research salient and relevant outside of the research community. Practitioners care about context because it can shape strategies and their implementation. User anonymity and community type constitute two salient contextual factors that seem to have impact on knowledge-sharing phenomena in SNS.

User anonymity refers to the degree to which online community members perceive themselves as being anonymous to other members (Yoon & Roland, 2012). Kane, Alavi, Labianca, and Borgatti (2014) argue that the correspondence between users and their digital profile affects their behavior and influences how they interact in social networks. Based on the online disinhibitation effect (Suler, 2004), people act differently in cyberspace compared to their usual offline behavior. Suler (2005) argues that, when users' actions are detached from their identity (e.g., by allowing users to use pseudonyms as an identifier rather than their real names (Pfitzmaan & Hansen, 2010)), their online actions may differ. For example, user anonymity can amplify individual independence when no shared identity exists (Postmes & Lea, 2000), can result in less support from group members (in this context, sharing of information), and can result in less commitment to the group (Reicher, Spears, & Postmes, 1995).

Based on the above discussion, we believe that user anonymity will have an effect on three antecedents of knowledge-sharing attitude. The more people remain anonymous in an online community and the more a SNS supports user anonymity, the fewer individuals will perceive reputation as a personal outcome expectation of knowledge sharing. When people stay anonymous via using fake user IDs, reputation would not be an individual motivation as it would in other contexts in which members of the community know the true identity of each other. Moreover, when users know others' true identities, they are more likely to reciprocate knowledge. Finally, when individuals hide behind fake user IDs, they have less information about others and, thus, feel less identification with the online community. Thus, we hypothesize:

H6a: User anonymity is negatively associated with identification in SNS.

H6b: User anonymity is negatively associated with reciprocity in SNS.

H6c: User anonymity is negatively associated with reputation in SNS.

Community type describes the purpose and nature of online communities (Stanoevska-Slabeva, 2002). Because SNS connects individuals with similar interests, these individuals "share a common language, world, values, and interests, obey a commonly defined organizational structure, and communicate and cooperate ubiquitously connected by electronic media" (Stanoevska-Slabeva, 2002, p. 72). Kane et al. (2014) argue that the type of social relations affects behavior in social networks. Based on actor-network theory, individuals are social entities who seek socialization in networks (Latour, 2005). Actor-network theory stresses relationships between individuals (nodes), the strength of such relationships (ties), and the effect of strong or weak ties in exchanging capital among individuals. However, it does not provide insight into the role of the nature of a network on these relationships. Our study helps fill this gap by providing insight on how different social network types affect the relationship between individuals and attitude towards social exchange.

Armstrong and Hagel (2000) identify four types of SNS: communities of transaction in which users can trade goods and services (e.g., eBay), communities of interest in which users can exchange information on certain topics (e.g., LinkedIn, CNET), communities of fantasy in which users can create new personalities (e.g., secondlife.com), and communities of relationship (i.e., emotional-support communities). Theoretically, in communities of relationship, users interact with each other through strong ties that have more importance than the topics they discuss. In other words, communities of relationship do not revolve around specific common themes or focus on solving particular issues. Communities of relationship bring together participants around various life experiences that can lead to stronger bonds. On the other hand, communities of interest involve people with same interests, issues, or goals. In communities of interest, users interact extensively with each other on specific topics and common concerns. What generates stronger and steadier ties in communities of interest is the fact that members seek to accomplish common goals or resolve shared concerns. Without this purpose, the ties seem desultory. A lack of purpose could eventually even destroy bonds in the social network.

Most of the literature on SNS focuses on communities of practice (e.g., Wasko & Faraj, 2005) and neglects the role of the type of community on knowledge sharing. As an exception, Ma and Agarwal (2007) address information exchange and communities of relationship as antecedents of knowledge contribution. However, Ma and Agarwal (2007) examine only perceived identity verification as an antecedent of knowledge contribution in online communities, though they call for future research to investigate other antecedents of knowledge sharing that consider the role of community type. Based on Armstrong and Hagel (2000), we conceptualize two types of SNS: communities of interest and communities of relationship. Communities of interest (i.e., information exchange communities) bring together users who share interest in various topics such as professional careers (e.g., LinkedIn) and advanced technologies (e.g., CNET). Communities of relationship (i.e., emotional-support communities) center on building social support and personal connections/experience (i.e., they center on general relations that do not focus on a specific purpose). Facebook exemplifies a SNS in which individuals focus on relationships and supportive ties rather than specific topics or professional practices.

We argue that community type will have an effect on the three proposed antecedents of knowledge-sharing attitude. In particular, we propose that, in communities of relationship, the degree of enjoyment in helping others and identification will be higher. In SNS and communities of relationship in particular, we do not expect reputation to be a personal outcome expectation and a motivational factor. Thus, we hypothesize:

H7a: Online communities of relationship have a stronger positive effect on identification than online communities of interest.

H7b: Online communities of interest have a stronger positive effect on reputation than online communities of relationship.

H7c: Online communities of relationship have a stronger positive effect on enjoyment of helping others than online communities of interest.

Following the steps that Hong, Chan, Thong, Chasalow, and Dhillon (2014) suggest to incorporate context into theorizing, we apply social capital theory in the context of knowledge sharing in SNS (focusing on the relevant social dimensions of relational capital and individual motivations) and add the contextual factors as the antecedents of core constructs, which our research model captures (see Figure 1).

