Privacy Coping and Information-Sharing Behaviors in Social Media: A Comparison of Chinese and U.S. Users

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Abstract:

Although many studies examine privacy in social media settings, few studies examine privacy issues that may arise due to characteristics of user populations. This study compares privacy issues among social media users in the United States and China. It also explores privacy issues among users with different levels of Internet addiction and different online identity perceptions. In doing so, it identifies several populations that are more susceptible to privacy violations due to their online behaviors. The study finds that U.S. and Chinese users differ in their privacy coping and information-sharing behaviors. Chinese users may be at greater risk to privacy violations because of their online behaviors. Additionally, users addicted to social media and users with different online identities may be vulnerable to privacy violations. Potential explanations for these findings are provided and directions for future research are offered.

Keywords: Cultural Differences | Information Sharing | Internet Addiction | Privacy Coping | Social Media

Article:

INTRODUCTION

The popularity of computer-mediated social media has sparked global discussion and concern about an individual's privacy online (Chen & Sharma, 2012; Yang, Lai, & Lu, 2012; Yin, Zhu, & Cheng, 2013). Social media platforms, such as Facebook and Renren, contain highly personal and private information, such as birthdates, phone numbers, e-mail addresses, physical addresses, political views, and personal photographs. Given that private information exists on social media, unwise use of social media can negatively affect individuals. For example, irresponsible use of social media can limit employment opportunities (Abril, Levin, & Riego, 2012; Riego, Abril, & Levin, 2012) and facilitate identity theft and other forms of fraudulent behavior (Acquisti, 2011; McDermott, 2012). Although social media users can employ privacy coping strategies to protect themselves, this article posits that some user populations may be less likely to adopt privacy coping strategies and safe information-sharing behaviors.

For example, some studies have compared privacy concerns between individuals in different countries (e.g., Lowry, Cao, & Everard, 2011; Zhang, Chen, & Wen, 2002). These studies find that national culture affects privacy concerns. Importantly, privacy concerns affect intentions to adopt privacy coping strategies (Smith, Milberg, & Burke, 1996). Thus, populations with lower privacy concern may engage in less privacy coping behavior, leading to privacy vulnerabilities. Expanding on previous research, the possibility that certain populations of social media users may be more vulnerable to privacy violations than others is explored. In particular, the effects that national origin (i.e., U.S. and Chinese users), Internet addiction, and online identity exert on privacy coping and information-sharing behaviors are examined. What differences exist in privacy coping and information-sharing behaviors in social media contexts for users from different countries (i.e., the United States and China), users with differing levels of Internet addiction, and users with different online identities?

To answer this question, U.S. and Chinese social media users were surveyed through an online survey. Measures were included for three dependent variables related to information-sharing and privacy coping behavior: users' comfort with sharing information with different groups of people (e.g., family, friends, strangers), users' breadth of online self-disclosure (e.g., sharing birthdates, addresses, phone numbers, personal interests, etc.), and users' willingness to engage in privacy coping behaviors. Using partial least squares structural equation modeling (PLS-SEM), 397 responses were analyzed—192 users from China and 205 users from the United States.

The analysis offers several important research contributions. First, populations were identified that may be particularly vulnerable to privacy violations in social media due to their privacy coping and information-sharing behaviors. Based on the findings, policy makers, managers of social media platforms, and social media users are implored to protect vulnerable user populations. Second, the study provides evidence to suggest that culture and politics in different countries may affect the privacy coping and information-sharing behaviors of users in different countries. Third, the findings suggest that users with Internet addiction may not adequately protect themselves. Finally, the study finds evidence that users' perceptions of their online identities may influence their information-sharing and privacy coping behaviors. Based on the results, future research should continue to study vulnerable populations in social media.

The remainder of this article continues as follows. First, a review of literature pertaining to privacy in social media is offered. Second, an exploratory conceptual model is presented for testing. Third, the methodology used to collect and analyze the data is described. Fourth, the results of the measurement and structural models are provided. Fifth, a discussion of the implications of the findings and directions for future research are provided.

LITERATURE REVIEW

Privacy is an increasingly important topic in information systems (IS) research. *Privacy* refers to "the ability of the individual to personally control information about one's self" (Stone, Gueutal, Gardner, & McClure, 1983). In IS research, privacy concern is often used as a surrogate for measuring and studying privacy (Smith, Dinev, & Xu, 2011; Smith et al., 1996). Privacy concern consists of individuals' perceptions and attitudes toward the collection of personal information, unauthorized secondary use of personal information, errors in personal information, and improper access to personal information (Smith et al., 1996). Research on privacy concern has focused on such outcome variables as information disclosure, engagement in ecommerce, and trust (Smith et al., 2011).

Privacy concerns drive users to engage in privacy coping strategies, such as removing or refusing to share information or misrepresenting information (Malhotra, Kim, & Agarwal, 2004; Smith et al., 1996). Privacy coping strategies can protect users against privacy invasions by governments, organizations, and criminals. However, some users may be more vulnerable to privacy invasion than others because of their information-sharing and privacy coping behaviors. For example, the influence of national culture on information-sharing and privacy coping behaviors has started to receive some notice. National culture may influence the use of social media (Chapman & Lahav, 2008; Gretzel, Kang, & Lee, 2008; Lowry et al., 2011). Culture may also influence privacy coping behavior on e-commerce sites (Zhang et al., 2002). We seek to further explore the relationships between information-sharing and privacy coping behaviors for vulnerable populations. Identifying vulnerable populations and understanding why they are vulnerable may help organizations and users to develop and implement appropriate protections to safeguard users' privacy.

In this study, we examine two primary outcome variables. First, we explore online information-sharing behavior. Because we are concerned with users' privacy in social media settings, we define *information-sharing behavior* as the act of disclosing information about oneself on social media platforms. We study two facets of information-sharing behavior: *a user's comfort with sharing personal information with multiple other people* (e.g., friends, family, co-workers, and strangers) and the *breadth of information users are willing to disclose to others* (e.g., birthdate, address, phone number, self-photographs, etc.). Second, we explore privacy coping behaviors in social media. We explore three types of coping behavior: *refusal to share information in social media*, *removal of information from social media*, and *misrepresentation of information in social media*. These are common coping strategies (Malhotra et al., 2004; Smith et al., 1996).

