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Trust or Consequences Replication: A Methodological Replication Study

René Moquin

Department of Information Systems & Technology, Northeastern State University

moquin@nsuok.edu

Abstract:

This paper reinvestigates the theories of planned behavior and the technology acceptance model regarding the adoption of cloud-based services by conducting a methodological replication of a study by Ho, Ocasio-Velázquez, and Booth (2017). The improvement of cloud-based services and their adoption by individuals and organizations alike continue to rise. For some organizations, releasing control of their IT infrastructure relies in part on their perception of a cloud service provider's trustworthiness. We found that the intent to trust cloud-computing firms relies on knowledge, perceived risk, and subjective norm. Also, perceived risk appears to moderate the interaction between knowledge and intent to trust. Future studies are encouraged to strengthen this study through construct validity, including the addition of relevant dimensions to intent to trust.

Keywords: Cloud Computing, Information Systems, Intent to Trust, Behavioral Outcome, Methodological Replication, Theory of Planned Behavior

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1 Introduction

Some organizations have maintained on-premise information technology (IT) resources, such as hardware and software, system administrators, and programmers. Off-premise technologies, such as cloud computing, provide a more flexible and cost-effective alternative to on-premise IT. Some organizations are investing more of their IT budgets in the on-demand structure that cloud computing provides. In 2019, a study by Kappelman et al. (2019) suggested that cloud computing services such as software-as-a-service (SaaS), platform-as-a-service (PaaS), and infrastructure-as-a-service (IaaS), are one of the top three organizational investments. Additionally, Gartner (2018) suggests that organizational cloud service implementations are estimated to rise from 17.3% ($175.8 Billion) in 2019 to 36.8% ($278.3 Billion) by 2021.

However, for some organizations, cloud-based solutions imply a paradigm shift. On-premise IT infrastructure provides several advantages, such as physical access to hardware, software, and data and control over operational functions, such as performance, security, and accessibility. Off-premise solutions house software and data in complex infrastructures, fostering perceptions of control loss (Jones, Irani, Sivarajah, & Love, 2019). This loss of control of physical access demands a high level of trust (and competence) between the organization and cloud service provider (Armbrust et al., 2010). Depending on the cloud service, the organization trusts that the cloud service provider adheres to appropriate availability (uptime), and security (International Information System Security Certification Consortium (ISC^2), 2015) as documented in a service level agreement (SLA). Current literature enumerates the potential risks of availability and security that organizations can face when adopting cloud services.

First, cloud service availability issues for large organizations can result in significant losses. For example, in March of 2018, Amazon Web Services (AWS) customers were denied access because of a hardware failure in Amazon’s datacenter. The outage lasted 30 minutes and rendered some customer data unrecoverable (Tsidulko, 2018). In another example, Microsoft’s Office 365 SaaS platform encountered an infrastructure problem that disrupted email services in Europe and the United Kingdom in April of 2018 (Katwala, 2018). Customers were unable to exchange emails with business partners and customers for a day because the Microsoft servers handling authentications became overloaded. In a final example, in May of 2019, Salesforce implemented a faulty database script in their customer relationship management (CRM) system that gave users broad and unrestricted access to all customer data. (Cimpanu, 2019). Salesforce subsequently blocked all access until they could resolve the issue. As a result, Salesforce suffered a drop of .85% in its market price (Witkowski, 2019). According to a Lloyd’s of London Research study, a cloud availability issue lasting three to five days results in losses between $6.9 and $14.7 Billion (Lloyd's, 2018).

Second, information security is an organizational concern (Kappelman et al., 2018). Recent studies on cloud adoption suggest that organizations perceive cloud security to be ineffective and a credible deterrent for cloud adoption (Ali, 2015; Khan, 2016). For example, in 2012, Dropbox suffered a widely publicized breach affecting approximately 63 million users (Bott, 2012). Salesforce’s software-as-a-service (SaaS) suffered a significant system outage because of a permissions change that gave users “broader access to data than intended” (Novet, 2019). Salesforce had to disable their service for 24 hours to correct the issue, which affected many of their customers. According to McAfee’s 2019 Cloud Adoption and Risk Report, misconfigurations, permission issues, and significant anomalous external events foster security threats (McAfee Corporation, 2019).

In sum, organizations are ultimately responsible and accountable for establishing and maintaining proper security and availability when considering cloud-based services. Since the development of the Ho et al. (2017) model, two competing developments have occurred. First, the adoption of cloud services continues to proliferate. According to Gartner (2018), cloud service revenue went from $153.5 Billion in 2017 to $197.7 Billion in 2018, up 28%. Gartner (2019) estimates that cloud service revenue for 2022 will be $354.6 Billion, an 80% increase from 2017. Firms continue to invest in cloud computing, likely reducing the importance of trust. Second, however, security and information availability continue to support fearful and uninformed perceptions regarding cloud services and their trustworthiness (Blandford, 2016; Gaudin, 2014; Khan, 2016; NetworkWorld Asia, 2018), thus supporting the notion that trust continues to be a relevant factor.