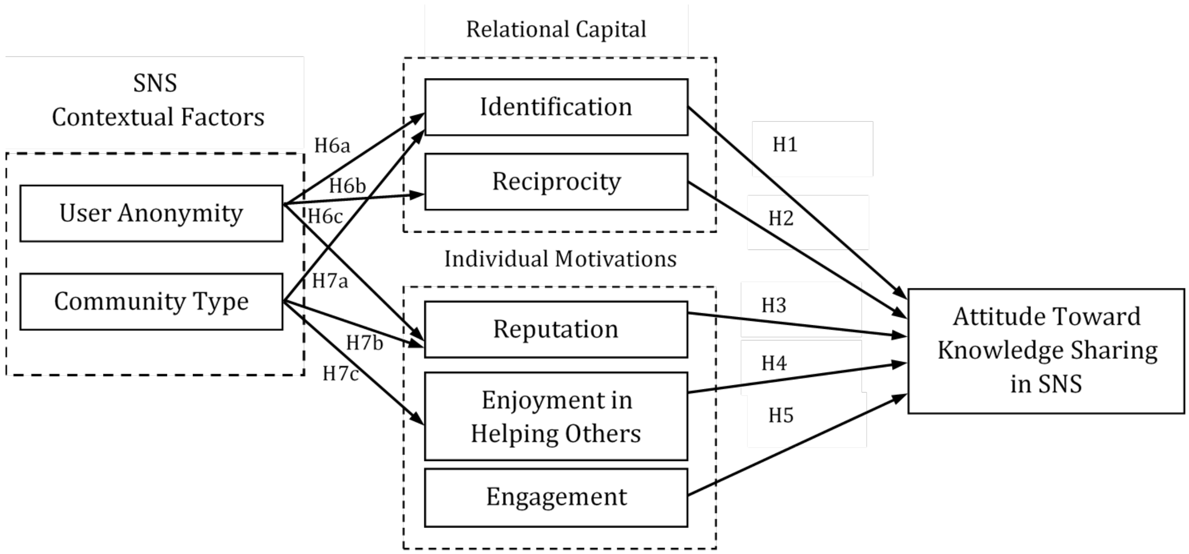

Figure 1. Proposed Research Model and Hypothesis

3 Methodology

We empirically operationalized and tested the proposed research model through a factorial design experiment and an online survey that involved individuals using SNS. We applied a two-by-two factorial design with two dichotomous categorical constructs as factors with two levels each. The first factor, community type, had communities of relationship and communities of interest as its levels. The second factor, user anonymity, had anonymous and known identity as its levels. We considered a community member as "known" if the community website displayed the member's real name and as anonymous if it displayed an alternative ID (e.g., username). Table 1 illustrates how we operationalized the SNS contextual factors and shows SNS examples that match the factors. Since communities of relationship typically require users to disclose their real names, the anonymous cell for such communities lacks real-world examples.

Table 1. Factorial Design for Two Categorical SNS Contextual Factors

Factor 2: user anonymity	Factor 1: community type	
	Level 1: Community of interest	Level 2: community of relationship
Level 1: known	LinkedIn, Meetup, Naukri	Classmates, Facebook, Google+, Orkut
Level 2: anonymous	Cnet, DPreview, Engadget	N/A

We chose Facebook to represent a community of relationship in which most members reveal their real identity. Facebook represents 53.8 percent of Internet users and is the most used social platform with two billion active members worldwide (Statista, 2017a). Additionally, it enforces a strict real-name policy and actively suspends accounts that it suspects of using pseudonyms (Holpuch, 2015). Google+ is another social network similar to Facebook in terms of type of community and user anonymity. However, although Google operates it, the platform suffered from a weak launch in 2011 and, thus far, has unsuccessfully competed with Facebook in terms of number of users and user activity time (Denning, 2015). Due to its broader audience and user base, we chose Facebook was for this study. LinkedIn serves as a community of interest in which users mostly use their real identity. With more than 500 million members worldwide, it is the largest SNS for business and employment-oriented professionals (Statista, 2017b) and one of the top 30 most visited websites in the world (Alexa, 2018b) with more than a 100,000 posts created and shared every week through its publishing platform (Lunden, 2015). CNET represents a community of interest with mostly anonymous users. Unlike DPreview, which focuses on digital photography, CNET offers a wide range of forums that focus on various technologies and gadgets. It is the most visited tech-savvy website with an Alexa (2018a) ranking of 154. Thus, we chose LinkedIn and CNET to represent known and anonymous communities of interest, respectively, in this study.

We drew all the reflective constructs from previously validated sources. We adopted knowledge-sharing attitude (KS) from Bock et al. (2005); identification (I) from Chiu et al. (2006); reciprocity (RE), reputation (R), and enjoyment in helping others (EH) from Wasko and Faraj (2005); And engagement (E) from Webster and Ahuja (2006). Borrowing from the extant literature on social capital theory, theory of reasoned action, and knowledge sharing, we define the constructs and the corresponding items in Appendix A.

We determined the sample size we needed to conduct the study with two generally accepted rules of thumb. First, Chin (1998b) suggests that the minimum sample required in partial least squares (PLS) is ten times the number of 1) items in the most complex construct or 2) paths that lead to the latent dependent construct with the most independent variables. Thus, we needed a sample size of at least 50 since five paths lead to knowledge sharing in our model. For the second approach, Cohen (1988) argues for a minimum number of participants needed to acquire sufficient statistical power and effect size for the relationships. We conducted a power analysis to achieve a sufficient statistical power of 0.8, medium effect size of 0.30, and probability level of 0.05 which produced a minimum sample size of 98 per treatment (Cohen, 1988; Chin & Newsted, 1999). As such, we targeted 100 participants for each treatment. Thus, we recruited a total of 300 participants in Canada to participate in the study.

4 Results

4.1 Measurement Model Evaluation

For the Facebook survey, we collected 129 completed (from 301 total) responses. Further, we collected 178 and 135 completed (from 226 and 234 total) surveys for the LinkedIn and CNET surveys, respectively. After discarding cases in which we identified gaming or lack of attentiveness (e.g., providing the same answer for every response) and removing univariate and multivariate outliers, 106, 118, and 105 completed responses for Facebook, LinkedIn, and CNET, respectively, remained. We recruited participants through a market research firm. Our sample contained 56 percent males, and the participants as a whole ranged from 22 to 63 years old with the largest age category being 31-40 years old (36%). Further, 60% of participants had some college education, but only 13 percent had a bachelor's degree or higher.

We administered PLS using the two-step approach hat Chin (2010) suggests to evaluate the measurement and structural models. Table 2 presents the descriptive statistics, reliability measures, VIF values, AVE values, and square root of AVE values. We assessed indicator reliability via item loadings and corrected item-total correlations. We excluded items KS1 and E4 from the analysis because they did not meet the reliability criteria. All other items passed the threshold value of 0.5 for corrected item-total correlations (Doll & Torkzadeh, 1988) and 0.5 for item loadings (Chin, 1998a; Fornell & Larcker, 1981). Hence, we can conclude the data had satisfactory individual item reliability.