Privacy in Social Media

The advent of social media has allowed individuals to communicate with family, friends, and business associates throughout the world. Although social media provides many benefits to society, social media has a dark side. Privacy invasions, such as cyberstalking (Spitzberg & Hoobler, 2002) and data mining (White, 2012), are rampant in social media platforms. Improper use of social media can negatively affect users (Abril et al., 2012; Acquisti, 2011; McDermott, 2012; Riego et al., 2012). Privacy research in social media settings is in a nascent state (Brandtzæg, Lüders, & Skjetne, 2010). Therefore, it is important to better understand information-sharing and privacy coping behaviors in social media settings, particularly for vulnerable populations. Privacy research in social media contexts has primarily focused on privacy concerns and social technology use (e.g., Lowry et al., 2011), trust (e.g., Fogel & Nehmad, 2009), and information-sharing behavior (e.g., Brandtzæg et al., 2010). This study expands upon existing research by exploring information-sharing behavior along with privacy coping behaviors for populations that may be vulnerable to privacy invasion. The exploration in this article provides a step toward identifying and protecting populations that are vulnerable to privacy invasion.

MODEL DEVELOPMENT

Prior research has noted that some user populations use IS in non-traditional ways based on the characteristics of the users. For example, users of different national origin may exhibit different computing behavior (Chapman & Lahav, 2008; Gretzel et al.,2008; Lowry et al., 2011). Similarly, users with Internet addictions use IS differently than users who are not addicted (Turel, Serenko, & Giles, 2011). Users with different personalities may also exhibit different privacy behavior (Junglas, Johnson, & Spitzmüller, 2008). We explore the extent to which differences in online behavior produce privacy vulnerabilities for certain populations of users. Figure 1 presents our exploratory conceptual model.

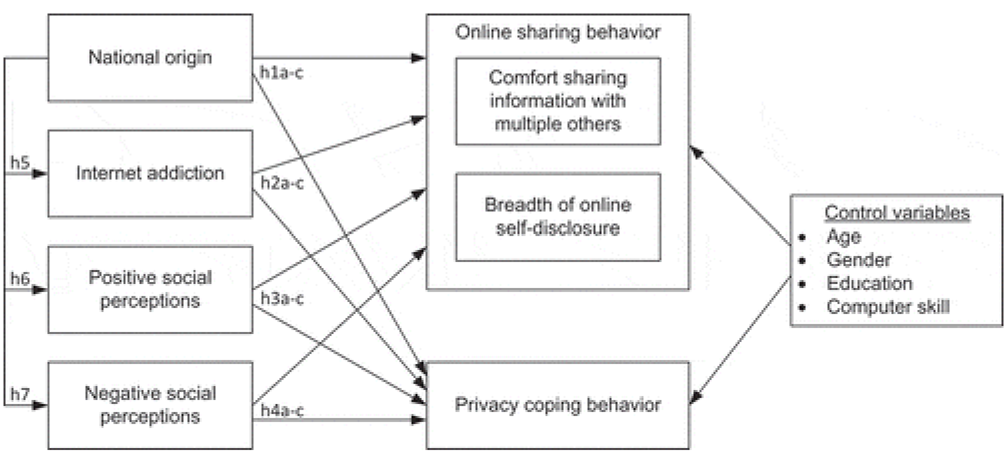

Figure 1. Conceptual model.

Privacy and National Origin

Individuals of different national origin may differ in their privacy coping and information-sharing behaviors. National culture in the United States and China, for example, affects users' attitudes (e.g., privacy concerns) toward self-disclosure technologies and influences subsequent use of those technologies (Lowry et al., 2011). Cross-cultural studies have examined relationships between culture and the social media use in the United States and China (Lowry et al., 2011); in the United States, France, China, and South Korea (Chapman & Lahav, 2008); and in Germany and China (Gretzel et al., 2008). The major finding across the studies is consistent: national culture influences users' social media behaviors. Online privacy coping behaviors may also differ across cultures, such as in e-commerce settings (Zhang et al., 2002).

We seek to extend previous research by exploring privacy coping and information-sharing behaviors in the United States and China for social media users. Few studies have examined both information-sharing and privacy coping behaviors in a single study. By studying both types of behavior, we provide a more holistic exploration of social media behavior across populations.

Building upon findings in previous research (Lowry et al., 2011), we argue that cultural, political, and economic factors in China may make Chinese social media users more likely to share information and less likely to use privacy coping strategies than U.S. users. Cross-cultural studies suggest that the collectivist culture in China leads many Chinese users to share information with their social groups to benefit those groups, whereas the individualistic culture in the United States leads U.S. users to share information only when it benefits the individual. This means that users from collectivist cultures, such as China, may be more likely to share information with members of their social groups than users in individualistic cultures (Lowry et al., 2011). In summary, we suggest the following hypotheses.

H1a:	In general, Chinese social media users are more comfortable sharing information with a diverse set of individuals than U.S. social media users.
H1b:	In general, Chinese social media users are more willing to disclose a greater breadth of information than U.S. social media users.
H1c:	In general, Chinese social media users are less likely to engage in privacy coping behaviors than U.S. social media users.

Privacy and Internet Addiction

Internet addiction is a growing problem worldwide (Chou & Hsiao, 2000; Turel et al., 2011; Wu & Zhu, 2004). *Internet addiction,* or compulsive Internet use, refers to a psychological dependency to information technology (IT) artifacts on the Internet (Turel et al., 2011), such as online auctions, gaming, or social media. Internet addiction exists at the level of specific IT artifacts (Turel et al., 2011); that is, users may be addicted to specific Internet-based IT, such as games or social media, but not to the Internet in general. We focus on addiction to social media platforms. Internet addiction is a behavioral addiction (Holden, 2001) that may result in negative outcomes for the user (Block, 2008; Ferraro, Caci, D'Amico, & Di Blasi, 2007; Morahan-Martin

& Schumacher,2000; Yellowlees & Marks, 2007). Importantly, users with Internet addiction may exhibit different behaviors online than non-addicted users (Turel et al., 2011). Therefore, we explore whether privacy coping and information-sharing behaviors differ for users with differing levels of Internet addiction.

