Transactions on Replication Research

Conceptual Replication DOI: 10.17705/1atrr.00047 ISSN 2473-3458

To Share or Not to Share: Consequential Impacts of IT Support on the Knowledge Processes of IT Project Teams

Gerard De Leoz
University of Tampa
gdeleoz@ut.edu

Stacie Petter
Baylor University
stacie_petter@baylor.edu

Abstract:

This study is a methodological replication of Choi et al.'s (2010) study that examines individuals' perceptions of team interaction for knowledge sharing and application to accomplish team goals. Choi et al. (2010) explain the impact of information technologies (IT) on the development of transactive memory systems on the promotion of knowledge management practices and, consequently, on team performance. The original study reveals that knowledge sharing does not have a direct impact on team performance. The current study methodologically replicates Choi et al.'s (2010) research in the context of IT project teams. Two identified potential differentiating contexts are (1) the contemporary IT capable of supporting knowledge management practices may have evolved into more sophisticated technologies compared to those that existed during the time the original study was conducted, and (2) the sample of individuals in this study specifically worked with IT project teams instead of more generic knowledge-based teams in an organization. In this replication study, we examined whether the hypotheses still hold at the individual level of analysis. Scrutinizing knowledge processes while accounting for the above-mentioned differences may help us understand better IT project team performance, and consequently, increase the likelihood of IT project success.

Keywords: Project teams, Transactive memory systems, Knowledge application, Knowledge sharing, Project success, MISQ replication project

The manuscript was received 03/06/2019 and was with the authors 10 months for 2 revisions.

1 Introduction

Organizations often employ teams to accomplish specific goals and objectives (Gasik, 2011). Within the information systems discipline, much research has sought to identify factors that influence team performance, including the role of information technology to support team interaction and collaboration. Research has sought to understand the role of information technology in the process of creating, sharing, and applying knowledge within a team setting (Choi, Lee, & Yoo, 2010; Nonaka, 1994; Pee & Kankanhalli, 2016).

Knowledge management practices create working knowledge within a collective (such as a team, department, or organization) through the practices of knowledge sharing and knowledge application that occur during the accomplishment of work. Knowledge sharing is the gathering and transferring of knowledge for use in another situation or context (Alavi & Leidner, 2001), and knowledge application is the use of knowledge to solve a given problem (Alavi & Tiwana, 2002). The ability of a collective, such as a team, to successfully apply the practices of knowledge sharing and knowledge application is posited to be affected by the presence of transactive memory systems within the team (Lewis & Herndon, 2011). Transactive memory systems are mental models shared by a team to encode, store, and retrieve of knowledge as part of an effort to specialize and divide knowledge among team members (Wegner, 1987). The creation of transactive memory systems prevents each team member from acquiring, maintaining, sharing, and applying all knowledge held by each individual team member. If team members know which team member has the needed knowledge to accomplish a task and if the team has strong knowledge practices to share and apply knowledge, then the team is likely to perform at a higher level than teams without a strong transactive memory system (Lewis & Herndon, 2011).

In a study of organizational teams, Choi et al. (2010) examine how information technology (IT) used to support knowledge management practices facilitates the development of transactive memory systems, consequently improving team performance through better knowledge application processes. Choi et al. (2010) examined their research model at the team level of analysis with team members from 139 teams across two organizations. The authors found support for each of the relationships in their study, with the exception that knowledge sharing did not affect team performance. The study by Choi et al. (2010) offered useful insights on understanding the relationship between IT for knowledge management and the development of transactive memory systems. The study also demonstrated a direct (positive) effect among IT for knowledge management and knowledge sharing and knowledge application.

This study methodologically replicates Choi et al.'s (2010) research in the context of IT project teams. We study the phenomenon of interest by examining how individuals perceive their interactions with others on the team in terms of sharing and applying knowledge to accomplish work. As a methodological replication, the intent is to identify if the results continue to support the original study's findings given that the context of the study has changed (Dennis & Valacich, 2015). This study has two differentiating contexts from the original study. First, the contemporary IT capable of supporting knowledge management practices may have evolved into more sophisticated technologies compared to those that existed during the time the original study was published. Second, the sample of individuals in this study are from IT project teams instead of more generic knowledge-based teams in an organization.

2 Original Study and Findings

The original study by Choi et al. (2010) was the first known study to examine the relationship between IT support and transactive memory systems. The authors also examine the downstream effects of transactive memory systems by considering the direct effects of transactive memory systems on knowledge application and knowledge sharing. Table 1 lists the hypotheses from the original study.

After analyzing the results of surveys administered to teams in two different organizations, Choi et al. (2010) found support for most of their hypotheses (only H6 was not supported in the original study). Figure 1 shows the research model, paths and results from Choi et al. (2010). The results suggest that IT support for knowledge management affects not only transactive memory systems, but also knowledge sharing and knowledge application. The authors state that "much of the impact of ITS [IT support] on knowledge sharing and knowledge application is mediated through [transactive memory systems]" (p. 865). This important finding suggests that it is not IT support for knowledge management alone that improves knowledge sharing and knowledge application within teams, but rather IT support provides an important role in the transactive memory system of the team, which influences knowledge processes.

Table 1. Hypotheses Tested by Choi et al. (2010)

No.	Hypothesis
H1	The use of IT to support knowledge management practices will lead to a more developed sense of TMS in teams.
H2	A more developed sense of TMS will lead to more effective knowledge sharing in teams.
H3	A more developed sense of TMS will lead to more effective knowledge application in teams.
H4	The use of IT to support knowledge management practice will lead to more effective knowledge sharing in teams.
H5	The use of IT to support knowledge management practice will lead to more effective knowledge application in teams.
H6	Knowledge sharing will lead to higher team performance.
H7	Knowledge application will lead to higher team performance.
H8	Knowledge sharing will lead to higher level of knowledge application in teams.

An unexpected result from Choi et al.'s (2010) study is that the authors did not find a relationship between knowledge sharing and team performance. The original study noted that knowledge application fully mediates the relationship between knowledge sharing and team performance. This finding was interesting because it demonstrates that knowledge sharing affects team performance only through the application of the knowledge shared within the team.

