Transactions on Replication Research

Conceptual Replication DOI: 10.17705/1atrr.00075 ISSN 2473-3458

Trust Building Mechanisms in Online Health Communities and Their Impact on Information Adoption and Close Relationship Formation

Xin Liu
Department of Business Analytics, Information Systems and Supply Chain
Florida State University
xl19d@fsu.edu

Ashley A. Bush
Department of Business Analytics, Information Systems and Supply Chain
Florida State University
abush@business.fsu.edu

Abstract:

This study conceptually replicates Fan and Lederman's (2018) work on trust formation mechanisms in online health communities (OHCs). Social capital theory sets the framework for the research. Contextualized in online health communities (OHCs), it is the content contributors' task to demonstrate trustworthiness by showing the credibility of the posted content in their previous postings. In contrast, the recipients, rather than the contributors, have to initially show trustworthiness in the sense of traditional social capital theory. We adopted the model, hypotheses, modified instrument, and statistical methods from the original study conducted by Fan and Lederman in 2018. Three out of nine hypotheses in our replication are not consistent with the original study results. The inconsistencies primarily lie in the antecedents of two types of trust. We discuss possible explanations for these discrepancies and suggest additional data and statistical tests to validate our replication results.

Keywords: Online Health Communities (OHCs), Social Capital Theory, Trust, Relational Closeness, Information Adoption.

The manuscript was received 10/13/2021 and was with the authors 3 months for 1 revision.

1 Introduction

Online health communities (OHC) provide excellent opportunities for patients to seek information, emotional support, and a better way of self-management. Ninety-two percent of cancer patients in one study claimed that the Internet helped them to make better health decisions (Nath, Huh, Adupa, & Jonnalagadda, 2016). About a quarter of Internet users suffering from chronic diseases engage in OHCs (Huang, Chengalur-Smith, & Pinsonneault, 2019). There are mainly two types of OHCs: one type is physician-driven (e.g., MedScape); the other type is patient-driven (e.g., HealthUnlocked). Information Systems (IS) researchers have done remarkable work to analyze the user behaviors of these two types of OHCs (Nambisan 2011; Fan & Lederman, 2018; Liu, Liu, & Guo, 2020).

To better understand patient-driven OHC user behaviors, Hanmei Fan and Reeva Lederman published the paper "Online health communities: how do community members build the trust required to adopt information and form close relationships" in the European Journal of Information Systems in 2018, hereinafter referred to as the "original study." This research was interested in how OHC users, who do not have any systematic medical training, discern advice, adopt information, and establish emotional bonds with each other. Social capital theory was used as the theoretical foundation for their research (Fan & Lederman 2018).

Our study aims to conceptually replicate Fan and Lederman's work in 2018. Although trust as a construct has been investigated in many IS contexts, limited work has been done to replicate their models and methods. Replication is a critical component of IS research development (Dennis & Valacich, 2014). We want to confirm the findings and understand any variations of the study being replicated. Also, healthcare as a context is an essential branch of IS research. The unique characteristics of healthcare in online communities, e.g., perceived similarity in medical status and perceived empathy, bring the study to the foreground of this context (MISQ HealthIT Curation, 2019).

The original paper's research hypotheses, replication results, and model are presented in Table 1 and Figure 1. The remainder of this paper is organized as follows. After presenting the original research method and our modifications, we summarize and discuss the results. Limitations are drawn from our replication work, followed by the conclusion.

Table 1. Research Hypotheses (Fan & Lederman, 2018)

Hypotheses	Original study	Replication study	Consistent?
H1: The perceived information credibility will positively contribute to the formation of cognitive trust in a text-based relationship-orientated OHC.	Supported	Supported	Yes
H2: Perceived similarity in medical status will contribute to cognitive trust in a text-based relationship-orientated OHC.	Supported	Not Supported	No
H3: Perceived similarity in values will positively contribute to affective trust in a text-based relationship-orientated OHC.	Supported	Not Supported	No
H4: Familiarity will influence affective trust towards a person in a text-based relationship-orientated OHC.	Supported	Not Supported	No
H5: Familiarity will influence cognitive trust towards a person in a text-based relationship-orientated OHC.	Supported	Supported	Yes
H6: Perceived empathy will positively contribute to affective trust in a text-based relationship-orientated OHC.	Supported	Supported	Yes
H7: Cognitive trust will contribute to information adoption in a text-based relationship-orientated OHC.	Supported	Supported	Yes
H8: Affective trust will contribute to information adoption in a text-based relationship-orientated OHC.	Supported	Supported	Yes
H9: Affective trust will contribute to the formation of relational closeness in a text-based relationship-orientated OHC.	Supported	Supported	Yes

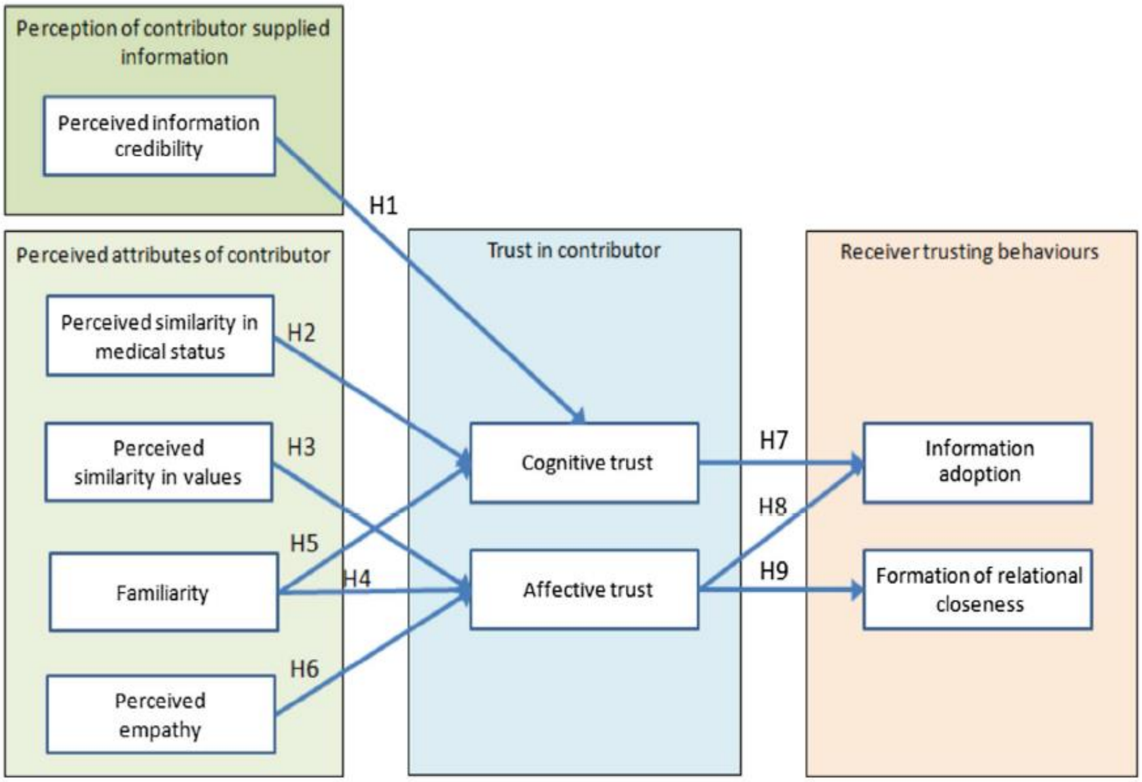

Figure 1. Research Model (Fan & Lederman, 2018)