Some Internet users are increasingly compulsive in their use of Internet-based IT artifacts (Chou & Hsiao, 2000; Turel et al.,2011; Wu & Zhu, 2004). Users addicted to social media and other IT artifacts may use those artifacts more frequently and for longer durations than non-addicted users (Turel et al., 2011). Addicted Internet users also tend to use Internet-based IT artifacts to share information, while non-addicted users tend to use the same artifacts to gather information (Leung, 2004). Further, addicted users may try to identify shortcuts or more efficient ways to use IT artifacts (Turel et al., 2011). In a social media context, Internet addiction could lead users to develop shortcuts that include ignoring privacy coping strategies and other privacy protections. In summary, we suggest the following hypotheses.

H2a:	Social media users with higher levels of Internet addiction are more comfortable sharing information with a diverse set of individuals than social media users with lower levels of Internet addiction.
H2b:	Social media users with higher levels of Internet addiction are more willing to disclose a greater breadth of information than social media users with lower levels of Internet addiction.
H2c:	Social media users with higher levels of Internet addiction are less likely to engage in privacy coping behaviors than social media users with lower levels of Internet addiction.

Privacy and Online Identity

Users' online identity is a growing interest in social media research (Xiao, Li, Cao, Tang, & Jiaotong, 2012). We define *online identity* as a user's perception about how others in the online social setting view the user based on the user's social media profile. This definition is consistent with studies that view identity as externally and socially defined (Hongladarom, 2011). Identities may differ in offline and online settings (Rodogno, 2012), although the ubiquity of social media use may merge individuals' online and offline identities (Hongladarom, 2011).

We divide online identity into two parts—a user's perception about the positive and negative character traits reflected by the user's social media profile. Thus, this study explores how negative and positive perceptions of one's online identity influence information-sharing and privacy coping behavior. Although positive or negative perceptions may dominate a user's perspective, it is likely that users' profiles reflect both positive and negative traits. Therefore, we do not explore differences between users with positive and negative identities, but rather, we explore the effect that positive and negative perceptions of identity have on privacy coping and information-sharing behavior.

Individuals with different character traits exhibit different privacy concerns and behaviors (Junglas et al., 2008). Thus, individuals with different online identities may be more or less susceptible to privacy threats. The link between social identity in social media and privacy behaviors has not been explored in great depth. Thus, we provide a preliminary exploration of online identity and privacy by examining how the positive and negative traits users believe are reflected in their social media profiles influence the users' online behaviors. Given the lack of evidence pertaining to online identity and privacy variables, we do not offer directional hypotheses but instead suggest the following.

H3a:	Social media users' perception that their profiles reflect positive personal characteristics affects their comfort with sharing information with a diverse set of individuals.
H3b:	Social media users' perception that their profiles reflect positive personal characteristics affects their willingness to disclose a breadth of information.
H3c:	Social media users' perception that their profiles reflect positive personal characteristics affects the users' likelihood of engaging in privacy coping behaviors.
H4a:	Social media users' perception that their profiles reflect negative personal characteristics affects their comfort with sharing information with a diverse set of individuals.
H4b:	Social media users' perception that their profiles reflect negative personal characteristics affects their willingness to disclose a breadth of information.
H4c:	Social media users' perception that their profiles reflect negative personal characteristics affects the users' likelihood of engaging in privacy coping behaviors.

National Origin and Internet Addiction

Research suggests that different populations may be more vulnerable to Internet addiction than others. For example, individuals with depression and low self-esteem and children and young adults may be vulnerable to Internet addiction (Soule, Shell, & Kleen, 2003). We posit that users from different nations may also be more or less vulnerable to privacy violation. Hofstede, Hofstede, and Minkov (2010) recently proposed a new cultural dimension: indulgence versus restraint. According to Hofstede and colleagues, *indulgence* refers to the extent to which members of a cultural group make efforts to control their desires and impulses. Thus, we expect that individuals who are socialized in an impulsive culture will be more likely to succumb to Internet addiction. Conversely, we expect individuals who are socialized in a culture of restraint to be more resistant to Internet addiction. The U.S. national culture is high on the indulgence dimension, while the culture in China is much lower on the indulgence dimension (Hofstede et al., 2010). Furthermore, the individualistic orientation of U.S. users emphasizes personal benefit, which the Internet and social media can provide in abundance (Ardichvili, Maurer, Li, Wentling, & Stuedemann, 2006). Thus, U.S. users may be more susceptible to Internet addiction than Chinese users. In summary, we suggest the following hypothesis.

H5:	In general, Chinese social media users are less likely to be addicted to social media platforms than U.S. social media users.

National Origin and Online Identity

We posit that national origin may also influence the perceptions of online identity. We conceptualize online identity as externally and socially defined (Hongladarom, 2011). Thus, cultural socialization may influence users' perceptions of their online identities. Compared to the U.S. culture, the Chinese culture socializes individuals to highlight and acknowledge their faults and to aggrandize others' strengths (Mascolo, Fischer, & Li, 2003). Preoccupation with personal faults may be the result of the collectivist culture in China (Mascolo et al., 2003). Research on the cross-cultural concept of "saving face" also posits that individuals from the U.S. and China differ in their preoccupation with positive and negative self-attributes. Individuals from the United States are preoccupied with gaining face (i.e., "Mianzigain"), while individuals from China are preoccupied with losing face (i.e., "Mianziloss") (Hwang, Francesco, & Kessler, 2003). In an online environment, this would suggest that U.S. users may be more preoccupied with their positive characteristics, while Chinese may be more preoccupied with their negative characteristics. Thus, we posit that Chinese users may be more likely to focus on negative aspects and less likely to focus on positive aspects of their online identity than US users.

H6:	In general, Chinese social media users are less likely to perceive that their profiles reflect positive personal characteristics than U.S. social media users.
H7:	In general, Chinese social media users are more likely to perceive that their profiles reflect negative personal characteristics than U.S. social media users.

