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Concern for Information Privacy and Online Consumer Purchasing in China

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Abstract:

Individuals' concern for information privacy (CFIP) impacts beliefs, intentions, and behaviors in a variety of contexts, including consumer electronic commerce. Most empirical studies on the impact of CFIP on electronic commerce have been conducted using consumers in the United States. Despite China's growing economy and increasing importance in the global economy, to date, there has been no empirical study of CFIP's impact on Chinese consumers' willingness to engage in transactions online. The purpose of this study is to test a widely-referenced model of CFIP's role in consumer e-commerce in the context of China. We conducted surveys of Chinese consumers' willingness to engage in transactions with two online merchants, a familiar merchant (Taobao) and a less-familiar merchant (Amazon). For both merchants, CFIP had only mediated impacts on consumers' willingness to transact with online merchants. While there were similarities between our results and those reported in the original study, there were also differences. Our findings provide a number of contributions for research and practice.

Keywords: concern for information privacy, e-commerce, China, risk, trust

1 Introduction

Consumer-oriented electronic commerce (e-commerce) has grown almost to the point of ubiquity. Making purchases online has become second nature to many consumers throughout the world. A considerable body of research into factors influencing consumers' use of e-commerce has developed. One aspect of this research concerns the influence of information privacy concerns on consumer e-commerce (e.g. Ackerman et al., 1999; Udo, 2001; Berendt et al., 2005; Liu et al., 2005; Dinev & Hart, 2006; Faqih, 2016; Bandara et al., 2019). Empirical results from these studies are inconsistent, with some studies finding a direct relationship between consumers' privacy concerns and their intentions to engage in e-commerce (e.g. Dinev et al., 2006; Dinev & Hart, 2006), while other studies failed to find such a relationship (e.g. Van Slyke et al., 2006; Huang & Liu et, 2012).

Numerous studies establish national differences in consumer e-commerce. For example, Sia et al. (2009) found that trusting beliefs directly influenced consumers' intentions to buy online in Australia. In contrast, these beliefs had only indirect impacts in Hong Kong. Mahrous (2011) found that privacy concerns affected e-commerce attitudes in Egypt, the United Kingdom and the United States. Some studies investigated country-based differences in the influence of consumers' privacy concerns on e-commerce. Dinev et al. (2006) investigated the impact of consumers' privacy concerns on consumers' e-commerce use in three countries, China, Singapore and the United States. Their results found impacts for all three countries, with the strongest influence found in the United States.

One study of the role of privacy concerns on consumer e-commerce, Van Slyke et al. (2006), developed and tested a comprehensive model that included concern for information privacy (CFIP) along with risk perceptions, trust, and familiarity with a merchant. As is the case with most studies of information privacy concerns and e-commerce, Van Slyke et al. (2006) used a sample of residents of the United States. It is unclear whether their results will generalize to other countries, given the differences in perceptions and impacts of information privacy concerns in different countries (Belanger & Crossler, 2011). Due to these differences, there is a clear need to understand how well established models of privacy concerns will generalize across cultures. To that end, in this paper, we report on a methodological replication (Dennis & Valacich, 2014) of the Van Slyke et al. (2006) article using samples of Chinese consumers.

Two further, related factors motivate this replication. First, consumer e-commerce has experienced significant growth since the original study was published. China's consumer economy has experienced explosive growth since the advent of consumer e-commerce in the late 1990s. In 2017, total retail trade in China reached 36.6 trillion yuan (China Statistics Press, 2018), up from 2.1 trillion yuan in 1999 (China Statistics Press, 2000). Similarly, consumer e-commerce has grown rapidly in China. The gross merchandise volume of China's consumer e-commerce is expected to grow from 1.9 trillion yuan in 2013 to 10.8 trillion yuan in 2020. By 2017 online retail sales represented almost 20% of China's total retail sales (China Statistics Press, 2018). Online sales in China increased by almost 24% from 2017 to 2018, growing to US$1.33 trillion (Melton, 2019). This is a considerably stronger growth than the overall retail sector, which grew 9% in the same period (National Bureau of Statistics of China, 2019).

For some Chinese, shopping online has become a cultural activity. "Singles Day" (11 November), also known as Double Eleven, has become embedded in the culture of Chinese youth that started in 1993 at Nanjing University as a celebration of bachelorhood. In 2009, the Chinese e-commerce giant Alibaba began using Singles Day to promote its consumer e-commerce sites by offering special discounts similar to those offered on Cyber Monday (the first Monday after American Thanksgiving). Singles Day has quickly become a major event in China. In 2018, Alibaba's gross merchandise value for Singles Day exceeded US $30.8 billion, which represented an increase of almost 27% from 2017 (Kharpal, 2018; Russell & Liao, 2018). In contrast, the sales volume for 2018's Cyber Monday was approximately $8 billion (Snider, 2018). For many Chinese youth the days leading up to Singles Day is filled with conversations about their upcoming purchases; the days immediately after the big day are often dominated by showing off Singles Day purchases. E-commerce in China is clearly a significant factor economically and culturally, making a study of e-commerce in China a worthwhile endeavor.

The second main motivator for this replication is the fluid, emerging nature of privacy in China. Privacy is a complex, context-dependent concept (Nissenbaum, 2009) that is affected by contextual factors such as cultural background and experiences (Zhang et al., 2018). Privacy is especially interesting in China.

Traditionally, the notion of privacy in the English sense of the word did not exist in China (Wang et al., 2016). In traditional Chinese culture, the basic unit of privacy was the kinship group, rather than the individual (Naftali, 2010). In fact, the most authoritative Chinese dictionaries did not include the Mandarin word for personal privacy, *yin si* (Wang et al., 2016). Interestingly, *yin si* has traditionally carried negative connotations associated with suspiciousness, illicit, conspiratorial, and selfish behavior (Farrall, 2008; Wang et al., 2016). The Maoist-era brought the very notion of privacy under attack through both rhetoric that painted the desire for private space as aberrant and governmental intervention, such as the banning of private property (Naftali, 2010). Unlike the United States Constitution, China's constitution does not contain a specific right of privacy. Instead, privacy is protected as part of the right of reputation in civil law (Xue, 2010).

More recently, however, the influence of consumerism combined with China's "new individualism" in the 1990s (McDougall, 2004) has led to shifting attitudes towards privacy. Coupled with the rise of electronic communication and the Internet, these evolving attitudes brought about more widespread concerns regarding data protection and surveillance through information technology (McDougall, 2004). Today, many Chinese view privacy as extending beyond personal property to include the right to autonomy, and individual freedom from constraints and surveillance (Naftali, 2010).

Due in part to the rapid growth of mobile services, companies now collect vast amounts of data about Chinese consumers. This has led to growing information privacy concerns in China (Cheng, 2018). In part, these concerns have led to the 2017 implementation of the People's Republic of China Cybersecurity Law, the first national-level cybersecurity and data protection law in China (DLA Piper, 2019).

China's emergent Social Credit System (SCS) is also shaping Chinese perspectives on privacy. The SCS is intended to integrate and centralize disparate data sources to allow big data-enabled surveillance (Zhang et al., 2018). Commercial behaviors are among the areas included in the SCS, with over half of the variables in the SCS backbone related to commerce and private firms (Zhang et al., 2018). The line between commercial and online activity and surveillance is further blurred the emergent ecosystem of mobile applications that may integrate with the SCS, either as providers of data or as an access point to scores (Schaefer, 2019).

To summarize, e-commerce is an important and growing force in China. In addition, privacy in China is a complex, dynamic issue, made even more complex by the growth in electronic commerce coupled with the growing surveillance culture in China, as exemplified by the SCS. Extant research indicates that culture and nationality influence both consumer e-commerce and privacy. Taken together, these factors clearly indicate that China provides a rich context in which to study the role of privacy in consumer-oriented e-commerce.

2 Original Study

Van Slyke et al. (2006) investigated two research questions:

> *How do consumers' concerns for information privacy affect their willingness to engage in online transactions?*
>
> *Does consumers' familiarity with a Web merchant moderate the impact of concern for information privacy on risk and trust?*

The model shown in Figure 1 was used to guide their research. Van Slyke et al. (2006) stated that they expected the impact of CFIP on willingness to transact to be fully mediated by CFIP's impact on risk perceptions and trust. However, as shown in Figure 1, their model includes a direct path from CFIP to willingness to transact, which they included because some prior research implied a direct relationship.

