Individual And Collective Innovative Use Of Enterprise System- Mediating Role Of Collective Learning

Yumei Luo  
*School of Management, Fudan University, ShangHai, China, and School of Business management and Tour management, Yunnan University, Kunming, China, luoyumei@fudan.edu.cn*

Hong Ling  
*School of Management, Fudan University, ShangHai, China, hling@fudan.edu.cn*

Cheng Zhang  
*School of Management, Fudan University, ShangHai, China, zhangche@fudan.edu.cn*

Yunjie Xu  
*School of Management, Fudan University, ShangHai, China, yunjiexu@fudan.edu.cn*

Follow this and additional works at: [http://aisel.aisnet.org/pacis2012](http://aisel.aisnet.org/pacis2012)

**Recommended Citation**  
[http://aisel.aisnet.org/pacis2012/20](http://aisel.aisnet.org/pacis2012/20)

This material is brought to you by the Pacific Asia Conference on Information Systems (PACIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in PACIS 2012 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.
INDIVIDUAL AND COLLECTIVE INNOVATIVE USE OF ENTERPRISE SYSTEM- MEDIATING ROLE OF COLLECTIVE LEARNING*

Yumei Luo, School of Management, Fudan University, ShangHai, China, and School of Business management and Tour management, Yunnan University, Kunming, China, luoym@fudan.edu.cn

Hong Ling, School of Management, Fudan University, ShangHai, China, hling@fudan.edu.cn

Cheng Zhang, School of Management, Fudan University, ShangHai, China, zhangche@fudan.edu.cn

Yunjie Xu, School of Management, Fudan University, ShangHai, China, yunjie@fudan.edu.cn

Abstract

Although information system researchers have long recognized the possibility for collective-level information system use patterns and outcomes to emerge from individual-level IT use behavior, few have empirical the key factors involved in this individual-collective innovative use process. This study builds a research model drawing on the concepts to investigate how between individual innovative use in group influences collective innovative use of enterprise systems. And this study argues that collective learning plays the role of interactive processing among individuals, such that it can mediate the effect of individual innovative use on collective innovative use. To test the research hypotheses, a field study is conducted on 200 users in 55 work group of different enterprise in China. The results indicated that individual innovative use in group has an effect on collective innovative use, and the effect of individual innovative use on collective innovative use are mediated by collective learning.

Keywords: individual Innovative Use, collective innovative use, Collective Learning, Enterprise System

*Supported by Natural Social Science Foundation of China (70972047)
INTRODUCTION

How information technology is utilized has been a central question for the information Systems research community (Benbasat and Zmud 2003). This question becomes particularly crucial in organizational settings, as IT use processes have been recognized as an important pathway for organizations to harvest values from IT investments (Jasper et al. 2005). Empirical evidence suggests that very few features of systems are actually used and that task or technology-related extensions to those features are rarely if ever used (Davenport et al. 1998; Lyytinen and Hirschheim 1988; Rigby et al. 2002). Large system implementations often fail to meet expectations partly because firms are not fully leveraging the potential value of them (Zmud 2005) and underutilization of the implemented IS (Jasper et al. 2005), which has recently attracted much attention from practitioners.

Innovative use of enterprise system (ES) has been a critical issue exploring value of ES (Jasper et al. 2005). Innovative use belongs to post-adoption stage where more extended use of system features can occur. Innovative use means that users approaching systems more mindfully means that users are getting more out of complex systems and therefore delivering more benefits to the organization. So, the current research will take a more in-depth look at how users can innovatively use in their approach to systems in the post-adoption stage of system implementation.

Also, we can see that many of ES are complex integrated systems that span many business functions and require coordination among users. And another feature of ES today is configurability that results of the processing of co-adaptation between employee and system (Beaudry and Pinsonneault 2005). The functional complexity of modern IS allows employees to apply these technologies extensively and/or creatively to support task activities more fully (Agarwal and Karahanna 2000; Ahuja and Thatcher 2005; Saga and Zmud 1994; Wang and Hsieh 2006). Moreover, these features of today’s ES pose the need to support users in overcoming knowledge barriers constraining the use of these systems. So support from organizational peers is critical given that formal support mechanisms, such as IT help desks, are often overwhelmed and, in most cases, IT support staff lack business domain expertise that is crucial in fully resolving users’ problems (Govendarajulu 2002). So ES use highlights the dynamic process where individual-level IT use behaviors and interactions collaboratively create collective-level IT use patterns (i.e., bottom-up IT use processes) (Nan 2011).