2 Method

Instead of recruiting participants from OHCs (Fan & Lederman 2018), we turned to Amazon Mechanical Turk Human Intelligence Tasks to get more extensive coverage of the targeted population. We realized that patient-driven OHCs are diminishing in activity, so it would be challenging to get a truly representative sample from OHC. More stakeholders are engaging in OHC to yield optimal benefits to the community. The trend of OHC is moving from patient-driven to multiple roles participation and cooperation: patients, clinicians, academics, and industry (Hodgkin, Horsley, & Metz, 2018). Using Amazon Mechanical Turk allowed us to reach a broader population of online health consumers than would otherwise be possible.

2.1 Construct Operationalization and Scale Development

The overall pool of candidate items (158 items) initially used by the original study was not accessible to us. So, our replication study chose to use the final scales in the original study and skip the q-sort procedure in the original scale development section. However, we modified the instrument by letting the respondents assess the OHC as a collective entity rather than an individual information contributor in the OHC. For example, we modified the item “If I encounter difficulty, I know this person would try and help me out” to “If I encounter difficulty, I know people in the OHC would try and help me out” (see Appendix Table A3). We did this because we believe that the purpose of the OHC is to tap into the collective wisdom of the group (Mamykina, Nakikj, & Elhadad, 2015; Surowiecki, 2004). All thirty-eight items in Fan and Lederman's (2018) final instrument were transformed to measure the respondents’ perspectives on their overall OHC experience based on the seven-point Likert scale. Demographic information was also collected to gain insight into the characteristics of the respondents and to conduct the post hoc test.

The validity analysis in our study showed that the overall Kaiser-Meyer-Olkin (KMO) is .939 (see Appendix Table A1), which is higher than the original study (.875). This is because the original study was using this step to pre-test the reliability and validity of the tentative instrument, which contained items dropped for further analysis. Our analysis only contains the final scales used in the original study. The larger the KMO value is, the stronger the items are correlated. The Bartlett’s Test of Sphericity is also significant in our replication study (alpha = .01, *df*=561, Chi-Square critical value = 641.85). The communality measures are also above .6 (see Appendix Table A2), which is consistent with the original study.

2.2 Data Collection

Unlike the instruction in the original study asking respondents about their most recent visit to an OHC in the past seven days, our survey was anchored on the OHC user's overall experience of visiting the OHC (see Appendix Table A3). At the beginning of the survey, we also specified that "When you are taking the survey, please think about your overall experience with your most recent visit of an online health community (OHC)."

Although Fan & Lederman (2018) did not mention their item-ordering approach (e.g., static presentation vs. individually randomized ordering) in their study, we think that it is still necessary to describe our item-ordering approach since it may impact the research result from different ways (e.g., construct reliability and validity, survey-taking effects, etc.) (Loiacono & Wilson, 2020; Wilson, Srite, & Loiacono, 2017, 2021). We chose the static grouped by construct item-ordering approach given its good construct reliability and fair validity statistics. Also, because Fan and Lederman (2018) already did instrument validation in their study and we are doing a replication study to further validated their instrument at the OHC level, the static grouped by construct item-ordering approach is appropriate in our study (Wilson et al., 2021).

Three rounds of data collection were conducted by using Amazon's Mechanical Turk (MTurk). We set up stringent filter functions at the beginning of the survey to target the potential respondents who are the users of the OHCs. The filter functions exclude the population who have received systematic medical education or training (i.e., certified nursing assistants, registered nurses, physician assistants, or physicians, etc.) and those who also suffer from mental illness besides physical illness. We restricted the MTurk user panel to the United States, the United Kingdom, Australia, Canada, and New Zealand to be consistent with the similar national culture boundary applied in the original study. All three data collection sessions were completed in seven days in a sequential manner. The first-round yielded 255 total responses. We manually checked each participant's response based on his/her medical conditions, ICD codes, and the property of the OHC he/she visited. To make sure that the respondent did visit an OHC in the last 30 days (we extended Fan and Lederman's (2018) time span of a respondent's most recent visit in the past 7 days in order to have a bigger pool for recruitment), we set the inclusion criterion as that at least two of the three feedbacks of the respondent's medical disease and condition, ICD codes, and the OHC website addresses or names have to be valid. We set this criterion also because Fan and Lederman (2018) used the ICD code to categorize respondent's medical conditions in their descriptive statistics. Among the 255 responses (33 did not complete the survey) from the first round, only 64 responses survived with those two valid feedbacks and met the inclusion criterion. After deleting one response that did not pass the attention check question, 63 responses were kept for analysis. We noticed that the respondents who provided valid information which met our inclusion criterion also had high survey completeness and attention check pass rate. We extended the recruiting pool to 450 for both second-round and third-round data collection on MTurk, which yield 439 and 445 responses respectively. We then applied the same inclusion criterion and checked the attention trap questions and survey completeness. In the end, we kept 98 and 112 responses from second-round and third-round data collection for analysis.

2.3 Characteristics of Respondents

The total response collected by three MTurk Human Intelligence Task (HIT) sessions is 1139. After deleting unusable cases and outliers and screening out the cases that did not pass the attention check questions, 273 cases were eligible and kept for further analysis. The sample size is a little smaller than that of the original study (320). The missing values were imputed by using an expectation maximization (EM) method.

The demographic information is shown in Table 2. The female respondents in the original study accounted for more than two-thirds of the sample. The gender in our sample was more equally distributed (53% were female). Around 80% of the respondents received at least tertiary education in our sample, which is higher than 60% in the original study. The respondents' average age in our sample (thirty-five) is younger than forty-two in the original study. The respondents' OHC visiting frequency is lower than that of the original study. In Fan and Lederman (2018), more than two-thirds (66.7%) of respondents visited OHC more than once per week. The ratio is less than 59% in our sample. Diseases of the respiratory system, circulatory system, nervous system, endocrine system, and neoplasms accounted for about 50% of all the symptoms in our responses based on the WHO ICD-10 codes (WHO, 2010). Cancer, nervous, and digestive diseases accounted for 46.9 of the cases in the original study.

