From Trust to Inter-organizational Innovation: The Differential Mediating Roles of IT-based Process and Knowledge Assets

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ABSTRACT
This study examines the relationship between trust, innovation and IT assets in the context of inter-organizational relationships (IORs). We parse two dimensions of inter-organizational IT-based assets – IT-based Process Institutionalizations and IT-based Knowledge Institutionalizations – based on the purposes for which these assets are deployed by the collaborating organizations. Based on prior literature, we also identify two dimensions each of trust, namely competence and benevolent trust; and of innovation, namely incremental and radical innovation. We then develop a model featuring two distinct pathways between trust and innovation: one pathway posits that competence trust between the parties will correspond with IT-based Process Institutionalizations between them and result in outcomes representing incremental innovation; the other pathway posits that benevolence trust between the parties will correspond with IT-based Knowledge Institutionalizations between them and result in outcomes representing radical innovation. We validate this model using meta-analysis and find support for all our hypotheses.

Keywords
Inter-organizational relationships; trust; competence trust; benevolence trust; innovation; incremental innovation; radical innovation; information technology; IT-based Assets; meta-analysis.

INTRODUCTION
Innovation in products, services and technologies is often central to the competitive advantage enjoyed by a business organization. Innovation often emerges as a result of leveraging resources and capabilities that are external to the firm and which the firm accesses by engaging in inter-organizational relationships (IORs) with other firms that possess the desired complementary attributes. Indeed, IORs are generally actuated by the quest for competitive advantage, as embodied in enhanced performance efficiencies, improvement of existing products and services and development of new products and services based on access to new resources and competences. In all such engagements between firms, trust between them is one potent determinant of outcomes; in recent years, the optimal leveraging of information technology is proving to be another.

Despite these evident and well-recognized dynamics involving trust, information technology and innovation-related outcomes in IORs, there is as yet no study known to us, which makes a direct connection between these three sets of constructs. There is on the one hand significant literature linking elements of trust to IT adoption and usage, and on the other hand, a fund of studies examining the role of IT in innovation-related outcomes; yet, these sets of literature have remained hitherto unrelated to each other. In this study, we supply this gap in the literature by linking trust, IT-based Assets and innovation-related outcomes with each other to present an integrated understanding of the relationship between these sets of constructs. While doing so, we also make a second significant contribution to MIS literature: we typify IT-based inter-organizational resources into two classes – IT-based Process Institutionalization (ITP) and IT-based Knowledge Institutionalization (ITK) – depending on the purposes for which they are used. Based on prior literature, we identify two dimensions of trust – competence (TC) and benevolence (TB) – and two types of innovation – incremental (INC) and radical (RAD) – and delineate two distinct pathways, depicted in figure 1, between trust and innovation.

The rest of the paper is organized as follows: in the next section, we summarize in three subsections the conceptual background and past literature which informs our study. In the section after that, we present the research model and develop the hypotheses related to that. In the following section, we detail the methodology followed by us in collecting and analyzing the data.
CONCEPTUAL BACKGROUND

Our research draws upon three streams of management literature: Trust, IT Usage and Innovation.

Trust

Prior research recognizes trust as a potent factor in relationships both within and between organizations (Zaheer, McEvily, & Perrone, 1998). Trust is a rather amorphous concept in management literature, often confounded with concepts like commitment, cooperation, confidence and predictability; detailed discussions parsing out these ideas obtain in Mayer, Davis, & Schoorman (1995) and Bhattacharya, Devinney, & Pillutla (1998). A widely popular framework of trust parses trust into three types: ability, benevolence and integrity (Mayer, et al., 1995), with ability being confidence in the competence of the other party, benevolence being affect-based goodwill, and integrity representing the congruence of worldview of the two parties. Whether the context is within or between organizations, a willingness to be vulnerable vis-a-vis the other party has been repeatedly recognized as being the essence of trust (Bigley & Pearce, 1998; Rousseau, Sitkin, Burt, & Camerer, 1998). Two broad dimensions have been identified in prior literature (McAllister, 1995) as forming the basis for this willingness to be vulnerable: affective trust, being feelings of mutuality and goodwill, referred to as affective trust; and cognitive trust, being the assessment that the other party is capable of doing the required work competently. Based on this extensive literature, we categorize trust into two types – competence trust and benevolence trust – defined as stated in table-1. These categories correspond to the affective-cognitive framework (Das & Teng, 2001; Hagen & Choe, 1998) identified in prior literature described above, with competence trust representing cognitions of competence and benevolence trust representing affect-based goodwill between the two parties.