METHODS

Sampling Frame

Respondents for the study were recruited using a convenience sample with a snowball method to perpetuate recruitment for the study. A total of 515 responses were received—224 users from China and 291 users from the United States. Several responses were dropped, however, due to excessive amounts of unanswered questions. After cleaning the data, 397 responses remained for analysis—192 users from China and 205 users from the United States.

Participants

Participants in the study were primarily young females. Most respondents had not completed education beyond a Bachelor's degree. Respondents in the Chinese sample were slightly older and more educated than respondents in the U.S. sample. Respondents were mostly young. This is not surprising, however, as studies have found that younger individuals tend to use social media more frequently (Chou, Hunt, Beckjord, Moser, & Hesse, 2009). In both samples, most respondents felt their computer skill level was amateur or intermediate. Table 1 provides detailed demographic data for the Chinese and U.S. samples.

Table 1. Responses to Demographic and Control Items

	Chinese Sample		U.S. Sample	
Demographic Item	**Count**	**Percent**	**Count**	**Percent**
Age				
18–20	50	26.0	101	49.3
21–25	134	69.8	65	31.7
26–30	8	4.2	19	9.3
31–35	0	0.0	9	4.4
36–45	0	0.0	7	3.4
46–55	0	0.0	3	1.5
55+	0	0.0	1	0.5
Education				
High school	24	12.5	168	82.0
Bachelor’s degree	152	79.2	33	16.1
Master’s degree	15	7.8	3	1.5
Doctoral degree	1	0.5	1	0.5
Gender				
Male	73	38.0	91	44.4
Female	119	62.0	114	55.6
Computer skill				
Beginner	3	1.6	6	2.9
Amateur	122	63.9	39	19.0
Intermediate	44	23.0	116	56.6
Professional	21	11.0	38	18.5

Expert	1	0.5	6	2.9

Instruments and Items

Questions for the survey were derived from previously published studies. The survey consisted of questions about general privacy coping behaviors (Malhotra et al., 2004; Smith et al., 1996), content-sharing behaviors (Gross & Acquisti, 2005), Internet addiction (Morahan-Martin & Schumacher, 2000), and respondents' demographics. National origin (NORI) was dummy-coded as 1 for China and 0 for the United States. The instrument was developed in English and then translated by a bilingual translator. After translation, the instrument was back-translated by two other bilingual translators (Brislin, 1986). The translations suggest the instrument was expressed equivalently in both languages.

The instrument included reflective and formative measures. Addiction and positive and negative perceptions of online identity were measured reflectively. Coping behavior was measured formatively by asking about the three common coping strategies (i.e., refusal to share information, removal of information, and misrepresentation of information; Malhotra et al., 2004; Smith et al., 1996). Further, we modeled comfort with sharing information with multiple others and breadth of online self-disclosure as formative constructs of a higher-order construct (i.e., information-sharing behavior).

Data Analysis and Results

The conceptual model presented in Figure 1 was analyzed through PLS-SEM. PLS-SEM is ideal for exploration of theoretical concepts and relationships (Goodhue, Lewis, & Thompson, 2012; Lowry & Gaskin, 2014; Tenenhaus, Vinzi, Chatelin, & Lauro,2005; Wetzels, Odekerken-Schöder, & Oppen, 2009). Given the exploratory nature of our study, PLS-SEM is an appropriate analysis method. We conducted the measurement and structural analyses with SmartPLS (Ringle, Wende, & Will, 2005).

Measurement Model

The model consisted of first- and second-order constructs. To assess the measurement model, we used the method proposed by Wetzels et al. (2009), who suggested that the measurement properties of first-order constructs should be assessed first, followed by an assessment of second-order constructs. Thus, we began by examining the measurement properties of the first-order constructs.

The measurement model for first-order constructs exhibited high reliability. Composite reliability for each reflective construct was greater than 0.80, suggesting internal consistency (Fornell & Larcker, 1981). Average variance extracted (AVE) for each reflective construct was also acceptable according to the 0.5 cutoff (Chin, 1998; Fornell & Larcker, 1981), suggesting convergent validity. Table 2 presents AVE and composite reliability for all reflective constructs. AVE and reliability are not valid assessments for first-order formative constructs (i.e., COPE), because items in first-order formative constructs are not expected to co-vary (Petter, Straub, & Rai, 2007). We also do not report AVE and composite reliability scores in Table 2 for SACS, because it was only measured by a single item.

Table 2. AVE and Composite Reliability for First-Order Constructs

Construct	**AVE**	**Composite Reliability**	**Number of Items**
Internet addiction (ADCT)	0.7360	0.8931	3
Coping behavior (COPE)	N/A	N/A	3
Negative identity perceptions (NEGI)	0.6919	0.8998	4
Positive identity perceptions (POSI)	0.7130	0.9084	4
Comfort sharing information with others			
Sharing with familiar individuals (FACS)	0.6874	0.8968	4
Sharing with strangers (SACS)	N/A	N/A	1
Breadth of online self-disclosure			
Basic photos (BPHO)	0.7116	0.8931	2
Contact information (CONT)	0.7595	0.8633	2
Personal history (HIST)	0.7355	0.8468	2
Personal interests (INTR)	0.9155	0.9774	4
Relationship information (RELA)	0.7593	0.9044	3
Sensitive photos (SPHO)	0.6882	0.8083	2

Discriminant validity was assessed for the first-order reflective constructs by ensuring that all item loadings were greater than cross-loadings and that the square root of AVE for each construct was larger than the associated inter-construct correlations (Chin,1998). The reflective indicators, except FACS4 and SPHO2, loaded highly on their associated factors, exceeding the 0.70 cutoff (Fornell & Larcker, 1981). FACS4 loaded at 0.67, and SPHO2 loaded at 0.63.

FACS4 was left in the model, because it was a very minor violation of the 0.70 cutoff. SPHO2 was also left in the model to maintain two reflective items for SPHO. Factor loadings were not assessed for COPE, because factor loadings are not fair assessments of the quality of formative constructs (Petter et al.,2007). In all cases, item loadings for reflective constructs were higher than cross-loadings. Table 3 shows factor loadings and cross-loadings for key variables.