Our intent in the present research is to examine Ho, Ocasio-Velázquez, and Booth (2017) focus on the effect that knowledge, attitude, perceived behavioral control, subjective norm, perceived risk, and trust intention have on the behavioral outcome to adoption a cloud-based service from a methodological perspective. Figure 1 provides the model used in their study.

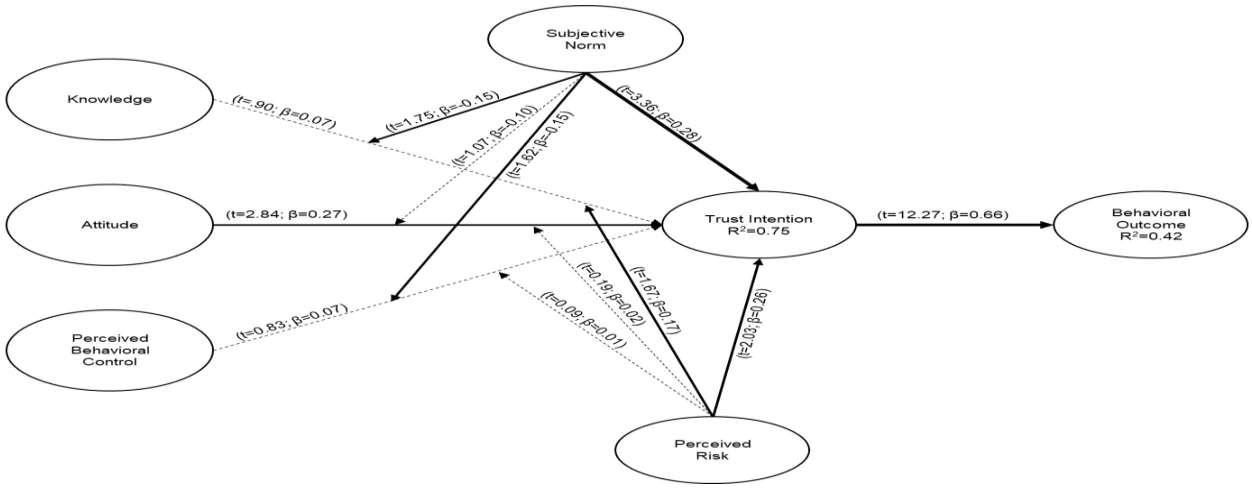

Figure 1. Ho et al. (2017) results

Ho et al. (2017) suggest that cloud-based service adoption depends more on attitude, perceived risk, and subjective norm. Also, subjective norm and perceived risk modify intent to trust and centers on an individual's knowledge, behavioral control, and the potential risks of using the cloud service. The unsupported hypotheses include knowledge, perceived behavioral control, and the interactive effects of subjective norm and perceived risk on attitude and perceived risk on perceived behavioral control.

The structure of our replication of Ho et al. (2017) involves describing the research method, data collection, and analysis, and findings. We continue by conducting a comparison of the replicated results to Ho et al.'s (2017) results. Finally, we close with a discussion of the implications arising from our study and suggestions for future research.

2 Research Hypotheses

Our primary objective was to test the methodological replicability of Ho et al.'s (2017) research model, which examines the influence that knowledge, attitude, subjective norm, perceived behavioral control, and perceived risk have on intention to trust and, ultimately behavioral control to engage in cloud-based solutions. The lens used to conduct the research is the theory of planned behavior (TPB), which posits that the likelihood of a specific behavioral outcome relies on volition, perceived social norm (how influential others feel), the attitude about performing the action and the intent to do so (Ajzen, 1991). Ho et al., employ the TPB concepts of subjective norm and perceived behavioral control as moderators between knowledge, attitude, and perceived risk on behavioral outcome (cloud technology adoption). Table 1 presents the hypotheses to be tested, taken directly from Ho et al. (2017).

Table 1. Hypotheses to be Tested

Hypothesis	Item
H1	Corporate users’ knowledge about Cloud technology has a direct effect on their intention to trust Cloud services.
H2	Corporate users’ attitude has a direct effect on their trust intention to adopt Cloud services.
H3	Corporate users’ perceived behavior control over the corporate data has a direct effect on their intention to trust Cloud services.
H4	Corporate users’ perceived risk of Cloud computing moderates the influence of knowledge on trust intention with respect to adopting Cloud services.
H5	Corporate users’ perceived risk of Cloud computing moderates the influence of attitude on trust intention with respect to adopting Cloud services.
H6	Corporate users’ perceived risk of Cloud computing moderates the influence of perceived behavioral control on trust intention with respect to adopting Cloud services.
H7	Corporate users’ perceived risk has a direct effect on their trust intention with respect to adopting such technology or services.
H8	Subjective norms moderate the influence of corporate users’ knowledge on trust intention with respect to the adoption of Cloud technologies or services.
H9	Subjective norms moderate the influence of corporate users’ attitude on trust intention with respect to the adoption of Cloud technologies or services.
H10	Subjective norms moderate the influence of corporate users’ behavioral control on trust intention with respect to the adoption of Cloud technologies or services.
H11	Subjective norms have a direct effect on corporate users’ trust intention with respect to adopting Cloud services.
H12	Corporate users’ trust intention has a direct effect on their intention to adopt Cloud services.