Numerous studies examine trust and its various paradigms as related to IT, often examining the role of trust in technology adoption and usage. Gefen (2004) makes the link between trust and outcomes of ERP implementation within an organization, while Hart & Saunders (1998) examine trust in connection to EDI usage between partner firms. Kim & Prabhatkar (2000) examines the adoption of internet banking from the trust perspective, and a number of studies explore aspects of trust as related to e-commerce (Bhattacharya, et al., 1998; Gefen, 2004; Ratnasingham & Kumar, 2000). Thus, studies have examined trust both within and between organizations and in in the latter case, both in the B2B and B2C contexts. We add to this literature examining the interplay of trust and information technology in the inter-organizational context.

IT Usage

The foundational concern of the field of Management Information Systems is to examine the antecedents and consequences of IT usage in various settings. While much literature on antecedence is based on the technology acceptance model (Davis, 1989) and its extensions, there is significant literature which approaches that issue from the perspective of social relationships. Issues such as trust (Jarvenpaa & Leidner, 1999) and interpersonal traits (Brown, Scott Poole, & Rodgers, 2004) have engaged the attention of researchers in the context of IT usage. Status-seeking and the expectation of pleasure or entertainment, in addition to perceptions of utility, have been identified as motivators of IT usage (Venkatesh & Brown, 2004). Other studies have examined the emergence from IT usage of outcomes related to social dynamics. These include skill development (Majchrzak, Beath, Lim, & Chin, 2005), organizational identification (Wiesenfeld, Raghuram, & Garud, 1999) cohesiveness in virtual teams (Jarvenpaa, Shaw, & Staples, 2004) and inter-organizational learning (Scott, 2000). IT usage has been shown to have an impact not only on group and organizational outcomes but also on work processes within the group and organization. IT usage may cause new practices and process structures to be put in place (Knox, O'Doherty, Vurdubakis, & Westrup, 2007) and may cause a move from technology adoption to technology adaptation (Majchrzak, Rice, King, Malhotra, & Ba, 2000). Other studies link IT usage to competitive advantage, as when Rai & Xinlin (2010) examine leveraging IT capabilities and process capabilities to enhance IORs and when Pavlou and El Sawy (2010) examine how the capacity of IT to enhance improvisation capability leads to competitive advantage. It is noteworthy that all of these outcomes embody innovation or change to some degree, and are all thus directly relevant to our study.

In this study, we draw a connection between these two sets of literature that have remained separate hitherto: the literature which examines the social dynamics that are antecedent to IT usage, and the literature examining the effects of IT usage, specifically in terms of innovation-related outcomes. We examine two specific dimensions of trust between organizations as antecedent for the establishment of mutual IT-based assets between them and then examine the outcomes emerging from the usage of these assets in terms of innovation in outcomes. In doing so, we also draw a connection between the antecedents of
IT usage, as located in various types of trust, and the effects of such usage, as manifested in various types of innovation-related outcomes.

Certain innate qualities of IT systems have been identified in prior literature as informing their impact on organizational outcomes. In the context of individual firms, Sambamurthy et al. (2003) identify two sets of IT-based qualities – process reach & richness and knowledge reach & richness – that have disparate repercussions on outcomes, and suggested that considerations of these qualities should inform a firm’s IT deployment strategy. Based largely on insights gleaned from that study, we identify two types of qualities in IT-based systems used in the context of IORs: IT-based process assets and IT-based knowledge assets. The functional definitions of these constructs are given in table-1; we conceptualize IT-based process assets as being those IT-based assets that facilitate the performance of the routine tasks for which the IOR exists; while IT-based Knowledge Assets are conceptualized as those that facilitate non-routine and strategic inter-organizational interaction, such as strategic information sharing. We examine how these two different types of mutual IT-based Assets relate to the types of trust existing between the organizations and the types of outcomes that emerge from the IOR.