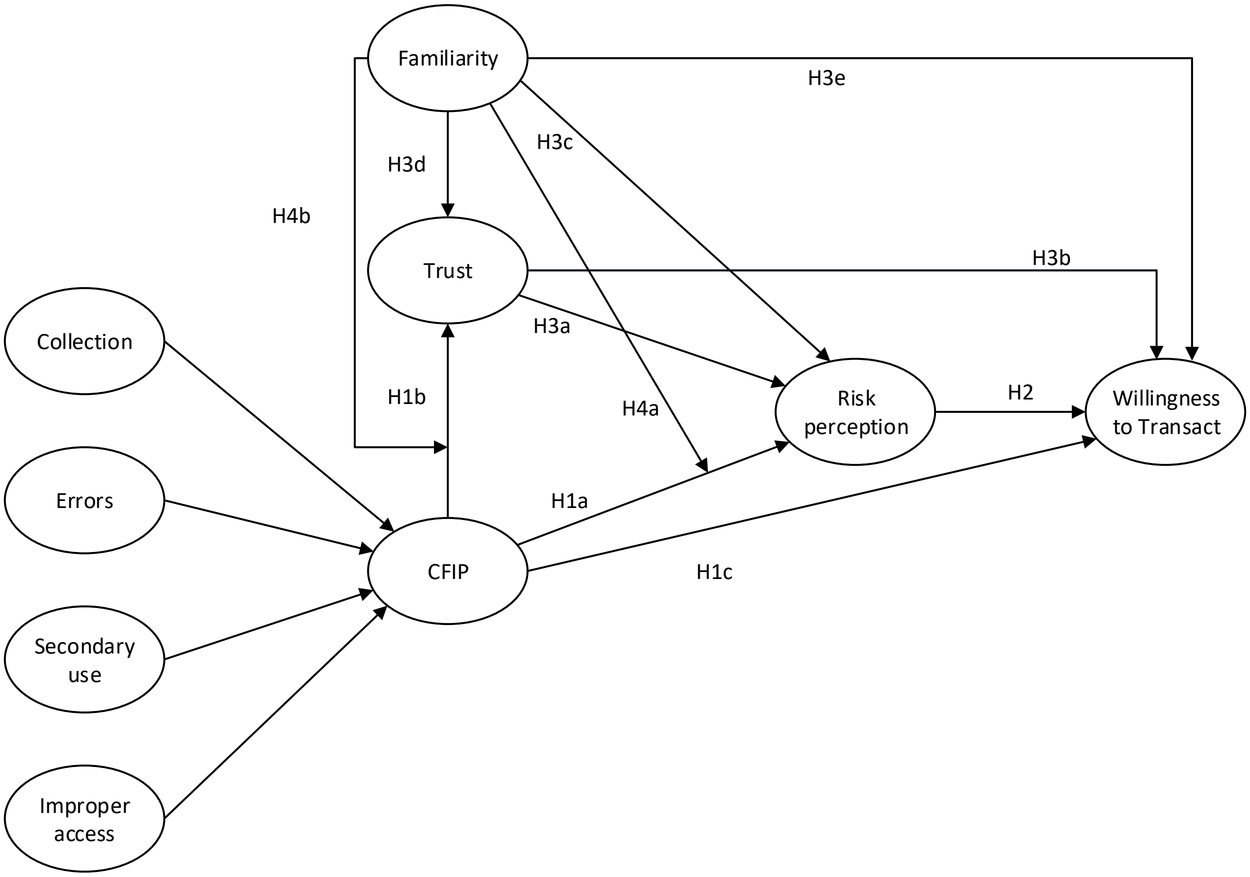

Figure 1 – Research Model

As indicated in Figure 1, hypotheses were derived from the research model. These hypotheses are shown below verbatim from Van Slyke et al. (2006).

H1a *Consumers' concerns for information privacy are positively related to their perceptions of the risk of conducting transactions with a Web merchant.*

H1b *Consumers' concerns for information privacy are negatively related to their trust in the Web merchant.*

H1c *Consumers' concerns for information privacy are negatively related to their willingness to conduct transactions with a Web merchant.*

H2 *Consumers' perceptions of the risk of conducting transactions with a Web merchant are negatively related to their willingness to conduct transactions with that merchant.*

H3a *Consumers' trust in a Web merchant is negatively related to their perceptions of risk of purchasing from that Web merchant.*

H3b *Consumers' trust in a Web merchant is positively related to their willingness to conduct transactions with that Web merchant.*

H3c *Consumers' familiarity with a Web merchant is negatively related to their perceptions of the risk of conducting transactions with that Web merchant.*

H3d *Consumers' familiarity with a Web merchant is positively related to their perceptions of trust in that Web merchant.*

H3e *Consumers' familiarity with a Web merchant is positively related to their willingness to conduct transactions with that Web merchant.*

H4a Consumers' familiarity will moderate the relationship between their concern for information privacy and perceptions of risk of a Web merchant.

H4b Consumers' familiarity will moderate the relationship between their concern for information privacy and trust in a Web merchant.

Van Slyke et al. (2006) tested their research model using data collected through two surveys, one asking about a well-known merchant (Amazon) and another about a less well-known merchant (Half.com). (Half.com was an online marketplace for used books, music, movies, video games, and game consoles. The service ceased operations in 2017.) They had 713 responses to the Amazon survey, and 287 to the Half.com survey. The scale items used in the original study are provided in Appendix A, as are their sources. Descriptive statistics for each scale items are also shown. The scales showed acceptable reliability and validity.

For the familiar merchant (Amazon), all but one hypothesis (H1c: CFIP => willingness to transact) was supported. Results were more equivocal for the less-familiar merchant (Half.com), with only H2 (risk => willingness to transact), H3a (trust => risk), H3c (familiarity => risk), H3d (familiarity => trust), and H3e (familiarity => willingness to transact) supported. (Full results from Van Slyke et al. (2006) are shown as comparisons to the results of the current study in the Analysis section.) Van Slyke et al. (2006) conclude that consumers' privacy concerns are important to consumer e-commerce but may be secondary to other concerns such as familiarity, risk, and trust. This is especially true when dealing with lesser-known merchants.

Having provided an overview of the original study, we turn attention to our replication, which closely followed the methods used in the original study. We describe the replication in the next section.

3 Research Method

As a methodological replication, the current study investigates the same hypotheses as Van Slyke et al. (2006). To the extent possible, we followed the methodology of the original study. In this section we describe the methodology used in the replication.

Following the original study, we collected data from two merchants: Taobao, which was expected to be familiar to most Chinese consumers; and Amazon China, which was expected to be less familiar. Note that although Amazon is the most prominent online merchant in the United States, it is less well-known in China. In contrast, Taobao, owned by Alibaba, is the largest consumer e-commerce website in the world. The respective means of the familiarity scale for the two merchants confirm that Taobao is better known among our Chinese participants. The familiarity mean for Taobao was 6.1, whereas it was 4.1 for Amazon (on a seven-point scale). This is a larger difference than that for Amazon and Half.com in the original study. Thus, we used Taobao as the familiar merchant and Amazon as the less familiar merchant.

We gathered data from Chinese MBA students, while the original study used undergraduate students in the United States. Our samples were smaller than those reported in Van Slyke et al. (2006), with n=152 for Taobao, and n=159 for Amazon. The Taobao sample consisted of 43% female participants. The Amazon sample was similar, with 45% of the participants being female. 95% of the Taobao sample and 97% of the Amazon sample were between 26 and 45 years of age.

The scale items from the original study were translated into Mandarin by one of the authors, another author then back-translated them. The resultant items were reviewed for accuracy by an information system scholar who was not a party to this paper, and they were deemed accurate.

4 Results

Following Van Slyke et al. (2006), we tested two measurement and two structural models: one each for the more familiar merchant (Taobao) and one each for the less familiar merchant (Amazon). The results are discussed in this section, starting with results related to the measurement models. We used SmartPLS 3 (Ringle et al., 2015) to analyze the various models using 152 cases for Taobao, and 159 cases for Amazon. When performing the bootstrapping, we used 5,000 subsamples.

4.1 Measurement Models

Tables 1 and 2 present the factor analyses for the Taobao and Amazon data, respectively. The maximum loading for each item is shown in bold. One item, Error1, cross-loaded on two factors: Errors and Improper Access. Only two other items, Trust1 and Trust2, had factor loadings of less than 0.80 (0.77 and 0.78, respectively). All items loaded as expected for the less-familiar merchant (Amazon). Overall, factor loadings were similar to those reported in Van Slyke et al. (2006).