Table 2. Descriptive Statistics, Reliability, VIF, and Discriminant Validity

Construct	Mean	Std. dev.	Cronbach's α	CR	VIF	AVE	KS	I	RE	R	EH	E
KS	4.468	1.332	.908	.902	n/a	.793	**.880**					
I	4.367	1.108	.783	.881	n/a	.703	.520	**.823**				
RE	4.207	1.102	.802	.912	n/a	.881	.377	.226	**.907**			
R	4.465	1.110	.866	.910	n/a	.791	.322	.212	.294	**.895**		
EH	4.485	1.280	.898	.906	n/a	.855	-.190	.107	.298	.518	**.905**	
E	4.506	1.292	.877	.870	2.009	.777	.655	.405	-.143	.504	.466	**.877**

KS = knowledge sharing, I = identification, RE = reciprocity, R = reputation, EH = enjoyment of helping others, E = engagement.

We demonstrated sufficient construct reliability using three criteria: Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). The results from Table 2 show that Cronbach's alpha values met the threshold value of 0.7 (Nunnally & Bernstein, 1994). Additionally, CR and AVE values were higher than the suggested values of 0.7 and 0.5, respectively (Chin, 1998b; Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). We used two approaches to assess the model's discriminant validity through confirmatory factor analysis (CFA). First, we constructed a matrix of item loadings (see Table 3). By comparing the loading value of each item on its corresponding factor, one can see that each item loaded on its latent construct stronger than other latent constructs (Chin, 1998b). Second, we created a latent variable correlation matrix in which the diagonal line represents the square root of AVE values. These values were greater than each correlation value on the associated row and column (Chin, 1998b). Additionally, all AVE values were greater than 0.5 as we mention above. Thus, given this analysis, the scales used in this investigation showed sufficient convergent and discriminant validity. Finally, we investigated the data set for multicollinearity using three widely accepted approaches. First, using a correlation matrix between variables, we identified whether the values were below the suggested critical value of 0.8 (Tabachnick, Fidell, & Osterlind, 2001). All values were below 0.8, which indicates no multicollinearity between the variables. Second, we calculated condition index values to diagnose multicollinearity. All the values were smaller than the suggested value of 30 (Meyers, Gamst, & Guarino, 2006). Lastly, we calculated the variance inflation factor (VIF) for all the independent variables. All the VIF values were below the suggested threshold value of 2.5 (Allison, 1999), while the tolerance remained less than 0.2. Thus, we found no indication of multicollinearity in the data set.

Table 3. Item Loadings Results

Item	Construct					
	KS	I	RE	R	EH	E
KS2	**0.807**	0.553	0.111	0.222	-0.124	0.434
KS3	**0.866**	0.503	0.119	0.322	-0.178	0.355
KS4	**0.902**	0.511	0.293	0.377	-0.202	0.343
KS5	**0.888**	0.583	0.228	0.344	-0.147	0.208
I1	0.642	**0.843**	0.209	0.508	0.244	0.466
I2	0.598	**0.883**	0.166	0.444	0.238	0.543
I3	0.545	**0.829**	0.055	0.388	0.328	0.422
RE1	0.345	0.214	**0.954**	0.227	0.166	-0.277
RE2	0.256	0.118	**0.894**	0.214	0.119	-0.119
R1	0.555	0.104	0.388	**0.844**	0.545	0.379
R2	0.268	0.101	0.204	**0.905**	0.560	0.327
R3	0.249	0.077	0.209	**0.899**	0.501	0.322
EH1	-0.481	0.070	0.207	0.544	**0.882**	0.311
EH2	-0.321	0.089	0.205	0.544	**0.893**	0.245
EH3	-0.328	0.034	0.277	0.534	**0.904**	0.236
E1	0.666	0.445	-0.055	0.522	0.339	**0.878**
E2	0.688	0.468	-0.102	0.478	0.489	**0.915**
E3	0.596	0.444	-0.104	0.551	0.430	**0.855**

KS = knowledge sharing, I = identification, RE = reciprocity, R = reputation, EH = enjoyment of helping others, E = engagement.

4.2 Manipulation Check

We asked participants about their perceptions of their assigned online community and their anonymity in this community: 96 percent of the Facebook participants perceived Facebook as a community of relationship, 90 percent of the LinkedIn participants perceived LinkedIn as a community of interest, and 93 percent of the CNET participants perceived CNET as a community of interest. We conducted the Kruskal-Wallis non-parametric test to compare the independent groups. The test resulted in a Chi-square value of 5.233 at p = 0.073, which suggests a marginal significant difference between members who perceived Facebook as a community of relationship and those who perceived it as a community of interest. It also produced a Chi-square value of 6.391 at p = 0.040, which suggests a significant difference between members who perceived LinkedIn and CNET as communities of interest and those who perceived them as communities of relationship.

We asked two questions about perceived user anonymity in participants' respective SNS as a part of a manipulation check (i.e., "I believe that other members of Facebook/LinkedIn/CNET to whom I am connected, perceive me as being identifiable (not anonymous)" and "I perceive Facebook/LinkedIn/CNET members whom I am connected to as being identifiable (not anonymous)").

For the first question, 78 percent of people on Facebook "strongly agreed", 12 percent "agreed", and eight percent "somewhat agreed". Two percent of participants responded with "neutral". These same values for LinkedIn were 83 percent, eight percent, seven percent, and two percent, respectively. On the other hand, 55 percent of individuals on CNET "strongly disagreed" with the statement, 28 percent "disagreed", 10 percent "somewhat disagreed", five percent were "neutral", and only two percent "somewhat agreed".

For the second question, 77 percent of participants on Facebook "strongly agreed", 18 percent "agreed", and five percent "somewhat agreed". The same values for LinkedIn were 67 percent, 18 percent, and 12 percent, respectively. In addition, three percent of LinkedIn members responded with "neutral". As for CNET, only five percent "agreed" with the statement, while 50 percent "strongly disagreed", 27 percent "disagreed", 12 percent "somewhat disagreed", and six percent were "neutral". The significant Chi-square values of 6.888 ($p = 0.031$), 6.101 ($p = 0.047$), and 6.790 ($p = 0.033$) show a significant difference between the groups (for the first and second questions) for Facebook, LinkedIn, and CNET, respectively. Thus, participants appropriately perceived the manipulations as per our study's parameters.