While systems use has been a common focus among researchers at different levels of analysis, there has been little integration of conceptions across levels. Although IS researchers may have learned a great deal from studying use at a single level, studying organizations one level at a time ultimately leads to unnatural, incomplete, and very disjointed view of how organizations really function in practice (Burton-Jones 2005). And, the empirical research from individual innovative use to collective innovative use is lack.

So, this study attempts to contribute to IS research by proposing a framework specifically suited to the examination of individual-collective innovative use processes. The collective behavior begin with individual behavior and interactive process among individual. So we provide that collective innovative use, in individual level, includes individual behaviors (e.g. individual innovative use). Drawing from dynamic process perspective, which proposes that collective innovative use is an interactive process among people, structures, and interaction processes (Agrèll and Gustafson 1996). This study proposes that collective learning is an interaction process. Hence, individual innovative use can influence collective innovative use via the collective learning. To test the research model and hypotheses, a field survey was conducted in different enterprise in China.

This study provides a better understanding of how individual innovative use can enhance collective innovative use through the mediating role of collective learning. Since this research helps enhance our understanding of the process of collective innovative use of enterprise technology.
2 THEORY DEVELOPMENT

2.1 IS Innovative use

The IS implementation process model was first conceived as consisting of six stages: initiation, adoption, adaptation, acceptance, routinization and infusion stages (Cooper and Zmud 1989)(see Figure 1)

<table>
<thead>
<tr>
<th>Initiation</th>
<th>Adoption</th>
<th>Adaptation</th>
<th>Acceptance</th>
<th>Routinization</th>
<th>Infusion</th>
</tr>
</thead>
</table>

Figure 1 IS implementation process model (Cooper and Zmud 1990)

Infusion refers to the stage where the fullest potential of an IS has been integrated with an organization’s operational and management processes (Jones et al. 2002; Zmud and Apple 1992). From a user’s viewpoint, the potential value of an IS could be realized through three alternative use behaviors: extended use, integrated use, and emergent use (Saga and Zmud 1993). Extended use is users’ applying more of IS features to support a more comprehensive set of tasks at work (Saga and Zmud 1993; Schwarz 2003). Extended use represents a form of exploitative use. Integrated use refers to users’ utilizing IS to establish or enhance work flow linkages among a set of tasks at work. The applicability of integrated use in current IS research is limited probably because it specifically posed restrictions on employees’ task nature. Emergent use means applying IS to accommodate tasks that were not feasible or recognized prior to the application of IS at work. Emergent use, similar to Jasperton et al.’s(2005) individual feature extension and Ahuja and Thatcher’s(2005) ‘trying to innovative with IT’, essentially represents a form of explorative use.

Burton-Jones (2005) provided that innovative use includes two ways to apply the IS. First, employees may engage in exploitative use or endeavor to use more of the available IS functions to support their work (Saga and Zmud 1993; Schwarz 2003). Incorporation of more IS features usually lead to better individual performance, and at the same time, more effective utilization of the implemented IS. Second, employees may engage in explorative use or experiment with the IS and apply it innovatively to enhance their job performance (Ahuja and Thatcher 2005; Jasperton et al. 2005). Explorative use further helps leverage the value potential of the implemented IS to an advanced level (Jasperton et al. 2005).

Innovative usage stage can manifest at both macro and micro levels (Cooper and Zmud 1990). Exploitative use and explorative use do not necessarily occur in sequence but can actually occur in parallel (Cooper and Zmud 1990). Since our study examines innovative stage which include exploitative and explorative use and IS usage behaviors at the both individual and collective level.

In light of the innovative nature of use behaviors and the emphasis on organizational contexts, this paper refers to Individual innovative use as using a technology in an exploitative and explorative manner to support an individual’s task performance. The functional complexity of modern IS allows employees to apply these technologies extensively and/or creatively to support task activities more fully (Agarwal and Karahanna 2000; Ahuja and Thatcher 2005; Saga and Zmud 1994; Wang and Hsieh 2006). The collection are groups that exist within the context of a larger organization, have clearly defined membership, and share responsibility for a team product or service (Hackman 1987). Collective innovative use is defined as adopting innovative behaviors by groups to support group’s task performance.