Table 2. Demographic Statistics

Variable	Replication result (n=273)	Original result (n=320)
Gender (Female/Total sample)	53%	2/3 (more than two-thirds)
Education (Percentage of having a tertiary education)	79.4%	>60% (more than 60%)
Average age	35	42
Standard deviation of age	10.88	15.74
Range of age	18-69	18-78
Frequency of visiting OHC (More than once per week)	<59.2%	>66.7 (more than two-thirds)
Country of residence (USA)	85%	55%
Country of residence (Australia)	1%	24%
Country of residence (UK)	7%	13%
Country of residence (New Zealand)	1%	4%
Country of residence (Canada)	6%	2%

Gender was a variable used in the original study to test the trust formation mechanism. Our study result is consistent with that of the original study: gender does not moderate the relationship between empathy and affective trust, nor the relationship between perceived information credibility and cognitive trust (Table 3).

Table 3. Moderation Effect Test

	Original study			Replicated study		
	$\beta_{interaction}$	T-value	p-value	$\beta_{interaction}$	T-value	p-value
Perceived empathy & Affective trust	.061	1.497	>.1	-.0331	-.326	>.1
Perceived info credibility & Cognitive trust	-.021	.697	>.1	.0735	.746	>.1

2.4 Assessing the Threat of Common Method Variance

We chose to use Harman's single factor test and marker variable adopted in the original study to access the common method variance. Following Harman's single factor method, the first factor contributes to 36.3% of total variance by constraining the number of factors extracted to be one in the unrotated EFA setting, which is lower than 42% in the original study. So, no one general factor contributes to more than the majority of the variance (>50%).

Like the original study, we also chose age as the marker variable to test the common method variance. The test result shows that age does not have any significant correlation with other constructs (see Appendix Table A4). The same effect applies to the outcome when partialing out the shared variance. So, common method variance is not an issue for the method design, which is consistent with the original study.

2.5 Factor Loadings

Although we chose to use the official instrument of the original study in our replication, the loading pattern is not quite similar to Fan and Lederman's (2018) result. Six latent factors were extracted based on the Eigenvalue (Eigenvalues greater than one). Loadings exceeding .5 were highlighted (see Appendix Table A3). Perceived similarity in values and close relation formation were loaded together. Cognitive trust and affective trust were cross-loading heavily.

After we deleted the items with low loadings on the latent factor and high cross-loadings (AFT1, EMP37, EMP44, and RCF15), the loading pattern became stable. However, affective trust and cognitive trust items loaded on one factor; familiarity and perceived empathy loaded on one factor; information adoption only retained two items, which made it hard to be kept for further analysis. We will explain these discrepancies in later sections.

2.6 Results and Analysis

SmartPLS 3 was chosen to conduct the hypothesis testing and model assessment. Fan and Lederman (2018) justified the method by their model complexity and the small sample size. They also emphasized that SmartPLS 3 improved the “potentially inflated PLS path coefficient estimation in SmartPLS 2.” Gefen Straub, and Boudreau (2000) argued that PLS is suitable for analyzing small samples sizes and for data that does not present multivariate normal distribution to meet covariance-based SEM’s stricter requirement, since neither of the PLS significance estimations of the model path nor the resulting R^2 requires parametric assumptions. On the other hand, Goodhue, Lewis, and Thompson (2012) found that PLS does suffer from increased standard deviations, decreased statistical power, and reduced accuracy when using small sample sizes. Although it is robust to counterbalance moderate departures from normality, but it has no advantage to fight against non-normal distributions. They also found that the small sample size and non-normality exert the same effect between the complex model and the simple model in PLS. Considering Hair et al. (2021) emphasized that distribution and scales are the two of major advantages of using PLS, we think that the PLS method fits into our study given its capacity against moderate departures from data distribution normality and is coherent with the original study we replicated.

2.7 Reflective Measurement Model Assessment

We tested the construct internal consistency reliability for both the original latent variables in Fan and Lederman (2018) and the ones generated by the EFA Varimax rotation method in our factor analysis. Instead of eight reflective factors that were extracted from the original study, six factors were extracted from our data set after deleting four items - affective trust and cognitive trust loaded on one factor (alpha = .892); familiarity and empathy loaded on another factor (alpha = .846). The Cronbach's Alpha for affective trust, cognitive trust, empathy, and familiarity are .781, .848, .823, and .71 respectively tested by our dataset (Table 4). All eight constructs’ alpha range is between .71 to.86. In exploratory research, .7 is the threshold (Hair, Black, Babin, & Anderson, 2014). Although .8 is recommended for basic research and .95 was preferable for applied research (Nunnally, 1978), we chose to use Fan and Lederman's (2018) eight reflective latent variables in our replication study to compare our analysis results with the original study. Moreover, the values of composite reliability between .7 and .9 can be seen as satisfactory in more advanced stages of exploratory research (Hair, Hult, Ringle, & Sarstedt, 2017), which justified our choice of testing the original model in Fan and Lederman (2018). The composite reliability values of all eight constructs exceeded .8 (Table 4).

Table 4. Correlations of Latent Variables of Trust Formation Model (n= 273)

	Mean	SD	Cronbach’s alpha	Composite reliability	AFT	COT	EMP	FAM	INA	INC	RCF	SIMV
AFT	5.06	0.936	0.781	0.86	**0.779**							
COT	5.03	0.949	0.848	0.892	0.737	**0.789**						
EMP	5.03	0.845	0.823	0.875	0.673	0.704	**0.765**					
FAM	5.02	0.948	0.71	0.838	0.568	0.67	0.747	**0.796**				
INA	5.16	0.875	0.793	0.866	0.562	0.602	0.662	0.569	**0.787**			
INC	5.13	0.860	0.855	0.896	0.573	0.696	0.673	0.642	0.718	**0.796**		
RCF	4.56	1.031	0.725	0.826	0.466	0.488	0.617	0.547	0.438	0.491	**0.742**	
SIMV	4.78	0.838	0.795	0.867	0.457	0.516	0.562	0.529	0.582	0.593	0.619	**0.787**
SIMM(F)	4.76	0.818	N/A	N/A	0.408	0.406	0.499	0.48	0.562	0.54	0.329	0.508
				AVE	0.607	0.623	0.585	0.633	0.619	0.633	0.551	0.62

Note: Bold values are the square root of AVE.