Table 1 – Factor Analysis for Taobao Data

	Collection	Errors	Familiarity	Imp Acc	Risk	Sec Use	Trust	WT
Access1	0.69	0.54	0.14	**0.89**	-0.16	0.66	0.19	0.19
Access2	0.48	0.55	0.21	**0.92**	-0.15	0.67	0.19	0.26
Access3	0.44	0.64	0.19	**0.87**	-0.24	0.56	0.25	0.23
Col1	**0.84**	0.33	0.10	0.39	-0.14	0.34	0.08	0.05
Col2	**0.87**	0.32	0.07	0.49	-0.17	0.43	0.10	0.16
Col3	**0.84**	0.28	0.10	0.54	-0.14	0.41	0.13	0.06
Col4	**0.92**	0.48	0.04	0.64	-0.17	0.53	0.16	0.08
Error1	0.38	**0.75**	0.13	0.75	-0.17	0.51	0.20	0.19
Error2	0.34	**0.90**	-0.05	0.52	-0.11	0.46	0.16	0.11
Error3	0.36	**0.89**	-0.07	0.43	-0.20	0.38	0.18	0.08
Error4	0.35	**0.94**	-0.07	0.51	-0.18	0.46	0.22	0.13
Fam1	0.09	-0.03	**0.97**	0.18	-0.27	0.10	0.34	0.33
Fam2	0.08	0.01	**0.98**	0.22	-0.31	0.13	0.35	0.34
Risk1	0.17	0.20	0.26	0.14	**0.88**	0.15	0.50	0.45
Risk2	0.18	0.18	0.22	0.21	**0.91**	0.20	0.61	0.55
Risk3	0.15	0.13	0.32	0.19	**0.93**	0.17	0.58	0.60
SecUse1	0.43	0.48	0.14	0.68	-0.19	**0.87**	0.18	0.31
SecUse2	0.51	0.52	0.08	0.63	-0.18	**0.85**	0.17	0.24
SecUse3	0.34	0.35	0.10	0.54	-0.12	**0.86**	0.15	0.27
SecUse4	0.42	0.43	0.08	0.55	-0.16	**0.84**	0.16	0.29
Trust1	0.15	0.27	0.31	0.23	-0.48	0.25	**0.77**	0.64
Trust2	0.06	0.18	0.34	0.12	-0.47	0.11	**0.78**	0.45
Trust3	0.11	0.16	0.22	0.19	-0.58	0.14	**0.89**	0.45
Trust4	0.09	0.18	0.27	0.19	-0.61	0.09	**0.89**	0.45
Trust5	0.12	0.18	0.27	0.19	-0.49	0.13	**0.85**	0.34
Trust6	0.10	0.11	0.26	0.17	-0.50	0.14	**0.84**	0.43
Trust7	0.17	0.19	0.37	0.26	-0.51	0.25	**0.83**	0.58
WT1	0.07	0.11	0.28	0.19	-0.55	0.28	0.44	**0.89**
WT2	0.08	0.12	0.28	0.21	-0.52	0.26	0.58	**0.90**
WT3	0.12	0.17	0.37	0.28	-0.56	0.34	0.56	**0.93**

Note: Bold indicates the maximum loading for each item.
Access – Improper access, SecUse – Secondary use, WT – Willingness to transact

Table 2 – Factor Analysis for Amazon Data								
	Collection	**Errors**	**Familiarity**	**Imp Acc**	**Risk**	**Sec Use**	**Trust**	**WT**
Access1	0.63	0.52	-0.07	0.90	0.08	0.57	0.03	-0.03
Access2	0.57	0.54	-0.08	0.93	0.07	0.64	0.06	-0.04
Access3	0.47	0.64	-0.04	0.89	-0.09	0.60	0.10	0.06
Col1	**0.89**	0.37	-0.04	0.49	-0.01	0.44	0.06	0.07
Col2	**0.87**	0.35	-0.03	0.48	-0.03	0.42	0.09	0.08
Col3	**0.91**	0.44	-0.05	0.56	-0.02	0.52	0.10	0.08
Col4	**0.91**	0.50	-0.09	0.66	-0.04	0.60	0.16	0.08
Error1	0.45	**0.86**	0.00	0.68	-0.12	0.54	0.16	0.02
Error2	0.44	**0.90**	-0.04	0.54	-0.07	0.52	0.13	0.01
Error3	0.39	**0.92**	0.00	0.51	-0.24	0.48	0.23	0.16
Error4	0.40	**0.93**	0.03	0.53	-0.20	0.54	0.21	0.13
Fam1	-0.05	0.03	**0.97**	-0.06	-0.37	-0.06	0.39	0.48
Fam2	-0.07	-0.03	**0.98**	-0.08	-0.38	-0.07	0.39	0.52
Risk1	-0.03	0.15	0.35	-0.03	**0.88**	0.05	0.67	0.61
Risk2	0.04	0.16	0.34	-0.05	**0.93**	0.08	0.63	0.66
Risk3	0.06	0.17	0.37	0.01	**0.93**	0.15	0.70	0.69
SecUse1	0.52	0.54	-0.04	0.60	-0.13	**0.89**	0.17	0.11
SecUse2	0.57	0.56	-0.02	0.59	-0.14	**0.91**	0.18	0.13
SecUse3	0.42	0.46	-0.10	0.60	-0.02	**0.88**	0.07	0.03
SecUse4	0.48	0.50	-0.09	0.61	-0.09	**0.91**	0.09	0.07
Trust1	0.18	0.20	0.40	0.14	-0.65	0.16	**0.86**	0.73
Trust2	0.12	0.17	0.35	0.07	-0.69	0.16	**0.89**	0.68
Trust3	0.08	0.14	0.32	0.03	-0.62	0.06	**0.90**	0.63
Trust4	0.09	0.24	0.30	0.09	-0.65	0.17	**0.92**	0.65
Trust5	0.09	0.17	0.31	0.06	-0.63	0.10	**0.92**	0.67
Trust6	0.12	0.17	0.33	0.06	-0.63	0.13	**0.89**	0.65
Trust7	0.04	0.16	0.47	0.01	-0.71	0.12	**0.90**	0.74
WT1	0.11	0.11	0.49	0.00	-0.72	0.11	0.74	**0.97**
WT2	0.08	0.07	0.48	-0.04	-0.71	0.07	0.75	**0.97**
WT3	0.05	0.07	0.52	0.02	-0.65	0.10	0.72	**0.96**

Note: Bold indicates the maximum loading for each item.
Access – Improper access, SecUse – Secondary use, WT – Willingness to transact

Descriptive statistics for the familiar (Taobao) and less-familiar (Amazon) merchants are given in Table 3. Descriptive statistics from the original study are shown for comparison. We used simple t-tests to compare mean values across countries for each merchant type, comparing the familiar merchant in the United States sample (from Van Slyke et al., 2006) to the familiar merchant in the Chinese sample, and comparing the less-familiar merchant in the United States sample (from Van Slyke et al., 2006) to that less-familiar merchant in the Chinese sample. Based on simple t-tests, there are significant differences in the scale means across the two studies when controlling for merchant type. These comparisons reveal interesting differences in how e-commerce and online merchants are viewed in the two countries, further establishing cross-national differences in consumers' perceptions of e-commerce.

For the familiar merchant, the Chinese sample had much higher perceptions of familiarity and risk, lower perceptions of trust, and higher willingness to transact than the American sample. There were also differences in the CFIP components, with collection, errors, and secondary use being significantly higher for the Chinese sample than the American sample. The differences were less pronounced for the less-familiar merchants. Interestingly, the Chinese sample was significantly more familiar with Taobao than the United States sample was for Amazon. However, familiarity with the less-familiar merchant was the same for the Chinese and American samples. There were significant differences in perceived risk, trust, and willingness to transact. For CFIP components, collection and errors were different, but secondary use and improper access concerns were not.

Table 3 – Descriptive Statistics for the Both Merchants

	Familiar				**Less-familiar**			
	China		**Original**		**China**		**Original**	
Construct	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Risk	5.2[1]	1.0	2.9	0.9	4.8[1]	1.2	3.3	1.1
Trust	5.1[1]	1.0	5.6	1.1	4.8[1]	1.2	5.3	0.9
Familiarity	6.1[1]	1.2	4.9	1.3	4.2[2]	1.7	4.2	1.7
WT	5.7[1]	1.1	4.7	1.2	4.4[2]	1.6	4.1	1.6
Collection	5.9[1]	1.2	5.5	1.0	5.8[1]	1.2	5.3	1.2
Errors	5.9[1]	1.1	5.5	1.0	6.0[2]	1.0	5.8	1.1
Sec use	6.6[2]	0.7	6.4	0.9	6.5[3]	0.8	6.4	1.1
Imp access	6.3[3]	0.9	6.4	0.9	6.3[3]	1.0	6.4	1.1

Notes: SD – Standard deviation; WT – Willingness to transact; Sec use – Secondary use; Imp access – Improper access.
[1] - $p < 0.001$, [2] - $p < 0.05$ [3] – non-significant for cross-study differences in means

Tables 4 and 5 show inter-scale correlations, reliability estimates, and validity data for the two Chinese samples. The average variance extracted (AVE) shown on the diagonals was high for all scales with a minimum value of 0.70. These results indicate acceptable convergent validity. In addition, the correlations, shown in the off-diagonal elements, were smaller than the diagonal elements, indicating acceptable discriminant validity. As a further test of discriminant validity, we examined the Heterotrait-Monotrait (HTMT) Ratio matrix. All ratios were below 0.80, indicating acceptable discriminant validity (Henseler et al., 2015).