2.2 Collective learning

In this paper we premise on this social-constructivist view of learning: learners linking new knowledge to their prior knowledge- i.e. learning as a cumulative process: learners constructing new internal representations of the information being presented. Learning is a process by which the learner personalizes new information by giving meaning to it, based upon earlier experiences. Meaning is
seen as rooted in, and indexed by experience (J. S. Brown et al. 1989). Each experience with an idea, and the environment of which that idea is part, becomes part of the meaning of that idea (Duffy and Jonassen 1992). Learning is therefore understood as situated in the activity in which it takes place (J. S. Brown et al. 1989). Whereas the social-constructivist perspectives makes a distinction between the individual cognitive activities and the environment in which the individual is present, the socio-cultural perspective regards the individual as being part of that environment. They point out that learning cannot be understood as a process that is solely in the mind of the learner. Knowledge distributed over mind, body, and its surroundings (Hewitt and Scardamalia 1998) and is constructed in settings of joint activity (Koschmann 1999). Learning is a process of participating in cultural practices a process that structures and shapes cognitive activity. The socio-cultural perspective gives prominence to the aspect of mutuality of the relations between members and emphasizes the dialectic nature of the learning interaction (Sfard 1998). Construction of knowledge takes place in a social context, such as might be found in collective activities.

Edmondson (1999) conceptualize collective learning as an ongoing process of reflection and action, characterized by asking questions, seeking feedback, experimenting, reflecting on results, and discussing errors or unexpected outcomes of actions. It is through these activities that learning is enacted at the collective level. This conceptualization is consistent with a definition of group learning proposed by Argote (1999) as both processes and outcomes of collective interaction activities through which individuals acquire, share, and combine knowledge, but it focuses on the processes and leaves outcomes of these processes to be investigated separately. So we adapted Edmondson definition for this study. Collective learning behaviors consists of activities carried out by team members through which a team obtains and processes data that allow it to adapt and improve. Examples of learning behaviors include seeking feedback, sharing information, asking for help, talking about errors, and experimenting.

### 3 Research Model and Hypotheses

We built upon Hackman (1987) widely accepted input-process-output(IPO) model of collective performance (Ilgen et al. 2005; Salas et al. 2004), which has also been adopted in the innovation literature (West and Anderson 1996). The IPO model therefore serves as a basis for classifying variables that have been studied in primary studies into input and process factors. This study investigates the effects of input factors of collective innovative usage that are exhibited via individual innovative usage. And the process factor is exhibited via collective learning. Specifically, the proposed model is shown in Figure 2. A total of hypotheses are developed herein, of which 3 describe direct relationships (i.e., H1,H2,H3a); and the other are used to depict mediating effects(i.e., H3b).

![Figure 2. Research Model](image_url)

#### 3.1 Effects of individual innovative use on collective innovative use

A key feature differentiating groups from collections of individuals is that in groups, the relational and interactional patterns among the members play a key role (Ellis and Fisher 1994). Hopkins(1964) asserts that “the term ‘aggregate’ is most frequently used to specify that the group is merely the mathematical sum of its parts-of the individuals who compose it.” And he cautions that it is not a group, for a group is based on characteristics aggregate. Thus, it is conceptual limitations to adopting a methodological individualist perspective in group studies(Sarker and Valacich 2010).

Some group researchers who argue that the structure of a group “can be viewed as a series of ongoing, events, and event cycles between the component parts (e.g., individuals)”. The collective structure
that emerges from this interaction (Morgeson and Hofmann 1999). Likewise, Klein et al. (1999) specifically argue that any group activity is influenced by individual members and the interaction. Thus, it is only by taking into consideration both the individual members’ and the group’s perspectives, are we able to understanding “deeper, richer portrait” of group life (Klein et al. 1999).

Multilevel theory provide that the form of collective innovative use include shared and configural constructs. So collective innovative usage is shared and configured among individual innovative use. So, we provide the hypothesis:

H1.individual innovative use influence positively collective innovative use.

3.2 Effects of Collective learning on Collective innovative use

According to Agrell and Gustafson (1996), although the innovation process begins with the production of ideas from individuals, often the innovation will be unfairly abandoned or defeated if these ideas are not properly discussed in a dialogue that involves the whole team.

Based on innovation diffusion theory, the diffusion of innovation should be viewed as an ongoing process. According to Rogers (1995), diffusion of innovation is the process by which an innovation is communicated to the members of a social community through certain channels over time. The collective behavior begins with individual behavior and interactive process among individual.