4.3 Structural Model Evaluation

Figure 2 shows the results from evaluating the structural model in SmartPLS with cross-sectional data via bootstrapping. To understand the effects of anonymity and community type groups, we coded cases with identified community members (i.e., Facebook and LinkedIn, n = 224) as 1 and cases with anonymous community members (i.e., CNET, n = 105) as 0. Similarly, we coded cases with community of relationship members (i.e., Facebook, n = 106) as 1 and cases with community of interest members (i.e., LinkedIn and CNET, n = 223) as 0. The R^2 value of 0.71 indicates the strong explanatory power of the research model. We discuss the hypotheses results in Section 5.

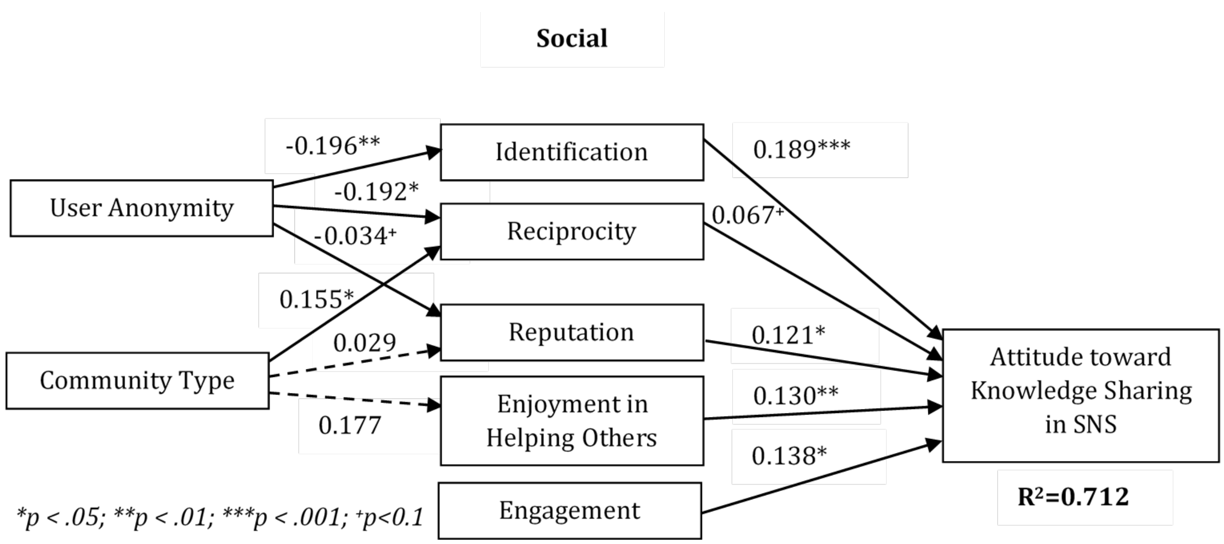

Figure 1. PLS Results for Direct Effects with Path Coefficients

5 Discussion

In this study, we investigate why people may have positive or negative feelings about sharing their knowledge in SNS. More specifically, we investigate how contextual factors (i.e., user anonymity, community type) of SNS impact the social antecedents of knowledge-sharing attitude in such communities. Table 4 summarizes the findings.

Table 4. Effects Hypotheses Validation Results

Hypothesis	Path	Path coefficient	Std. dev. / Std. error	t-stat.	Sig. level (p value)	Validation
H1	I → KS	0.189	0.102	3.922***	0.000	Supported
H2	RE → KS	0.067	0.091	1.735^{+}	0.083	Marginally supported
H3	R → KS	0.121	0.066	2.004*	0.046	Supported
H4	EH → KS	0.130	0.065	2.868**	0.004	Supported
H5	E → KS	0.138	0.061	2.332*	0.020	Supported
H6a	UA→ I	-0.196	0.024	2.931**	0.003	Supported
H6b	UA→ RE	-0.192	0.066	1.996*	0.046	Supported
H6c	UA→ R	-0.034	0.087	1.844^{+}	0.066	Marginally supported
H7a	CT→ I	0.155	0.069	2.114*	0.035	Supported
H7b	CT→ R	-0.029	0.033	1.454	0.146	Not supported
H7c	CT→ EH	0.177	0.051	1.577	0.115	Not supported

*p < .05; **p < .01; *** p < .001; $^{+}$p<0.1
KS = knowledge sharing, I = identification, RE = reciprocity, R = reputation, EH = enjoyment of helping others, E = engagement, UA = user anonymity, CT = community type.

We found identification to have a positive significant relationship with knowledge-sharing attitude in SNS, which supports H1. In other words, a higher mutual understanding between an individual and the online community results in a more positive attitude towards sharing the knowledge that individual possesses (Dholakia et al., 2004), which supports Nahapiet and Ghoshal's (1998) argument on identification as a social capital that could cultivate resource exchange. From a broader perspective, our results favor Kramer and Tyler's (1996) discussion that identification enhances members' concern for collective results.

Reciprocity's impact on knowledge-sharing attitude was only marginally significant[1], which indicates slight support for H2. People's mutual indebtedness seems not to encourage individuals to share their knowledge on SNS as much as other motivations, which aligns with Wasko and Faraj's (2005) conclusion on the impact of reciprocity on knowledge-contribution behavior in terms of helpfulness (t = 0.07). Based on their discussion, one could interpret the above marginal significance finding based on the meaning of indirect reciprocity: that, in the context of SNS, individuals tend to help each other with sharing knowledge in an indirect chain pattern (e.g., A→B→C) rather than a direct reciprocal one (e.g., A→B→A). This interpretation supports Ekeh's (1974) discourse of social exchange theory, which argues that, in social exchanges, an individual may reciprocate help in a generalized manner and not necessarily to the individual who initially provided it. Wasko and Faraj (2000) also found that direct reciprocity does not drive knowledge exchange in online communities of practice.

Reputation had a significant positive relationship with knowledge-sharing attitude in SNS, which supports H3. This result aligns with Wang and Lai's (2006) conclusion that reputation increases knowledge-sharing contribution in technology-related virtual communities. It also aligns with Wasko and Faraj's (2005) study: they found that reputation, as an individual motivating factor, positively impacts knowledge sharing in terms of helpfulness and volume.