Overall, these results were similar to those reported in the original study, although the inter-scale correlations are generally higher for the Chinese data than for the American data. From these results, we can conclude that the scales are acceptable for the Chinese samples. This demonstrates the robustness of the Van Slyke et al. (2006) scales.

Table 4 – Correlations, Reliability, and Validity Data for Taobao Data

Construct	**CR**	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
Risk	.93	**.83**							
Trust	.94	-.62	**.70**						
Familiarity	.98	-.30	.35	**.87**					
Willingness to transact	.93	-.60	.58	.34	**.83**				
Collection	.94	-.18	.58	.09	.10	**.83**			
Errors	.93	-.19	.22	-.01	.15	.42	**.76**		
Secondary use	.92	-.20	.19	.12	.32	.50	.52	**.73**	
Improper access	.92	-.20	.24	.20	.25	.60	.64	.71	**.80**

Notes: CR – Composite reliability
Average variance extracted is shown on the diagonal.
Off-diagonal elements are inter-scale correlations.

Table 5 –Correlations, Reliability, and Validity Data for Amazon Data									
Construct	**CR**	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
Risk	.94	**.84**							
Trust	.97	-.73	**.81**						
Familiarity	.98	-.39	.40	**.95**					
Willingness to transact	.98	-.72	.76	.51	**.94**				
Collection	.94	-.03	.12	-.06	.09	**.80**			
Errors	.95	-.17	.20	.00	.09	.47	**.81**		
Secondary use	.94	-.11	.15	-.07	.10	.56	.58	**.81**	
Improper access	.93	-.02	.07	-.07	.01	.62	.63	.67	**.82**
Notes: CR – Composite reliability Average variance extracted is shown on the diagonal. Off-diagonal elements are inter-scale correlations.									

We assessed common method bias using two methods, following the methods used in Vance et al. (2008). First, we performed an exploratory factor analysis to determine whether the degree of common method variance was high. Common method variance is high if a single factor emerges from the unrotated factor analysis or if the majority of the covariance among the measures is accounted for by one factor (Podsakoff et al., 2003). Our exploratory factor analysis resulted in more than one factor, indicating that high common method bias does not exist for our data. We employed an additional technique, controlling for the effects of an unmeasured latent methods factor (Podsakoff et al., 2003)[1]. In this test, none of the paths from the common method latent variable to our measurement items were significant. In contrast, all paths between measurement items and their intended latent variables were significant at $p < 0.001$. Taken together, these results indicate a lack of common method variance in our data.

We also assessed the relationship between CFIP and its components. These results are shown in Table 6 results from the original study are provided for comparison. In all cases, the path between the components and CFIP were significant at $p < 0.001$. Secondary use had the highest path coefficients for both merchants in both studies. As was the case in Van Slyke et al. (2006) the strengths of the paths differed across CFIP components and across merchants, although the within-country differences are small in the case of China. The largest merchant-based difference for the Chinese samples is 0.017 (errors), compared with 0.116 for the United States. The median difference (using absolute values) for China (0.016) is approximately half of that for the United States (0.033). From these results, it appears that CFIP is more stable in China than in the United States. This is interesting given that CFIP is conceptualized as a general concern, which should be relatively stable across contexts for any given individual. This seems to be the case with the Chinese sample, but not the American sample.

Table 6 – Path Coefficient for CFIP Components				
	China		**Original**	
	Familiar	**Less familiar**	**Familiar**	**Less familiar**
Collection	0.286	0.301	0.321	0.205
Errors	0.311	0.328	0.271	0.334
Secondary use	**0.333**	**0.332**	**0.351**	**0.351**
Improper access	0.288	0.246	0.291	0.294
Note: All paths were significant at $p < 0.001$, boldface indicates the largest path coefficient for each column.				

[1] We used IBM SPSS AMOS 24 for this analysis.

4.2 Structural Models

We analyzed two structural models: one for the familiar merchant (Taobao), and one for the less-familiar merchant (Amazon).

Results related to each hypothesis are shown in Table 7. As was the case in the original paper, CFIP failed to have a significant direct impact on willingness to transact, regardless of the merchant. For the familiar merchant, H2, H3a, H3b, and H3d were supported, while H1a, H1b, H1c, H3c, H3e, H4a, and H4b were not supported. For H1b, a significant positive relationship between CFIP and trust was found, although a negative relationship was hypothesized.

Table 7 – Hypothesis Test Results

	China				Original	
Path	**Beta**	**t-value**	**p-value**	**Support?**	**Beta**	**p-value**
Familiar Merchant						
H1a: CFIP => Risk (+)	-0.085	1.522	0.128	No	0.121	< 0.05
H1b: CFIP => Trust (-)	0.216	3.093	0.002	No+	0.208	< 0.01
H1c: CFIP => WT (+)	0.089	1.142	0.253	No	0.061	n.s.
H2: Risk => WT (-)	-0.353	4.364	< 0.001	Yes	-0.328	<0.001
H3a: Trust => Risk (-)	-0.573	8.054	< 0.001	Yes	-0.187	<0.001
H3b: Trust => WT (+)	0.297	3.433	0.001	Yes	0.147	<0.001
H3c: Familiarity => Risk (-)	-0.083	1.210	0.226	No	-0.331	<0.001
H3d: Familiarity => Trust (+)	0.361	4.482	< 0.001	Yes	0.211	<0.001
H3e: Familiarity => WT (+)	0.123	1.531	0.126	No	0.363	<0.001
H4a: Familiarity moderates CFIP => Risk	0.001	0.023	0.981	No	n.r.	n.s.
H4b: Familiarity moderates CFIP => Trust	0.078	1.626	0.104	No	n.r.	n.s.
Less Familiar Merchant						
H1a: CFIP => Risk (+)	0.025	0.514	0.607	No	0.001	n.s.
H1b: CFIP => Trust (-)	0.193	2.815	0.005	No+	0.121	n.s.
H1c: CFIP => WT (+)	-0.005	0.121	0.903	No	0.002	n.s.
H2: Risk => WT (-)	-0.301	3.866	< 0.001	Yes	-0.267	<0.001
H3a: Trust => Risk (-)	-0.692	9.422	< 0.001	Yes	-0.443	<0.001
H3b: Trust => WT (+)	0.453	5.705	< 0.001	Yes	0.051	n.s.
H3c: Familiarity => Risk (-)	-0.093	1.274	0.203	No	-0.243	<0.001
H3d: Familiarity => Trust (+)	0.414	4.865	< 0.001	Yes	0.292	<0.001
H3e: Familiarity => WT (+)	0.214	3.842	< 0.001	Yes	0.506	<0.001
H4a: Familiarity moderates CFIP => Risk	-0.119	2.874	0.004	Yes	n.r.	n.s.
H4b: Familiarity moderates CFIP => Trust	-0.013	0.177	0.859	No	n.r.	n.s.

Notes: CFIP – Concern for information privacy, WT – Willingness to transact, TR – Trust
n.s. – Non-significant, n.r. – Not reported
+ - For both merchants, H1b posited negative relationships, but the relationships were positive, therefore H1b is not supported for either merchant.

The current results showed fewer similarities with the original study for the less-familiar merchant, as shown in Table 7. CFIP had neither direct nor indirect impacts on willingness to transact in the original paper, but CFIP had an indirect impact through trust for the current study. (Note that, once again, this relationship was in the opposite direction of that hypothesized.) For the less-familiar merchant H2, H3a, H3b, H3d, H3e, and H4a were supported for the current study.

Interestingly, the moderating effect of familiarity on the relationship between risk and CFIP is supported for the less-familiar merchant. This was the only significant moderating effect among the four we hypothesized. (Recall that Van Slyke et al. (2006) did not find significant moderating effects for either merchant.) We may interpret the result as indicating that as familiarity increases, the influence of CFIP on risk decreases as indicated by the negative sign on the moderation path coefficient. However, this is only the case for less familiar merchants.