As mentioned, on the process level, we chose to focus on collective interaction processes (Van Offenbeek and Koopman 1996). Almost all models addressing the issue of promoting collective outcomes such as collective innovation have emphasized the important role of collective interaction processes as key antecedent variables (Hackman 1987; Tannenbaum et al. 1996). In the specific context of promoting collective innovation, empirical results have identified the roles of developing a collective climate of trust and openness, vision and shared objectives, collective collaboration (West and Wallace 1991), and the collective belief in its potency to perform well and attain its goals (Farr and Ford 1990).

In the innovative context, the learning function is more important. Empirical evidence indicates that organizational and collective learning is a prerequisite for the development and adoption of innovation at the organizational level (Argyris 1999). Although not directly investigating innovation, research has revealed that collective learning results in improvements in detecting and identifying problems (Hirokawa 1990), scanning the environment (Ancona and Caldwell 1992), and producing creative solutions (Maier and Solem 1962), all of which might be crucial to collective innovation.

Learning in work is practice-based and participative: embedded in action, not centered in an individual’s head but distributed among activities, continuous interactions and relationships of people (and tools, texts, architecture, etc.) within a system. Learning can be understood as expansion of capacity for more sophisticated, more flexible and more creative action (Fenwick 2008).

For instance, team-learning studies indicate that the collective knowledge generation, dissemination, and implementation have a positive influence on new usage. Therefore, it is hypothesized that:

H2: Collective learning is positively associated with collective innovative use

3.3 Effects of Individual Innovative Use on Collective Learning

Innovation is often linked with the notion of ‘learning’- the ability to acquire and/or create new knowledge, because learning is critical for organization innovation, may it be incremental or radical forms Gupta (Gupta et al. 2006).

Individual innovative use acquire new knowledge to be able to use new IS applications effectively (Sein et al. 2001). Synthesizing the literature, Kang and Santhanam (2003) identify three knowledge domains: application knowledge covering commands and tools embedded in IS applications; business context knowledge covering the use of IS applications to effectively perform business tasks; and
collaborative task knowledge covering how others use the application in their tasks. So the individual would have such a willingness to learn.

Fenwick (1999) investigates learning as knowledge-creation processes on individual and collective levels. The empirical study suggests that conflicts and crises experienced on individual level were some kind of incidental starting points for individual learning processes. Whether these processes continued to the collective level depended on how the individual learner or the collective recognized the significance of sharing knowledge as well as on opportunities, willingness and ability of individuals to share their experiences. Conceptually speaking, the aforementioned concepts that relate to exploitive use and explorative use, respectively, concern two essential aspects of IS use: (1) using more of the available IS functions than expected in regular work processes and (2) using the IS innovatively.

The social comparison theory (SCT) holds that Social comparison is the process through which a group interaction ensues, and the final group decision/opinion emerges (Meyers and Brashers 1989). This comparison process revolves around the individual members’ a prior attitude or behavior (e.g., innovative use), and influence by each other, which consequently play an important role in shaping the overall group’s preference (Gopal et al. 1992). Therefore, we propose

H3a: Individual innovative usage is positively associated with collective learning.

H3b: The effect of individual innovative use on collective innovative use is mediated by collective learning.

4 RESEARCH METHOD

4.1 Sample and Procedure

In order to test the hypothesis, a survey study was conducted in China. The sample consisted of individuals who worked in primary work group ranging in size from 3 to 12 members. A work group was defined as a group of personnel who (1) formed the smallest functional unit in the organization, (2) reported directly to the same supervisor, and (3) worked together on a permanent basis. All work teams were well-delineated; the members identified themselves with the team, and the management identified the members with team. The teams engage in work with information systems.

The leader, in conjunction with the researchers, contacted the potential work teams and their members who might be included in the study. Only work teams conforming to the above definition of a team were approached. An introduction letter each of the teams informed the potential respondents about the nature of the study, and then a questionnaire contained all information. Thus, complete confidentiality was guaranteed. Participation was voluntary. The researchers distributed questionnaires among the members of the work teams who had agreed to participate. The questionnaires included measures of individual innovative use, collective Learning, collective innovative use, and a number of control variables. A total of 507 invited letters were distributed and 213 were responded. And there were 76 groups meet the above requirements and questionnaires distributed to these groups, and 64 groups questionnaires were completed. Because of missing data (e.g., incompletely answered questionnaires), invalidity data (e.g., 7 groups answer all 1 or 7) and 2 groups response rate less than 50%, the final sample consisted of 220 respondents distributed across 55 work teams. The group age was 25-34 years (SD=0.54), 121 of the respondents were men.