The enjoyment of helping others also had a significant positive relationship with knowledge-sharing attitude, which supports H4. It appears that higher perceptions of altruistic behavior in online communities can increase positive feelings about sharing knowledge in such communities. As Ba, Stallaert, and

[1] While research in the social sciences tends to focus on significance levels less than 0.05, it is recognized that significance levels of 0.10 do suggest a possible trend (Cramer & Howitt, 2004). As such, several researchers in Information Systems have been adopting the "modest" or "marginal" significance terminology to indicate *p*-values between 0.05 and 0.10 (examples include Dabbish & Kraut 2008; Dimoka, Hong, & Pavlou, 2012; Maity & Dass, 2014).

Whinston (1991) assert, altruism is a socio-psychological motivation for sharing knowledge. Our results align with Hew and Hara's (2007) qualitative finding in online networks of practice.

Similarly, engagement had a strong positive effect on knowledge-sharing attitude, which supports H5. The more members experience the perception of involvement in social networking sites, the more they possess a positive attitude about sharing their knowledge on such websites. If individuals sense isolation in an environment that other members find captivating, they are less likely to be in a productive mood to participate and share their knowledge with other members. Our results align with previous work such as Venkatesh et al. (2012) and Moon and Kim (2001). While most of these studies focus on behavioral intention (Venkatesh & Bala, 2008), our research in the context of online communities acknowledges that a higher perception of involvement in a community positively impacts an individual's behavioral attitude towards knowledge sharing as well.

We tested two contextual constructs for possible effects on the social antecedents of knowledge-sharing attitude: user anonymity and community type. We found that user anonymity had a positive strong effect on identification, which supports H6a. Thus, for members of Facebook and LinkedIn who used their true identities, they more strongly identified with their community compared to members of CNET who used pseudonyms. These results align with the cognitive perspective of the social model of deindividuation effects, which explains that anonymity may decrease the salience of social identity in a group when group members carry a feeling of belonging to that group (Lea, Spears, & de Groot, 2001; Reicher et al., 1995). We also found that the effect of user anonymity on reciprocity was statistically significant, which supports H6b. When individuals perceive that other members in a community know their true identity, they are more likely to feel positive about sharing their knowledge with those members in terms of reciprocation. Additionally, the effect of user anonymity on reputation appeared to be marginally significant, which slightly supports H6c. Based on social exchange theory, reputation is valuable for individuals and, thus, drives them towards sharing knowledge in social networks. In the case of online communities, building a reputation encourages members to share their experience, judgment, expertise, or insight to improve their status on the subject at hand.

In terms of community type, we selected two categories to investigate: communities of relationship and communities of interest. We found that community type had a significant relationship with identification, which supports H7a. Individuals who use a community relationship (e.g., Facebook) are more likely to develop a sense of belonging and establish a stronger bond with the community. Facebook users care about the community itself and reinforcing personal relationships with others more than those who perceive it as a community of interest. Members of LinkedIn and CNET tend to use these communities as a gateway to find relevant information in a particular domain. LinkedIn members care about building professional relationships to help their careers, while those on CNET care about furthering their technology-related knowledge. Our results show that communities of relationship strengthen the effect of community type on identification. Community type appeared to have no significant effect on reputation (H7b) and enjoyment of helping others (H7c). As such, individuals are more likely to have positive feelings about sharing their knowledge with other community members when triggered by the concept of reputation or enjoyment of helping others regardless of the type of the online community they belong to. Both reputation and enjoyment of helping others constructs considered intrinsic motivators (Wasko & Faraj, 2005), and, unlike extrinsic motivators, they are more independent in terms of their impact on human attitude or behavior (Kankanhalli et al., 2005). For example, people who perceive supporting others as a pleasant act or those who place high value on altruism are more prone to help others regardless of the context in which they act. In the case of this research, regardless of whether users used a community of relationship (i.e., Facebook) or a community of interest (i.e., LinkedIn, CNET), they seemed to have a positive mindset on sharing their knowledge if they valued their reputation and helping others. Considering the inherent career related and competitive nature of LinkedIn, this result is both interesting and surprising.

6 Contributions, Limitations, and Future Research

Overall, this investigation further clarifies our understanding of knowledge sharing in SNS. Existing literature on knowledge sharing mostly focuses on online communities of practice. We argue that knowledge sharing constitutes an essential facet of socialization and that it can occur in more diverse venues in organizational contexts, and, thus, we call for a research agenda to explore the nature of knowledge sharing beyond organizational boundaries. This study helps to bridge the gap between SNS and conventional knowledge-sharing research. Additionally, to the best of our knowledge, previous research has not examined the contextual concepts of anonymity and community type in the context of SNS. User anonymity is central to studying social networks. When it comes to non-organizational online communities, individuals may not have to register or display their true identity. This research investigates the impact of anonymity on the antecedents of knowledge-sharing attitude in SNS. Likewise, previous research has conceptualized community type but not investigated it for its potential impact on knowledge sharing in this context. This work helps to fill this gap.

From a practitioner's perspective, organizations in general and SNS and developers and companies in particular may find our results useful. Businesses can use online communities, such as Facebook fan pages, LinkedIn profiles, and CNET forums, as a reliable gateway to introduce their company, gather intelligence on followers globally, and enhance the marketing of their products and services. Businesses can also use SNS to collect valuable insights and draw on collectively created knowledge for research and development, planning, and marketing purposes. However, to best leverage these potential benefits, organizations should use those online communities that best encourage knowledge sharing among their members. Our investigation shows the positive impacts that various social factors can have on knowledge-sharing attitudes in SNS. Additionally, we demonstrate the influence of contextual factors on these social factors, which, in turn, encourages knowledge sharing. While the potential utility of a SNS for an organization may vary by purpose, communities of relationship that identify members' real identity encourage positive attitudes around knowledge sharing via positive impacts on social mediators. From a SNS and company's viewpoint (e.g., CNET), when members have positive attitudes towards sharing knowledge, they convey better information. In turn, as members and/or customers become more satisfied with the content, the company's reputation and ultimately its revenues may improve.