Table 8 shows the percentage of variance explained for trust, risk perceptions, and willingness to transact for the familiar and less-familiar merchants. Values for the original study are provided for comparison. In both cases, the model accounted for a significant portion of the variance in willingness to transact (44% for Taobao, and 66% for Amazon). Van Slyke et al. (2006) reported 45% for both merchants. The model explained more of the variance in trust and risk for the Chinese sample than in the original paper.

Table 8 – R-Square (Adjusted) for the Both Merchants

	Familiar		**Less-familiar merchant**	
Variable	China	Original	China	Original
Trust	0.16	0.10	0.18	0.10
Risk	0.39	0.17	0.55	0.32
Willingness to transact	0.44	0.45	0.66	0.45

Note: The original paper reported squared multiple correlations.

4.3 Total Effects

CFIP plays a less important role with a less-familiar merchant. Table 9 shows the total effects of CFIP, familiarity, trust, and risk on willingness to transact as calculated by SmartPLS. For the familiar merchant, CFIP has a total effect of 0.227, versus 0.143 for the less-familiar merchant. In both cases, trust has the largest total effect on willingness to transact, but the total effects of trust and familiarity are noticeably higher for the less familiar merchant than for the familiar merchant, while the total effects for risk are similar. These results imply a hierarchy of effects. Factors that are directly related to the merchant are more important than the general factor (CFIP) especially when the merchant is less familiar.

Table 9 – Total Effects on Willingness to Transact

Predictor	**Taobao Total effect**	**Amazon Total effect**
CFIP	0.227	0.143
Familiarity	0.333	0.515
Trust	0.499	0.660
Risk	-0.353	-0.301

Our results are summarized in Figures 2 and 3. Figure 2 compares the replication and the original study for the familiar merchants, and Figure 3 compares the results for the less-familiar merchants. In both cases, the replication results are shown by the top number along each path, and the values for the original study are shown by the bottom number.

Overall, our results demonstrate the efficacy of the Van Slyke et al. (2006) model. While the results from the replication differed from those presented in the original study, the model has utility for understanding consumer e-commerce in both contexts. Further, the measurement scales demonstrated acceptable reliability and validity for the Chinese sample, indicating the suitability of the scales across contexts. In the next section, we further explore the implications of the results of the replication.

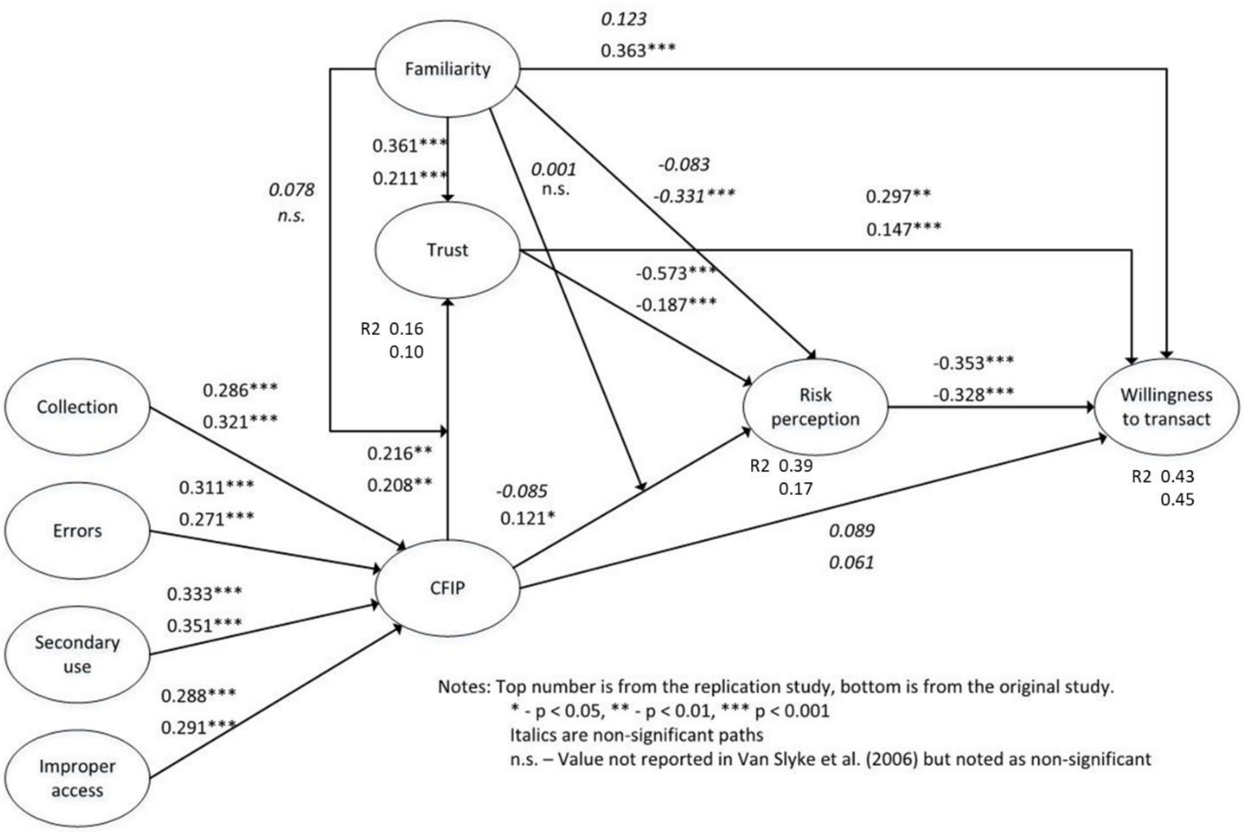

Figure 2 – Results for the Familiar Merchant

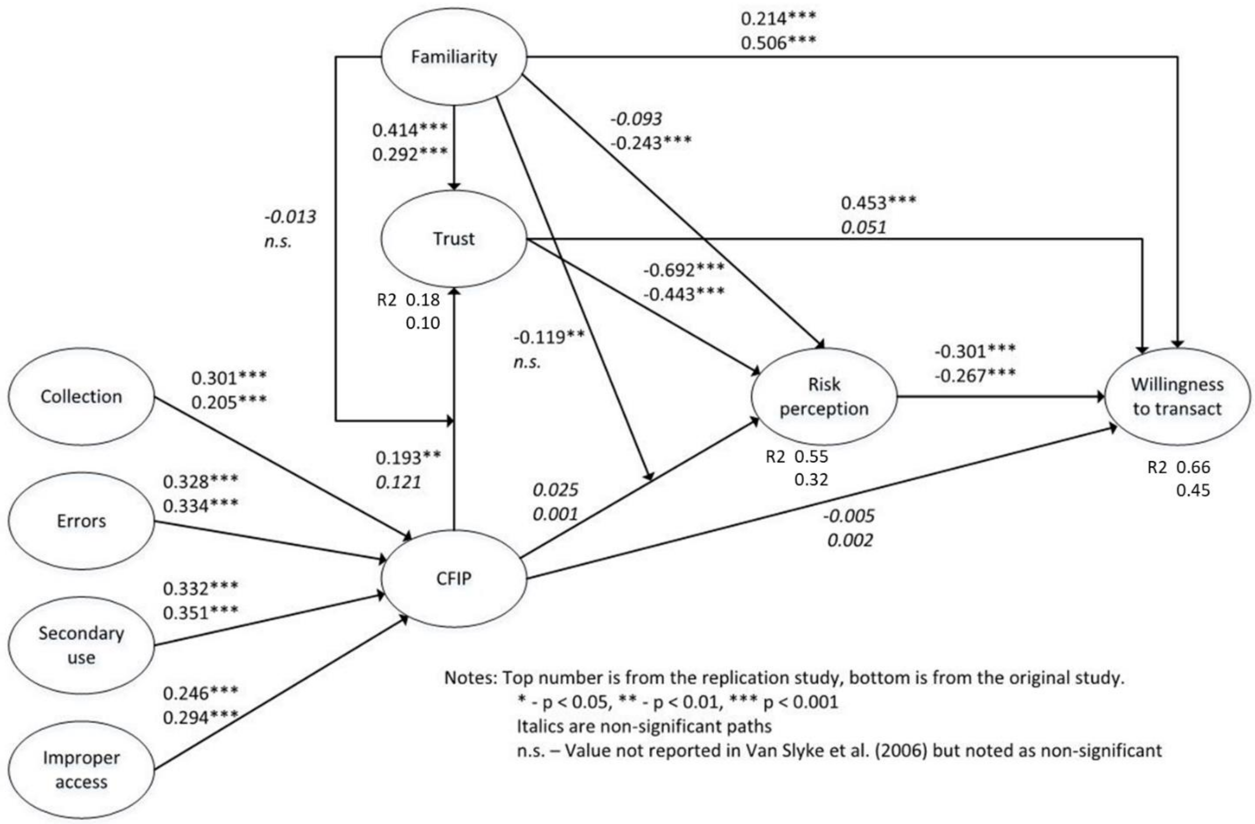

Figure 3 – Results for the Less-Familiar Merchant

In this section, we presented the results of the replication study. In the next section, we further explore the implications of the results of the replication.