3 Method

A cross-sectional survey design that was facilitated by panel data from an organization specializing in Internet-based research served as our data collection method. Management literature has successfully conducted this type of sampling, particularly when specific participant characteristics are required (Carlson, Ferguson, Hunter, & Whitten, 2012; Judge, Ilies, & Scott, 2006). We included all measurement items (Table 2), scales, and respondent selection criteria in their entirety from Ho et al. (2017). During the survey creation process, we were unable to determine the exact descriptive text used for each section of the questions. We, therefore, constructed a primary orienting question for each section to minimize possible inconsistencies between the two studies. For example, “*For the next <u>five (5) questions</u>, please indicate the extent to which you agree or disagree regarding your attitude toward cloud usage*” and “*For the next <u>four (4) questions</u>, please indicate the extent to which you agree or disagree regarding your perception of the security risk of cloud-based services*.”

Table 2. Example Constructs, Items, and Descriptive Statistics

Construct	Item	Mean	STD	Loading
Attitude (ATT)				
ATT2	Using cloud service is an acceptable solution to my corporate data storage.	5.65	1.35	0.910
ATT3	Using cloud storage is a good idea.	5.86	1.24	0.917
ATT4	I am excited about the idea of using the cloud storage.	5.53	1.39	0.899
Perceived Risk (PR)				
PR1	I believe that my corporate data stored on, and managed by, this cloud storage service provider is secure.	5.36	1.52	0.875
PR3	I perceive that my corporate data stored on, and managed by, this cloud storage service provided is well protected.	5.59	1.38	0.894
PR4	believe the service provider of this cloud storage solution will perform due diligence and secure our corporate data.	5.76	1.24	0.849
Knowledge (KN)				
KN1	I have sufficient knowledge about the cloud storage security.	5.32	1.50	0.861
KN2	I possess enough knowledge to use and work with cloud storage.	5.88	1.07	0.832
KN3	I have sufficient experience in knowing the security of the cloud storage services.	5.56	1.43	0.836
KN4	I am confident that the service provider has sufficient and knowledgeable technical personnel to manage and secure the cloud storage.	5.52	1.26	0.724
Perceived Behavioral Control (PBC)				
PBC1	I am certain that the personal information I provide to the services provider is secure.	5.24	1.56	0.847
PBC2	I feel I have sufficient control over the methods used by my service provider in collecting my personal data.	5.50	1.43	0.827
PBC3	Using the cloud storage service is under my control.	5.46	1.39	0.846
Subjective Norm (SN)				
SN1	Most people who are important to me think it is a good idea to use cloud storage.	5.38	1.40	0.794
SN2	The advertisement of the services provider influence me in my decision whether to use cloud storage.	5.19	1.56	0.819
SN3	The competitiveness in my industry influences me in my decision whether to use cloud storage.	5.31	1.46	0.827
SN4	Most people who are important to me would use cloud storage.	5.57	1.28	0.826
Trust Intention (TI)				
TI1	For me, using the cloud storage in the next six months is important.	5.47	1.46	0.763
TI2	I plan to use cloud storage in the next six months.	5.26	0.95	0.790
TI3	I anticipate I will use cloud storage in the next six months.	5.88	1.26	0.828
TI4	The Platform as a Service (PaaS) of this service provider is dependable and honest in providing secure cloud storage services.	5.51	1.08	0.827
TI5	The services provider is competent and trustworthy in handling and securing my data.	5.66	1.10	0.808
Behavioral Outcome (BO)				
BO1	Is my company currently likely to adopt and use the cloud storage technology?	5.62	1.57	0.731
BO2	Is my company likely to continuously use the cloud storage technology in the next three years?	5.96	1.19	0.883
BO3	Do I expect my company to continuously use the cloud storage technology in the next three years?	5.81	1.38	0.859

A purposive sampling methodology was necessary to select respondents based on the criteria set by the original study (Mangal & Mangal, 2013). Table 3 presents the selection criteria used for this study.