As with any empirical investigation, our study has certain limitations. First, we used self-reported measures for the dependent variable and social antecedents. Although analyses showed that common method variance was not an issue in our investigation, it could be more accurate to measure the dependent variable through the actual behavior of participants. For instance, in the case of knowledge sharing, it would be valuable to measure subjects' behavior in term of quantity and quality of knowledge they shared. However, measuring knowledge and knowledge sharing is ambiguous and problematic. Second, we obtained an appropriate cross-sectional representation of Canadians who belonged to the three online communities. While we can confidently generalize to the Canadian population, we cannot generalize beyond Canadian online communities' members. Further investigations can examine the validity of the research findings in cross-country studies. Third, this study focuses on SNS as one type of online communities. Aggregators (e.g., Digg, Reddit) and Publicators (e.g., Wikipedia) represent other types of websites that offer social collaboration artifacts. The generalizability of the current investigation is limited to online social networks. It is also important to note that some of our finding showed marginal relationships (in particular, user anonymity's impact on reputation and reciprocity's impact on attitude towards knowledge sharing). While marginal relationship may indicate a possible trend (Cramer & Howitt 2004), future research should further explore them in particular.

This domain contains several interesting research questions that researchers still need to answer. One potential investigation lies in the concept of self-efficacy or one's perceived ability to conduct a behavior. Research has identified self-efficacy to pose an important role in motivating individuals (Bandura, 1986) and employed it to study Internet usage (Hsu & Chiu, 2004) and virtual communities (Hsu et al., 2007). Knowledge sharing self-efficacy would represent an interesting topic to investigate in non-organizational SNS. Furthermore, investigating the effects of different SNS and artifacts (e.g., social bookmarking, commenting, blogging) on knowledge-sharing attitude would advance our model to a socio-technical one.

In sum, this study helps to fill a gap in the extant knowledge management literature by exploring knowledge sharing in non-organizational online communities that feature members who behave voluntarily. Our results can guide future IS researchers and practitioners who deal with knowledge sharing in understanding the impacts of social constructs and contextual factors in SNS environments.

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References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior.* Englewood Cliffs, NJ: Prentice-Hall.

Alavi, M. (2000). Managing organizational knowledge. In R. W. Zmud (Ed.), *Framing the domains of IT management: Projecting the future through the past* (pp. 15-28). Cincinatti, OH: Pinnaflex.

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly*, *25*(1), 107-136.

Alexa. (2018a). *CNET.com traffic statistics.* Retrieved from https://www.alexa.com/siteinfo/cnet.com

Alexa. (2018b). *Linkedin.com traffic statistics*. Retrieved from https://www.alexa.com/siteinfo/linkedin.com

Allison, P. D. (1999). *Multiple regression: A primer*. Thousand Oaks, CA: Pine Forge Press.

Ardichvili, A., Page, V., & Wentling, T. (2003). Motivation and barriers to participation in virtual knowledge-sharing communities of practice. *Journal of Knowledge Management*, *7*(1), 64-77.

Armstrong, A., & Hagel, J. (2000). The real value of online communities. In E. Lesser, M. A. Fontaine, & J. A. Lusher (Eds.), *Knowledge and communities* (pp. 85-95). Boston, MA: Butterworth-Heinemann.

Ba, S., Stallaert, J., & Whinston, A. B. (2001). Research commentary: Introducing a third dimension in information systems design—the case for incentive alignment. *Information Systems Research*, *12*(3), 225-239.

Bandura, A. (1986). *Social foundations of thought and action*. Englewood Cliffs, NJ: Prentice-Hall.

Belk, R. (2014). Sharing versus pseudo-sharing in Web 2.0. *The Anthropologist*, *8*(1), 7-23

Bock, G. W., Zmud, R. W., Kim, Y. G., & Lee, J. N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Quarterly*, *29*(1), 87-111.

Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Quarterly*, *29*(3), 399-426.

Cappelli, P., & Sherer, P. D. (1991). The missing role of context in OB—the need for a meso-level approach. *Research in Organizational Behavior*, *13*, 55-110.

Chai, S., & Kim, M. (2010). What makes bloggers share knowledge? An investigation of the role of trust. *International Journal of Information Management*, *30*(5), 408-415.

Chai, S., & Kim, M. (2012). A socio-technical approach to knowledge contribution behavior: An empirical investigation of social networking sites users. *International Journal of Information Management*, *32*(2), 118-126.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, *36*(4), 1165-1188.

Chin, W. W. (1998a). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), vii-xvi.

Chin, W. W. (1998b). The partial least squares approach for structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295-336.

Chin, W. W. (2010). How to write up and report PLS analyses. In In V. E. Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 655-690). Berlin: Springer.

Chin, W. W., & Newsted, P. R. (1999). Structural equation modeling analysis with small samples using partial least squares. *Statistical Strategies for Small Sample Research*, 1(1), 307-341.

Chiu, C.-M., Hsu, M.-H., & Wang, E. T. G. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories*. Decision Support Systems*, *42*(3), 1872-1888.

Chow, W., & Chan, L. S. (2008). Social network, social trust and shared goals in organizational knowledge sharing. *Information & Management*, *45*, 458-465.

Cohen J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cramer, D., & Howitt, D. L. (2004). *The Sage dictionary of statistics: A practical resource for students in the social sciences*. Thousand Oaks, CA: Sage.

Dabbish, L., & Kraut, R. (2008). Research note: Awareness displays and social motivation for coordinating communication. *Information Systems Research*, *19*(2), 221-238.

Davenport, T. H., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know.* Boston, MA: Harvard Business School Press.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111-1132.

Dholakia, U. M., Baggozi, R. P., & Pearo L. K. (2004). A social influence model of consumer participation in network- and small-group based virtual communities. *International Journal of Research in Marketing*, *21*(3), 241-263.

Deltour, F., Plé, L., & Roussel, C. S. (2014). Knowledge sharing in the age of Web 2.0: A social capital perspective. In Information Resources Management Association (Ed.,) *Cyber behavior: Concepts, methodologies, tools, and applications.*

Dimoka, A., Hong, Y., & Pavlou, P. (2012). On product uncertainty in online markets: Theory and evidence. *MIS Quarterly*, *36*(2), pp.395-426.