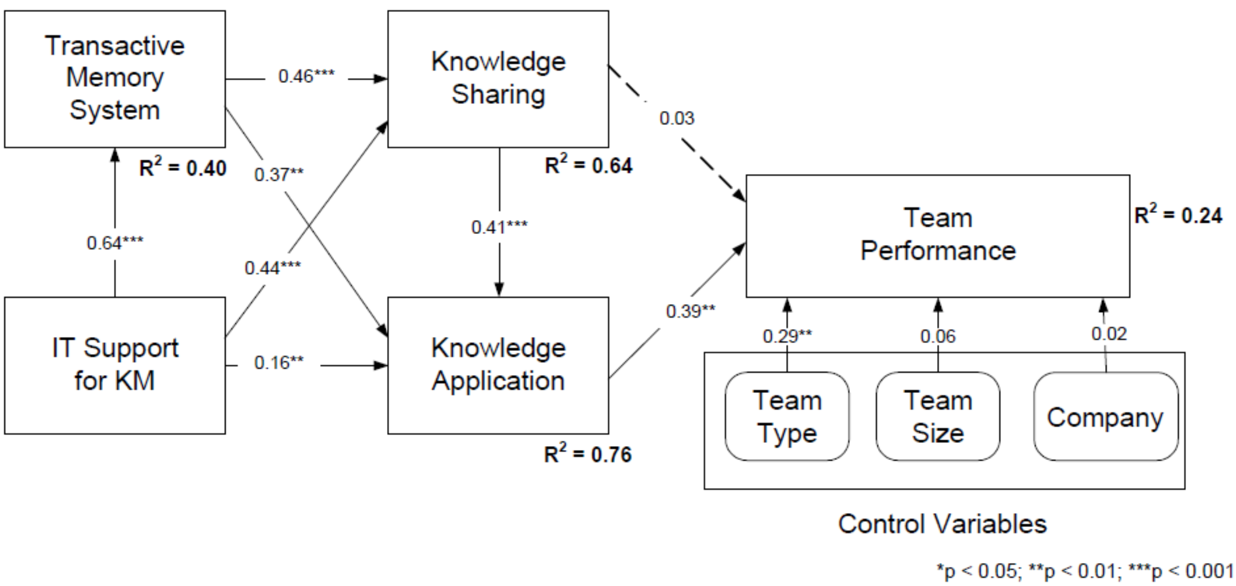

Figure 1. Results of the Original Study (Choi et al., 2010)

3 Research Method

To examine the applicability of Choi et al.'s model to other contexts, this research replicates the original study in a different context – IT project teams. While IT project teams may be similar to other types of teams in an organization, IT projects possess inherent characteristics that make knowledge processes more challenging for IT project teams. For example, IT projects are time-bounded, which increase the likelihood of engaging team members who may have never worked together before and may not work again in the future after the project (Ajmal, Helo, & Kekäle, 2010). IT project teams have changing membership, and knowledge learned from previous projects may be lost when a new set of members become part of the project (Shapiro, 1999). IT project teams are typically comprised of members with diverse yet complementary skills and expertise, which compel IT project teams to communicate and collaborate more frequently to ensure that knowledge is processed more effectively. The interdependencies across various impacted business functions and partners in IT projects also increase the complexity of knowledge that need to be processed across organizational boundaries, and consequently the need to tease such complexities apart (Nelson & Cooprider, 1996; Obaide, 2008). Many IT project teams typically engage members that are geographically distributed from other members, making communication and knowledge processes more challenging, thereby increasing the reliance upon IT to effectively communicate and share knowledge (Zigurs, 2008). Furthermore, while IT project teams need to share and apply knowledge for project success, the level of support for knowledge management may vary across teams or organizations. Scrutinizing knowledge processes while accounting for these differences may help us understand IT project team performance, and consequently, increase the likelihood of IT project success.

3.1 Differences between the Original Study and the Replication Study

This study provides a methodological replication of Choi et al.'s (2010) original study in that we use nearly the same measures and analysis techniques as the original study; however, there are some differences in data collection and in the measurement of items.

In the original study by Choi et al. (2010), data was analyzed based on responses from 743 individuals from 139 teams in two firms in South Korea – an oil company, OilCo, and a steel company, SteelInc. Both companies are known to have well-established knowledge management practices and knowledge management systems. Also, the teams in Choi et al. (2010) were broadly based in that there was no mention of classification of teams that participated in the study other than the teams of being manufacturing type or non-manufacturing type. As such, Choi et al. (2010) gathered data from multiple respondents within a team of at least three members, as well as performance data from the managers separately from the team survey. The level of analysis in Choi et al. (2010) was the team, and team size, team type and company served as control variables in the original study.

This replication uses the individual level of analysis in the specific context of IT project teams. As a result, we developed a replication study that solicited responses from individuals who participated in IT projects. IT project management has been a common practice globally, and these teams are often guided by standards, such as the Project Management Body of Knowledge (PMBOK, 2015) or methodologies, such as traditional or agile development methodologies. Therefore, we consider an individual's response to represent the team member's perception of the team's process and performance. Since the original questions used by Choi et al. (2010) asked about individual's perceptions, we did not need to alter the original questions for our analysis. In the original study, Choi et al. (2010) aggregated individual responses to obtain a measure for each team and then analyzed the results at a team level. However, we chose for this methodological replication to examine if the research model remains consistent if we consider the responses at an individual level of analysis.

In this replication, team type and company are not used as control variables given that this study seeks to analyze IT project teams from single individual responses coming from a wide variety of organizations. As a result, this replication uses team size, project duration, team dispersion (co-located vs. dispersed or virtual) and project methodology as control variables. The control variables used in this replication study are relevant to examining if these differences among project teams affect the study results.

The original study recruited participants through two organizations. In this study, we gathered data using two different platforms, Amazon Mechanical Turk (or MTurk, for short) and Prolific. To participate in this study, respondents were required to meet two qualifications: (1) the respondent recently participated in at least one completed technology-related or software project within a team for any organization in any role or capacity (except for an "end user" role) within the past 18 months; and (2) the research participant had to be at least 18 years old.

The survey questions in this study are similar to those in the original study with slightly altered wording to match the IT team project context. As such, respondents are asked to recall a project team with whom they have recently completed a technology-related or a software development project at the beginning of the survey. Appendix A provides a list of the measures used for the replication study.

The original study by Choi et al. (2010) minimized the threat of common method bias by having team leaders complete the performance measures within the survey. Given that our survey approach differs from the original, this technique to minimize common method bias is not possible. Therefore, we included a marker variable to provide a means to examine the threat of common method bias within this study (Liang, Moreland, & Argote, 1995; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

3.2 Data Collection

Prior to collecting data for the replication, we performed a power analysis to determine an appropriate sample size. Choi et al. (2010) aggregated the responses from the 743 participants into 139 teams for analysis. The smallest significant path in the model was 0.16, and the smallest R^2 value within the model was 24%. We used this information to guide our determination for the minimum sample size for this study *a priori* to data collection. Hair, et al. (2014) offer a means to determine the minimum sample size based on the maximum number of arrows leading into a construct and the minimum R^2 for a given construct. In the original model by Choi et al. (2010), the dependent variable has the highest number of exogenous constructs (i.e., five, counting control variables) and the smallest R^2 value (i.e., 24%). Using the guidelines by Hair et al. (2014), for a variable with five arrows leading into the construct and an R^2 of 25%, our minimum sample size would be 70. We also used GPower to calculate the minimum sample size for "Linear Multiple Regression: Fixed model, R^2 deviation from zero" using parameters consistent with the findings by Choi et al. (2010). Based on this analysis, the sample size required for a power of 0.8 is 92. Choi et al.'s (2010) effective sample size after aggregating team responses was 139. We sought to collect approximately 200 responses to ensure sufficient power. A sample size of this magnitude allows detection of effect sizes of approximately 0.05.