Table 3. Selection Criteria	
Criteria	**Item**
Location	United States
Subject	Employed in information technology
Age	18+
Organization Size	At least 100 or more employees
Work Experience	Five or more years of IT work-related experience
Job Position	IT professionals, managers, C-Suite, and other decision-makers
Knowledge of Cloud-Based Solutions	Yes

4 Findings

A total of 110 participants completed the survey. According to sample size guidelines, the respondent sample should be at least ten times the largest number of paths to any single construct to ensure appropriate power to detect significant relationships in the model (Hair, Black, Babin, & Anderson, 2010). Five exogenous constructs connect to the endogenous variable, trust intention, setting the minimum number of cases to 50. Thus, our sample size meets this requirement. All data cases were usable, resulting in a 100% response rate. Table 4 presents the demographic results.

Table 4. Descriptive Statistics

Category	Description	%	Category	Description	%
Gender	Male	66%	Industry	Real estate/rental & leasing	3%
	Female	33%		Mining	3%
	Undisclosed	1%		Professional, scientific/technical services	7%
Age	20 - 29	8%		Utilities	2%
	30 - 39	40%		Management of companies/enterprises	2%
	40 - 49	36%		Construction	5%
	50 - 59	15%		Admin, support, waste management or remediation services	4%
	60 - 69	1%		Manufacturing	3%
Edu	Less than High school	1%		Educational services	6%
	High school/GED	6%		Wholesale trade	2%
	Some college	9%		Retail trade	4%
	2-year college degree	6%		Transportation or warehousing	2%
	4-year college degree	37%		IT/IS	43%
	Master's degree	35%		Finance or insurance	9%
	Professional degree (M.D/J.D.)	4%		Computer Reseller	1%
	Doctorate Ph.D.	1%		Government	1%
Title	IT staff	13%		Healthcare	3%
	Manager of IT	22%		Medical	1%
	Senior IT Manager	14%		Tourism	1%
	Director	18%	Exp	5 - 9	19%
	Vice President	5%		10 - 19	29%
	CFO	4%		20 - 29	18%
	CIO	3%		30 - 39	25%
	President or CEO	5%		40 - 49	7%
	Other	18%		50+	2%

4.1 Construct Assessment

The research model for the current study was analyzed using partial least squares structural equation modeling (PLS-SEM) techniques via SmartPLS 3.2.9 software (Ringle, Wende, & Becker, 2015). PLS-SEM assesses the psychometric properties of the measurement items and models the relationships among the independent and latent dependent variables simultaneously. PLS is a correlation-based method with fewer stringent assumptions on data distribution. We configured the bootstrapping and PLS procedures using the recommended 5,000 resamples of the original 110-case dataset. We were able to generate a stable set of standard error estimates via the bootstrap process. The following sections describe the results of the model's reliability and validity. It is crucial to note that we ran the model with all measurement indicators. We also removed low-loading measurement items to improve the model's fit.

We began by examining the possibility of common method bias (CMB). Several statistical remedies exist to test for CMB. We selected Harman's single factor test. While it does not correct for the existence of CMB, it does act as a diagnostic tool (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The results indicated that no single factor explains more than 50% of the variance, which suggests that, at a minimum, no significant common method bias exists. However, this result does not preclude the existence of such a result. No CMB tests exist in Ho et al. (2017), thus eliminating cross-model comparisons.

Composite reliability (CR) values indicate the reliability of the scales, and Cronbach's alpha (CA) assesses the internal consistency within the scales (Straub, Boudreau, & Gefen, 2004). All values for CR and CA were above the acceptable 0.7 thresholds (Nunnally, 1978). The CR values ranged from .86 to .93, and Cronbach's alpha ranged from .83 to .91 (see Table 5). A shortfall of the CA is its tendency to underestimate internal consistency because of "its sensitivity to the number of items in the scale" (Hair et al., 2017, p. 111). CR addresses this limitation by examining the items' outer loadings (Hair et al., 2017).

Convergent validity measures the amount of error-free variance in a set of measurements captured by their assigned construct through average variance extracted (AVE). The AVE results appear to capture at least 50% of the measurement variance (Fornell & Larcker, 1981; Hair Jr. et al., 2017). AVE values ranged from .64 to .75, as shown in Table 5.

Table 5. Composite Reliability, Cronbach's Alpha, Ave, and Correlations

Variable	CR	CA	AVE	ATT	BO	TI	KN	PBC	PR	SN
Attitude (ATT)	0.938	0.918	0.753	**0.867**						
Behavioral Outcome (BO)	0.866	0.765	0.684	0.630	**0.827**					
Intention to Trust (TI)	0.901	0.863	0.646	0.728	0.649	**0.804**				
Knowledge (KN)	0.887	0.830	0.664	0.658	0.597	0.736	**0.815**			
Perceived Behavioral Control (PBO)	0.878	0.792	0.706	0.621	0.601	0.675	0.785	**0.840**		
Perceived Risk (PR)	0.895	0.844	0.684	0.742	0.579	0.784	0.769	0.747	**0.827**	
Subjective Norm (SN)	0.889	0.834	0.667	0.656	0.516	0.743	0.684	0.669	0.665	**0.817**

CA=Cronbach's Alpha, CR=Composite Reliability, AVE=Average Variance Extracted, Sqrt/AVE=Bolded numbers on the diagonal

Convergent validity also occurs when measurement items thought to theoretically reflect a given construct converge on their assigned factor (Hair et al., 2017). In other words, the magnitude of the measurement items should exhibit high outer loadings on its assigned construct than with other constructs in a model. Table 6 presents all cross-loadings on all measurement items on their associated construct (column). The results show appropriate convergent validity since all measurement items loaded higher on their associated construct and were at or above the minimum recommended loading value of 0.70 (Gefen, Straub, & Boudreau, 2000).