Table 3. Factor Loadings and Cross-Loadings for First-Order Reflective Constructs

	ADCT	**BPHO**	**CONT**	**FACS**	**HIST**	**INTR**	**NEGI**	**POSI**	**RELA**	**SACS**	**SPHO**
ADCT4	**0.87**	−0.13	0.10	−0.08	0.01	−0.14	0.31	−0.08	−0.05	0.14	−0.06
ADCT5	**0.82**	−0.09	0.07	−0.04	0.01	−0.07	0.26	−0.10	0.01	0.17	0.03
ADCT6	**0.88**	−0.07	0.07	−0.14	−0.05	−0.18	0.28	−0.10	−0.06	0.13	0.03
BPHO1	−0.13	**0.91**	0.15	0.12	0.47	0.38	−0.10	0.19	0.40	0.11	0.34
BPHO2	−0.06	**0.78**	0.14	0.07	0.46	0.34	−0.08	0.13	0.57	0.21	0.75
CONT1	0.08	0.14	**0.86**	0.07	0.23	0.19	0.10	−0.07	0.25	0.17	0.22
CONT2	0.08	0.15	**0.89**	−0.02	0.28	0.19	0.13	−0.03	0.25	0.13	0.27
FACS1	−0.11	0.13	−0.02	**0.90**	0.10	0.09	−0.10	0.23	0.06	0.15	0.05
FACS2	−0.07	0.05	0.04	**0.84**	0.04	0.06	−0.10	0.23	0.03	0.17	−0.01
FACS3	−0.09	0.13	0.04	**0.88**	0.12	0.17	−0.06	0.19	0.11	0.30	0.07
FACS4	−0.07	0.09	0.09	**0.67**	0.12	0.16	−0.04	0.03	0.03	0.41	0.05

HIST1	0.06	0.53	0.22	0.09	**0.79**	0.49	−0.03	0.10	0.54	0.30	0.42
HIST2	−0.05	0.43	0.28	0.09	**0.92**	0.50	−0.08	0.17	0.56	0.21	0.41
INTR1	−0.10	0.41	0.22	0.16	0.59	**0.89**	−0.03	0.12	0.53	0.30	0.34
INTR2	−0.15	0.41	0.22	0.12	0.54	**0.98**	−0.02	0.16	0.48	0.28	0.36
INTR3	−0.18	0.42	0.19	0.12	0.54	**0.98**	−0.02	0.14	0.49	0.28	0.35
INTR4	−0.15	0.41	0.20	0.09	0.54	**0.97**	−0.03	0.15	0.49	0.29	0.36
NEGI1	0.29	−0.13	0.06	−0.10	−0.05	0.01	**0.83**	−0.20	−0.06	0.15	−0.01
NEGI2	0.27	−0.08	0.12	−0.11	−0.11	−0.09	**0.86**	−0.15	−0.03	0.04	0.03
NEGI3	0.30	−0.04	0.13	−0.08	0.00	−0.02	**0.83**	−0.18	0.05	0.05	0.07
NEGI4	0.25	−0.11	0.12	−0.03	−0.05	0.03	**0.81**	−0.17	−0.02	0.11	0.07
POSI1	−0.13	0.26	0.01	0.14	0.15	0.10	−0.19	**0.82**	0.22	−0.06	0.16
POSI2	−0.10	0.19	−0.08	0.26	0.13	0.15	−0.17	**0.91**	0.14	−0.02	0.06
POSI3	−0.09	0.08	−0.13	0.24	0.14	0.13	−0.21	**0.85**	0.08	0.00	−0.02
POSI4	−0.03	0.08	0.00	0.18	0.13	0.13	−0.13	**0.80**	0.14	0.00	0.02
RELA1	−0.09	0.41	0.19	0.09	0.54	0.48	−0.01	0.16	**0.85**	0.21	0.36

RELA2	−0.03	0.56	0.27	0.05	0.60	0.45	−0.03	0.15	**0.91**	0.17	0.56
RELA3	0.01	0.48	0.30	0.04	0.51	0.41	−0.02	0.14	**0.85**	0.17	0.51
SACS1	0.17	0.17	0.17	0.25	0.28	0.30	0.11	−0.03	0.22	**1.00**	0.26
SPHO1	−0.02	0.59	0.25	0.05	0.47	0.37	0.03	0.09	0.53	0.26	**0.99**
SPHO2	0.05	0.34	0.32	0.00	0.29	0.21	0.08	−0.03	0.37	0.14	**0.63**

The bold text indicates item loadings.

Further, the square root of AVE for each first-order reflective construct was higher than the associated inter-construct correlations. Table 4 presents latent variable correlations with the square root of AVE on the diagonals. Together, the measurement properties of the first-order reflective constructs demonstrated discriminant validity (Chin, 1998).

Table 4. Latent Variable Correlations With AVE on Diagonal

	ADCT	**BPHO**	**CONT**	**FACS**	**HIST**	**INTR**	**NEGI**	**POSI**	**RELA**	**SACS**	**SPHO**
ADCT	**0.86**										
BPHO	−0.12	**0.84**									
CONT	0.09	0.17	**0.87**								
FACS	−0.11	0.12	0.03	**0.83**							
HIST	−0.01	0.54	0.30	0.10	**0.86**						
INTR	−0.15	0.43	0.22	0.13	0.57	**0.96**					
NEGI	0.33	−0.11	0.13	−0.10	−0.07	−0.02	**0.83**				

POSI	−0.11	0.19	−0.05	0.24	0.16	0.15	−0.21	**0.84**			
RELA	−0.05	0.55	0.29	0.07	0.63	0.52	−0.03	0.17	**0.87**		
SACS	0.17	0.17	0.17	0.25	0.28	0.30	0.11	−0.03	0.22	**1.00**	
SPHO	0.00	0.59	0.28	0.04	0.48	0.37	0.05	0.08	0.54	0.26	**0.83**

The bold text indicates item loadings.