Survey data was collected from individuals of at least 18 years old and who had recently participated in an IT project in any organization. At the time of data collection, in particular, a prospective research participant should have completed a technology-related or software development project in the last 18 months and had performed a non-user role in the project, such as a programmer, developer, tester, analyst, business sponsor, project manager, business manager or director, or subject matter expert. Survey participants were asked to recall experiences and answer related questions in the survey about this particular IT project, IT project team, and their organization.

As mentioned, we recruited prospective participants for the study using two online crowdsourcing facilities – MTurk and Prolific. For both MTurk and Prolific, recruitment of participants involved paying a remuneration fee as a means to incentivize qualified participants (Steelman, Hammer, & Limayem, 2014). We ensured that our remuneration rates were above the mean and median hourly wages of workers on MTurk, which have been reported $3.13/hour and 1.77/hour, respectively (Hara et al., 2018). We paid respondents, regardless of platform, a wage more consistent with the federal minimum wage in the United States at the time of the study ($7.25/hour).

We performed a series of procedures to increase scrutiny and improve the quality of responses gathered for data analysis. Specifically, for those completing the survey on MTurk, we enabled a list of internal screening functionalities to recruit highly-qualified workers. Only those having a master-level rank, a HIT (human intelligence task) approval rate of 98% or above, and a job function of 'information technology' could participate in the study. MTurk's master qualification feature is said to be extensive to prescreen workers (Schmidt & Jettinghoff, 2016), which is highly desirable in doing research. With these criteria, however, we received only 16 responses. As such, we disabled the requirement of master rank, reduced the HIT approval rate to at least 95%, increased the remuneration rate, and also allowed those with a 'management' job function to complete the task. With this adjustment, a total of 97 usable responses were obtained, but this number of responses was insufficient to proceed with data analysis.

To increase the number of responses, we recruited additional participants through another online crowdsourcing platform, Prolific. Prolific screens individuals prior to allowing them to be contacted as part of a panel, unlike MTurk. Prolific's internal screening features are not as readily restrictive as MTurk's but Prolific can exclude invitation of individuals who also participate in other crowdsourcing platforms. As such, we enabled exclusion of participants who also partake in MTurk studies. In addition, we conducted a pre-screening survey to identify and invite only highly qualified participants prior to taking them to the main survey of the study. We acquired a total of 129 responses through Prolific; this resulted in a total of 226 usable responses for data analysis.

We tracked IP addresses and filtered out multiple responses potentially done by the same individuals, while maintaining anonymity of the individuals (Mason & Suri, 2012; Steelman et al., 2014). In addition, responses that failed our attention-checking questions were immediately removed from the pool. We also purged cases whose response times appeared to have been very short, particularly, those with answers that were completed on an average of 2 seconds or less per survey-question, which translates to a total of less than 3 minutes per completed survey (Huang, Curran, Keeney, Poposki, & DeShon, 2012). We also deleted other cases of low-effort and attention such as those that showed straighline patterns (DeSimone, Harms,

& DeSimone, 2014). We further screened our data for potential outliers. After removing 29 cases, we were left with 197 responses for further data analysis.

Choi et al. (2010) collected data from individuals in teams across two different companies, and the authors performed tests to confirm that the data could be pooled across the organizations for additional analysis. In this replication, we also collected data using two different sources (i.e., Amazon's MTurk and Prolific). We ran independent sample t-tests to confirm that there were no significant differences in item responses between the two groups. None of the item responses were significantly different for MTurk respondents versus Prolific respondents. As a result, we pooled the data for further analysis.

Table 2 provides information about the demographics of respondents in this replication study. One important difference to note regarding the demographics between the original study and this study is gender. In the original study, only 15.8% of the participants were female; however, in this replication, 33.5% of respondents were female.

Table 2. Demographics of Respondents in Replication Study

Individual Characteristics		Frequency	Percent	Project Characteristics		Frequency	Percent
Gender	Male	130	66.0%	Methodology	Traditional	120	60.9%
	Female	66	33.5%		Agile	75	38.1%
	Prefer to Self-Describe	1	0.5%		Other	2	1.0%
Project Role	Programmer/ Developer/Tester	72	36.5%	Duration	< 1 year	101	51.3%
	Analyst	17	8.6%		1 to 2 years	69	35.0%
	Systems Architect	7	3.6%		2 to 3 years	17	8.6%
	Project Manager	64	32.5%		3 to 4 years	9	4.6%
	Department Manager or Director	17	8.6%		4 to 5 years	0	0.0%
	Subject Matter Expert (SME)	14	7.1%		> 5 years	1	0.5%
	Other	6	3.0%				
				Team Size	3-5	87	44.2%
					6-10	71	36.0%
					11-15	27	13.7%
					16+	12	6.1%
					Mean	**Std Dev**	**Scale**
				Team Dispersion	3.97	3.29	1-10

4 Data Analysis and Findings

In reviewing the means and standard deviations of the replication, as compared with the original study (see Appendix A), the means were 5.3 or higher (on a 7-point scale, consistent with the original study), but the standard deviations were much higher in the replication. This finding is reasonable given that we conducted our survey with individuals across teams and organizations, unlike the original study. We also compared the means of the original items with the means of the replication items using an independent sample t-test to identify if any item means are significantly different between the studies. As noted in Appendix A, several item means were significantly different between the original study and the replication study (particularly items within the construct of Transactive Memory Systems and Knowledge Application).

For the analysis, we analyzed the constructs for transactive memory system, knowledge application, and knowledge sharing as reflective measures, and IT support and team performance were analyzed as formative measures. Before analyzing the structural model, we performed the same approaches used by

Choi et al. (2010) to examine the measurement model's construct validity and reliability. We also performed tests for common method bias as part of our assessment of the measurement model.

4.1 Measurement Model Analysis

4.1.1 Exploratory Factor Analysis

We first performed an exploratory factor analysis of the reflective measures (transactive memory system, knowledge application, and knowledge sharing). We used an oblique rotation method[1] consistent with Choi et al. (2010). The results of the original study and the replication are shown below. In the original study, Choi et al. (2010) noted cross-loadings among some items, but also reported that each item loaded on its own factor. The authors also report that the reliability (measured using Cronbach's alpha) for each construct was greater than 0.85.