Innovation

The study of innovation in its various aspects comprises an extensive field of research in management. While various classifications of innovation have been proposed, two closely related paradigms are predominant today. One paradigm classifies innovation into two types – incremental and radical – based on the extent and type of novelty (Dewar & Dutton, 1986; Subramaniam & Youndt, 2005). Incremental innovations are those that refine or reinforce existing products or services, while radical innovations constitute major transformations of existing products or services (Subramaniam & Youndt, 2005). The other paradigm focuses on the purpose and effect of the innovation to classify it as either explorative or exploitative (Gupta, Smith, & Shalley, 2006; March, 1991). Exploitative innovations are those innovations which “involve improvements in existing components and build on the existing technological trajectory, whereas exploratory innovation involves a shift to a different technological trajectory” (Benner & Tushman, 2002, p.679). Similarly He and Wong (2004) define exploitative innovation as “technological innovation activities aimed at improving existing product-market domains” and exploratory innovation as “technological innovation aimed at entering new product-market domains.”

There is thus striking congruence between these two classifications of innovation: innovations that improve and refine existing products and services are incremental in nature and conduce to the better exploitation of existing, established offerings; while innovations that effect major transformations of goods and services are radical in nature and produce new offerings which enable the exploitation of new opportunities and market domains. At a more subtle level, there is binary commonality in these classifications from the perspective of examining the learning processes involved and the types of knowledge drawn upon to create the innovation: radical innovation involves extensive learning and exploration activities and requires the application of new knowledge, while incremental innovation involves intensive study of existing systems, routines and offerings and development of novel exploitation mechanisms that harness existing strengths (Gupta, et al., 2006).

Given our understanding of the congruence of these two paradigms of innovation, we use the classification of incremental and radical innovation as understood in previous literature (Subramaniam & Youndt, 2005) with the constructs defined as stated in table-1, and with the firm understanding that the concepts of exploitation and exploration are intrinsic to and inherent in incremental and radical innovation respectively.

RESEARCH MODEL AND HYPOTHESES

The research model developed by us is presented in figure-1 and the functional definitions of the constructs used in the model are listed in Table 1.

Trust and inter-organizational IT-based institutionalization

As noted in a preceding section, there is substantial literature linking trust to IT adoption and usage (Bhattacharya, et al., 1998; Gefen, 2004; Hart & Saunders, 1998; Kim & Prabhakar, 2000). It can be inferred from this literature that trust plays a pivotal role in determining the paradigms of IT usage: not only does trust influence IT adoption, it also informs the extent and purpose of continued use of available IT-based Assets. We extend this insight further to suggest that the type of trust abiding between the two parties informs the nature of mutual IT-based Assets that two organizations will establish between themselves and the purpose to which existing IT-based Assets are employed in inter-organizational interactions. We hypothesize that the two types of trust delineated above correspond with distinct qualities in the IT systems existing between them and the use to which available IT-based Assets are employed by them.
Table 1. Operational definitions of the constructs used in the research model

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Construct</th>
<th>Definition</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Benevolence Trust</td>
<td>Feelings of mutuality, empathy and goodwill existing between parties</td>
<td>Bhattacharya et al. (1998), Zaheer et al. (1998)</td>
</tr>
<tr>
<td>2</td>
<td>Competence Trust</td>
<td>The expectation of competent discharge of role performance from the other party</td>
<td>Barber (1983), Das and Teng (2001)</td>
</tr>
<tr>
<td>3</td>
<td>IT-based Process Institutionalization</td>
<td>IT-based routines and systems to facilitate value chain operations between the interacting parties and IT usage for such purposes</td>
<td>Sambamurthy et al. (2003)</td>
</tr>
<tr>
<td>4</td>
<td>IT-based Knowledge Institutionalization</td>
<td>IT-based channels and systems to facilitate strategic knowledge-intensive interaction between the transacting parties and IT usage for such purposes</td>
<td>Sambamurthy et al. (2003)</td>
</tr>
<tr>
<td>5</td>
<td>Incremental Innovation</td>
<td>Innovations that refine and reinforce existing products, services and capabilities</td>
<td>Subramaniam and Youndt (2005)</td>
</tr>
<tr>
<td>6</td>
<td>Radical Innovation</td>
<td>Major transformations of existing products, services or capabilities.</td>
<td>Chandy and Tellis (2000), Subramaniam and Youndt (2005)</td>
</tr>
</tbody>
</table>