5 Discussion

Context is important to information system research (Hong et al., 2014; Niederman & March, 2015), so understanding how extant theories and models hold across different contexts strengthens our understanding of information systems-related phenomena. In order to better understand how information privacy concerns influence consumer e-commerce, we engaged in a cross-context theory replication, as recommended by Hong et al. (2014).

Combining our results with those of Van Slyke et al. (2006) allows us to examine two different aspects of context, country, and merchant[2]. Elements of Van Slyke et al.'s model that hold across both of the contextual elements may be considered to be robust relationships that are less context-dependent than other relationships in the model. Relationships that remain consistent across one, but not both of the contextual elements are somewhat robust, but not as much as those that hold across country and merchant. Figure 4 illustrates the robust elements of the model. Solid lines represent relationships that were significant for both familiar and less-familiar merchants in both the original study and the replication. Dashed lines represent relationships that were significant for less-familiar merchants in both studies. The dash-dot lines show significant relationships that were significant for the familiar merchant for both studies.

The most robust elements of the model are the CFIP components, and the relationships between familiarity and risk perceptions, familiarity and trust, trust and risk perceptions, and risk perceptions and willingness

[2] Note that time also varied across the two data collections. However, the purpose of the replication is to examine country-based differences, so we do not include time in this discussion. We do address the potential confounding role of time in the Limitations sub-section.

to transact. The influence of CFIP on trust and the direct relationship between trust and willingness to transact were significant for less-familiar merchants in both countries, while the influence of familiarity on willingness to transact was significant for familiar merchants in both countries. So it appears that some elements of the model are robust with respect to context, but others are not.

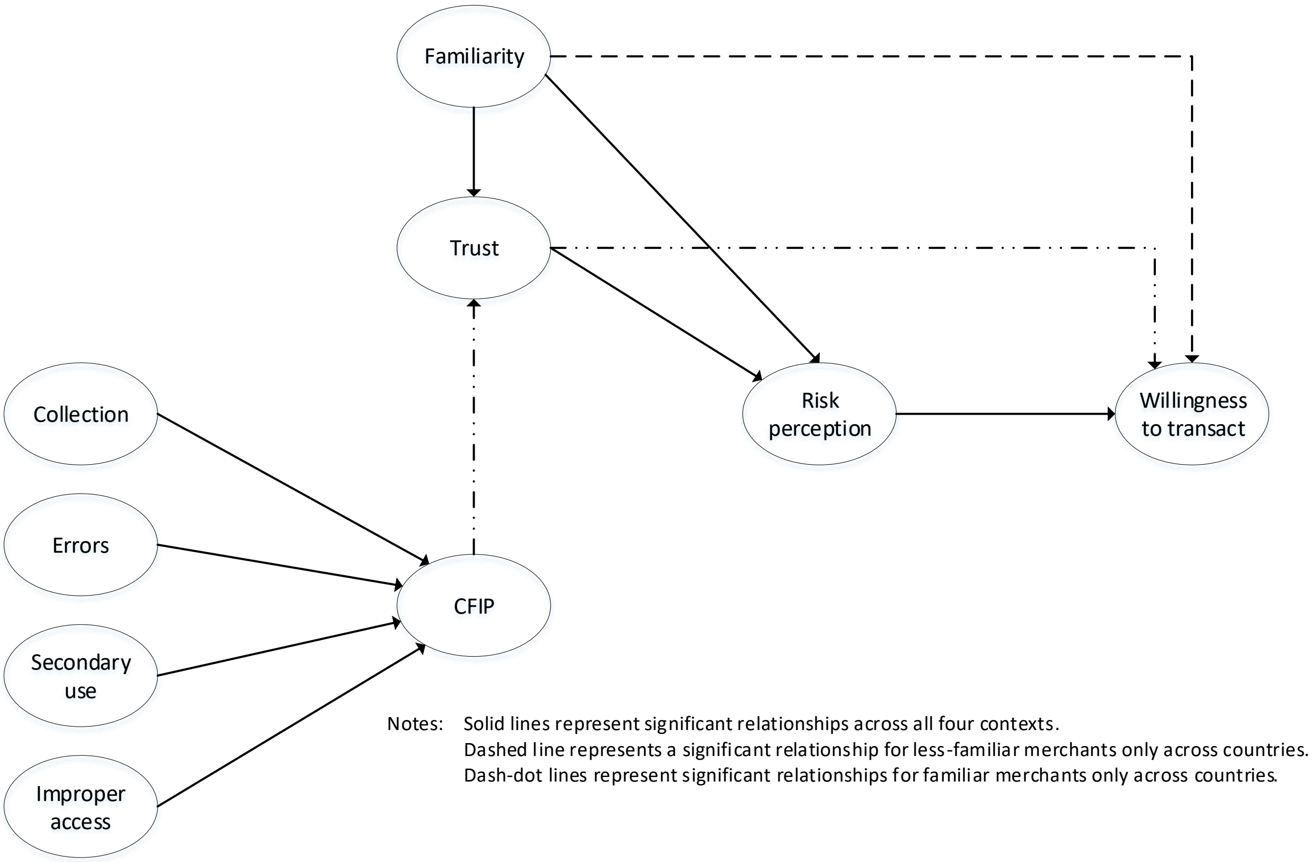

Figure 4 – Results across the Four Contexts

Although the influence of CFIP is context-dependent, in no case did CFIP have a significant direct impact on willingness to transact. In fact, CFIP had relatively little effect either directly or indirectly. However, CFIP did have indirect impacts on willingness to transact for familiar merchants in both countries, and for the less-familiar merchant in the United States, but not China. Given the non-significant path from CFIP to willingness to transact, we can state that CFIP's effects are fully mediated. From this, we can draw several conclusions. First, in the context of consumer e-commerce, privacy concerns are secondary to other factors. This is not surprising; as noted earlier, much of the risk in e-commerce comes from the potential for fraud and non-performance. These are likely more direct, salient concerns than those related to information privacy. Second, context-specific beliefs such as trust and risk perceptions are more important in determining intentions than are general concerns, such as CFIP. This may have to do with the nature of the potential harm that may occur when transacting online. The salience of non-performance risks is likely higher than the vaguer potential harm that may come from information-related risks. For example, if I want to purchase a laptop online, I risk the chance that the merchant may fail to deliver, that the merchant may have misrepresented the product, and that the merchant may deliver a defective product. These risks are all easily imagined. Information risks (as represented by CFIP) are vaguer. The merchant may share my information without my knowledge, a hacker may access my information, the merchant's system may introduce errors, or the merchant may collect more data than is required to carry out the transaction. However, in all of these cases, the actual harm is a second-order harm. In order to be harmed by one of these actions, the privacy violation must occur, then there must be some loss due to the violation. Our data implies that the more direct potential harms are more important to transaction willingness.

It is possible, even likely, that this situation will change as China's social credit score (SCS) system becomes more fully implemented. When fully implemented, the costs of perceived privacy violations may increase to the point where privacy concerns have a strong, direct impact on consumers' e-commerce behaviors. At the time of our data collection, the SCS system was not fully implemented across China – in fact, many details of how the system will operate are still unclear (Zhou & Xiao, 2020). As these details emerge, and consumers begin to gain knowledge of how the system will operate and be used, their privacy concerns may increase, along with the impacts of these concerns.

Also, privacy concerns matter to consumer e-commerce, but only in how they impact other salient beliefs. The replication, like the original study, found that CFIP has only indirect effects on consumers' willingness to transact online. CFIP did influence willingness to transact through trust and risk for the familiar merchant, and through trust for the less-familiar merchant. The Van Slyke, et al. (2006) model seems more robust for more familiar merchants. Not only did the model receive more support for familiar merchants in both studies, but the results across the studies are also more similar for the familiar merchants. The most interesting difference pertains to the less familiar merchant for the replication. While CFIP did not have a significant relationship with risk perceptions, it did with trust. In the original study, CFIP did not influence either. One potential explanation for this is that the United States has a stronger tradition of consumer protection than China. China has only recently begun implementing consumer protection regulations, which have been in place for many years in the United States, either through direct legislation or through business practices such as liability limits for credit card transactions. As noted in much of the early consumer e-commerce literature, such consumer protections are important when transacting over the Internet.