In our results, we also had problems with cross-loadings. Unless we specified the number of factors, all items wanted to load on a single factor. Unlike the original study, not all items loaded highest on their own factor. One measure of transactive memory systems and an item for knowledge sharing loaded on a third factor. Furthermore, transactive memory sharing and knowledge application loaded on the same factor. The Cronbach's alpha for the constructs in the replication was 0.73 or higher, which suggests a reasonable level of reliability for each construct. Table 3 shows the results of the exploratory factor analysis as conducted by Choi et al. (2010) and from our replication study. The cells in bold represent the highest loading of an item on a given factor. The reliability for each factor, as measured by Cronbach's alpha, is also provided.

Table 3. Exploratory Factor Analysis Results

	Original Study				**Replication Study**		
	Factor				*Factor*		
Item	*1*	*2*	*3*		*1*	*2*	*3*
TMS1	**0.70**	0.14	0.03		0.19	0.01	**0.66**
TMS2	**0.85**	-0.06	-0.15		**0.47**	0.34	0.14
TMS3	**0.89**	-0.07	-0.11		**0.91**	0.04	-0.23
TMS4	**0.88**	-0.10	-0.09		**0.65**	-0.03	0.26
TMS5	**0.73**	0.21	0.25		**0.72**	0.28	-0.21
TMS6	**0.84**	0.16	0.28		0.34	**0.44**	0.11
KS1	0.55	**0.68**	0.17		0.01	0.29	**0.69**
KS2	0.47	**0.76**	0.08		-0.05	**0.90**	0.03
KS3	0.49	**0.75**	0.11		0.18	**0.51**	0.36
KA1	0.54	0.14	**0.66**		**0.75**	-0.14	0.22
KA2	0.61	0.13	**0.69**		**0.75**	-0.07	0.25
KA3	0.62	0.17	**0.67**		**0.67**	0.05	0.16
	TMS	*KS*	*KA*		*TMS*	*KS*	*KA*
Cronbach's α	0.90	0.88	0.90		0.84	0.73	0.85

4.1.2 Confirmatory Factor Analysis

Given the issues associated with high cross-loadings among the reflective constructs in the original study, Choi et al. performed confirmatory factor analysis of the three reflective constructs using covariance-based SEM (i.e., AMOS). The authors performed three separate analyses: (1) all items loading on a single factor; (2) items loading on each construct, with the correlations among constructs constrained to one; and (3)

[1] Choi et al. (2010) do not report which type of oblique rotation method was used in their analysis. The data reported below is based on an oblimin rotation within SPSS 26.0. Since there are alternative rotation methods to generate oblique rotations, we performed the same factor analysis using a promax rotation, which is another form of oblique factor rotation. Similar cross-loadings occurred with both the promax rotation and oblimin rotation methods.

items loading on each construct, with the correlations among construct being free to covary. Based on model comparisons and model fit of the third model, the authors concluded that the confirmatory factor analysis suggests the model fits well with the data.

We performed the same confirmatory factor analysis as the original study by Choi et al. (2010) using EQS 6.4. The original study results and our results are shown below in Table 4. One issue that arose in our analysis of Model 2 was that the model with the constrained correlations was not positive definite. As a result, the model would not converge, and we could only examine the one-factor model and the three-factor model with freely correlated constructs. Yet, Model 3 has a strong model fit with items loading on their appropriate constructs (see Figure 2). Even with this issue associated with Model 2, the confirmatory factor analysis supports a three-factor model using the same criteria as Choi et al. (2010).

Table 4. Confirmatory Model Comparisons

		Original Study		Replication Study	
Model	**Description**	**X^2**	**df**	**X^2**	**df**
M_1	One-factor model	1491.62	54	119.70	54
M_2	Three-factor model (factor correlations fixed to 1)	763.18	51	no results	54
M_3	Three-factor model (factors are freely correlated)	657.62	51	74.56	51

In the replication, the model fit was much improved compared to the original study (see Table 4). However, as demonstrated in the comparison of the item loadings of the original study and the replication study, the item loadings on each construct were lower, with several below 0.70.

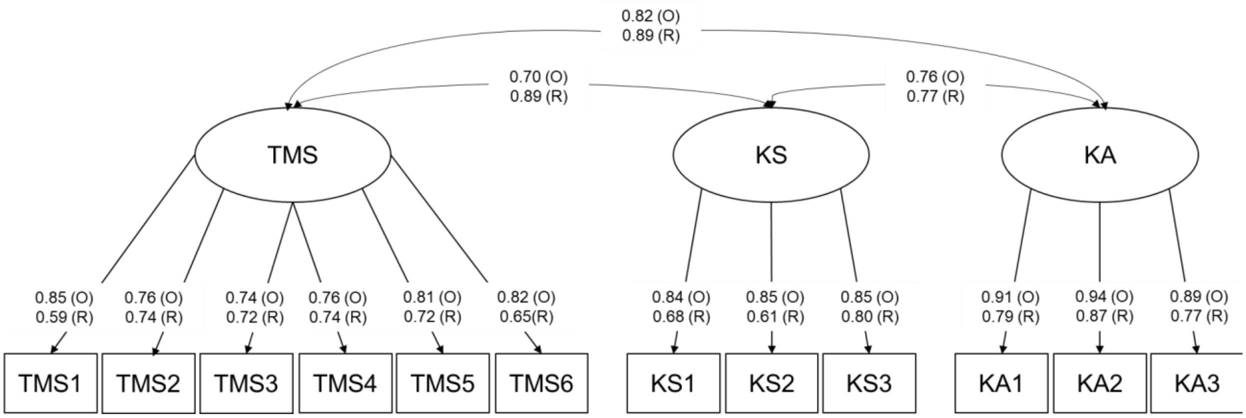

Figure 2. Confirmatory Factor Analysis Results

4.1.3 Common Method Bias

In addition to the methods used by Choi et al. (2010), we recognize that the cross-sectional nature of the survey makes it more prone to common method bias (Liang, Saraf, Hu, & Xue, 2007; Podsakoff et al., 2003). Hence, we tested for common method bias using the same approach as Choi et al. (2010) by examining the model in PLS-SEM with a common method variance factor (Liang et al. 2007).

Using the common method variance factor technique examines the threat of common method bias by considering not only the potential for common method bias based on items from the principal constructs (reflective) of the model, but also by examining the effect of a common method factor. The procedure entailed calculating for the variances as explained by the principal construct and by the method factor, R12 and R22, respectively. Table 5 summarizes the variances per indicator. Our results show that the average variance of items explained by the constructs is approximately 0.6379, whereas the average variance of items explained by the method is 0.0034. By comparison, the ratio between these average variances is 187:1. In addition, all method factor loadings, except for KA1’s, are insignificant. Per Liang et al. (2007), the ideal magnitude of the method variance should be substantially less than that of the substantive constructs, while the factor loadings should be insignificant.

