Knowledge Integration in Software Teams

Nikhil Mehta
*Florida A&M University*, nikhil.mehta@famu.edu

Dianne Hall
*Auburn University*, halldia@auburn.edu

Terry Byrd
*Auburn University*, byrdter@auburn.edu

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Knowledge Integration in Software Teams

Nikhil Mehta
Florida A&M University
nikhil.mehta@famu.edu

Dianne Hall
Auburn University
halldia@auburn.edu

Terry Byrd
Auburn University
byrdter@auburn.edu

ABSTRACT
Software teams possess diverse knowledge resources, which have to be combined with knowledge from external sources to achieve project goals. Teams achieve this objective by integrating skills, know-how, and expertise of the team members to develop collective knowledge, and buttressing it with critical knowledge inputs from external sources. Researchers continue to look for ways to improve this integration of internal and external knowledge resources in software teams. In this research we examine two areas that influence knowledge integration in software teams.

Keywords: Knowledge integration, software teams, knowledge heterogeneity, relational capital, information technology

INTRODUCTION
Knowledge typically exists in specialized pockets scattered across the firm and becomes a valuable corporate asset only if it is widely accessible (Nonaka, 1991). A firm’s capacity to manage its knowledge resources is linked with its ability to better integrate its dispersed pockets of specialized knowledge (Tsoukas, 1996). Teams, supported by information technologies, are better able to facilitate this integration, as compared to individual employees (Faraj, and Sproull, 2000). Team members possess diverse knowledge resources, and teams perform knowledge integration, which is defined as the process of absorbing knowledge from external sources and blending it with internal knowledge resources, to bear upon the project outcomes (Cohen, and Bailey, 1997).

Software development is an appropriate example of how teams carry out extensive integration of various knowledge domains to create outcomes. Prior research suggests that two types of knowledge integration happens in software teams - internal knowledge integration (IKI), which includes combining internally available knowledge into collective knowledge, and external knowledge integration (EKI), absorbing new knowledge from external sources to buttress internal knowledge resources (Tiwana, Bharadwaj, and Sambamurthy, 2003). Walz, Elam, and Curtis (1993) noted a strong presence of both IKI and EKI activities in a four-month long observation of a software project teams; IKI activities were more prominent during requirements determination and during the software design phase. They also found that when the team did not possess all the knowledge necessary to execute the project, it integrated knowledge from external sources, such as outside experts, relevant research papers, and the end users.

Despite the criticality of knowledge integration in software development, little research exists in the area, although much research has been done on similar concepts (e.g., knowledge transfer, knowledge application). Therefore, a knowledge integration-specific study within the software development field about the impact of behavioral antecedents and information technology (IT) presents a needed contribution to the literature. Accordingly, this study focuses on two issues: what are some of the behavioral antecedents to knowledge integration in software teams and what is the nature of their influence? Similarly, are these antecedents more or less powerful than the well-established impact of IT on knowledge integration?

A search of the literature in information systems (IS), knowledge management (KM), management science, and group research identified potential behavioral antecedents as well as support for the importance of IT. Prior studies in IS have argued that software teams’ usage of IT-based systems, such as collaborative systems and KM systems, has implications for KI. Conceptual studies have offered explanations of possible implications (Alavi, and Leidner, 2001), but empirical examinations of the influence of IT-usage on KI have been rarely conducted.
Prior studies on group research suggest that behavioral issues pertaining to team’s characteristics and capabilities have a strong influence on group processes, which could further influence team’s KI efforts (Gladstein, 1984; McGrath, 1984). For example, knowledge heterogeneity has been studied as an antecedent to knowledge sharing (Cummings, 2004), as have trust-related issues on KI in technical teams (Tiwana, Bharadwaj, et al., 2003). Tiwana and McLean (2005) examined the influence of both knowledge heterogeneity and relational capital on expertise integration among IS development teams, and found that only relational capital has a significant influence. Expertise integration is related to, but differs from KI. Expertise integration is the coordinated application of individual knowledge to a group task (Tiwana and McLean 2005). While such application is part of the KI process, KI itself begins with actively searching outside the team for knowledge not found within the team (external KI). Internal KI consists not only of expertise integration, but also of increased efficiency, sharing ideas (as opposed to knowledge), and sharing individual perspectives. Whereas the primary purpose of expertise integration is to complete a task, KI is about the process of identifying knowledge gaps, filling those gaps, and engaging in a learning process while completing the task. Thus, KI goes beyond expertise integration, knowledge sharing, and knowledge transfer.

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

The IT perspective promotes that a software team’s usage of IT-based systems has a deciding influence on a team’s KI. Contemporary teams rely on various IT-based systems (e.g., knowledge repositories, expert directories, and electronic forum software) to search for and absorb external knowledge (Kankanhalli, Tan, and Wei, 2005; Sher, and Lee, 2003). Teams also rely heavily on collaborative systems (e.g., e-mail, telephone, listserves, and group support systems) to help them communicate and collaborate (Jarvenpaa, and Staples, 2000; Sher et al., 2003).

People use IT systems to seek knowledge (Goodman, and Darr, 1998), which may improve the quality of team members’ inputs to IKI. IT systems such as expert directories and electronic forums also facilitate interpersonal connections to improve the likelihood of EKI (Hansen, Nohria, and Tierney, 1999). Firms are increasingly investing in collaborative technologies with the hope that providing such technologies to team members would improve their chances of knowledge exchange and integration (Kogut, and Zander, 1992). This study examines the effect of IT on KI by examining the nature of use (coordinate, search, retrieve) and how often IT systems are used.