To assess the reliability of the first-order formative construct (i.e., COPE), we examined the variance inflation factor (VIF) for each item. All items demonstrated acceptable VIF values according to the 3.3 cutoff value (Petter et al., 2007). Each item of COPE captures unique aspects of the construct, suggesting that multicollinearity is not an issue. Thus, the formative measurement demonstrated reliability (Petter et al., 2007). Further, item weights in the PLS-SEM analysis were significant ($p < 0.01$), suggesting the validity of the COPE construct (Bollen & Lennox, 1991; Petter et al., 2007). Table 5 presents the VIF for the items of the COPE construct and the *t*-values for the item weights.

Table 5. VIF and *t*-Values for First-Order Formative Items

Item	**VIF**	**t-Value**
COPE1	1.0781	3.621
COPE2	1.0044	3.531
COPE3	1.0759	3.817

To assess the validity of the second-order formative constructs, the breadth of online self-disclosure (SHAR) and comfort sharing information with multiple others (CACS), we examined the significance of the weights of the first-order constructs in relation to the second-order constructs. This is similar to the procedure we used to assess the validity of the first-order formative COPE construct, except we are concerned with the weights between the first- and second-order constructs instead of the weights between the items and first-order construct. The weights of all first-order constructs were statistically significant, suggesting that the second-order formative constructs exhibit validity. Table 6 shows the *t*-values for the weights of the first-order constructs in relation to the second-order constructs.

Table 6. *t*-Values for First-Order Construct Weights

Relationships	t-Value
BPHO → SHAR	25.3152
CONT → SHAR	5.8193
HIST → SHAR	27.3275
INTR → SHAR	26.3042
RELA → SHAR	35.5770
SPHO → SHAR	16.4479
FACS → CACS	73.8765
SACS → CACS	9.2668

Structural Model

SmartPLS (Ringle et al., 2005) was used to examine the structural model. Because the model included second-order formative constructs, a two-step process was necessary to analyze the structural paths (Becker, Klein, & Wetzels, 2012). To begin, an analysis of the full structural model with all constructs and items was conducted. However, the results of this first model are misleading because the first-order constructs of the second-order formative constructs perfectly predicted the variance of the second-order construct; therefore, variance from other sources (i.e., the independent constructs) cannot be determined. This is common of all PLS-SEM models that include second-order formative constructs (Becker et al., 2012). To fix this issue, the latent variable score of the highest level representation of each construct (i.e., ADCT, POSI, NEGI, SHAR, CACS, and COPE) was used as a measure for the respective construct (Becker et al., 2012). Thus, the first-order constructs of SHAR and CACS were discarded and represented by the latent variable scores of the second-order constructs (Becker et al., 2012). The structural paths were analyzed with this second model containing latent variable scores. We found statistical support for several of the important relationships in the model. Table 7 presents a summary of statistical support for the conceptual model.

Table 7. Statistical Support for Hypotheses

Hypothesis	p-Value	Supported
H1a: NORI → CACS	$p < 0.05$	Yes
H1b: NORI → SHAR	$p > 0.05$	No

H1c: NORI → COPE	$p < 0.01$	Yes
H2a: ADCT → CACS	$p > 0.05$	No
H2b: ADCT → SHAR	$p > 0.05$	No
H2c: ADCT → COPE	$p < 0.01$	Yes
H3a: POSI → CACS	$p < 0.01$	Yes
H3b: POSI → SHAR	$p < 0.01$	Yes
H3c: POSI → COPE	$p < 0.01$	Yes
H4a: NEGI → CACS	$p > 0.05$	No
H4b: NEGI → SHAR	$p > 0.05$	No
H4c: NEGI → COPE	$p > 0.05$	No
H5: NORI → ADCT	$p > 0.05$	No
H6: NORI → POSI	$p < 0.01$	Yes
H7: NORI → NEGI	$p < 0.01$	Yes

Through direct and indirect effects, national origin was found to be an influential predictor of information-sharing and privacy coping behavior. National origin exhibited a direct and statistically significant relationship with privacy coping ($\beta = -0.4132, p < 0.01$). National origin also exhibited a direct and statistically significant effect on a user's comfort with sharing information with multiple others ($\beta = 0.2052$, $p < 0.05$). National origin did not express a direct, statistically significant relationship on comfort with sharing with multiple others and breadth of online self-disclosure ($\beta = -0.1492$, $p > 0.05$). Thus, we found support for H1a and H1c but failed to find support for H1b. Although we did not find a direct relationship between national origin and the breadth of online self-disclosure, we did find indirect relationships through mediation. These indirect relationships will be described shortly.

Internet addiction also exhibited a statistically significant relationship with privacy coping ($\beta = -0.1507$, $p < 0.01$). However, Internet addiction did not have a statistically significant relationship with sharing with multiple others ($\beta = -0.0191$, $p > 0.05$) and breadth of online self-disclosure ($\beta = -0.0923$, $p > 0.05$). Although these relationships were insignificant, the implications of the insignificant relationships are somewhat alarming. These implications are discussed later. We found support for H2c; however, statistical support was not found for H2a and H2b.

Positive identity perceptions exhibited a statistically significant relationship with privacy coping ($\beta = 0.1213$, $p < 0.01$). Positive identity perceptions also exhibited statistically significant relationships with sharing with multiple others ($\beta = 0.2198$, $p < 0.01$) and breadth of online self-disclosure ($\beta = 0.1826$, $p < 0.01$). Thus, we found support for H3a, H3b, and H3c. Negative identity perceptions did not exhibit statistically significant relationships with privacy coping ($\beta = -0.0714$, $p > 0.05$), sharing with multiple others ($\beta = -0.0604$, $p > 0.05$), and breadth of online self-disclosure ($\beta = 0.0528$, $p > 0.05$). We did not find support for H4a, H4b, and H4c.

National origin did not exhibit a statistically significant relationship on Internet addiction ($\beta = -0.0569$, $p > 0.05$). However, national origin exhibited statistically significant relationships with positive identity perceptions ($\beta = -0.2729$, $p < 0.01$) and negative identity perceptions ($\beta = 0.2061$, $p < 0.05$). Thus, we found support for H6 and H7 but not for H5. The results offer preliminary evidence that national origin may partially mediate the relationship between identity perceptions and information-sharing and privacy coping behaviors. All control variables were not statistically significant.