We can make several additional, useful observations from our results. First, we note that the Van Slyke et al. (2006) model was useful in explaining the variance in willingness to transact, regardless of the merchant. The model explained a large portion of the variance in willingness to transact for both merchants, although the R^2 value was especially high for the less-familiar merchant (66% versus 43% for the more-familiar merchant). Interestingly, however, given its relatively small total effect sizes, CFIP contributed less to the predictive power of the model than did the other components.

CFIP has only an indirect impact on willingness to transact – this was the case for both the familiar and less-familiar merchants. For both merchants, CFIP had an indirect impact on willingness to transact through trust, but not through risk. However, as was the case with Van Slyke et al. (2006), the relationship between CFIP and trust was positive, rather than negative, which is contrary to what we expected.

The mean values of the CFIP components for the replication differed from those in the original study. Mean values for the CFIP components were generally higher for the Chinese samples than those reported in Van Slyke et al. (2006). Although we can only speculate, we suspect that these higher mean values may be the result of two factors, increasing awareness of the potential harm from information privacy violations and the volume of consumer e-commerce in China. As noted earlier, the SCS system and other factors seem to be leading to increased awareness of the risks associated with the loss of privacy. Such knowledge would naturally lead to increased CFIP. At the time of our data collection, consumer e-commerce was much more common in China than it was in at the time of Van Slyke et al.'s (2006) data collection. In 2017, the National Bureau of Statistics of China estimated that consumer e-commerce would represent almost 20% of China's retail sales (China Statistical Press, 2018). In 2005, consumer e-commerce in the United States accounted for only 2.4% of retail sales (United States Census Bureau, 2007). The higher prevalence of e-commerce in China may have led to the higher values of CFIP. However, CFIP may have increased in the United States between the time of Van Slyke et al.'s (2006) data collection and the time of our data collection. So, we caution against reading too much into the differences in CFIP component mean values. Further research is needed to determine whether the differences are artifacts of time or nationality.

The perceptions of risk were higher and trust was lower for the Chinese samples when compared to the corresponding merchant in the original study. These results were not surprising given China's relatively newer and weaker consumer protections when compared to those provided in the United States. As e-commerce and consumer protection regulations continue to evolve in China, we may see these differences reduced.

Finally, we were somewhat surprised by the moderation effect results in the current study. Van Slyke et al. (2006) failed to find significant moderating effects for familiarity. We, in contrast, found that for the less-familiar merchant familiarity moderated the impact of CFIP on perceived risk, such that CFIP's influence on risk decreased as familiarity increases. So, it seems that for less-familiar merchants, as consumers gain experience with the merchant, their experiences ameliorate the extent to which their concerns over information privacy issues impact their assessments of the risks in transacting with that merchant online.

5.1 Limitations

One notable limitation of our research concerns the fact that our data and the data for the original study were collected in different time periods (2006 vs. 2019). The thirteen-year difference is noteworthy given the development and diffusion of e-commerce and its enabling technologies. Because of the time difference, we have two potential sources of differences between our findings that those in the original study, the sample, and the time period. Although it not possible to determine which source accounts for the differences in findings, we can state that the stability of the scales and the lack of a direct effect from CFIP are robust across both time and sample.

Another limitation comes from our sample sizes, which were smaller than those reported in Van Slyke et al. (2006), even though our sample sizes were adequate for the analyses we performed. Larger samples would have increased the power of our statistical tests. However, all of our non-significant coefficients had p-values well above the commonly used $p < 0.05$ significance heuristic, so it is unlikely that larger samples would have changed our results substantially.

Finally, as a replication, weaknesses in the original study's methodology carried over into this study. One particularly interesting issue concerns the measures of perceived risk. Although Van Slyke et al. (2006) used a well-validated scale for perceived risk, close inspection of the measurement items reveals that these items may be measuring *net* risk (the balance of risk and gain) rather than risk alone. Future studies may find it worthwhile to consider a more pure measure of perceived risk.

6 Conclusion

To our knowledge, the replication reported in this paper is the first attempt to apply the Van Slyke et al. (2006) model to a non-United States sample. While the specific results differed from those reported in the original study, the replication indicates that the model is useful for studying the effects of CFIP on consumer e-commerce across national contexts. The results confirm that CFIP affects willingness to transact online only indirectly; no direct effect was found in the original study or in the replication.

This research makes several contributions. First, we examined CFIP's role in consumer e-commerce in a new, important context. Our research also adds to the field's knowledge regarding two important issues – privacy, and consumer e-commerce, in the context of an increasingly-important economy. In addition, our findings further establish the importance of familiarity with a merchant as an important driver of consumers' willingness to transact with a specific online merchant. We also add to the privacy literature by establishing the efficacy of CFIP and its measurement in an under-researched context. Finally, we reinforce the idea of first- and second-order concerns as they relate to e-commerce intentions.

Van Slyke et al. (2006) provide researchers interested in studying the effects of privacy concerns with a robust model and set of scales. Although the strength of specific relationships may vary across contexts, the results of this replication indicate that the model and scales provide a useful foundation upon which to build future research on the effects of CFIP.

7 References

Ackerman, M. S., Cranor, L. F., & Reagle, J. (1999). Privacy in e-commerce: Examining user scenarios and privacy preferences. *In Proceedings of the 1st ACM conference on Electronic commerce,* 1-8.

Bandara, R., Fernando, M., & Akter, S. (2019). Privacy concerns in E-commerce: A taxonomy and a future research agenda. *Electronic Markets*, 1-19.

Bélanger, F., & Crossler, R. E. (2011). Privacy in the digital age: A review of information privacy research in information systems. *MIS Quarterly*, 35(4), 1017-1042.

Berendt, B., Günther, O., & Spiekermann, S. (2005). Privacy in e-commerce: Stated preferences vs. actual behavior. *Communications of the ACM*, 48(4), 101-106.

Bhattacherjee, A. (2002). Individual trust in online firms: Scale development and initial test. *Journal of Management Information Systems*, (19)1, 211-241.

Cheng, E. (2018). Data privacy issues may be capturing more attention in China, CNBC, Retrieved from https://www.cnbc.com/2018/12/05/data-privacy-issues-may-be-capturing-more-attention-in-china.html.

China Statistical Press (2000). China Statistical Yearbook, Retrieved from http://www.stats.gov.cn/english/statisticaldata/yearlydata/YB2000e/index1.htm.

China Statistical Press (2018). China Statistical Yearbook, Retrieved from http://www.stats.gov.cn/tjsj/ndsj/2018/indexeh.htm.

Dennis, A. R., & Valacich, J. S. (2014). A replication manifesto, *AIS Transactions on Replication Research*, 1, Article 1.

Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, 17(1), 61-80.

Dinev, T., Bellotto, M., Hart, P., Russo, V., Serra, I., & Colautti, C. (2006). Privacy calculus model in e-commerce–a study of Italy and the United States. *European Journal of Information Systems*, 15(4), 389-402.

DLA Piper (2019). Data Protection Laws of the World: China, Retrieved from https://www.dlapiperdataprotection.com/index.html?t=law&c=CN.

Faqih, K. M. (2016). An empirical analysis of factors predicting the behavioral intention to adopt Internet shopping technology among non-shoppers in a developing country context: Does gender matter? *Journal of Retailing and Consumer Services*, 30, 140-164.

Farrall, K. N. (2008). Global privacy in flux: Illuminating privacy across cultures in China and the US. *International Journal of Communication*, 38(2).

Gefen, D. (2000). E-commerce: the role of familiarity and trust. *Omega,* 28(6), 725-737.

Henseler, J., Ringle, C. & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling, *Journal of the Academy of Marketing Science*, 43(1), 115-135.

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.

Huang, Y. & Liu, W. (2012). The impact of privacy concern on users' usage intention of mobile payment, *Proceedings of the 2012 International Conference on Information Management, Innovation Management and Industrial Engineering*, 2, 90-93, Sanya, China: IEEE.

Jarvenpaa, S. L., Tractinsky N., and Vitale M. (2000). Consumer trust in an Internet store. *Information Technology and* Management, 1(1-2), 45-71.

Kharpal, A. (2018). Alibaba sets new Singles Day record with more than $30.8 billion in sales in 24 hours, CNBC. Retrieved from https://www.cnbc.com/2018/11/11/alibaba-singles-day-2018-record-sales-on-largest-shopping-event-day.html.

Liu, C., Marchewka, J. T., Lu, J., & Yu, C. S. (2005). Beyond concern—a privacy-trust-behavioral intention model of electronic commerce. *Information & Management*, 42(2), 289-304.