Competence trust is the expectation of proper discharge of role performance from the other party. It is based on cognitions of professional reliability and dependability. IORs are built on pragmatic considerations involving access to goods and services that one requires for one’s own efficient functioning. Perceptions of competence and reliability are therefore arguably latent in any IOR at inception. It may be surmised further that the existence of competence trust between organizations will correlate with the use of IT systems predominantly for purposes where the perceived competence of the other party can be more effectively garnered with IT usage. That field of activity is manifestly the routine operational functions and processes for which the IOR has been established. A positive cycle of competence and reinforced IT usage for routine purposes may ensue; for instance, in buyer-supplier relationships, consistent competence of the buyer in making accurate requirement forecasts results in suppliers being able to handle inventories more efficiently, thus building competence trust between them. This may induce the two parties to invest in IT assets required for the discharge of such routine functions between them, for instance by substituting periodic person-to-person information sharing regarding inventory levels with an IT system designed to automatically convey such information, and may result in implementation of specific EDI systems for that purpose. Such IT systems and usage are consonant with our definition of IT-based process institutionalization since they will be used, and meant for use, in routine processes and functions between the organizations. Based on this discussion, we hypothesize that:
Benevolence trust refers to the affect-based feelings of mutuality, empathy and goodwill that may exist between two parties. It is associated with the perception that the other party means well to the trustor, acts and negotiates fairly, and will behave similarly in future. It is the antithesis of opportunism and embraces the notion that the other party will desist from behavior harmful to oneself even in the presence of adverse incentive (Hart & Saunders, 1998). These perceptions conduce to a greater willingness to take risks where the other party is involved, and indeed, benevolent or affective trust has been shown to mitigate both business risk and performance risk in IOR contexts (Das & Teng, 1998). Benevolence and affective trust also engender a favorable disposition to enhanced levels of interaction and impact both the extent and the diversity of purposes to which mutual IT-based Assets are employed (Hart & Saunders, 1998). Such purposes are likely to be often strategic in nature; benevolence trust conduces to the ready sharing of knowledge that might benefit the other party. Kumar & van Dissel (1996) identify a class of systems, termed “networked IOS systems,” that facilitate such interactions. Benevolence trust also enhances openness and transparency between parties and encourages exchanges of knowledge as distinct from, and superior to, basic information. All of these dynamics benefit from information technology; for instance, in retailer-manufacturer relationships, parties may opt for a system which relays sales information directly to the manufacturer and parties in IORs may discuss market expansion insights and strategies with each other. Thus, the presence of benevolence trust is likely to correlate with the existence of IT systems facilitating strategic exchanges and the use of IT systems for non-routine interactions that may benefit one or both parties in ways that are not necessarily related to the routine operations carried out between them; in other words, of IT-based knowledge institutionalization as defined by us. Based on this discussion, we hypothesize that

H-2: There is a positive relationship between the existence of Benevolence Trust and of IT-based Knowledge institutionalization between parties in IORs.

Innovation and inter-organizational IT-based institutionalization

In a preceding section, we have parsed out two types of innovation, namely incremental and radical, and delineated the characteristics of each. A significant section of MIS literature examines the role of IT with reference to innovation. While much of this literature concerns itself with application development and improvements in IT offerings themselves, a large section deals with the role of IT in facilitating innovation. This includes not only new product development, but also studies examining the salient role of IT in instituting new work processes and innovative organizational structures and the resultant outcomes. Thus, the ambit of IT in innovation literature is wide, ranging from examining the dynamics of virtual teams to BPOs to new product development to application development. In all of these instances, the paradigm of incremental versus radical innovation may be applied to categorize innovations.

Incremental innovations are those that improve and refine existing products and services, along existing technological paradigms, based on intensive study of whatever already obtains, and result in better exploitation of existing, established offerings. These characteristics are manifestly associated with those of IT-based process institutionalization (ITP), which comprises routine process operations focused on systemized replication and repetition of set routines. They therefore provide scope for personnel to develop intensive understandings of that process. This dynamic is reinforced by the fact that ITP is underpinned by competence trust between the two parties – therefore interactions characteristic of and facilitated by ITP are typically related to the focal process operations and exchange of information will tend to deepen and enhance process-related understandings. Any innovations emerging from such an environment will likely be concerned with the nuanced improvement of the focal interest rather than a quantum shift in basic paradigm. Based on this discussion, we hypothesize that:

H-3: In IORs, there is a positive relationship between the existence of IT-based Process institutionalization and Incremental Innovation.