Discriminant validity involves assessing a construct's cross-loadings, Fornell-Larcker criterion, and heterotrait-monotrait values. First, the cross-loadings assess a construct's uniqueness measuring a phenomenon that is uncaptured by other constructs in a model (Hair et al., 2017). Each construct's measurement items should load higher on their associated construct than with other items. Table 6 shows that items loaded higher on their associated construct than with others.

Table 6. Cross Loadings

Variable	Attitude	Behavioral Outcome	Knowledge	Perceived Behavioral Control	Perceived Risk	Subjective Norm	Intention to Trust
ATT1	**0.837**	0.480	0.498	0.442	0.552	0.452	0.475
ATT2	**0.888**	0.552	0.580	0.581	0.674	0.585	0.680
ATT3	**0.885**	0.580	0.609	0.534	0.653	0.552	0.648
ATT4	**0.892**	0.585	0.604	0.576	0.679	0.649	0.654
ATT5	**0.833**	0.573	0.626	0.580	0.677	0.570	0.581
BO1	0.610	**0.731**	0.566	0.587	0.563	0.434	0.502
BO2	0.587	**0.883**	0.466	0.471	0.462	0.417	0.510
BO3	0.413	**0.859**	0.456	0.440	0.422	0.429	0.587
KN1	0.555	0.456	**0.861**	0.724	0.656	0.577	0.564
KN2	0.597	0.552	**0.832**	0.640	0.696	0.573	0.684
KN3	0.479	0.418	**0.836**	0.627	0.606	0.573	0.586
KN4	0.563	0.511	**0.724**	0.568	0.626	0.503	0.549
PBC1	0.597	0.518	0.670	**0.847**	0.697	0.553	0.521
PBC2	0.539	0.433	0.655	**0.827**	0.615	0.579	0.553
PBC3	0.464	0.557	0.656	**0.846**	0.665	0.554	0.620
PR1	0.704	0.492	0.687	0.636	**0.875**	0.650	0.715
PR2	0.419	0.353	0.591	0.628	**0.671**	0.433	0.441
PR3	0.611	0.538	0.716	0.734	**0.894**	0.523	0.712
PR4	0.705	0.512	0.641	0.615	**0.849**	0.596	0.658
SN1	0.661	0.516	0.577	0.561	0.611	**0.794**	0.658
SN2	0.487	0.398	0.550	0.586	0.531	**0.819**	0.529
SN3	0.503	0.389	0.485	0.470	0.439	**0.827**	0.575
SN4	0.467	0.372	0.611	0.564	0.593	**0.826**	0.647
ITT1	0.637	0.529	0.617	0.501	0.639	0.632	**0.763**
ITT2	0.552	0.496	0.480	0.470	0.514	0.443	**0.788**
ITT3	0.616	0.595	0.511	0.457	0.554	0.513	**0.827**
ITT4	0.514	0.482	0.649	0.593	0.676	0.709	**0.828**
ITT5	0.528	0.502	0.680	0.674	0.719	0.661	**0.810**

ATT=Attitude, BO=Behavioral Outcome, KNW=Knowledge, PBC=Perceived Behavioral Control, PR=Perceived Risk, SN=Subjective Norm, ITT=Intent to Trust

The Fornell-Larcker criterion indicates that the square root of the AVE for each construct should load higher than its highest correlation with all other model constructs (Hair et al., 2017). The square root of the AVE for each construct achieved the Fornell-Larcker criterion (see Table 5). Hair et al. (2017) indicate that the Fornell-Larcker criterion performs somewhat poorly when loadings are slightly different. Therefore, we conducted a heterotrait-monotrait (HTMT) ratio of correlation analysis, which evaluates the degree that a construct's items correlate with other constructs relative to the correlation with their assigned construct. Henseler, Ringle, and Sarstedt (2015) suggest that an HTMT value of between-trait correlations and within-trait correlations for all pairs of constructs should be above 0.85, which indicates discriminant validity. Our results show that while the majority of items exhibited values below the suggested threshold, perceived behavioral control/knowledge (0.97), perceived risk/intention to trust (0.89), perceived risk/knowledge (0.95), perceived risk/perceived behavioral control (0.97), and subjective norm/intention to trust exhibited values above 0.85, thus suggesting a discriminant validity issue.