Table 5. Common Method Variance Analysis

	Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
TMS1	0.660***	0.436	-0.018	0.000
TMS2	0.773***	0.598	0.054	0.003
TMS3	0.785***	0.616	-0.071	0.005
TMS4	0.784***	0.615	-0.094	0.009
TMS5	0.796***	0.634	0.075	0.006
TMS6	0.704***	0.496	0.056	0.003
KA1	0.907***	0.823	-0.087*	0.008
KA2	0.868***	0.753	0.026	0.001
KA3	0.850***	0.722	0.067	0.004
KS1	0.799***	0.638	-0.025	0.001
KS2	0.770***	0.592	-0.019	0.000
KS3	0.856***	0.733	0.038	0.001
AVERAGE		**0.6379**		**0.0034**

Note: ***p<0.001; **p<0.01; *p<0.05

We also used the common marker variable approach (Lindell & Whitney, 2001) to identify the potential threat of common method bias given the differences in our survey approach compared to Choi et al. (2010). A marker variable approach uses a theoretically unrelated construct, called a marker variable, to adjust the correlations among the principal constructs. We used an individual's attitude towards the color blue (i.e., blue attitude) as the marker variable in this study. Blue attitude is a set of items that were specifically created for the purpose of serving as a marker variable in that these items should not be correlated with any items in our study (Miller & Chiodo, 2008).[2] High correlations among any of the item-measures of the principal constructs with the marker variable indicate the presence of common method bias. Table 6 shows that none of the indicators in our principal constructs show a high correlation with the marker variable.

Table 6. Correlations with Marker Variable

Item	Marker Variable
TMS1	-0.094
TMS2	-0.031
TMS3	-0.163
TMS4	-0.187
TMS5	-0.012
TMS6	-0.021
KA1	-0.192
KA2	-0.069
KA3	-0.025
KS1	-0.126
KS2	-0.117
KS3	-0.068

[2] The items for the blue marker variable include the following items: (1) I like the color blue; (2) I prefer blue to other colors; (3) I hope my next car is blue; and (4) I like blue clothes.

4.2 Structural Model Analysis

Figure 3 shows a comparison of this study's PLS results with the original study results. It should be noted that in this replication study, none of the control variables (team size, team dispersion, project duration, and project methodology) have a significant impact on the dependent variable, team performance.

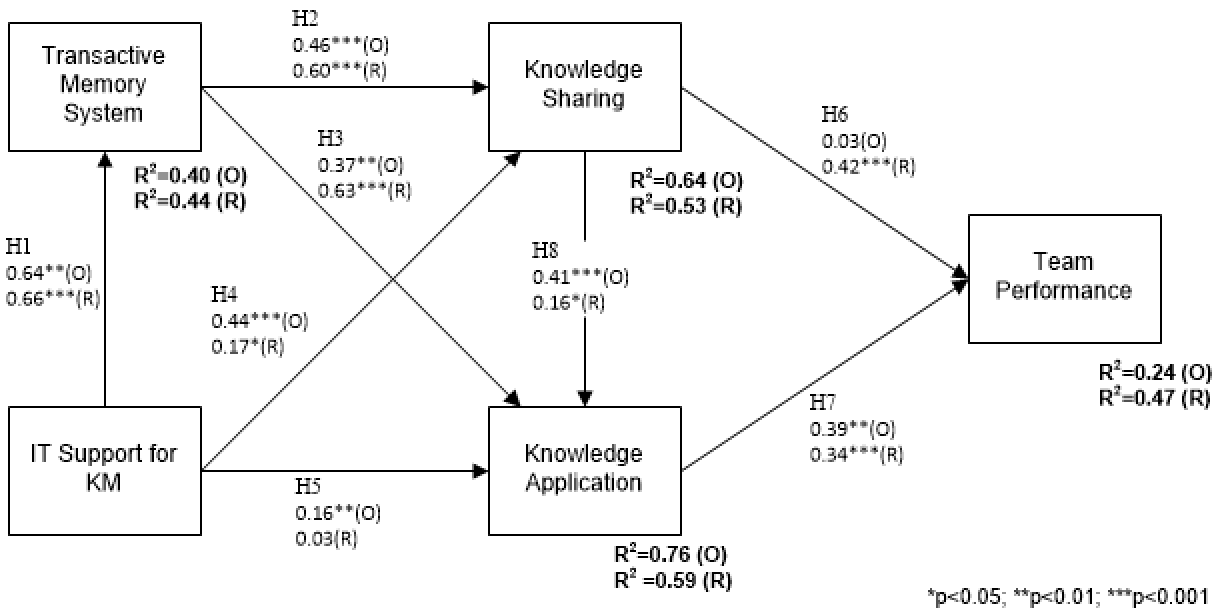

Figure 3. Structural Model Results of the Original Study and Replication Study

Additionally, Table 7 summarizes the results of the original study and the replication study. The hypothesized path supporting IT support to TMS is significant, supporting H1 for both the original and this replication study. Consistent with the original study, this study also shows that transactive memory systems has a significant impact on knowledge sharing (H2) and knowledge application (H3). IT support has a significant impact on knowledge sharing (H4), but in the replication, IT support does not have a significant impact on knowledge application (H5). In addition, both knowledge sharing and knowledge application have a significant impact on team performance supporting both H6 and H7. In contrast, the original study (Choi et al. 2010) found no direct relationship between knowledge sharing and team performance, suggesting that knowledge application fully mediates the relationship between knowledge sharing and team performance. Lastly, knowledge sharing impacts knowledge application (H8), which supports the finding of the original study.

Table 7. Hypotheses Tested by Choi et al. (2010)

No.	Hypothesis	Original Study	Replication Study
H1	The use of IT to support knowledge management practices will lead to a more developed sense of TMS in teams.	Supported	Supported
H2	A more developed sense of TMS will lead to more effective knowledge sharing in teams.	Supported	Supported
H3	A more developed sense of TMS will lead to more effective knowledge application in teams.	Supported	Supported
H4	The use of IT to support knowledge management practice will lead to more effective knowledge sharing in teams.	Supported	Supported
H5	The use of IT to support knowledge management practice will lead to more effective knowledge application in teams.	Supported	Not Supported
H6	Knowledge sharing will lead to higher team performance.	Not Supported	Supported
H7	Knowledge application will lead to higher team performance.	Supported	Supported
H8	Knowledge sharing will lead to higher level of knowledge application in teams.	Supported	Supported