The model explained 37.4% of the variance in privacy coping behavior, which corresponds to a Cohen's f^2 value of 0.60. This Cohen's f^2 value represents a large effect size in the social sciences (Cohen, 1988, 1992). The model also explained 8.0% of the variance in users' comfort with sharing information with different groups of people, which corresponds to a Cohen's f^2 value of 0.09. Additionally, the model explained 5.6% of the variance in users' willingness to share a breadth of information online, which corresponds to a Cohen's f^2 value of 0.06. Thus, the effect sizes for the information-sharing constructs were small. The effect sizes for the effect of national origin on Internet addiction and positive and negative identity perceptions were also small. The model explained less than 1.0% of the variance in Internet addiction, 7.3% of the variance in positive identity perceptions, and 4.2% of the variance in negative identity perceptions.

Common Method Bias

When a single method is used for a study and the entire method is completed by a single respondent, common method bias may be an issue (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Common method bias can skew results in systematic but unintended ways. Thus, it is crucial to test for common method bias. Although several methods exist to test for common method bias, few are well suited for testing common method bias in SEM-PLS models (Chin, Thatcher, & Wright, 2012; Rönkkö & Ylitalo, 2011). However, a new method has been proposed (Rönkkö & Ylitalo, 2011). In this method, marker variables are used to assess common method bias. If common method bias is an issue, a method factor based on the marker variables is included in the PLS-SEM model to compensate for common method bias. To assess the extent of common method bias, a correlation matrix is calculated that includes the marker variables and the indicators used in the model. After calculating the correlation matrix, the mean of the correlations between the marker variables and model indicators is calculated. Mean values less than 0.05 suggest that common method bias is not an issue (Rönkkö & Ylitalo, 2011).

We included three questions in the survey that were unrelated to the topic of the model that we used as marker variables. The mean of the correlations between the three marker variables and the model indicators was −0.0038, which is below the 0.05 cutoff (Rönkkö & Ylitalo, 2011). Thus, we find evidence that common method bias is not an issue.

DISCUSSION

Our study explores privacy coping and information-sharing behaviors on social media platforms for several populations that may be more susceptible to privacy violations due to unsafe information-sharing and privacy coping behaviors. In particular, we compare differences between U.S. and Chinese social media users, users with differing levels of Internet addiction, and users with different online identities. We find several interesting differences between the populations that suggest the need for future research. Since this study is only exploratory in nature, future research should seek to explain in greater detail why these differences exist. This study provides initial evidence that privacy vulnerabilities may exist for users of different national origins, with different levels of Internet addiction, and with different online identities.

We find evidence that privacy coping and information-sharing behaviors differ by national origin. U.S. respondents report a higher likelihood that they would use privacy coping strategies (e.g., refusing to share or removing private information from social media platforms) than Chinese respondents. Additionally, we find evidence that Chinese respondents are more comfortable sharing information with a wider variety of people (e.g., family, friends, and strangers) than U.S. users, though the effect size was small. National origin, however, had no statistical effect on the breadth of online self-disclosure. Although Chinese and U.S. users seem to share the same breadth of information, Chinese users are more likely to share with a more diverse set of people. The privacy coping and information-sharing behavior of Chinese users suggests that they may be at greater risk of privacy violations than U.S. users. Our findings complement others studies that compare privacy concerns between users in the United States and China (e.g., Lowry et al., 2011; Zhang et al., 2002). We extend these previous studies by showing that national origin not only affects privacy concerns but may also affect privacy coping and information-sharing behaviors.

A possible explanation for these differences in U.S. and Chinese users could be differences between national cultures. For example, Lowry et al. (2011) found evidence that collectivist cultures, such as in the Chinese culture, are “more likely to desire committed, close, and strong relationships with others” (p. 176). It may be that Chinese users are more willing to share information and less likely to refuse or remove information from social media platforms to develop and maintain close and strong ties with others. Other explanations might include political and regulatory differences between countries or differences in social media platforms and their privacy controls (e.g., Facebook versus Renren). Cross-cultural differences in collectivistic versus individualistic and losing face versus gaining face orientations also suggest that very real differences may exist in how Chinese and U.S. users share, seek, and use the Internet for collective and individual benefit (Ardichvili et al., 2006; Hwang et al., 2003). Our findings add to the growing body of research that these cultural differences are real and consistent across different users. These avenues should be examined in future research.

We also find that users with higher levels of Internet addiction may be more susceptible to privacy violations. Users with higher levels of Internet addiction are less willing to engage in privacy coping behavior than non-addicted users. Although addicted users spend more time on social media (Soule et al., 2003; Turel et al., 2011), we provide evidence that they are less likely to protect themselves through privacy coping strategies. This may be explained by addicted users adoption of shortcuts when using IT artifacts (Turel et al., 2011). We find no statistical evidence to suggest that higher levels of Internet addiction influence information-sharing behavior; this lack of evidence is somewhat disconcerting. Internet addiction is associated with increased frequency and duration of social media use (Turel et al., 2011). Therefore, addicted users are likely to share information more frequently than non-addicted users, even if the breadth of information is not different. Due to increased frequency and duration of use, addicted users may need to be more aware and attentive to their information-sharing behavior than non-addicted users. However, our results suggest that this is not the case. To our knowledge, this is the first study to explore the relationships between Internet addiction and privacy coping and information-sharing behaviors.

We find evidence that online identity perceptions influence privacy coping and information-sharing behaviors. We find that users who believe their profiles reflect positive personal character traits are more likely to engage in privacy coping behavior. Additionally, we find that users who possess higher positive perceptions are more willing to share a greater breadth of information with a greater variety of people. We do not find that negative perceptions of online identity influence privacy coping and information-sharing behavior; this finding is also disconcerting. To protect themselves from privacy violations, users whose profiles reflect negative character traits would need to share less with a smaller diversity of people and engage in more privacy coping behavior. However, we find this is not the case. Users with negative online identities may be particularly vulnerable to privacy violations by potential employers that screen the users' social media profiles. This vulnerability should be examined in future research. Our findings are complementary to studies that examine personality as predictors of technology use (Ehrenberg, Juckes, White, & Walsh, 2008).