In sum, a portion of the model's constructs fit within the guidelines of discriminant validity. However, inflated correlates exist with some of the constructs. Based on these findings, we conducted a post hoc analysis to resolve the high correlations and improve the model's explanatory power. We examined the model by observing the quality that each measurement item provided to their assigned construct using principal factor analysis (PFA). According to Hair et al. (2017), the loading factor of each measurement item should be at a minimum of 0.70 for non-exploratory studies (Hair Jr. et al. (2017). Therefore, we examined the loading factors and began the process by removing a single item and re-running the model. Based on the resultant path weight, R^2, and indirect effects, we either retained or removed the item from the model. However, we found that no optimum solution resulted from the model assessment process without reducing explanatory power. Therefore, we retained all measurement items in the hypothesis testing to maximize the comparability with the Ho et al. model.

4.2 Structural Model

Figure 2 presents the results of the structural model. Ho et al. (2017), assessed significance using a one-tailed test (p. 591). Therefore, we conducted the analysis using a one-tailed test using the critical values of 2.33, 1.65, and 1.28 for significance levels .01, .05, and .10, respectively. Knowledge, attitude, perceived behavioral control, subjective norm, and perceived risk were the independent variables to intention to trust, which is the dependent variable. Intention to trust was the independent variable to behavioral outcome. Table 7 in the discussion section presents the results of the hypotheses, which include the tests for the moderators. It also compares our findings to those of the original study.

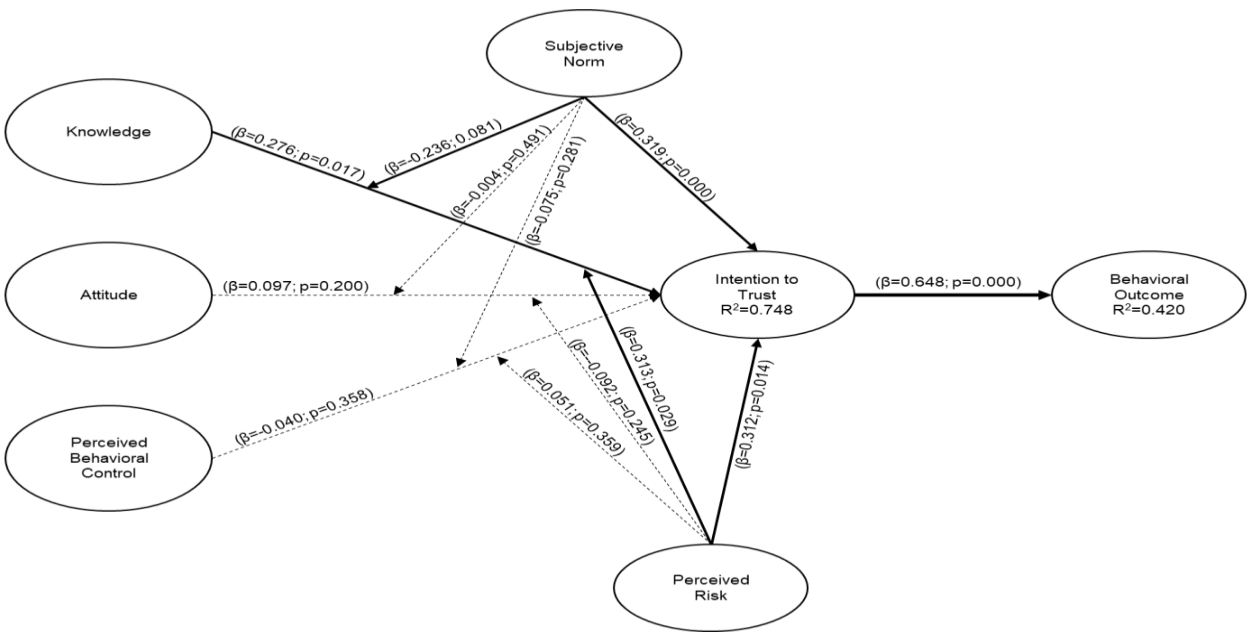

Figure 2. Replication Structural Model Results

Stone-Geisser's Q^2 value provides additional information regarding the quality of the research model's path estimates (Stone, 1974). Q^2 is a measure of predictive relevance of the model's ability to predict data not used in the model estimation. We applied the blindfolding procedure to estimate the model after omitting every seventh data point in an iterative process. The model's estimates predicted the omitted data. Q^2 values greater than zero indicate that the model has predictive relevance for the dependent variable (Hair et al., 2017). The model's Q^2 of 0.418 and 0.268 are indicative of predictive relevance about the intention to trust and behavioral outcomes, respectfully. That is, the model performs well in predicting data not used in the model estimation.