For indicator reliability, all indicators have loadings above .7, except EMP37, AFT10, and AFT1, which were removed for further analysis (see Appendix Table A5).

The average variance extracted (AVE) of all constructs exceeds .5. So, the convergent validity is supported. The square root of the AVE is higher than the correlation between the latent variable and all other latent variables (Table 4). So, the Fornell-Larcker criterion is met, and the discriminant validity is valid, so far. However, when we further examine the cross-loading criterion, at least .2 difference between each factor loading and its corresponding cross-loading is not satisfied for some indicators (see Appendix Table A5). The smaller differences exist mainly on FAM1, EMP33, EMP35, EMP37, and COT1, COT10, AFT2, which explains the previous result of EFA factor extraction of familiarity and empathy loaded on one factor, and cognitive trust and affective trust loaded on one factor. As a result, the discriminant validity is not totally met in our replication study. Compared with .87 to .93 Cronbach's Alpha scores in Fan and Lederman (2018), the alpha scores falling between .71 to .86 in our replication study indicates that the reliability of the reflective measurement is not as strong as in the original study. These slightly lower scores might be caused by the instrument modification – we transformed Fan and Lederman's (2018) final instrument to measure the respondents' perspectives on their overall OHC experience rather than on an individual OHC content contributor.

2.8 Formative Measurement Model Assessment

The weight of item SIM12F (medical background) and SIM21F (age) on the construct Perceived Similarity in Medical Status are not significantly different from zero (p>.1) (see Appendix Table A5). The t-values of these two items' outer weights indicate their contribution to the construct is not significantly different from zero. The p-value of SIM22F (treatment) is .07, which shows the item barely contributing to the construct. Therefore, the validity of the formative construct is challenged in our replication study. However, the outer loadings of four items are at least borderline .5 (Table 5) and show absolute importance to the construct (Cenfetelli & Bassellier, 2009).

Table 5. Outer Loadings of Formative Measurement - Perceived Similarity in Medical Status

SIM (status)		
	Replication study	**Original study**
SIM11F	0.918	0.585
SIM12F	0.554	0.768
SIM21F	0.458	0.497
SIM22F	0.723	0.482

The result of the variance inflation factor (VIF) analysis in our study is consistent with that of the original study. All items' VIF values are below 5 (see Appendix Table A6), which shows that multicollinearity is not a problem in the formative measurement.

The correlation between the formative construct and other exogenous constructs was less than .7 (Table 4), which indicated that the discriminant validity is supported (Bruhn, Georgi, & Hadwich, 2008).

2.9 Structural Model Assessment

The path coefficients estimates and the explained variance was analyzed by bootstrapping resampling method. Fan and Lederman (2018) did not mention the bootstrapping settings in their study, we chose the default setting of the software: the number of subsamples is 500; test type is Two Tailed; and assuming a 5% significant level.

Perceived information credibility and familiarity are significantly and positively associated with cognitive trust, which is consistent with the original study (Table 6). Perceived similarity in medical status is not significantly correlated with cognitive trust (β = -.03, T-value = .582, P > .1, effect size = .001). According to Vinzi, Chin, Henseler, and Wang (2010), the cutoff for small, medium, and large effect size are .02, .15, and .35, respectively. Both perceived that information credibility and familiarity has a medium to large effect on cognitive trust. The variance explained in cognitive trust is .569 (Table 7).

Only empathy is significantly associated with affective trust, and has a medium to large effect on it, based on our replication result. Familiarity (β = .12, T-value = 1.421, P > .1, effect size = .012) and perceived similarity in values (β = 0.095, T-value = 1.501, P > .1, effect size = .011) do not significantly correlate with affective trust. The variance explained in affective trust is .448, which is lower than .694 in the original study.

Affective trust significantly contributes to relational closeness formation and information adoption. The variance explained in relational closeness formation is .19, which is lower than .426 in the original study. Cognitive trust is significantly associated with information adoption and explains 40% of the variance in the latter, together with affective trust. Both cognitive trust and affective trust have a small to medium effect on information adoption. Affective trust has a medium to large effect on relationship formation. The IVs explain moderate variance in the DVs, except the variance in relational closeness formation, according to R-square cutoff referred by Fan and Lederman (2018): weak-.19, moderate-.33, substantial-.67.

Table 6. Path Analysis

		Replication study				Original study			
Hypo-thesis	**Path**	**Path coefficient**	**T statistics**	**P-value**	**Effect size**	**Path coefficient**	**T statistics**	**P-value**	**Effect size**
H1	INC -> COT	0.463	5.647	<0.001	0.258	0.448	6.785	<0.001	0.29
H2	SIMM -> COT	-0.03	0.582	0.561	0.001	0.159	2.661	<0.01	0.05
H3	FAM -> COT	0.386	4.098	<0.001	0.195	0.341	6.026	<0.001	0.14
H4	FAM -> AFT	0.12	1.421	0.156	0.012	0.339	5.21	<0.01	0.22
H5	SIMV -> AFT	0.095	1.501	0.134	0.011	0.105	2.126	<0.01	0.02
H6	EMP -> AFT	0.517	6.378	<0.001	0.208	0.487	7.108	<0.01	0.27
H7	COT -> INA	0.386	4.099	<0.001	0.114	0.252	3.587	<0.001	0.04
H8	AFT -> INA	0.292	2.971	<0.01	0.065	0.259	3.318	<0.001	0.04
H9	AFT -> RCF	0.436	7.765	<0.001	0.235	0.653	15.221	<0.001	0.74

Table 7. Variance Explained in the Dependent Variable

	Replication study **R square**	**Original study** **R square**
COT	0.569	0.572
AFT	0.448	0.694
INA	0.401	0.219
RCF	0.19	0.426

To further analyze the model's out-of-sample predictive power, we conducted both root mean squared error (RMSE) and mean absolute error (MAE) methods to quantify the amount of prediction error. We prefer the RMSE over MAE for two reasons. Firstly, it puts a greater weight on large errors for punishment, which is preferred in the business research context. Secondly, most of the prediction error distribution of the endogenous variables (except for the cognitive trust) are not highly non-symmetric, the RMSE is the more appropriate prediction statistic (Hair, Risher, Sarstedt, & Ringle, 2019). We compared the value of RMSE between PLS and linear regression model (naïve benchmark), the result is shown in Table 8. As we can see, affective trust and cognitive trust show high predictive power. Information adoption has medium predictive power. Formation of relational closeness manifests low predictive power.