Doll, W. J., & Torkzadeh, G. (1988). The measurement of end-user computing satisfaction. *MIS Quarterly*, *12*(2), 259-274.

Ekeh, P. P. (1974). *Social exchange theory: The two traditions*. Cambridge, MA: Harvard University Press.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research.* Reading, MA: Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Fu, E. S., Yang, S. J., & Huang, J. J. (2012). A snapshot of students' blogging profiles in Taiwan: From the viewpoint of knowledge sharing. *Knowledge Management & E-Learning: An International Journal*, *4*(1), 7-15.

Gruber, T. (2007). Collective knowledge systems: Where the social Web meets the semantic Web. *Web Semantics: Science, Services and Agents on the World Wide Web*, *6*(1), 4-13.

Hars, A., & Ou, S. (2002). Working for free? Motivations for participating in open-source projects. *International Journal of Electronic Commerce*, *6*(3), 25-39.

Hau, Y. S., Kim, B., Lee, H., & Kim, Y. G. (2013). The effects of individual motivations and social capital on employees' tacit and explicit knowledge sharing intentions. *International Journal of Information Management*, *33*(2), 356-366.

Hew, K. F., & Hara, N. (2007). Knowledge sharing in online environments: A qualitative case study. *Journal of the American Society for Information Science & Technology*, *58*(14), 2310-2324.

Holpuch, A. (2015). Facebook still suspending Native Americans over "real name" policy. *The Guardian*. Retrieved from https://www.theguardian.com/technology/2015/feb/16/facebook-real-name-policy-suspends-native-americans

Hong, W., Chan, F. K., Thong, J. Y., Chasalow, L. C., & Dhillon, G. (2014). A framework and guidelines for context-specific theorizing in information systems research. *Information Systems Research*, *25*(1), 111-136.

Hsu, C. L., & Lin, J. C. C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & Management*, *45*(1), 65-74.

Hsu, M. H., & Chiu, C. M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems*, *38*(3), 369-381.

Hsu, M. H., Ju, T. L., Yen, C. H., & Chang, C. M. (2007). Knowledge sharing behavior in virtual communities: The relationship between trust, self-efficacy, and outcome expectations. International *Journal of Human-Computer Studies*, *65*(2), 153-169.

Internet World Stats. (n.d.). *Internet usage statistics: The Internet big picture*. Retrieved from http://www.internetworldstats.com/stats.htm

Johns G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review*, *31*(2), 386-408.

Kane, G. C., Alavi, M., Labianca, G., & Borgatti, S. P. (2014). What's different about social media networks? A framework and research agenda. *MIS Quarterly*, *38*(1), 275-304.

Kankanhalli, A., Tan, B. C. Y., & Wei, K. K. (2005). Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly*, *29*(1), 113-143.

Ko, D. G., Kirsch, L. J., & King, W. R. (2005). Antecedents of knowledge transfer from consultants to clients in enterprise system implementations. *MIS Quarterly*, *29*(1), 59-85.

Kramer, R. M., & Tyler, T. R. (Eds.). (1996). *Trust in organizations: Frontiers of theory and research*. Thousand Oaks, CA: Sage.

Krebs, D. (1975). Empathy and altruism. *Journal of Personality and Social Psychology*, *32*(6), 1134-1146.

Latour, B., (2005). *Reassembling the social: An introduction to actor-network-theory.* Oxford: Oxford University Press.

LinkedIn. (2018). *About us.* Retrieved from https://press.linkedin.com/about-linkedin

Lea, M., Spears, R., & de Groot, D. (2001). Knowing me, knowing you: Anonymity effects on social identity processes within groups. *Personality and Social Psychology Bulletin*, *27*(5), 526-537.

Lunden, I. (2015). Who's viewed your posts? LinkedIn adds analytics to its publishing platform. *Techcrunch*. Retrieved from https://beta.techcrunch.com/2015/05/07/whos-viewed-your-posts-linkedin-adds-analytics-to-its-publishing-platform/

Lu, H., & Hsiao, K. (2007). Understanding intention to continuously share information on weblogs. *Internet Research*, *17*(4), 345-361.

Ma, M., & Agarwal, R. (2007). Through a glass darkly: Information technology design, identity verification, and knowledge contribution in online communities. *Information Systems Research*, *18*(1), 42-67.

Maity, M., & Dass, M. (2014). Consumer decision-making across modern and traditional channels: E-commerce, m-commerce, in-store. *Decision Support Systems*, *61*(1), 34-46

Meyers, L. S., Gamst, G., & Guarino, A. J. (2006). *Applied multivariate research: Design and interpretation.* Thousand Oaks, CA: Sage.

Moon, J., & Kim, Y. (2001). Extending the TAM for a World Wide Web context. *Information & Management*, *38*(4), 217-230.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192-222.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, *23*(2), 242-266.

Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, ba and leadership: A unified model of dynamic knowledge creation. *Long Range Planning*, *33*(1), 5-34.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory*. New York: McGraw.

Pfitzmann, A., & Hansen, M. (2010). *A terminology for talking about privacy by data minimization: Anonymity, unlinkability, undetectability, unobservability, pseudonymity, and identity management* (ver. 34). Technical University Dresden.

Pi, S. M., Chou, C. H., & Liao, H. L. (2013). A study of Facebook groups members' knowledge sharing. *Computers in Human Behavior*, *29*(5), 1971-1979.

Postmes, T., & Lea, M. (2000). Social processes and group decision making: Anonymity in group decision support systems. *Ergonomics*, *43*(8), 1252-1274.

Pulakos, E. D., Dorsey, D. W., & Borman, W. C. (2003). Hiring for knowledge-based competition. In S. E. Jackson, M. A. Hitt, & A. S. DeNisi (Eds.), *Managing knowledge for sustained competitive advantage: Designing strategies for effective human resource management* (pp. 155-177). San Francisco: Jossey Bass.

Reicher, S. D., Spears, R., & Postmes, T. (1995). A Social Identity Model of Deindividuation Phenomena. European Review of Social Psychology, 6(1), 161-198.

Sheng, M., & Hartono, R. (2015). An exploratory study of knowledge creation and sharing in online community: A social capital perspective. Total Quality Management & Business Excellence, 26(1-2), 93-107.