We tested several control variables to evaluate their impact on the model. Employee demographic variables, including age, gender, education, years of experience, and industry were included in the model. It was thought that a respondent's education, experience, or age might significantly influence his/her intention to trust and subsequently influence the behavioral outcome. For example, employees with more significant experience might be more aware of the state of cloud security and would, therefore, be inclined to trust this technology as a viable resource, as compared to employees with less experience. However, we found no significant relationships between any of the controls and intention to trust and behavioral outcomes, which suggests that trust and behavior are predicted mainly by the respondents' salient beliefs.

5 Discussion

Table 7 represents the results of the replication study and reveals mixed support for the original study's outcome. The results from our study were reasonably comparative with Ho et al. (2017), in strength and direction. Despite some relationship inconsistencies, variances for the trust intention and behavioral outcome constructs were similar ($r^2 = .73$ and r^2 .76) and ($r^2 = .43$ and $r^2 = .42$) respectively.

We found some potentially non-generalizable constructs and relationships. First, Ho et al. suggest that attitude is positively associated with intention to trust. Our replication, however, found that no relationship exists. Second, subjective norm was hypothesized to moderate perceived behavioral control and intent to trust. Our replication indicated that no such relationship exists.

One explanation for our results may be the sample size. We examined the data sampling methodology to ensure that we captured all the attributes used in the original study. We followed Hair et al.'s process of calculating the appropriate sample size of ten subjects multiplied by the largest number of paths pointing to an endogenous variable. In our case, five exogenous variables are associated with intent to trust, thus setting the minimal sample size at 60. Subsequently, the number of replication and original respondents differed, at 110 and 153, respectively. Differing respondent sizes could generate inflated or degraded results. However, both met the required minimum number of respondents for power and significance in SEM analyses (Hair et al., 2007).

A second explanation for the replication results may exist in the construct definitions and the indirect effects of the other antecedents in the model. First, Ho et al. (2017) found that knowledge played no role in intention to trust ($t = .90$, $\beta = .07$, ns). However, in our study, we found that knowledge did negatively influence intention to trust ($t = 2.10$, $\beta = - .27$, $p \leq .05$). A possible explanation for the inconsistent findings may exist in the indirect effects of the antecedents and trust intention.

Finally, trust intention contains two conceptually different ideas, use intention, and trust. The model defines use intention using three reflective measures. Conceptually, intent refers to one's proclivity to consider a behavioral action depending on a cognitive assessment of personal and social influences (Ajzen & Fishbein, 1980). Trust is measured using two measurements. Conceptually, trust refers to one's perception of an agent's integrity, competence, and benevolence (McKnight et al. 2003). The convergence of these two concepts, despite the significant Cronbach's Alpha result, potentially perturbs the association with its associated exogenous constructs. Previous research typically conceptualizes trust and intent as separate constructs to measure the explained variance (Asadi, Nilashi, Husin, & Yadegaridehkordi, 2017; Gao & Waechter, 2017; Gefen, Karahanna, & Straub, 2003).

Table 7 presents a comparative analysis between our replication with Ho et al. Model 1 contains the original findings and serves as our comparative baseline. In model 2, the data sample for this study, like that of Ho et al., included "senior management as well as systems managers, staff in the information systems area..." (p. 588). However, information systems staff might or might not be cloud computing decision-makers. Thus, as a robustness check of our findings, we removed 21 respondents who did not indicate a managerial role. We subsequently re-ran the model with the adjusted sample size. The findings were mostly consistent with the model presented in Table 7, except for the moderating effects of perceived risk and subjective norm on the relationship between knowledge and intention to trust. The former becomes non-significant, and the latter becomes significant with the smaller sample size. In model 3, we re-ran the model with our full data sample. The results appeared to mirror the adjusted sample size.

Table 7. Model Results

H_n	Association	Model #1 (Original) (N=153) t	β	p	Model #2 (N=89) t	β	p	Model #3 (N=110) t	β	p
1	KNW -> ITT	0.901	0.071	0.110	1.596	0.224	**0.055**	2.128	0.276	**0.017**
2	ATT -> ITT	2.844	0.272	**0.010**	1.254	0.175	0.105	0.843	0.097	0.200
3	PBC -> ITT	0.835	0.071	0.110	1.246	-0.139	0.106	0.364	-0.040	0.358
4	PR on KNW -> ITT	1.670	0.174	**0.100**	1.412	0.275	**0.079**	1.889	0.313	**0.029**
5	PR on ATT -> ITT	0.186	0.018	0.110	0.001	0.000	0.500	0.691	-0.092	0.245
6	PR on PBC -> ITT	0.086	0.008	0.110	0.774	-0.119	0.219	0.360	0.051	0.359
7	PR -> ITT	2.028	0.264	**0.050**	2.151	0.338	**0.016**	2.188	0.312	**0.014**
8	SN on KNW -> ITT	1.746	-0.147	**0.010**	1.984	-0.345	**0.024**	1.396	-0.236	**0.081**
9	SN on ATT -> ITT	1.065	0.098	0.110	0.150	0.030	0.441	0.023	-0.004	0.491
10	SN on PBC -> ITT	1.616	-0.154	**0.050**	0.414	0.052	0.339	0.581	-0.075	0.281
11	SN -> ITT	3.357	0.275	**0.001**	2.884	0.281	**0.002**	3.901	0.319	**0.000**
12	ITT -> BO	12.272	0.659	**0.001**	12.597	0.751	**0.000**	8.773	0.648	**0.000**
R_2	ITT		**0.748**			**0.759**			**0.748**	
R_2	BO		**0.420**			**0.564**			**0.420**	