Table 8. Model's Out-of-Sample Predictive Power (RMSE)	
RMSE	**Predictive power**
Affective trust	High
Cognitive trust	High
information adoption	Medium
Formation of relational closeness	Low
*Note: Detailed RMSE value of PLS and Linear Regression Model can be found in Appendix Table A8. If the PLS-SEM analysis (compared to the LM) yields higher prediction errors in terms of RMSE for a dependent construct's all indicators, there is no predictive power; if the majority of indicators have higher prediction errors, there is low predictive power; if the minority or the same number indicators have higher prediction errors, there is medium predictive power; if none of the indicators have higher prediction errors, there is high predictive power (Hair et al., 2019).	

3 Result and Discussion

Our study replicates the model of trust-building mechanisms and their impact on information adoption and relationship closeness formation in Fan and Lederman (2018). The model extended social capital theory and the research that applies a technology acceptance model (e.g., perceived usefulness) to information adoption in the online community (Casaló, Flavián, & Guinalíu, 2011). Instead of recruiting the survey participant from the OHCs, we invited the qualified respondents from Amazon Mechanical Turk by setting up stringent filter functions. Among the nine hypotheses in the original study, six have consistent results in our replication (Table 9). The instrument was adapted to measure the participant's perception of the overall experience of using OHCs.

Table 9. Comparison of Original and Replication Studies			
Dimension	**Original study**	**Replication study**	**Consistent?**
Theoretical framework	Social capital theory	Same	Yes
Sample size	320	273	No
Survey platform	Online OHCs	Amazon Mechanical Turk	No
Instrument measurement	Individual information contributor	Overall OHC experience	No
Analysis tools	SmartPLS 3 and others	Same	Yes
Hypothesis 1	Supported	Supported	Yes
Hypothesis 2	Supported	Not supported	No
Hypothesis 3	Supported	Not supported	No
Hypothesis 4	Supported	Not supported	No
Hypothesis 5	Supported	Supported	Yes
Hypothesis 6	Supported	Supported	Yes
Hypothesis 7	Supported	Supported	Yes
Hypothesis 8	Supported	Supported	Yes
Hypothesis 9	Supported	Supported	Yes

The inconsistent results in our replication are perceived similarity in medical status contributing to cognitive trust, perceived similarity in values contributing to affective trust, and familiarity contributing to affective trust. In the original study, perceived similarity in medical status and perceived similarity in values had a weak impact on cognitive trust and affective trust respectively, but were still statistically significant.

Perceived similarity in medical status is a formative construct. Fan and Lederman (2018) created it by adapting two (medical background and medical condition) out of six items (reflective construct of Homophily) from Nambisan (2011) and adding two new items (age and medical treatment). Our result shows that similarity in medical condition makes an important contribution to the construct. Similarity in medical treatment makes a weak contribution to the construct. Neither similarity in age nor medical background makes a significant contribution to the construct. The measurement of each item in the formative construct should overlap as little as possible. Although the multicollinearity analysis and discriminant validity in our result shows that the items are measuring the different aspects of the construct, one possible explanation is that there are other aspects of perceived similarity in medical status that have not been captured by the items (e.g., similarity in perceived severity).

Perceived similarity in values was loaded on the same construct with relational closeness formation in the first phase of dimension reduction in our study (see Appendix Table A3). One possible explanation is that participants cannot distinguish between the two very clearly (e.g., “SIM2, SIM16: People in the OHC and I have similar principles/morals.” vs. “RCF15: People in the OHC and I are very close to each other.”)

The impact of familiarity is not significant on affective trust; however, it is significant on cognitive trust. One possible explanation is that the respondents from MTurk tend to process the information rationally when they navigate the OHCs. Only perceived empathy can impact affective trust significantly. Even though the postings may come from the familiar content contributors, the recipients still manage the information cautiously.

Overall, we validated and confirmed Fan and Lederman’s (2018) contribution to the theory that text-based online health communities, as an online social capital exchange platform, is structured asymmetrical. The advice seeker does not need to provide any return of favors to the content contributor. However, the content contributor must provide the trustworthiness for information adoption. This inverses the relationship that the recipient needs to show trustworthiness in the face-to-face social capital exchange context. Second, we revised the instrument to measure OHC user’s perception of the whole platform rather than any individual with whom he/she used to interact. By aggregating individual interactions on OHC, we gauge the overall OHC’s utility to its users. Perceived similarity in medical status and values are more idiosyncratic and vary significantly among individuals, which are hard to capture and represent at the OHC level. This may explain the inconsistencies in our replication result. Future studies can design more suitable instruments to measure the perception of the whole OHC.

There are two practical implications based on our replication result. Firstly, besides the recommendation to the similarity and familiarity in the original study, we think it is feasible to add some gamification elements (e.g., points and badges) to the OHCs. To be specific, points can be given by the recipients based on their perceived credibility of the posted information. So, the content contributor will receive average points for each post they provided. Similarly, empathetic content contributors will receive empathy badges from the recipients. This is an easy way to prove their trustworthiness. Secondly, gig workers may not be generalizable to all people. As we discussed earlier, MTurk workers may tend to be more transactional rather than relational with rational thinking dominating most of their information processing. So, when researchers try to explore any emotional related constructs and their causal relationships, MTurk may not be the best sample.

4 Limitations

There are three potential limitations of this replication study. Firstly, using Amazon Mechanical Turk can assist us in reaching out to a broader targeted population. However, the quality of the participants from the platform is hard to control. Although we set up stringent filter functions and attention check questions in our survey, there was still a possibility that an unqualified participant (e.g., having medical education background, not an active member of the OHCs, etc.) may work around it and seem to be qualified.

Secondly, the sample size is smaller in our replication. In the original study, the authors recommended larger sample sizes to extend their research in the future (Fan & Lederman, 2018). Although our sample size is smaller than the original study, we used multiple methods to prove whether the sample size is sufficient or not in our study. Firstly, we run the power analysis by using GPower 3.1 application. A power table (see Appendix Table A7) is provided based on Cohen’s (1992) recommendation. The α error probability was set as 0.05, and the power (1-β error probability) was set as 0.95. The table shows that our sample size is sufficient to work with medium and large effect size, but not sufficient for the small effect size. According to the “10-times rule”, the sample size should be greater than “10 times the number of independent variables in the most complex regression in the PLS path model” (Hair et al., 2021, p.16; Kock & Hadaya, 2018). Given that the number of independent variables in the most complex regression in our model is 2, the minimum required sample size in our study is 20. We also adopted the inverse square root method (Kock & Hadaya, 2018) to assess the minimum sample size for our study. Given that the minimum path coefficient in the original study is 0.11, the minimum sample size should be 511 when significance level is 0.05[1]. When significance level is 0.01, the minimum sample size should be 829. So, in summary, our sample size is not ideal for replication. Eventually, the proportion of men and women was balanced in our sample. More women self-selected to participate in the original study.