5 Discussion

The original study by Choi et al. (2010) has been cited over 600 times at the writing of this article (according to Google Scholar). Some citations use the findings from Choi et al. (2010) to report what has been learned about transactive memory systems within the literature (e.g., Lewis & Herndon, 2011) or to support the role of transactive memory systems in the context of team settings (e.g., Whelan & Teigland, 2013). Other research, for example, use Choi et al. (2010) to support the argument that transactive memory systems indirectly influence team performance mediated by knowledge quality and knowledge use satisfaction (e.g., Huang, Liu, & Zhong, 2013). Some studies have relied on the findings of Choi et al. (2010) to discuss the importance of information technology on knowledge sharing and/or knowledge application among teams (e.g., Leonardi & Treem, 2012). Only a small number of studies have examined specific relationships consistent with Choi et al. (2010). Park and Lee (2014) cite Choi et al. (2010) to support their purported relationship between knowledge sharing and team performance. Yet, Reich, Gemino, and Sauer (2014) use the results from Choi et al. (2010) to provide support for the lack of relationship between knowledge sharing and team performance in their study of IT project teams. Many of the studies we reviewed citing Choi et al. (2010) leverage the theorizing, findings, and context to support their own research, and few studies examine the relationships within the study.

This methodological replication examines the impact of IT support for knowledge management on the development of transactive memory systems (TMS) towards promoting knowledge management practices, and consequently, influencing team performance, in the context of IT project teams. This replication has many consistencies with the original model with some exceptions.

First, it is relevant to note how well the model replicated given the differences in both the context and unit of analysis between the two studies. The original study focused on knowledge management teams within two organizations. Choi et al. (2010) were able to control for certain differences between organizations, and they selected organizations with known and well-developed knowledge management systems. In the original study, the authors had access to at least three team members per team as well as information provided by a team leader. This allowed the original study to focus on the team as the unit of analysis. In this replication, we narrowed the context to IT project teams. Furthermore, by sampling individuals, rather than teams within organizations, we offered the potential for further confounds not present in the original study. We did not know the level of support for knowledge management systems and practices prior to collecting our data. Furthermore, we did not have access to multiple team members for our analysis. As a result, we rely on the perceptions of a single team member to examine the model. Even with these substantial changes to the level of analysis, the structural model performed similarly across both studies for six of the eight hypotheses.

A second key point to note is the differences in our replication compared to the original study as it relates to the measurement model. Similar to Choi et al. (2010), we had issues with cross-loadings for the reflective constructs in the model. In our case, the cross-loadings were even more severe than the original. We used the same techniques as the original authors (i.e., oblique rotation), but there were problems with both convergent and discriminant validity in the replication (see Table 3). We also used the same procedures as Choi et al. (2010) to examine the model using confirmatory factor analysis. If we examine the fit statistics alone, the chi-square of the model in our replication is an improvement over the original study; however, a closer look at the loadings of each construct on a model tells a different story. Multiple items have a path less than 0.70 in the confirmatory factor analysis. Also, given that this is a replication study, we chose not to use techniques that we might use to address measurement problems in an original research study. If this had been an original study, we may have purged items, such as TMS1, from further analysis. Also, had this been an original study, instead of a replication, we would have identified other measures for knowledge application and conducted the survey again.

We are not certain why the measurement model performed more poorly in the replication as opposed to the original study. It could be argued that our use of an individual level of analysis as opposed to a team level of analysis comprised the measurement of the constructs. Another concern could be our choice to use cross-sectional data gathered through sources, such as MTurk and Prolific, as opposed to data gathered with permission of an organization. In regards to our use of MTurk and Prolific, we took care to increase the quality of responses consistent with recommendations provided in the literature: tracking IP addresses for multiple responses, embedding attention-checking questions, and reviewing cases for low-effort patterns and attention (DeSimone et al., 2014; Huang et al., 2012; Mason & Suri, 2012; Schmidt & Jettinghoff, 2016; Steelman et al., 2014).

In interpreting the differences between the structural model in the original study by Choi et al. (2010) and our replication, we must note that some of the findings may be due to the measurement model problems. We performed an independent samples t-test to compare the means of each item in the original study to the mean of the item in the replication study. Several items were significantly different between the studies. However, given many items performed according to expectations and the overall structural model had many consistencies with the original study, we further consider the similarities and differences between the original study and our replication.

Consistent with the original study, the replication found the strongest path coefficient emanating from IT support to be to transactive memory systems as opposed to knowledge sharing and knowledge application. IT project teams have long relied upon the use of IT tools that support file sharing, communication and collaboration. As IT projects teams are increasingly distributed (Karlsen & Gottschalk, 2004; Ruggles, 1998; Zigurs, 2008), the reliance on technology to support the transactive memory system within the IT project team becomes even more critical.

There are two primary differences between the original study findings and our findings: (1) in our study, IT support does not predict knowledge application (H5); and (2) the original study found no direct relationship between knowledge sharing and team performance and suggested a fully mediating relationship; however, we found a significant relationship between these constructs. It may be that the characteristics of IT project teams and the way teams work on IT projects explain these differences (Ajmal et al., 2010; Nelson & Cooprider, 1996; Obaide, 2008; Shapiro, 1999; Zigurs, 2008).

The lack of relationship between IT support and knowledge application (i.e., H5) in an IT project team context appears unusual initially. However, mediation analysis (Zhao, Lynch Jr, & Chen, 2010) finds that knowledge sharing fully mediates the relationship between IT support and knowledge application (known as indirect mediation). The lack of a direct relationship between IT support and knowledge application may be due to a project team's ability to apply knowledge with or without the use of IT tools. Perhaps the ubiquity and familiarity with IT tools, not to mention the proliferation of project work being done virtually, create too common a notion to notice the significant impacts of, and "natural" reliance on, IT on an individual's everyday life (Galloway, 2004). In other words, technology has woven a multiplicitious fabric in our everyday lives in that IT has become unnoticeable. Individuals may take for granted that IT will "always" be there to support IT projects; otherwise, it would be infeasible to start an IT projects if the IT support tools were not available. If this study were performed a couple of decades ago, the use of IT to support knowledge application would be perceived significantly differently and more importantly. Another reason for the difference between the two studies is that we adapted the items for IT support slightly from the original study. The original study asked respondents to evaluate IT support for knowledge sharing provided to the team; however, the items in the replication asked respondents to evaluate IT support for knowledge management by the organization. The final reason for the difference between the two studies could be due to the choice of measuring IT support at the organizational level versus the team level. Yet, we did note that there is no significant difference between the means of the items for IT support for knowledge management between the two studies.