Radical innovations involve major transformations of existing products or services, based on extensive application of external knowledge and learning, often involving a shift in existing technological paradigms, and aimed at exploration of new opportunities and market domains. These characteristics are clearly associated with those of IT-based knowledge institutionalization (ITK), which comprises interactions and systems that facilitate non-routine, strategic exchanges and interventions. At its most advanced, ITK can include IT systems providing utmost transparency and openness in operations between the two parties, possibly working on shared platforms with access to the same systems of data capture, analysis and decision support. Even at its most rudimentary, ITK would include systems facilitating interaction between personnel to exchange strategic information and communicate insights, forecasts and plans. Such interaction would be the richer, more timely, potent and insightful due to the fact that it would be actuated, as we have hypothesized, by benevolent, affect-based
trust. Further, such interaction and knowledge sharing, being idiosyncratic, would bring to the table a much wider range of experience, training and boundary-spanning expertise. All of these factors would conduce improvements that will likely be of significant novelty. We therefore hypothesize that:

\[ H-4: \text{In IORs, there is a positive relationship between the existence of IT-based Knowledge institutionalization and Radical Innovation.} \]

**DATA AND METHODOLOGY**

Meta-analysis is a survey procedure wherein data is collected from existing research studies that examine issues and constructs germane to the research question. The procedure aggregates the findings of numerous existing studies and standardizes them quantitatively in a manner that allows for overall inferences to be drawn (Lipsey & Wilson, 2001).

<table>
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<tr>
<th>Sl. No.</th>
<th>Author and Year of Publication</th>
<th>Journal</th>
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<tbody>
<tr>
<td>3</td>
<td>Daekwan &amp; Lee (2010)</td>
<td>Decision Sciences</td>
</tr>
<tr>
<td>4</td>
<td>Fang (2011)</td>
<td>Organization Science</td>
</tr>
<tr>
<td>7</td>
<td>Jean, Sinkovics, &amp; Kim (2010)</td>
<td>Journal of International Marketing</td>
</tr>
<tr>
<td>8</td>
<td>Kang, Mahoney, &amp; Tan, (2009)</td>
<td>Strategic Management Journal</td>
</tr>
<tr>
<td>9</td>
<td>Klein &amp; Rai (2009)</td>
<td>MIS Quarterly</td>
</tr>
<tr>
<td>11</td>
<td>Koh et al. (Koh, et al., 2004)</td>
<td>MIS Quarterly</td>
</tr>
<tr>
<td>16</td>
<td>Rai &amp; Xinlin (2010)</td>
<td>Information Systems Research</td>
</tr>
<tr>
<td>17</td>
<td>Rai, Patnayakuni, &amp; Seth (2006)</td>
<td>MIS Quarterly</td>
</tr>
<tr>
<td>19</td>
<td>Saeed, Malhotra, &amp; Grover (2005)</td>
<td>Decision Sciences</td>
</tr>
<tr>
<td>23</td>
<td>Subramani (2004)</td>
<td>MIS Quarterly</td>
</tr>
<tr>
<td>25</td>
<td>Vijayasarathy &amp; Robey (1997)</td>
<td>Information and Management</td>
</tr>
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</table>

Table 2. Papers comprising the meta-analytic sample
While some amount of subjectivity does exist in meta-analysis, for instance in coding of constructs, the fact that actual analysis in this methodology follows a strictly quantitative procedure makes meta-analysis less subjective than other forms of review. The researchers considered meta-analysis a suitable procedure to follow to get a sense of the overall view on the questions of interest; theoretical development of the ideas examined in this manner could later be validated by other empirical methods.

The meta-analytic procedure we followed was as described in Lipsey & Wilson (2001) and Viswesvaran & Ones (1995) and followed in numerous prior studies (Geyskens, Steenkamp, & Kumar, 2006; Kirca et al., 2011). After formulating our research question, we identified the constructs of interest and revisited the literature to understand the various perspectives from which prior researchers had approached these constructs and the various operationalizations that resultanty obtain. We defined each construct formally as presented in table-1 and developed a coding sheet which detailed the guidelines that would govern the coding process. This document contained guidelines on what factors would result in the inclusion or exclusion of a paper or study in the meta-analytic set; what data to collect; what characteristics would mark a variable in a given study for being coded as one of the constructs of interest to us; and what markers would result in the exclusion of that variable.