KNW=Knowledge, ITT=Intention to Trust, ATT=Attitude, PBC=Perceived Behavioral Control, PR=Perceived Risk, SN=Subjective Norm, BO=Behavioral Outcome

The purpose of replicating the Ho et al. study involved concerns regarding the affected subjects, the measurement instrument structure, and the study’s practical implications. First, the purpose of the original research was to examine the influence that perceived risk and subjective norm have on a user’s intent to adopt cloud technology. Our replication is interested in testing the replicability, stability, and effectiveness of the original study. As a result, we present several contributions regarding our replication.

In sum, we contend that our replication adequately simulates Ho et al. A critical argument of the replication, however, focuses on the effectiveness of examining intention to trust to behavioral outcomes because of its reliance on the central social psychological phenomenon of trust. Trust embodies benevolence, integrity, and competence (Baumeister & Vohs, 2007). As such, the central argument of the Ho et al. study is *“identifying the extent to which the intention of corporate users’ trust the Cloud influences their decisions to adopt this technology*” through the latent variables of perceived risk and subjective norms (p. 582). According to Gambetta (1988), the notion of trust implies a probabilistic distribution between distrust and trust. In other words, higher levels of trust (≥ .5) or more imply an enhanced perception of trustworthiness, thus, potentially influencing technology adoption decisions. For example, intent to trust includes two separate dimensions, trust, and use intentions. More critically, only two indicators measure trust. The remaining three indicators measure use intentions, therefore, obscuring the distribution of significance between these two ideas.

We argue that to adequately measure trust, which is a foundational aspect of this study, it is critical to disentangle it from use intentions. For example, Oliveira et al. (2017) examined the trustworthiness consumers perceived of e-commerce through three separate constructs: competence, integrity, and benevolence. Also, Gao and Waechter (2017) examined the adoption of consumer trust in mobile payment services using positive valance (perceived system, information, and service quality) and negative valance (perceived uncertainty and asset specificity). The consideration of cloud computing adoption centers on trust perceptions between the consumer and cloud service vendors, such as those offering e-commerce and mobile-based systems. Thus, in the absence of what Gambetta (1988) calls “blind trust,” trust should encompass a complete definition when regressed on intent and behavioral outcomes (Mayer, Davis, & Schoorman, 1995).

To address the issues with the trust concept, we conducted additional post hoc tests. We attempted to correct high correlations and separate intent to trust into two separate constructs, trust, and intent. However, we were unable to improve the model’s explanatory despite multiple orientations. At a minimum, two likely explanations are possible for the weakness of the trust/intent constructs. First, trust is inadequately measured, thus requiring a more comprehensive definition vis-vis Oliveria et al. (2017). Second, the removal of high cross-loadings resulted in volatile outcomes. A likely explanation could involve the context and wording of the constructs. While the bootstrap and PLS metrics appear to support discriminant and convergent validity, the high cross-loadings on several constructs require additional examination.

6 Limitations and Future Research

We identified four limitations in our replication of Ho et al. (2017). First, we were unable to ascertain the survey's section questions and order from the original study. To compensate, we created fundamental question stems and ordered the questions as logically as possible. Some methodological variance in the survey implementation likely exists between the studies. Second, while Ho et al. (2017) included a domestic and international participant base, our study focused only on a domestic population. It is, therefore, likely that the addition of an international participant base may alter the results. Third, the use of cross-sectional data promotes common method bias making it difficult to establish causal relationships. Finally, we found that the definition of "corporate users" (Ho et al., 2017, p. 587) was methodologically insufficient. The term corporate user can define at least two separate groups, management, and employees. From the perspective of interpretation, future research should more clearly delineate the level of analysis.

7 Conclusion

This research sought to replicate the study presented by Ho et al. (2017) on the intent to trust cloud providers and behavioral outcomes based on this perception. We validated the model proposed in the original study through a methodological replication and found support for the relationships between knowledge, subjective norm, perceived risk, trust intention, and the interaction of knowledge and trust through perceived risk. The contextual and measurement discrepancies found in the results of the replication study highlight the generalizable (e.g., subjective norm, perceived risk, trust intention, and behavioral outcome) and non-generalizable (e.g., knowledge, attitude, perceived behavioral control) relationships presented in the original study.

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About the Authors

René Moquin is an Assistant Professor in the Department of Information Systems & Technology in the College of Business & Technology at Northeastern State University.