Stanoevska-Slabeva, K. (2002). Toward a community-oriented design of internet platforms. *International Journal of Electronic Commerce, 6*(3), pp. 71-95.

Statista. (2017a). *Number of daily active Facebook users worldwide as of 3rd quarter 2017 (in millions)*. Retrieved from https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/

Statista. (2017b). *Weekly LinkedIn usage of registered users as of March 2016 (in hours).* Retrieved from https://www.statista.com/statistics/264116/weekly-linkedin-usage-of-registered-users/

Suler, J. (2004). The online disinhibitation effect. *Cyber Psychology and Behavior*, *7*(3), 321-326.

Suler, J. (2005). The online disinhibitation effect. *International Journal of Applied Psychoanalytic Studies*, *2*(2), 184-188.

Tabachnick, B. G., Fidell, L. S., & Osterlind, S. J. (2001). *Using multivariate statistics.* Boston: Allyn and Bacon.

Thong, J. Y., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies*, *64*(9), 799-810.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 28(4), 695-704.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273-315.

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178.

Wang, C. C., & Lai, C. Y. (2006). Knowledge contribution in the online virtual community: Capability and motivation. In *Proceedings of the International Conference on Knowledge Science, Engineering, and Management.*

Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, *20*(2), 115-131.

Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, *29*(1), 35-57.

Wasko, M., & Faraj, S. (2000). It is what one does: Why people participate and help others in electronic communities of practice. *The Journal of Strategic Information Systems*, *9*(2), 155-173.

Webster, J., & Ho, H. (1997). Audience engagement in multimedia presentations. *DATA BASE for Advances in Information Systems*, *28*(2), 63-77.

Webster, J., & Ahuja, J. S. (2006). Enhancing the design of Web navigation systems: The influence of user disorientation on engagement and performance. *MIS Quarterly*, *30*(1), 661-378.

Wu, J., & Lu, X. (2013). Effects of extrinsic and intrinsic motivators on using utilitarian, hedonic, and dual-purposed information systems: A meta-analysis. *Journal of the Association for Information Systems*, *14*(3), 153-191.

Yao, C.-Y., Tsai, C.-C., & Fang, Y.-C. (2015). Understanding social capital, team learning, members' e-loyalty and knowledge sharing in virtual communities. *Total Quality Management & Business Excellence*, *26*(5-6), 619-631.

Yang, H. L., & Lai, C. Y. (2011). Understanding knowledge-sharing behavior in Wikipedia. *Behavior & Information Technology*, *30*(1), 131-142.

Yoon, C., & Rolland, E. (2012). Knowledge-sharing in virtual communities: Familiarity, anonymity and self-determination theory. *Behavior & Information Technology*, *31*(11), 1133-1143.

Yuan, Y. C., Zhao, X., Liao, Q., & Chi, C. (2013). The use of different information and communication technologies to support knowledge sharing in organizations: From e-mail to micro-blogging. *Journal of the American Society for Information Science and* Technology, *64*(8), 1659-1670.

Appendix: Construct Information

Table A1. Construct Definitions and References

Construct	Definition	References
Knowledge-sharing attitude	The degree to which users possess positive or negative feeling about knowledge sharing.	Fishbein & Ajzen (1975), Ajzen & Fishbein (1980), Bock et al. (2005), Chow & Chan (2008)
Reputation	The degree to which users believe that sharing knowledge would enhance their status.	Wasko & Faraj (2005), Moore & Benbasat (1991), Kankanhalli et al. (2005)
Reciprocity	The degree to which users believe that their relationships in an online community is fair with mutual benefits.	Wasko & Faraj (2005)
Identification	The degree to which users feel they belong to the community.	Chiu et al. (2006), Nahapiet & Ghoshal (1998)
Enjoyment in helping others	The degree to which users enjoy helping others through knowledge sharing beyond personal gains.	Kankanhalli et al. (2005), Wasko & Faraj (2005)
Engagement	The degree to which users experience perception of involvement.	Webster & Ho (1997), Webster & Ahuja (2006)
User anonymity	The degree to which online community members perceive themselves as being anonymous to other members.	Yoon & Roland, (2012)
Community type	The purpose and nature of the online community.	Stanoevska-Slabeva (2002), Armstrong & Hagel (2000)

Table A2. Measurement Items for Variables

Construct	Item
Knowledge-sharing attitude (KS) (Bock et al., 2005)	KS1*: My knowledge sharing with other (online community) members in my network on (online community) is good.
	KS2: My knowledge sharing with other (online community) members in my network on (online community) is harmful.
	KS3: My knowledge sharing with other (online community) members in my network on (online community) is an enjoyable experience.
	KS4: My knowledge sharing with other (online community) members in my network on (online community) is valuable to me.
	KS5: My knowledge sharing with other (online community) members in my network on (online community) is a wise move.
Identification (I) (Chiu et al., 2006)	I1: I have a sense of belonging to (online community).
	I2: I have the feeling of togetherness/closeness on (online community).
	I3: I really care about (online community).
Reciprocity (RE) (Wasko & Faraj, 2005)	RE1: I know that other (online community) members in my network will help be by sharing their knowledge, so it is only fair that I help them by sharing my knowledge.
	RE2: I trust that other (online community) members in my network would help me by sharing their knowledge if I were in a situation in which I need their help.
Reputation (R) (Wasko & Faraj, 2005)	R1: I earn respect from other (online community) members in my network by sharing my knowledge.
	R2: I feel that sharing knowledge with other (online community) members in my network improves my status on (online community).
	R3: Sharing knowledge with other members of (online community) in my network improves my image on (online community).

Table A2. Measurement Items for Variables

Enjoyment in helping others (EH) (Wasko & Faraj, 2005)	EH1: I like helping other (online community) members in my network through sharing my knowledge.
	EH2: I enjoy sharing my knowledge with other (online community) members in my network.
	EH3: It feels good to help other (online community) members in my network through sharing my experiences/knowledge.
Engagement (E) (Webster & Ahuja, 2006)	E1: This online community keeps me absorbed.
	E2: This online community excites my curiosity.
	E3: This online community is engaging.
	E4*: This online community is inherently interesting.
* Denotes item dropped from original scale	

About the Authors

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