_Meta-analytic Dataset._ Having established the functional definitions of each construct, we searched journals pertaining to the fields of Information systems, strategic management, operations management and marketing, restricting our search to scholarly papers published in the last 20 years. Over 500 papers _prima facie_ relevant to IORs obtained; these papers were examined further to ensure that several requirements were met: firstly, the paper must be empirical and quantitative, not qualitative or conceptual; secondly, regression data must be available; thirdly, IT usage at the inter-organizational level must obtain; finally, two or more of the variables in each paper must pertain prima facie to a construct of interest to our study, and one of them must be IT-based, in order to yield a relationship of interest. A total of 25 papers met these exacting criteria and were used in our meta-analysis; these are listed in Table 2.

_Coding of variables and data collection._ The first author perused each paper in the set to code variables occurring in each paper, where suitable, as one of the six constructs of interest. For papers that provided their survey instruments, coding judgment was based on survey items. For papers that did not provide instruments or relied on non-survey data, coding judgment was based on the definitions and understandings of each construct as stated in that paper. Some variables were reverse-coded so that the correlation sign could be correctly specified; for instance, opportunism was coded as the negative of benevolence trust. At this point, required quantitative data was collected from each paper. This included correlation coefficients pertaining to the specific relationships of interest; reliability estimates of each variable, where available; and the sample size of each study

_Meta-analysis procedure_

Thus, we recorded the correlation coefficients for each relevant bivariate relationship and the reliability estimates of each variable in each dataset. We used this data to correct the correlation coefficients using the formula given in Lipsey & Wilson (2001):

\[
ES_i = \frac{ES}{\sqrt{r_{xx} r_{yy}}},
\]

Where \(ES_i\) is the raw correlation effect size taken from each dataset and \(r_{xx}\) and \(r_{yy}\) are the reliability estimates of the two relevant variables. This correction is done to decrease the unreliability of the variables contributing to the correlation. In cases where the reliability estimate was unknown, the average unreliability value for that variable type was imputed. The next step in the meta-analytic procedure was to transform the corrected correlation values using Fisher’s Z-transform formula, being:

\[
ES_{Z} = 0.5 \log \left[ \frac{1+r}{1-r} \right],
\]

Where \(r\) is the corrected correlation coefficient and \(\log_e\) is the natural algorithm (Lipsey & Wilson, 2001). It often happened that two or more variables in a dataset to be coded as one of the constructs of interest to us, say benevolent trust (TB). In such cases, we calculated the average of the transformed values of the relationships containing such variables. Thus, each dataset would contain exactly one effect size for any relationship of interest. The average values were transformed back into standard correlation form by using the formula to inverse of the \(Z_r\)-transformation, being:
Where \( r \) is the individual or mean correlation (from now on referred to as the “Effect Size” in this paper), \( ES_Z_r \) is the corresponding individual or mean \( Z \)-transformed correlation, and \( e \) is the base of the natural logarithm or approximately 2.718. The \( r \) calculated here is the critical Effect Size statistic for each relationship in each dataset which makes aggregations and analysis across studies possible. In order to perform such operations, we created separate tables pertaining to each bivariate relationship between two constructs. These tables contained, in each row, the effect sizes for that relationship derived from each individual dataset. This process of simultaneously disaggregating each study into its constituent relationships and aggregating those relationships into single tables makes comparisons and other analyses possible within and across relationships. In each of these tables, we performed operations to ascertain the Weighted Mean Effect Size (WMES) and Standard Error (SE) for the relationship, and used that to construct a confidence interval for the effect size values. At the 95% level, the confidence interval is constructed by using the formula \( CI = WMES \pm 1.96 \times SE \). The formula used to calculate WMES was:

\[
WMES = \frac{\sum (n - 3) \times ES}{\sum (n - 3)}
\]

While the Standard Error was calculated using the formula:

\[
SE = \sqrt{\frac{1}{\sum (n - 3)}}
\]