Lastly, even though we specified that “When you are taking the survey, please think about your overall experience with your most recent visit of an online health community (OHC)” at the beginning of the survey, there is one item (i.e., item AFT1 “We would both feel a sense of loss if we could no longer interact with each other”) that may not help the respondent to refer to “people in the OHC” collectively as do our other items. This minor inconsistency in our rewording may result in item loading inconsistency. We excluded this item from the structure model analysis due to low loading on its factor.

5 Conclusion

Our work conceptually replicated Fan and Lederman's (2018) study on trust establish mechanisms in OHCs and how different types of trust lead to information adoption and close relationship formation. We exert the same theory, statistical methods, and modified instrument with respondents selected from the Amazon Mechanical Turk platform rather than those who were recruited from OHCs directly. Through all of the nine hypotheses in the original study, six are consistent with our replication result. The inconsistent ones concentrate upon the antecedents of two types of trust. More data and statistical tests are needed to validate our replication result.

[1] Significance level=1%: $n_{min} > (3.168/|p_{min}|)^2$; Significance level=5%: $n_{min} > (2.486/|p_{min}|)^2$. p_{min} is the minimum path coefficient.

References

Bruhn, M., Georgi, D., & Hadwich, K. (2008). Customer equity management as formative second-order construct. *Journal of Business Research*, 61(12), 1292–1301.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2011). Understanding the intention to follow the advice obtained in an online travel community. *Computers in Human Behavior*, 27(2), 622–633.

Cenfetelli, R. T., & Bassellier, G. (2009). Interpretation of formative measurement in information systems research. *MIS Quarterly*, 33(4), 689–707.

Cohen, J. (1992). *Statistical power analysis*. Cambridge, UK: Cambridge University Press.

Dennis, A. R., & Valacich, J. S. (2014). A replication manifesto. *AIS Transactions on Replication Research*, 1, 1–4.

Fan, H., & Lederman, R. (2018). Online health communities: How do community members build the trust required to adopt information and form close relationships? *European Journal of Information Systems*, 27(1), 62–89.

Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, 4.

Goodhue, Lewis, & Thompson. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS Quarterly*, 36(3), 981- 1001.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis (7th Ed.)*. New Jersey: Pearson Education Limited.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.)*. Los Angeles, CA: Sage Publications.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Switzerland: Springer International Publishing.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.

Hodgkin, P., Horsley, L., & Metz, B. (2018, April 10). The emerging world of online health communities. *Stanford Social Innovation Review*. Retrieved from https://ssir.org/articles/entry/the_emerging_world_of_online_health_communities.

Huang, K.-Y., Chengalur-Smith, I., & Pinsonneault, A. (2019). Sharing is caring: Social support provision and companionship activities in healthcare virtual support communities. *MIS Quarterly*, 43(2), 395–423.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods: Sample size in PLS-based SEM. *Information Systems Journal*, 28(1), 227–261.

Liu, Q. B., Liu, X. X., & Guo, X. T. (2020). The effects of participating in a physician-driven online health community in managing chronic disease: Evidence from two natural experiments. *MIS Quarterly*, 44(1), 391–419.

Loiacono, E., & Wilson, E. V. (2020). Do we truly sacrifice truth for simplicity: Comparing complete individual randomization and semi-randomized approaches to survey administration. *AIS Transactions on Human-Computer Interaction*, 12(2), 45–69.

Mamykina, L., Nakikj, D., & Elhadad, N. (2015). Collective sensemaking in online health forums. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (pp. 3217–3226).

MISQ HealthIT Curation. (2018, June 21). Health information technology. *MIS Quarterly*. Retrieved from https://www.misqresearchcurations.org/blog/2018/6/20/health-information-technology.

Nambisan, P. (2011). Information seeking and social support in online health communities: Impact on patients' perceived empathy. *Journal of the American Medical Informatics Association*, 18(3), 298–304.

Nath, C., Huh, J., Adupa, A. K., & Jonnalagadda, S. R. (2016). Website sharing in online health communities: A descriptive analysis. *Journal of Medical Internet Research*, 18(1), e11.

Nunnally, J. C. (1978). *Psychometric theory (2nd ed.)*. New York, NY: McGraw-Hill.

Surowiecki, J. (2004). *The wisdom of crowds*. New York, NY: Anchor Books.

Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of partial least squares-concepts, methods and applications*. Berlin: Springer Berlin Heidelberg.

WHO. (2010). International statistical classification of disease and related health problems 10th revision. *World Health Organization*. Retrieved from https://icd.who.int/browse10/2010/en

Wilson, V., Srite, M., & Loiacono, E. (2017). A call for item-ordering transparency in online IS Survey Administration. In Proceedings of the Twenty-Third Americas Conference on Information Systems (pp. 1).

Wilson, V., Srite, M., & Loiacono, E. (2021). The effects of item ordering on reproducibility in information systems online survey research. *Communications of the Association for Information Systems*, 49(1), 760–799.

Appendix A: Detailed Analysis

Table A1. Kaiser-Meyer-Olkin statistic and Bartlett's Test

		Replicated	Original
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.939	.875
Bartlett's Test of Sphericity	Approx. Chi-Square	4673.238	Significant
	df	561	
	Sig.	.000	

Table A2. Communality Measures of the Items

	Initial	Extraction		Initial	Extraction
AFT14	1.000	.674	RCF15	1.000	.735
AFT16	1.000	.670	RCF16	1.000	.728
AFT1	1.000	.720	RCF18	1.000	.749
AFT2	1.000	.769	AFT10	1.000	.622
COT1	1.000	.746	INC3	1.000	.645
COT5	1.000	.656	INC4	1.000	.755
COT6	1.000	.701	INC5	1.000	.715
COT7	1.000	.626	INC7	1.000	.682
COT10	1.000	.662	INC9	1.000	.759
FAM1	1.000	.726	INA2	1.000	.706
FAM2	1.000	.647	INA3	1.000	.702
FAM7	1.000	.632	INA5	1.000	.774
EMP33	1.000	.721	INA6	1.000	.728
EMP35	1.000	.712	SIM2	1.000	.628
EMP37	1.000	.683	SIM13	1.000	.696
EMP38	1.000	.695	SIM15	1.000	.694
EMP44	1.000	.652	SIM16	1.000	.669

Note: Extraction Method: Principal Component Analysis.