4.2 Measures

A key issue in the measurement of our model’s constructs was to choose an appropriate level of analysis (Gallivan and Benunan-Fich 2005). Three ways to measure these constructs at the collective level are: (1) a single, global measure for the entire group (e.g. an independent assessment of a group’s performance), (2) obtaining responses from each respondent on items defined at the individual level (e.g., what was performance? (3) obtaining responses from each respondent on items
defined at the group level (e.g., what was your group’s performance?) and aggregating scores to the group level (Chan 1998). There is no firm rule regarding which approach to use (Kozlowski and Klein 2000).

About the individual-level construct, we adopted the second approach to measure individual innovative use. About the collective-level constructs, we adopted the third approach to measure collective learning. These measurements were adapted from the 7-item measure. The instruments are shown in Appendix A. About collective innovative use, we adopted the social network data.

Individual innovative use. This variable was measured using the scale developed by Schwarz (2003). Specifically, this scale measures two different subconstructs of innovative use: individual exploitative use and individual explorative use.

Collective learning, as perceived by the group, was measured using the scale developed by Edmondson (1999). Specifically, this scale measures both processes and outcomes of collective interaction activities.

Collective innovative use, as perceived by the group, was measured by social network data using a roster-based sociometric approach (Wassermann and Faust 1994). This approach employs a fixed contact roster and asks respondents to describe their relationship with every individual on the roster. The benefit of this approach is that it provides information on all interactions in a network. These data were used to compute the collective innovative use. A social network is seen as a set of individuals and the ties or linkages between them, where the ties represent communication or work interaction directed toward teaching to peers to new function or use system in novel ways. A teaching network matrix was created by having each person in the group assess their frequency of teaching vis-a-vis all others (with values ranging from 1 to 5, where 1 indicated not connected and 2 through 5 indicated the extent of teaching). This resulted in the matrices for each respondent I with respect to an alter j: Teach$_{ij}$ (Assessment of frequency of contacts made by employee j teaching using new function or new ways). We computed the density of the Teach network as collective innovative use. The density is given by weighted total connections among users divided by the number of possible pairs.

We controlled for several variables that were perceived to be common predictors of innovative behaviors. First, in team innovative context, process effectiveness (e.g., team learning), for instance, is influenced by the size of team. Also, knowing who knows what may not be clear in a large team, because people may not know each other and be familiar with the degree of their expertise. Accordingly, we controlled for group size in all of our analyses. Group size is measured as the number of persons in the group. Second, we included a measure of complexity of technology in our survey. Previous research has shown that the group’s perception regarding the complexity of the technology will negatively affect the group’s valence toward that technology (Sarker and Valacich 2010). Two items were drawn from prior studies (Karahanna et al. 2006).

These constructs were measured at the individual level, but all analyses were conducted at the group level. Therefore, these constructs need to aggregate to the group level after checking for intra-class agreement (Sarker and Valacich 2010). The recommend method to assess within-group agreement and inter-group reliability in such cases where aggregation is unavoidable is to calculate ICC(1), ICC(2). The large ICC(1) suggested that group membership exerted a large influence on group member ratings; ICC(2) suggested that the mean score could reliably distinguish between groups. For ICC(1), a value of 0.25 might be considered a “large” effect, and for ICC(2) was over .70. We calculate ICC(1) and ICC(2) on these constructs (see table1). The results suggest good levels of agreement and reliability.

<table>
<thead>
<tr>
<th>Construct</th>
<th>ICC(1)</th>
<th>ICC(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual Innovative Use</td>
<td>0.49</td>
<td>0.79</td>
</tr>
<tr>
<td>Complexity</td>
<td>0.51</td>
<td>0.84</td>
</tr>
<tr>
<td>Collective Learning</td>
<td>0.50</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Table 1. intra-class correlation
5 DATA ANALYSIS AND RESULTS

To ensure that groups participating in the study perceived the adoption of the technology as voluntary, the mean of the item measuring the voluntariness was calculated. Results indicated that the mean was 5 (on a scale of 1, a mandatory setting, to 7, a voluntary setting), reflecting, in general, that group perceived they were in a voluntary setting.