Where ‘\( n \)’ is the sample size of each dataset. We then tested the effect size distribution for homogeneity. In a homogeneous distribution, the dispersion of the effect sizes around their mean value does not exceed sampling error. We based the homogeneity test on the \( Q \) statistic, which is distributed as a chi-square with \( k - 1 \) degrees of freedom where \( k \) is the number of effect sizes. The formula used to calculate \( Q \) was:

\[
Q = \sum w_i (ES_i - \overline{ES})^2
\]

Where \( ES_i \) is the individual effect size for \( i = 1 \) to \( k \), \( \overline{ES} \) is the weighted mean effect size over the \( k \) effect sizes, and \( w_i \) is the individual weight for \( ES_i \). We compared the calculated \( Q \) values with critical values for a chi-square with \( (k - 1) \) degrees of freedom from standard tables. The presence of a significant \( Q \)-statistic would suggest that the effect sizes are not estimating the same population mean.

Next, to address the publication bias problem often associated with meta-analysis (Lipsey & Wilson, 2001; McDaniel, Rothstein, & Whetzel, 2006), we calculated the Fail-safe \( k \) statistic, which refers to the number of studies with null effects needed to reduce a statistically significant meta-analytic effect to non-significance (Sedikides & Ostrom, 1988). For a 5% significance level, the fail-safe \( k \) is calculated using the formula:

\[
k = \frac{Z^2}{(2.33)^2} - 1
\]

Where the \( Z \)-value is calculated using the formula

\[
Z = \sum (ES_i \times \sqrt{n_i})
\]

where \( ES_i \) is the Effect Size of the relevant bivariate relationship in the \( i^{th} \) dataset and \( n_i \) is the sample size for that dataset.

RESULTS AND DISCUSSION

The results obtained by testing out hypotheses using the meta-analysis procedures described above are summarized in Table 3.
It may be observed in table-3 that the total number of studies analyzed add up to 35, whereas the list of papers mentioned above numbers 25. There are two reasons for this. Firstly, some of the 25 papers contained more than one dataset each; for instance, a paper may contain two regression tables pertaining to responses received from buyers and suppliers respectively. In that case, each dataset may yield relationships of interest. Secondly, it was at the level of the individual variable that coding was done as to which of our six constructs of interest a certain variable corresponded to, if at all. It was therefore possible for a study to yield more than one relationship of interest: if a study had two variables, each corresponding to one of the two types of trust, and also two variable corresponding to the two types of IT institutionalization, then that study would yield not one but two relationships, being TC→ITP and TB→ITK. However, if two variables in a study were coded as TC, the average of the corrected Z-transformed values obtained from the two available TC→ITP relationships would be used, as mentioned in the procedure description above. All of this is as per standard meta-analytic procedure. For these reasons, the number of relationships obtaining was large than the number of papers listed in table 2.

Competence Trust → IT-based Process institutionalization. H-1 posits a positive relationship between the existence of TC and ITP. A positive relationship is indeed evident from table-3, with a weighted mean effect size (WMES) of 0.278. While the hypothesis is supported, the effect size is among the lowest in the table; further, due to the small number of studies, the Q statistic is less than chi-square table value; null hypothesis regarding homogeneity cannot be rejected. Also, the failsafe k, being the number of studies required to invalidate these findings, is relatively low at 36. While support for the hypothesis is gratifying, the relatively deficient robustness of the result is dismaying. We suggest that the existence of ITP, while no doubt actuated by perceptions of confidence, may be sustained by circumstantial compulsions in the face of disenchantment with the performance and competence of the other party. Therefore the existence of ITP resources may not always correlate to the currency of competence trust between the two parties.

Benevolence Trust → IT-based Knowledge institutionalization. H-2 receives robust support from the data, whether in terms of WMES (0.329), the test for homogeneity, the failsafe k, or indeed the number of studies where the relationship is discerned, which is the largest in this study. We infer that the existence of benevolence trust and ITK do correlate positively. It seems intuitive in hindsight that the dynamic which possibly undermined the TC→ITP relationship can hardly obtain in this case; benevolence trust would not be evident in respondent responses in cases where disenchantment existed. This relation is robustly established; from the practitioner perspective, it indicates that in cases where benevolence (affect-based) trust exists, there is a tendency among managers to deploy IT assets that can be used for non-routine, strategic purposes.