Table A3. Exploratory Factor Analysis on Trust Formation Constructs (n=273)							
Rotated Component Matrixa		**Extract: Based on Eigenvalue_Eigenvalues greater than:1**					
	Component	1	2	3	4	5	6
Affective trust							
AFT1	We would both feel a sense of loss if we could no longer interact with each other.	0.212	0.646	0.132	-0.009	0.199	0.059
AFT14	I'm confident that people in the OHC will always care about my personal needs.	0.536	0.467	0.262	0.016	0.21	0.087
AFT16	If I encounter difficulty, I know people in the OHC would try and help me out.	0.7	0.278	0.122	0.046	0.102	0.231
AFT2	If I share my problems with people in the OHC, I know they would respond constructively and caringly.	0.794	0.05	0.06	0.137	0.124	0.25
Cognitive trust							
COT1	Given the track records of those people in the OHC, I have no reason to doubt their competences in giving advice.	0.447	0.166	0.247	0.566	0.11	-0.041
COT10	People in the OHC generally try to back up their words with their actions.	0.645	0.217	0.238	0.23	0.222	0.137
COT5	I would feel easy if I needed to depend on the research and interpretation abilities of the people in the OHC.	0.563	0.365	0.311	0.237	0.006	-0.029
COT6	I am confident in the knowledge people in the OHC have on the medical condition.	0.4	0.356	0.542	0.299	-0.014	0.121
COT7	I would characterize people in the OHC as honest.	0.577	0.21	0.244	0.304	0.055	0.24
Empathy							
EMP33	People in the OHC understand my emotions, feelings, and concerns.	0.12	0.613	0.32	0.283	0.077	0.367
EMP35	People in the OHC seem to understand my state of being.	0.224	0.493	0.335	0.234	0.08	0.297
EMP37	People in the OHC understand my problems by putting themselves in my place.	0.112	0.282	0.147	0.682	0.195	0.213
EMP38	People in the OHC are interested in knowing what my experience means to me.	0.282	0.568	0.257	0.113	0.25	0.328
EMP44	People in the OHC help me work through situations and problems/concerns.	0.412	0.368	0.098	0.239	0.149	0.472
Familiarity							
FAM1	I am familiar with OHC people's medical condition through reading their postings.	0.187	0.322	0.177	0.689	0.017	0.273

FAM2	I am familiar with people in the OHC through observing the interactions between them and others.	0.381	0.321	0.292	0.201	0.091	0.371
FAM7	I am familiar with OHC people's strengths and weaknesses through observation and/or direct interaction.	0.255	0.556	0.187	0.312	0.207	0.013
Relationship closeness formation							
RCF15	People in the OHC and I are very close to each other.	0.188	0.658	0.08	0.34	0.342	-0.006
RCF16	I like people in the OHC much more than most people I know.	0.107	0.399	0.073	0.385	0.561	-0.265
RCF18	I willingly disclose a great deal of positive and negative things about myself, honestly and fully (in-depth) to people in the OHC.	0.219	0.351	-0.23	0.247	0.608	0.272
AFT10	I would reveal information to people in the OHC that I don't want others to know about.	-0.055	0.147	0.065	-0.068	0.671	0.28
Information adoption							
INA2	The information from the messages contributes to my knowledge of the medical condition.	0.31	-0.075	0.279	0.565	0.194	0.389
INA3	The messages provided by people in the OHC make it easier for me to cope with my medical condition.	0.261	0.113	0.312	0.205	0.115	0.68
INA5	The messages provided by people in the OHC motivate me to cope with my medical condition.	0.299	0.102	0.187	0.195	0.225	0.712
INA6	I closely follow the suggestions from the messages provided by people in the OHC.	0.121	0.276	0.617	0.097	0.26	0.278
Information credibility							
INC3	I think the messages provided by people in the OHC are credible.	0.522	0.169	0.375	0.355	0.172	0.181
INC4	I think the messages provided by people in the OHC are believable.	0.166	0.146	0.45	0.481	0.118	0.187
INC5	I think the messages provided by people in the OHC are trustworthy.	0.423	0.193	0.577	0.177	0.219	0.21
INC7	I think the messages provided by people in the OHC are truthful.	0.348	0.213	0.508	0.23	0.162	0.239
INC9	I think the messages provided by people in the OHC are reliable.	0.252	0.121	0.717	0.301	0.167	0.167
Similarity in values							
SIM13	People in the OHC share my attitudes.	0.257	-0.023	0.248	0.38	0.596	0.163
SIM15	People in the OHC share my beliefs.	0.28	0.2	0.374	0.192	0.585	0.014

SIM16	People in the OHC and I have similar morals.	0.059	0.282	0.47	0.155	0.503	0.036
SIM2	People in the OHC and I have similar principles.	0.2	0.163	0.422	-0.02	0.608	0.071

Note: Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Note: Red shadow indicates loading > .5

Table A4. Partial Correlations between DVs and IVs

Correlations

	X_{Age}	X_{EMP}	X_{FAM}	X_{INC}	X_{SIMV}	Y_{AFT}	Y_{COT}	Y_{RCF}
X_{Age}								
X_{EMP}	-0.023							
X_{FAM}	-0.008	.750**						
X_{INC}	-.138*	.672**	.639**					
X_{SIMV}	0.044	.568**	.529**	.589**				
Y_{AFT}	0.037	.661**	.566**	.561**	.456**			
Y_{COT}	-0.055	.698**	.666**	.688**	.517**	.730**		
Y_{RCF}	0.067	.593**	.533**	.491**	.637**	.448**	.461**	
Y_{INA}	-0.109	.663**	.564**	.715**	.582**	.553**	.594**	.428**
rAFTi-M		0.662**	0.566**	0.572**	0.455**			
rCOTi-M		0.698**	0.667**	0.688**	0.521**	0.734**		
rRCFi-M		0.596**	0.534**	0.506**	0.636**	0.447**	0.467**	
rINAi-M		0.665**	0.566**	0.71**	0.591**	0.561**	0.592**	0.439**

Note: n=273
* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table A5. Factor Loadings of Trust Formation Model (n=273)[&]

	AFT	COT	EMP	FAM	RCF	INA	INC	SIMV	SIMM
AFT1	0.675* (0.59)	0.435	0.463	0.389	0.387	0.284	0.312	0.323	0.245
AFT14	0.834 (0.757)	0.618	0.567	0.458	0.423	0.457	0.503	0.439	0.341
AFT16	0.831 (0.737)	0.594	0.568	0.455	0.374	0.478	0.484	0.316	0.339