PLS-Graph Version 3.00 was used for analyzing the data. Our choice of the analysis technique was based on the following two considerations ((Bhattacherjee and Premkumar 2004; Chin et al. 2003): (1) PLS does not require any assumptions of multivariate normality and (2) PLS has been shown to be a superior technique when it comes to analyzing interaction terms and second-order factors. To ensure stability of our estimates using PLS, we conducted the widely used (and highly recommended) “reactive Monte Carlo analysis” (Marcoulides and Saunders 2006), specifically the bootstrapping approach, while analyzing our data. Consistent with prior research using PLS models (S. A. Brown and Venkatesh 2005; Marcoulides and Saunders 2006), we analyzed our model in two stages: The first stage involved “the assessment of the reliability and the validity of the measurement model,” and the second stage involved “the assessment of the structural model” (Hulland 1999).

5.1 Assessment of the Measurement Model

Convergent validity was established by satisfying the following three criteria (Bhattacherjee and Premkumar 2004) (Gefen and Straub 2005): First, each item loaded significantly on their respective constructs, and none of the items loaded on their construct below the cutoff value of .50. Second, the composite reliabilities of all constructs were over .70. Finally, the AVEs of all constructs were over the threshold value of .50 (see Table 2 and 3). The means and standard deviation of the constructs are reported in Table 3.

Discriminant validity was established by examining the correlation between the latent variable scores with the measurement items, requiring that the measurement items loaded higher on their “assigned factor” than on any other factor (see Table 3) (Gefen and Straub 2005). Discriminant validity was further confirmed by ensuring that for each construct, the square root of its AVE exceeded all correlations between that factor and any other constructs (see table 3).

<table>
<thead>
<tr>
<th>Scale</th>
<th>Construct</th>
<th>Item Loading</th>
<th>Item Mean</th>
<th>Item S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERU1</td>
<td>Individual innovative use</td>
<td>0.965</td>
<td>5.18</td>
<td>1.45</td>
</tr>
<tr>
<td>ERU2</td>
<td></td>
<td>0.954</td>
<td>5.12</td>
<td>1.34</td>
</tr>
<tr>
<td>ERU3</td>
<td></td>
<td>0.898</td>
<td>5.17</td>
<td>1.31</td>
</tr>
<tr>
<td>ETU1</td>
<td></td>
<td>0.844</td>
<td>4.86</td>
<td>1.41</td>
</tr>
<tr>
<td>ETU2</td>
<td></td>
<td>0.952</td>
<td>4.82</td>
<td>1.59</td>
</tr>
<tr>
<td>CL1</td>
<td>Collective Learning</td>
<td>0.8994</td>
<td>4.72</td>
<td>1.29</td>
</tr>
<tr>
<td>CL2</td>
<td></td>
<td>0.8747</td>
<td>4.44</td>
<td>1.30</td>
</tr>
<tr>
<td>CL3</td>
<td></td>
<td>0.9282</td>
<td>4.97</td>
<td>1.39</td>
</tr>
<tr>
<td>CL4</td>
<td></td>
<td>0.9291</td>
<td>4.97</td>
<td>1.24</td>
</tr>
<tr>
<td>CL5</td>
<td></td>
<td>0.8888</td>
<td>4.99</td>
<td>1.21</td>
</tr>
<tr>
<td>COMP1</td>
<td>Complexity of the Technology</td>
<td>0.982</td>
<td>3.53</td>
<td>1.66</td>
</tr>
<tr>
<td>COMP2</td>
<td></td>
<td>0.981</td>
<td>3.65</td>
<td>1.58</td>
</tr>
</tbody>
</table>

*All items loaded at p<0.01

Table 2. Descriptive Statistics and Item Loading
<table>
<thead>
<tr>
<th>Construct</th>
<th>Mean</th>
<th>Composite Reliability</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  Collective Learning</td>
<td>4.80</td>
<td>0.95</td>
<td><strong>0.82</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2  Complexity</td>
<td>3.61</td>
<td>0.98</td>
<td>0.51</td>
<td><strong>0.96</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3  Collective Innovative use</td>
<td>3.38</td>
<td>1.00</td>
<td>0.76</td>
<td>0.51</td>
<td><strong>1.00</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4  Individual Innovative use</td>
<td>5.01</td>
<td>0.97</td>
<td>0.69</td>
<td>0.22</td>
<td>0.49</td>
<td><strong>0.85</strong></td>
<td></td>
</tr>
<tr>
<td>5  SIZE</td>
<td>4.00</td>
<td>1.00</td>
<td>-0.04</td>
<td>-0.01</td>
<td>-0.16</td>
<td>0.00</td>
<td><strong>1.00</strong></td>
</tr>
</tbody>
</table>

Number in the diagonal represent the square root of the AVEs of the constructs.