This replication study found that knowledge sharing has a strong significant impact on team performance, contrary to the original study's findings (H6). A post hoc mediation test reveals that knowledge application is a partial mediator, specifically a complementary mediator (Zhao et al. 2010) for the relationship between knowledge sharing and team performance. Choi et al (2010) argues that the lack of relationship between knowledge sharing and team performance was due to the role of knowledge application mediating the relationship knowledge sharing and team performance. The authors suggested this finding is consistent with a translation of the "knowing-doing gap" phenomenon (Pfeffer & Sutton, 2000). In other words, team performance cannot be enhanced by only sharing knowledge; knowledge must be shared and effectively applied, usually in the context of completing an objective or moving closer to a desired outcome. Our replication study found direct effects for knowledge sharing and knowledge application on team performance. In an IT project context, there is a need to share and apply different types of knowledge to create shared mental models of the tasks to be performed and the role of the members in the team (Yu & Petter, 2014). Given the need to develop shared mental models within an IT project team related to the tasks and people within the team, the knowing-doing gap phenomenon may not be as prominent in the context IT project teams. The partially mediating role of knowledge application in the relationship between knowledge sharing and team performance suggests that future research may consider if the activity of sharing knowledge is intertwined with the activity of applying knowledge in certain contexts.

6 Conclusion

In this examination of the role of IT support on transactive memory systems, and the effect of those systems on knowledge sharing and application and team performance in the context of IT project teams, we found similarities and differences with the original study by Choi et al. (2010). Given that Choi et al. (2010) focused on teams employing knowledge management and our study was more narrowly focused on IT project teams, we considered for the possibility of differences between the two studies. Of the eight hypotheses tested across both studies, six of the eight hypotheses are consistent in both contexts. The two hypotheses that varied across the two studies may be due to the context of the replication (i.e., IT project teams instead of general teams), the level of analysis (i.e., individuals instead of teams), or the issues that arose with the measurement model (i.e., lack of convergent and discriminant validity for the reflective items).

As a result of this study, we wish to note the following contributions and lessons learned. First, given the differences and issues in the measurement model between the original study and the replication, it bears repeating that adapting items to new contexts can impact the results of the study (Straub, Boudreau, & Gefen, 2004; Straub, 1989) Choi et al. (2010) disclosed some challenges with their original measurement model (e.g., cross-loadings, suggesting a lack of discriminant validity), and these issues can be exacerbated when adapting items for a new context. Second, we note that we confirm the important mediating role of Transactive Memory Systems in the relationship among IT support, knowledge sharing, and knowledge application. This important finding by Choi et al. (2010) is further confirmed by the replication. Third, as future research examines the relationships among knowledge sharing, knowledge application, and team performance, it is important to consider the context of the study. While knowledge sharing only had an indirect effect on team performance in a general team context (i.e., Choi et al. 2010), in an IT project team context, we found a direct effect between knowledge sharing and team performance. It may be that the type of team influences whether knowledge sharing has a direct or indirect effect on team performance.

Lastly, we wish to share the potential contributions of this study to both the communities of practice and research. Results of this study may provide an idea of a potential direct value of IT support on the development of transactive memory systems in IT project teams, knowledge sharing and application processes in more contemporary contexts. That is, IT project teams may simply need to focus more on the development of transactive memory systems as it would imply that knowledge processes would follow naturally afterwards. IT support, whether meant for knowledge processes or not, inherently enhances knowledge processes via a more developed transactive memory system in the project team. As for the research community, our findings may suggest additional evidence for validation of the original study findings based on our replicated findings, but also calls for attention to be mindful of slight differences in team characteristics that may impact the measurement of, and effects between, constructs. This study also identifies the potential similarities and differences that may occur when replicating studies at different levels of analysis. In this study, we examine the perceptions at an individual-level within a team, and the findings have similarities to the original study which considered the team-level perspective. Conducting methodological replications at differing levels of analysis may offer new insights on boundary conditions for theories and models related to team-level phenomena.

References

Ajmal, M., Helo, P., & Kekäle, T. (2010). Critical factors for knowledge management in project business. *Journal of Knowledge Management, 14*(1), 156-168.

Alavi, M., & Leidner, D.E. (2001). Research commentary: Technology-mediated learning—A call for greater depth and breadth of research. *Information Systems Research, 12*(1), 1-10.

Alavi, M., & Tiwana, A. (2002). Knowledge integration in virtual teams: The potential role of KMS. *Journal of the American Society for Information Science and Technology, 53*(12), 1029-1037.

Choi, S.Y., Lee, H., & Yoo, Y. (2010). The impact of information technology and transactive memory systems on knowledge sharing, application, and team performance: A field study. *MIS Quarterly, 34*(4), 855-870.

Dennis, A.R. & Valacich, J. (2015). A replication manifesto. *AIS Transactions on Replicaton Research, 1*(1), 1-4.

Desimone, J.A., Harms, P.D., & Desimone, A.J. (2014). Best practice recommendations for data screening. *Journal of Organizational Behavior,36*(2), 171-181.

Galloway, A. (2004). Intimations of everyday life: Ubiquitous computing and the city. *Cultural Studies, 18*(2-3), 384-408.

Gasik, S. (2011). A model of project knowledge management. *Project Management Journal, 42*(3), 23-44.

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equations Modeling (PLS-SEM).* Los Angeles: SAGE.

Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C., & Bigham, J. (2018). A data-driven analysis of workers' earnings on Amazon Mechanical Turk. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (pp. 1-14).

Huang, J. L., Curran, P. G., Keeney, J., Poposki, E.M., & Deshon, R.P. (2012). Detecting and deterring insufficient effort responding to surveys. *Journal of Business and Psychology, 27*(1), 99-114.

Huang, Q., Liu, H., & Zhong, X. (2013). The impact of transactive memory systems on team performance. *Information Technology & People, 26*(2), 191-212.

Karlsen, J.T., & Gottschalk, P. (2004). Factors affecting knowledge transfer in IT projects. *Engineering Management Journal, 16*(1), 3-11.

Leonardi, P.M., & Treem, J.W. (2012). Knowledge management technology as a stage for strategic self-presentation: Implications for knowledge sharing in organizations. *Information and Organization, 22*(1), 37-59.

Lewis, K., & Herndon, B. (2011). Transactive memory systems: Current issues and future research directions. *Organization Science, 22*(5), 1254-1265.

Liang, D. W., Moreland, R., & Argote, L. (1995). Group versus individual training and group performance: The mediating role of transactive memory. *Personality and Social Psychology Bulletin, 21*(4), 384-393.

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of enterprise systems: The effect of institutional pressures and the mediating role of top management. *MIS Quarterly, 31*(1), 59-87.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114-121.

Mason, W., & Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior Research Methods, 44*(1), 1-23.

Miller, B., & Chiodo, B. (2008). Academic entitlement: Adapting the equity preference questionnaire for a university setting. Paper presented at the *Southern Management Association* M*eeting*, St. Pete Beach, FL.

Nelson, K.M., & Cooprider, J.G. (1996). The contribution of shared knowledge to IS group performance. *MIS Quarterly, 20*(4), 409-432.