IT-based Process institutionalization → Incremental Innovation. H-3 receives very robust support from the data, with both WMES and failsafe k being the highest in the table, and the Q-test being satisfactory. It is clear that ITP and incremental innovations correlate strongly with each other, perhaps even in the absence of the reinforcing that could accrue due to the existence of competence trust. We can infer that routine and repetitive processes and operations have strong dynamics that produce minor improvements and innovations almost by default; this insight may produce a fruitful field of future inquiry.

IT-based Knowledge institutionalization → Radical Innovation. H-4 is supported by the data and quite robustly so, with a failsafe k of 108 and a satisfactory Q statistic. However, the WMES, while positive, is among the lowest in the table. We suggest that strategic exchanges between organizations are informed by pragmatic considerations that are not easily disregarded even when benevolence trust strongly exists. Also, such exchanges are generally idiosyncratic, and where structured ITK systems exist, their usage probably grows routinized and banal with time. Despite these factors, the hypothesis is supported, indicating the strength of this association.

### Table 3. Results of the meta-analytic study.

<table>
<thead>
<tr>
<th>Hypotheses and Relations</th>
<th>Results</th>
<th>No. of studies</th>
<th>Total sample n</th>
<th>WMES</th>
<th>SE</th>
<th>95% CI</th>
<th>Q</th>
<th>Failsafe k</th>
</tr>
</thead>
<tbody>
<tr>
<td>H-1 TC→ITP Supported</td>
<td>4</td>
<td>835</td>
<td>0.278</td>
<td>0.035</td>
<td>(0.21, 0.346)</td>
<td>2.31</td>
<td>36.57</td>
<td></td>
</tr>
<tr>
<td>H-2 TB→ITK Supported</td>
<td>12</td>
<td>1433</td>
<td>0.329</td>
<td>0.027</td>
<td>(0.277, 0.312)</td>
<td>66.22</td>
<td>310.65</td>
<td></td>
</tr>
<tr>
<td>H-3 ITP→INC Supported</td>
<td>10</td>
<td>1464</td>
<td>0.404</td>
<td>0.026</td>
<td>(0.352, 0.455)</td>
<td>40.61</td>
<td>338.32</td>
<td></td>
</tr>
<tr>
<td>H-4 ITK→INR Supported</td>
<td>9</td>
<td>859</td>
<td>0.278</td>
<td>0.035</td>
<td>(0.21, 0.346)</td>
<td>79.91</td>
<td>108.29</td>
<td></td>
</tr>
</tbody>
</table>

*The Q statistic is less than chi-square table value; null hypothesis regarding homogeneity cannot be rejected.*
CONTRIBUTIONS, LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study makes two important contributions to MIS literature: firstly it draws a connection between two hitherto distinct fields of study: the literature which examines various aspects of IT usage as located in social dynamics, and that which examines the effects of such IT usage in terms of innovation-related outcomes. Secondly, while doing so, this study delineates a new and hopefully serviceable classification of IT-based IOR systems and interactions. Further theoretical development of this typology may prove serviceable to several fields of management research, since it is consonant with widely popular classifications of innovation and is also related to the type and paradigms of learning and knowledge sharing involved. Several theoretical extensions of the model suggest themselves. For instance, the moderating role of IT in the focal relationships can be examined in addition the mediating role delineated here. Further, the correlation of each dimension of trust on both types of IT Institutionalization can be examined, as can the correlation of the latter on both dimensions of innovation. The model can be revisited from the perspective of strong versus weak ties existing between the organizations. From a practitioner perspective, the results of this study are also relevant to business managers in that, based on the type of innovative performance they wish to achieve, they could think in terms of instituting the appropriate IT-based systems and routines conducive to that, and make efforts to engender the appropriate type of trust.

This study has some limitations, the most important of which arises from the fact that we searched for published studies in major journals that included one or more relevant variables: the problem of “publication bias” (Lipsey & Wilson, 2001; McDaniel, et al., 2006) potentially exists at this stage. By calculating and providing the Failsafe k for each relationship, we have sought to quantify the effect of such bias and the results are encouraging. Yet expansion of paper set and the inclusion of unpublished studies can only improve robustness.

REFERENCES