Table 3. Composite Reliability, Correlation between Constructs, and Square Root of AVEs

<table>
<thead>
<tr>
<th>Constructs</th>
<th>CIU as DV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complexity</td>
<td>0.053</td>
</tr>
<tr>
<td>Size</td>
<td>-0.129**</td>
</tr>
<tr>
<td>CL</td>
<td>0.737***</td>
</tr>
<tr>
<td>IIU</td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Correlations between the Items and the Constructs

5.2 Assessment of the Hypothesized Relationships

Table 5 summarizes the results of direct effects. The results indicated that collective learning was positively related to collective innovative use ($\beta=0.737, p<0.001$), such that H2 was supported. In the research model, a total of 61 percent of variance in collective innovative use was explained. Individual innovative use ($\gamma=0.429, p<0.001$) was found to be significantly and positively related to collective learning, thus H1 was supported.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>CIU as DV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complexity</td>
<td>0.053</td>
</tr>
<tr>
<td>Size</td>
<td>-0.129**</td>
</tr>
<tr>
<td>CL</td>
<td>0.737***</td>
</tr>
<tr>
<td>IIU</td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Results of direct effects analysis
According to the procedures proposed in prior research, the mediating effects test was conducted. As shown in Table 6, though the direct effects of individual innovative use ($\beta=0.429, p<0.01$) on collective innovative use was significant, the direct effects become insignificant for individual innovative use ($\beta=-0.038, p>0.1$) in the presence of collective learning. Frazier et al. (2004) provide that the step 1 is unnecessary, and based on MacKinnon et al. (1998) z-test method, the effects of individual innovative use on collective innovative use were mediated by collective learning. H3a and H3b were thus supported.

<table>
<thead>
<tr>
<th>STEP1</th>
<th>STEP2</th>
<th>STEP3</th>
<th>z-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>CIU as DV</td>
<td>CL as DV</td>
<td>CIU as DV</td>
<td></td>
</tr>
<tr>
<td>Control variables</td>
<td>complexity</td>
<td>0.325***</td>
<td>0.374***</td>
</tr>
<tr>
<td>size</td>
<td>-0.155**</td>
<td>-0.036</td>
<td>-0.128**</td>
</tr>
<tr>
<td>IV</td>
<td>IIU</td>
<td>0.429***</td>
<td>0.607***</td>
</tr>
<tr>
<td>Mediating variable</td>
<td>CL</td>
<td>0.766***</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.381</td>
<td>0.614</td>
<td>0.610</td>
</tr>
</tbody>
</table>

Note: The significance of mediating effect was estimated by following MacKinnon et al.'s (1998) z-test method, that is $z = \alpha \beta \sqrt{\frac{\sigma_\alpha^2 + \sigma_\beta^2 + 2 \sigma_\alpha \sigma_\beta \rho}{\sigma_\alpha^2 + \sigma_\beta^2 + \sigma_{\alpha \beta}^2}}$, where $\alpha$ is the path coefficient of independent variable on mediator, and $\sigma_\alpha$ is the standard error of $\alpha$; $\beta$ is the path coefficient of mediator on dependent variable, and $\sigma_\beta$ is the standard error of $\beta$; IIU—Individual innovative use; CL—Collective learning; CU—Collective innovative use; IV—Independence variables; DV—Dependence variables

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

Table 6. Results of Mediating Effects Test

6 DISCUSSION

Overall, results indicate a strong support for our research model of collective innovative use by groups. Two critical cues for system innovative use stimulate an interest in investigating the impact of individual innovative use on collective innovative use. The first is the phenomenon that enterprise systems are often adopted by group-level and individual-level use, and systems innovative use includes individual and collective innovative behaviors. Within these groups, collective innovative use is individual-collective innovative use processes. The second is the critical reality in the group that collective innovative use is not simply sum of individual innovative use, rather than interactive process among individual. Results also indicated that the affect of average individual innovative use in a group on the group’s innovative use was mediated by collective learning. So we suggest that the method of individual innovative use averaging to the collective innovative use may be inaccurate. The results also demonstrated the collective innovative behaviors are interactive process among individual.