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science, 5*(1), 14-37.

Obaide, A. (2008, 28-30 June 2008). Management of project knowledge and experiences: The role of technologies and social processes. Paper presented at the *2008 IEEE International Engineering Management Conference*.

Park, J.-G., & Lee, J. (2014). Knowledge sharing in information systems development projects: Explicating the role of dependence and trust. *International Journal of Project Management, 32*(1), 153-165.

Pee, L.G., & Kankanhalli, A. (2016). Interactions among factors influencing knowledge management in public-sector organizations: A resource-based view. *Government Information Quarterly, 33*(1), 188-199.

Pfeffer, J., & Sutton, R.I. (2000). *The Knowing-Doing Gap: How Smart Companies Turn Knowledge into Action.* Harvard Business Press.

Pmbok. (2015). *A Guide to the Project Management Body of Knowledge: PMBOK® Guide* (5th Edition ed.): Project Management Institute.

Podsakoff, P.M., Mackenzie, S.B., Lee, J.-Y., & Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903.

Reich, B.H., Gemino, A., & Sauer, C. (2014). How knowledge management impacts performance in projects: An empirical study. *International Journal of Project Management, 32*(4), 590-602.

Ruggles, R. (1998). The state of the notion*. California Management Review, 40*(3), 80-89.

Schmidt, G.B., & Jettinghoff, W.M. (2016). Using Amazon Mechanical Turk and other compensated crowdsourcing sites. *Business Horizons, 59*(4), 391-400.

Shapiro, G. (1999). Inter-project knowledge capture and transfer: An overview of definitions, tools and practices. *CoPS Innovation Centre Working Paper*(62).

Steelman, Z.R., Hammer, B.I., & Limayem, M. (2014). Data collection in the digital age: Innovative alternatives to student samples. *MIS Quarterly, 38*(2), 355-378.

Straub, D., Boudreau, M.-C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information systems, 13*(1), 24.

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly, 13*(2), 147-169.

Wegner, D.M. (1987). Transactive memory: A contemporary analysis of the group mind. In *Theories of Group Behavior* (pp. 185-208): Springer.

Whelan, E., & Teigland, R. (2013). Transactive memory systems as a collective filter for mitigating information overload in digitally enabled organizational groups. *Information and Organization, 23*(3), 177-197.

Yu, X., & Petter, S. (2014). Understanding agile software development practices using shared mental models theory. *Information and Software Technology, 56*(8), 911-921.

Zhao, X., Lynch Jr, J.G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197-206.

Zigurs, I., Khazanchi, D., & Mametjanov, A. (2008). The practice and promise of virtual project management. In *Virtual Technologies: Concepts, Methodologies, Tools, and Applications* (pp. 177-184). IGI Global.

Appendix A: Survey Items

Table A1 identifies the survey items and the means and standard deviations of the items for the original study and replication study. We performed an independent samples t-test to compare the differences of the means of the original study and the replication study (assuming unequal variances). Items with statistically different means are noted in the table below.

Table A1. Measurement Items, Means, and Standard Deviations

Construct	Item #	Survey Question	Original Study Mean (Std Dev)	Replication Study Mean (Std Dev)
Transactive Memory System	TMS1	Our project team members have specialized knowledge of some aspects of our task.	5.95 (0.50)	6.12 (0.81)*
	TMS2	Our project team members are comfortable accepting procedural suggestions from other team members.	5.46 (0.51)	5.82 (0.92)***
	TMS3	Our project team members trust that other members' knowledge about the project is credible.	5.64 (0.46)	6.03 (0.80)***
	TMS4	Our project team members are confident of relying on the information that other team members bring to the discussion.	5.79 (0.61)	5.89 (0.89)
	TMS5	Our project team members know each other and have the ability to work together in a well-coordinated fashion.	5.80 (0.51)	5.75 (1.03)
	TMS6	Our project team members have the capability to respond to the task-related problems smoothly and efficiently.	5.76 (0.50)	5.90 (0.88)
IT Support	ITS1	Our company provides IT support for collaborative works regardless of time and space.	5.56 (0.54)	5.36 (1.31)
	ITS2	Our company provides IT support for communication among team members.	5.73 (0.45)	5.80 (1.01)
	ITS3	Our company provides IT support for searching for and accessing necessary information.	5.72 (0.51)	5.61 (1.15)
	ITS4	Our company provides IT support for systematic storing of knowledge.	5.55 (0.51)	5.62 (1.20)
Knowledge Sharing	KS1	Our project team members share their work reports and official documents with other project team members.	5.66 (0.59)	5.78 (1.06)
	KS2	Our project team members provide their manuals and methodologies for other project team members	5.73 (0.59)	5.51 (1.16)*
	KS3	Our project team members share their experience or know-how from work with other project team members.	5.81 (0.55)	5.90 (0.93)
Knowledge Application	KA1	Our project team members apply knowledge learned from experience.	5.91 (0.43)	6.25 (0.74)***
	KA2	Our project team members use knowledge to solve new problems.	5.92 (0.45)	6.15 (0.73)**
	KA3	Our project team members apply knowledge to solve new problems.	5.79 (0.45)	6.15 (0.73)***
Team Performance	TP1	The project team's deliverables were of excellent quality.	5.83 (0.71)	5.84 (0.85)
	TP2	The project team managed time effectively.	5.68 (0.77)	5.67 (1.18)
	TP3	The project team met important deadlines on time.	5.84 (0.81)	5.51 (1.12)**

*p < 0.05; **p < 0.01; ***p < 0.001

About the Authors

Gerard De Leoz is an assistant professor of Business Information Technology at the University of Tampa. He obtained his Ph.D. in Information Systems from Baylor University. His primary research stream focuses on exploring team-related issues in information systems project management. He also is performing research in the areas of IS research methodology and large-scale impacts of IT, such as e-commerce and social media. Currently, he has published in major IS conference proceedings and has published his research in premier IS journals such as the *European Journal of Information Systems*. He is an active member of the Association for Information Systems.

Stacie Petter is the Ben H. Williams of Information Systems and Business Analytics at the Hankamer School of Business at Baylor University. Her research focuses on positive and negative impacts of information systems, research methodology, and software project management. Her work appears in outlets including, *Journal of the Association for Information Systems*, *MIS Quarterly*, *Journal of Management Information Systems*, the *European Journal of Information Systems*, among others. She has served as Editor-in-Chief of *The DATA BASE for Advances in Information Systems*, Associate Editor for *MIS Quarterly* and *Information Systems Journal*, and she is currently a Senior Editor for *AIS Transactions on Replication Research* and a member of the editorial review board for the *Journal of the Association for Information Systems*. She has also served as Vice President of Region 1 on the Association for Information Systems Council.