Finally, we find that culture may have small indirect effects on privacy coping and information-sharing behaviors through the development of online identities. We find that Chinese users are more likely to perceive negative identity perceptions and less likely to perceive positive identity perceptions. This may be explained by collectivist and individualist ideas in China and the United States, respectively. This relationship should be explored further in future research. We do not find that national origin influences Internet addiction. Thus, Internet addiction may exist much the same in the United States and China. Internet addiction across cultures should be studied further in future research.

Implications for Practitioners

Social media users, policy makers, social media platforms, and clinical psychologists should become aware of the potential privacy vulnerabilities identified in this study. Awareness is shown to increase secure computer behavior in individuals (Bulgurcu, Cavusoglu, & Benbasat, 2010). Thus, users should seek to understand the cultural and psychological factors that may influence their vulnerability to privacy violations. Policy makers, social media platforms, and clinical psychologists should also be involved in developing users' awareness of potential privacy vulnerabilities and coping behaviors. Policy makers and social media platforms might develop campaigns to make users aware of potential privacy vulnerabilities, particularly for populations that are susceptible to privacy violations. Clinical psychologist should also be aware of the privacy vulnerabilities that exist for users with Internet addiction. Clinical psychologists should make their addicted patients aware of the potential privacy harms that exist in overusing social media and should identify privacy coping behaviors in which their patients can engage as they work with their patients to overcome their Internet addiction.

Limitations and Future Research

As with any research, our study possesses limitations that provide directions for future research. First, data were collected through convenience sampling; therefore, claims of generalizability may be limited. However, the demographic data of respondents in this study is similar to data in other social media studies (Chou et al., 2009), which suggests that our sample is not peculiar. Future research should use more sophisticated sampling and recruitment methods to examine populations that are susceptible to privacy violations in social media.

Second, we have limited our examination of susceptible populations to Chinese and U.S. users, users with Internet addiction, and users with different online identities. To avoid survey fatigue, we only examined these three populations. Future research should examine other populations that may be more susceptible to privacy violations. Other susceptible populations may exist and should be considered in future research. For example, users with depression may be at risk due to self-destructive behaviors.

Finally, this study is exploratory, and no particular theory was tested. Future research should consider the theoretical reasons behind our findings. Researchers may use qualitative methods, such as the grounded theory approach, to better understand the reasons for the differences we found in privacy coping and information-sharing behaviors. We have identified several possible explanations for the findings; however, these were not tested fully. For example, future studies might examine Hofstede et al.'s (2010) cultural dimensions or political views in other countries to further explain information-sharing and privacy coping behaviors across nations. Representing cultural and political differences across nations with a dummy variable coded for U.S. and Chinese users is a crude method for understanding cross-cultural relationships. However, our study is intended only as an exploration of privacy coping and information-sharing behavior in different nations. Thus, we were less concerned with the nuanced reasons for the behavioral differences and more concerned about whether broad relationships existed. Future research should include cultural and political variables related to the phenomenon to offer a more nuanced view of the phenomenon.

CONCLUSION

Protecting vulnerable populations from privacy violations is an important endeavor for researchers and practitioners. Researchers should continue to explore privacy concerns and privacy coping and information-sharing behaviors among vulnerable populations, especially within the context of cross-cultural differences. Explanations for the behavioral differences should be proposed and tested. Additionally, practitioners and researchers should work together to develop methods to protect the privacy of vulnerable populations, especially as they relate to cultural differences. Appropriate and customized safeguards can be taken by service providers to protect the unique global citizens they serve.

APPENDIX A

SURVEY INSTRUMENT

Construct	**Item**	**Question**	**Type**
Internet addiction (ADCT)	1	I prefer to use the Internet instead of spending time with others (e.g., partner, children, parents, friends)	Reflective
	2	I’m short of sleep because of the Internet	
	3	I think about the Internet even when not online	
Coping behavior (COPE)	1	I would refuse to disclose information to my friends on an online social network because I think it is too personal	Formative
	2	I would probably falsify some of my personal information that my friends see when using an online social network	
	3	If my personal information were mishandled while using an online social network, I would probably remove that information from the	

		network's database	
Negative identity perceptions (NEGI)	1	Because of my social media profile, others will believe I am emotionally unstable	Reflective
	2	Because of my social media profile, others will believe I am arrogant	
	3	Because of my social media profile, others will believe I am irresponsible	
	4	Because of my social media profile, others will believe I am offensive	
Positive identity perceptions (POSI)	1	Because of my social media profile, others will believe I am likeable	Reflective
	2	Because of my social media profile, others will believe I am friendly	
	3	Because of my social media profile, others will believe I am good-natured	
	4	Because of my social media profile, others will believe I am reliable	
Comfort Sharing Information With Others (Second-Order Formative Construct)			
Sharing with familiar individuals (FACS)	1	I am okay with friends accessing my social network profile	Reflective first-order dimension
	2	I am okay with family accessing my social network profile	
	3	I am okay with classmates accessing my social network profile	
	4	I am okay with prospective or current employers accessing my social network profile	
Sharing with strangers (SACS)	1	I am okay with strangers accessing my social network profile	Single item
Breadth of Online Self-Disclosure (Second-Order Formative Construct)			

Basic photos (BPHO)	1	I'm willing to share a profile image	Reflective first-order dimension
	2	I'm willing to share a traditional self-photo	
Contact information (CONT)	1	I'm willing to share my address	Reflective first-order dimension
	2	I'm willing to share my phone number	
Personal history (HIST)	1	I'm willing to share my birthday	Reflective first-order dimension
	2	I'm willing to share my high school	
Personal interests (INTR)	1	I'm willing to share my interests	Reflective first-order dimension
	2	I'm willing to share my favorite music	
	3	I'm willing to share my favorite books	
	4	I'm willing to share my favorite movies	
Relationship information (RELA)	1	I'm willing to share my dating interests	Reflective first-order dimension
	2	I'm willing to share my relationship status	
	3	I'm willing to share my relationship partner	
Sensitive photos (SPHO)	1	I'm willing to share a humorous self-photo	Reflective first-order dimension
	2	I'm willing to share a sexy self-photo	

Notes

The bold text indicates item loadings.

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