Finally, collective learning is positively related to collective innovative use. A high degree of collective learning in a group implies that members in group can more likely to help each other use the system effectively and leverage the value potential of implemented system (Sykes et al. 2009). Innovative use which is exploit and explore implemented system pose the need more domain knowledge and skills. Collective learning is collective interactive process to share and combine knowledge through which a group more adopt the innovative behaviors.

7 POTENTIAL ACADEMIC AND PRACTICAL CONTRIBUTIONS OF THE RESEARCH

This study, we believe, has a number of theoretical and practical implications. First, this paper develops a model of the process from individual innovative use to collective innovative use (Figure
2). We provide collective innovative use begin with individual innovative use and through interactive process among individual. The nature of collective innovative use is individual- collective processes. This study demonstrated that individual innovative use facilitates the collective-learning process, and collective learning as processes mediated the relationship between individual and collective innovative use. Earlier research has focused on explaining the effects of collective level factors on individual level. Extending the context to which this theory has been applied, we speculate that individual behavior effects extend to collective behavior through the process factor.

Second, our study contributes by providing a step towards understanding the multilevel relationship between individual system use and collective system use. Collective studies within the MIS discipline have often adopted methodological individualism, failing to consider the concept of collection and a possible lack of uniformity among collective members prior to a group interaction. This study provide that collective innovative use is not simply average of individual innovative use, and the result of the effect of individual innovative use on collective innovative use was mediated by collective learning process. Our study adopted referent-shift consensus models to measure the collective innovative use, and encourages researchers to adopt alternate approaches to studying groups within the MIS discipline.

The study’s primary finding which groups should be treated as a separate entity and not only as an agregation of individual member points to an important practical implication. We see that use of the system is a dynamic process, there is a very important process from individual behavior to collective behavior. In innovative context, learning is an important process factor, and collective learning promotes collective innovation. This tells us that the effect from individual behavior to collective behavior is not direct, but through some factors to impact the process. Our study suggests that the process factors be collective learning. And our study highlights that individual innovative use has an effect in shaping collective learning toward a technology.

Finally, we believe that the model presented in this paper can be applied to many organizational arenas, including that of information systems development (ISD), which is typically performed by groups. In many cases, ISD groups may innovative use information systems to promote their tasks performance. Often, such innovation of a technology by a group is reasonably voluntary, and is not mandated by top management or dictated by technological infrastructure compatibility constraints. The results of this study provide guidance to better understand such situations.

8 LIMITATION AND FURTHER RESEARCH

While we believe that our study makes a number of interesting contributions, it too has some limitations. First, there are some methodological limitations to this study. We adopted two kind of composition model: direct consensus composition and referent-shift consensus composition. But there is no firm rule regarding which approach to use. So we encourage researchers to adopt alternate approaches to studying groups within the MIS discipline. Second, while our study averaged individual innovative use as strength of individual innovative use in group, we have not specifically examined individual characters in group.

From the perspective of internal validity, the theoretical model is very limited in scope, only comprising a small set of constructs. We controlled for system complexity and group size, but additional variables (e.g., task interdependence, efficacy) may have been important. The limitations is worthy of research.

Future research should investigate some group context (e.g., task interdependence) and explore, in different group context, whether there are different effects of individual innovative use on collective learning. Collective innovative use is result from interactive processes, so future research needs to examine the process through a more processual understanding of technology innovative use by groups, perhaps by engaging in in-depth case studies.
Appendix A: Survey Items

**Individual innovative use (IIU)**: Adapted from Schwarz (2003)
- ETU1. I often use more features than the average user of the ERP system installed in my organization to support my work.
- ETU2. I often use other features of the system installed in my organization to support my work.
- ERU1. I intention to explore the system installed in my organization to support my work.
- ERU2. I try to use the system installed in my organization in novel ways to support my work.
- ERU3. I try to provide some requirement of the system installed in my organization to support my work.

**Collective learning (CL)**: Adapted from Edmondson (1999)
- CL1: We regularly take time to figure out ways to improve the information system’s work processes.
- CL2: Team members go out and get all the information they possibly can from others parts of the organization.
- CL3: This team frequently seeks new information about the information system that promote the team performance.
- CL4: People in this team often test assumptions about the information system issues under discussion.
- CL5: We invite people from outside the team to present information or have discussions with us.

References


Koschmann, T. Toward a dialogic theory of learning: Bakhtin’s contribution to understanding learning in settings of collaboration. In, 1999 (pp. 38-es): International Society of the Learning Sciences