Mahrous, A. A. (2011). Antecedents of privacy concerns and their online actual purchase consequences: A cross-country comparison. *International Journal of Electronic Marketing and Retailing*, 4(4), 248-269.

McDougall, B. S. (2004). Privacy in modern China. *History Compass*, 2(1).

Melton, J. (2019). Online retail sales in China grew nearly 24% its government says, Internet Retailer, Retrieved from https://www.digitalcommerce360.com/2019/01/24/chinas-online-sales-grew-almost-24-in-2018/.

Naftali, O. (2010). Caged golden canaries: Childhood, privacy and subjectivity in contemporary urban China. *Childhood*, *17*(3), 297-311.

National Bureau of Statistics of China (2019). National economic performance maintained within an appropriate range in 2018 with main development goals achieved. Retrieved from http://www.stats.gov.cn/english/PressRelease/201901/t20190121_1645832.html.

Niederman, F., & March, S. (2015). Reflections on replications. *AIS Transactions on Replication*, 1, 1-16.

Nissenbaum, H. (2009). Privacy in context: Technology, policy, and the integrity of social life. *Stanford University Press.*

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. (2015). SmartPLS 3. Bönningstedt: SmartPLS. Retrieved from http://www.smartpls.com.

Russell, J. & Liao, R. (2018). Singles' Day: China's $25 billion shopping festival explained, Tech Crunch, Retrieved from https://techcrunch.com/2018/11/09/alibaba-singles-day-11-festival/.

Schaefer, K. (2019). The apps of China's social credit system, Trivium China, Retrieved from http://ub.triviumchina.com/2019/10/long-read-the-apps-of-chinas-social-credit-system/.

Sia, C. L., Lim, K. H., Leung, K., Lee, M. K., Huang, W. W., & Benbasat, I. (2009). Web strategies to promote internet shopping: Is cultural-customization needed? *MIS Quarterly*, 33(3), 491-512.

Smith, H. J., S. J. Milberg, and S. J. Burke (1996). Information privacy: Measuring individuals' concerns about organizational practices. *MIS Quarterly,* (20) 2, 167-196.

Snider, M. (2018). Cyber Monday sales likely hit $7.9 billion, surpassing record estimate. USA Today. Retrieved from https://www.usatoday.com/story/money/2018/11/27/cyber-monday-sales-7-9-billion-top-record-online-sales-estimate/2123414002/.

Stewart, K. A. and A. H. Segars (2002). An empirical examination of the concern for information privacy instrument. *Information Systems Research*, 13(1), 36-49.

Udo, G. J. (2001). Privacy and security concerns as major barriers for e-commerce: A survey study. *Information Management & Computer Security*, 9(4), 165-174.

United States Census Bureau (2007). Annual Retail Trade Survey. Retrieved from https://www2.census.gov/programs-surveys/e-stats/tables/2005/table4.xls.

Van Slyke, C., Shim, J. T., Johnson, R., & Jiang, J. J. (2006). Concern for information privacy and online consumer purchasing. *Journal of the Association for Information Systems*, 7(6), 415-444.

Vance, A., Elie-Dit-Cosaque, C., and Straub, D. (2008). Examining trust in information technology artifacts: The effects of system quality and culture. *Journal of Management Information Systems*, 24(4), 73-100.

Wang, Y., Xia, H., & Huang, Y. (2016). Examining American and Chinese Internet users' contextual privacy preferences of behavioral advertising. *In Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, 539-552.

Xue, H. (2010). Privacy and personal data protection in China: An update for the year 2009. *Computer Law & Security Review*, 26, 284-289.

Zhang, L., Liang, P., & Mu, Y. (2018). Improving privacy-preserving and security for decentralized key-policy attributed-based encryption. *IEEE Access*, 6, 12736-12745.

Zhou, C. & Xiao, B. (2020) China's Social Credit System is pegged to be fully operational by 2020 – but what will it look like? Australian Broadcasting Corporation. Retrieved from https://www.abc.net.au/news/2020-01-02/china-social-credit-system-operational-by-2020/11764740.

Appendix A – Scale Items

Note: Scale items are directly from Van Slyke et al. (2006) except for merchant names. Unless otherwise specified, all anchors on 7-point scale anchored on Very Strong Disagree to Very Strongly Agree.

Item	**Scale/item text**	**Taobao**		**Amazon**	
		Mean	**StDev**	**Mean**	**StDev**
	Concern for information privacy (Smith et al., 1996; Stewart & Segars, 2002)				
	Collection				
Col1	It usually bothers me when companies ask me for personal information.	5.566	1.495	5.572	1.430
Col2	When companies ask me for personal information, I sometimes think twice about providing it.	5.737	1.441	5.755	1.251
Col3	It bothers me to give personal information to so many companies.	6.661	1.242	5.943	1.289
Col4	I'm concerned that companies are collecting too much personal information about me.	5.980	1.344	6.000	1.253
	Improper access				
Access1	Companies should devote more time and effort to preventing unauthorized access to personal information.	6.217	1.121	6.283	1.068
Access2	Companies should take more steps to make sure that unauthorized people cannot access personal information on their computer.	6.467	0.913	6.302	1.089
Access3	Computer databases that contain personal information should be protected from unauthorized access—no matter how much it costs.	6.211	1.120	6.208	1.056
	Errors				
Error1	All the personal information in computer databases should be double-checked for accuracy - no matter how much this costs.	5.993	1.176	6.063	1.123
Error2	Companies should have better procedures to correct errors in personal information.	5.987	1.174	6.088	1.070
Error3	Companies should devote more time and effort to verifying the accuracy of the personal information in their databases.	5.776	1.293	5.862	1.183
Error4	Companies should take more steps to make sure that the personal information in their files is accurate.	5.849	1.259	5.899	1.208
	Secondary Use				
SecUse1	Companies should not use personal information for any purpose unless it has been authorized by the individuals who provided the information.	6.526	0.876	6.447	0.925
SecUse2	When people give personal information to a company for some reason the company should never use the information for any other reason.	6.349	1.025	6.472	0.920
SecUse3	Companies should never sell the personal information in their computer databases to other companies.	6.697	0.728	6.623	.0785
SecUse4	Companies should never share personal information with other companies unless it has been authorized by the individuals who provided the information.	6.697	0.737	6.535	0.877
	Risk Perceptions (Note: These were re-coded for the analysis.) (Jarvenpaa et al., 2000)				
Risk1	How would you characterize the decision of whether to buy a product from this Web retailer (Taobao/Amazon.cn)? (Anchors: Very significant risk to Very Significant opportunity)	2.875	1.075	3.176	1.240
Risk2	How would you characterize the decision of whether to buy a product from this Web retailer (Taobao/Amazon.cn)? (Anchors: Very high potential for loss to Very high potential for gain)	2.941	01.123	3.252	1.201

Risk3	How would you characterize the decision of whether to buy a product from this Web retailer (Taobao/Amazon.cn)? (Anchors: Very negative situation to Very positive situation)	2.757	1.016	3.252	1.283
	Familiarity (Gefen, 2000)				
Fam1	I am familiar with Taobao/Amazon.cn.	6.211	1.205	4.258	1.762
Fam2	I am familiar with inquiring about book ratings at Taobao/Amazon.cn.	6.046	1.278	4.182	1.786
	Trust (Bhattacherjee, 2002)				
Trust1	Taobao/Amazon.cn has the skills and expertise to perform transactions in an expected manner.	5.309	1.225	4.836	1.373
Trust2	Taobao /Amazon.cn has access to the information needed to handle transactions appropriately.	5.072	1.367	4.717	1.419
Trust3	Taobao/Amazon.cn is fair in its conduct of customer transactions.	4.954	1.262	4.767	1.388
Trust4	Taobao/Amazon.cn is fair in its customer service policies following a transaction.	4.980	1.210	4.774	1.396
Trust5	Taobao/Amazon.cn is open and receptive to customer needs.	5.059	1.257	4.805	1.362
Trust6	Taobao/Amazon.cn makes good-faith efforts to address most customer concerns.	5.138	1.271	4.799	1.386
Trust7	Overall Taobao/Amazon.cn is trustworthy.	5.362	1.077	4.931	1.313
	Willingness to Transact (Jarvenpaa et al., 2000)				
WT1	I intend on using Taobao/Amazon.cn for some of my future purchases.	5.822	1.169	4.396	1.699
WT2	I am inclined to purchase Taobao's/Amazon.cn's goods and/or services.	5.566	1.160	4.403	1.639
WT3	I am likely to utilize the goods/services provided by Taobao.	5.638	1.177	4.528	1.590

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