AFT2	0.765 (0.678)	0.634	0.489	0.465	0.27	0.513	0.466	0.343	0.338
COT1	0.584	0.769 (0.671)	0.511	0.48	0.398	0.43	0.518	0.403	0.238
COT10	0.635	0.797 (0.767)	0.579	0.538	0.465	0.515	0.576	0.475	0.353
COT5	0.556	0.759 (0.66)	0.508	0.522	0.369	0.402	0.496	0.369	0.245
COT6	0.554	0.838 (0.771)	0.618	0.546	0.367	0.511	0.581	0.421	0.326
COT7	0.578	0.78 (0.759)	0.553	0.553	0.327	0.503	0.566	0.365	0.423
EMP33	0.523	0.56	0.818 (0.71)	0.63	0.479	0.511	0.518	0.383	0.352
EMP35	0.462	0.529	0.751 (0.628)	0.604	0.424	0.453	0.525	0.456	0.395
EMP37	0.397	0.477	0.694* (0.539)	0.531	0.502	0.499	0.478	0.443	0.363
EMP38	0.595	0.556	0.787 (0.807)	0.559	0.501	0.514	0.496	0.477	0.408
EMP44	0.558	0.562	0.769 (0.757)	0.543	0.462	0.553	0.558	0.401	0.391
FAM1	0.416	0.544	0.627	0.801 (0.657)	0.413	0.5	0.496	0.377	0.42
FAM2	0.49	0.546	0.584	0.807 (0.704)	0.399	0.507	0.55	0.419	0.405
FAM7	0.447	0.509	0.574	0.779 (0.651)	0.497	0.346	0.485	0.468	0.321
RCF15	0.45	0.472	0.591	0.505	0.84 (0.857)	0.37	0.403	0.489	0.294
RCF16	0.309	0.383	0.428	0.42	0.778 (0.588)	0.244	0.398	0.504	0.191
RCF18	0.373	0.364	0.48	0.408	0.801 (0.711)	0.414	0.381	0.457	0.29
AFT10	0.184	0.143	0.249	0.233	0.502* (0.352)	0.251	0.269	0.43	0.174

INA2	0.432	0.528	0.469	0.469	0.342	0.776 (0.746)	0.606	0.443	0.418
INA3	0.436	0.451	0.562	0.463	0.3	0.818 (0.676)	0.578	0.42	0.509
INA5	0.467	0.448	0.55	0.471	0.334	0.833 (0.692)	0.51	0.406	0.41
INA6	0.43	0.459	0.503	0.382	0.401	0.715 (0.68)	0.558	0.561	0.432
INC3	0.531	0.61	0.57	0.559	0.42	0.588	0.806 (0.814)	0.471	0.405
INC4	0.365	0.448	0.489	0.486	0.346	0.515	0.722 (0.598)	0.358	0.437
INC5	0.494	0.577	0.585	0.534	0.404	0.586	0.837 (0.77)	0.536	0.423
INC7	0.428	0.555	0.518	0.489	0.423	0.542	0.788 (0.74)	0.445	0.432
INC9	0.441	0.56	0.511	0.484	0.357	0.62	0.822 (0.748)	0.534	0.464
SIM13	0.349	0.434	0.452	0.425	0.474	0.478	0.446	0.768 (0.684)	0.381
SIM15	0.397	0.447	0.458	0.486	0.524	0.484	0.491	0.848 (0.777)	0.373
SIM16	0.311	0.412	0.465	0.403	0.523	0.445	0.458	0.765 (0.608)	0.343
SIM2	0.374	0.335	0.401	0.348	0.435	0.427	0.472	0.765 (0.733)	0.495
SIM11(F)									0.717 (0.717) t:5.296##
SIM12(F)									0.124 (0.124) t:0.695
SIM21(F)									0.119 (0.119) t:0.686

SIM22(F)									0.303 (0.303) t:1.812#
Note:&Factor analysis is run using both SmartPLS 3 and consistent PLS algorithm (values of consistent PLS algorithm are in the brackets). (F) Indicator for a formative construct. The value shown is a weight rather than a loading. * Item excluded from the structure model analysis due to low loading or weight on its factor. ## p < .01. # p < .1									

Table A6. Multicollinearity Analysis- VIF Values	
	VIF
SIM11F	1.292
SIM12F	1.336
SIM21F	1.319
SIM22F	1.579

Table A7. Sample Size Planning Table				
Effect size f^2	**α err prob**	**Power (1-β err prob)**	**Number of predictors**	**Total sample size**
0.02 (small)	0.05	0.95	7	1099
0.15 (medium)				153
0.35 (large)				70

Table A8. Comparison of RMSE value between PLS and LM		
	PLS RMSE	**LM RMSE**
Q1_AFT14	1.001	1.052
Q2_AFT16	0.958	0.992
Q4_AFT2	1.011	1.016
Q6_COT5	1.073	1.177
Q5_COT1	1.072	1.134
Q9_COT10	0.929	0.968

Q8_COT7	0.863	0.910
Q7_COT6	0.971	0.993
Q28_INA3	0.902	0.879
Q27_INA2	0.963	0.976
Q29_INA5	0.965	0.994
Q30_INA6	0.952	0.908
Q19_RCF16	1.356	1.263
Q18_RCF15	1.232	1.163
Q20_RCF18	1.186	1.222

About the Authors

Xin Liu is a doctoral student in the Department of Business Analytics, Information Systems and Supply Chain at Florida State University's College of Business. He holds a Master of Science degree in Information Technology and Management (MSITM) and a Master of Business Administration (MBA) from Bryan School of Business and Economics at the University of North Carolina at Greensboro. Xin teaches management information systems at the undergraduate level. He has also served as the ad hoc reviewer for several MIS conferences proceedings. Before joining the Ph.D. Program, he gained four years of field experience in health information systems management at a large regional health care network. He has both a strong understanding of HIPAA requirements as well as excellent organizational skills. His research interests include Electronic Health Record (EHR) systems training, EHR software evolutions, health & wellness app user engagement, and ride-hailing market.

Ashley A. Bush is the Sprint Professor of Management Information Systems and chair of the Department of Business Analytics, Information Systems and Supply Chain at Florida State University's College of Business. She also serves as the director of the Master of Science in Business Analytics (MS-BA) and the Master of Science in Management Information Systems programs. Bush teaches management information systems at the undergraduate, graduate and doctoral levels. Her research has appeared in *Information Systems Research, Journal of Management Information Systems, IEEE Transactions on Engineering Management, Communications of the ACM, Information and Organization*, among others. She has served on the editorial board of *Communications of the AIS* and *IEEE Transactions on Engineering Management*, as program co-chair for the *Americas Conference on Information Systems*, as an associate editor for the *International Conference on Information Systems*, and on the executive committee of the *International Conference on Information Systems*.