A software team’s knowledge heterogeneity is defined as the diversity of its members’ technical and functional background and their expertise and skills (Anand, Clark, and Zellmer-Bruhn, 2003; Smith, Collins, and Clark, 2005). Compared to a homogeneous team, a heterogeneous team has members with diverse backgrounds, who bring in multiple sets of expertise and skills (Tiwana, and McLean, 2005). Teams with members holding multiple sets of expertise and skills also possess the opportunity to integrate (Curtis, Krasner, and Iscoe, 1988; Nahapiet, and Ghoshal, 1998).

Over a period of time, a certain degree of mutual trust develops among team members (Gulati, 1995), which helps them form close working relationships characterized by a positive give-and-take attitude (Kale, Singh, and Perlmutter, 2000). Such mutual trust, closeness of relationships, and reciprocity that develops among team members is referred to as team’s relational capital (Tiwana et al., 2005). Team members with high levels of relational capital enjoy close working relationships, which may help them exchange knowledge relatively easily with each other (Teigland, and Wasko, 2003), improve their interactions (Szulanski, 1996), and reciprocate with unique knowledge beyond that necessary to complete the task (Lakhani, and von Hippel, 2000).

A team’s IKI refers to the synthesis of specialized knowledge into team-level systemic knowledge, and its application to accomplish team objectives (Alavi, and Tiwana, 2002; Tiwana et al., 2005). Teams create an appropriate environment for integration of specialized knowledge (Grant, 1996a; Nahapiet et al., 1998). Software teams, which are typically formed anew for each project, need to not only integrate specialized knowledge and expertise about new technologies and practices into project-level knowledge, but also create a learning environment in which to expand their knowledge base (Mathiassen, and Pourkomeylian, 2003). This process may be strongly influenced by a team’s knowledge heterogeneity and relational capital as well as IT.

EKI refers to the extent to which the teams seek knowledge from external sources (Tiwana et al., 2005). Teams typically improve operational efficiency by integrating knowledge from external sources (Nonaka, and Takeuchi, 1995). Benefits are more pronounced for software teams working on interdependent projects with inflated information requirements (Kim, and Umanath, 1992-93), or those working on highly uncertain projects that lack information (Zmud, 1980). Despite its benefits, EKI is difficult for teams to carry out (Szulanski, 1996; Zellmer-Bruhn, 2003); this may be a result of little IT use (Kankanhalli et al., 2005).
The potential for IT to facilitate knowledge processes is well founded (e.g., Alavi and Leidner 2001). This potential is more pronounced in software teams because of some typical characteristics of software development process such as the frequent lack of critical knowledge (Zmud, 1980) and the need to absorb knowledge from external sources and integrate them within the team (Hoegl, Weinkauf, and Gemuenden, 2004). Using IT systems can facilitate this process and accrue the efficiencies of knowledge aggregation as well as integration. We therefore posit:

**Hypothesis 1:** Information technology positively influences knowledge integration in software teams.

A team’s knowledge heterogeneity fulfills a fundamental pre-condition for KI – the presence of differing knowledge among the team members (Moran, and Ghoshal, 1996). Members of heterogeneous teams are likely to understand that others in the team do not possess the specialized knowledge they do, and that successful learning and task completion are dependent on a collaborative, sharing environment (Hollingshead, 2001; Lewis, 2004). Additionally, teams with heterogeneous members are more likely to have divergent worldviews and motivations than homogeneous teams (Lawrence, and Lorsch, 1986), and may find it difficult to reach an agreement on key issues (Jehn, and Mannix, 2001). This creative abrasion leads to expanded knowledge bases, task efficiency, and team-wide learning. Such teams may need to stimulate task-related debates to create an overlapping understanding of each other’s worldview, identify gaps that must be filled externally, and actively integrate divergent perspectives and ideas. Further, heterogeneous teams have diverse networks in which to search for and retrieve information during the external integration process.

A team with high level of relational capital enjoys close of working relationships among its members, which may assist them to interact more frequently and communicate more effectively. This may help them develop a shared awareness of team’s knowledge requirements and who possesses relevant knowledge internally or has access to external knowledge sources (Ko, Kirsch, et al., 2005). This shared awareness may facilitate team’s internal and external integration. Additionally, close interactions between team members improves the exchange and subsequent integration of tacit knowledge across individuals (Marsden, 1990; Tiwana et al., 2005); team members sharing close, trustworthy relationships freely exchange their knowledge with each other (Kale et al., 2000). Thus, we posit:

**Hypothesis 2:** Behavioral antecedents positively influence knowledge integration in software teams.

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**METHODOLOGY**

Data were collected through an online questionnaire-based survey administered to project leaders of software teams. These individuals led software development project teams; they were chosen because typically they are more familiar with the team’s characteristics and behaviors than others (e.g., managers, individual team members). Nine mid- to large-size software organizations participated; these firms provide custom-made software solutions to Global 1000 clients, and were chosen because of similarity in their nature of operations and certification (each firm had capability maturity model (CMM) Level 5 certification). Data were collected from project leaders - each representing one of 149 teams. Additional information regarding the teams was also collected, including length of project, nature of project, and the number of team members. None of these were found to have an effect and are therefore excluded from the model below.
All constructs were measured using multi-item scales on a seven-point Likert scale; items were derived from previously-existing instruments (Table 1). KI was measured formatively by two multi-items scales for internal knowledge integration (IKI) and external knowledge integration (EKI). The formative conceptualization of this construct is based on empirical findings that internal and external KI co-vary and exhibit a strong relationship (Tiwana et al., 2003).

<table>
<thead>
<tr>
<th>Constructs and Sub-Constructs</th>
<th>No. of Items</th>
<th>Items Modified From</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Integration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Internal integration</td>
<td>4</td>
<td>Tiwana et al. (2003); Tiwana and McLean (2005)</td>
</tr>
<tr>
<td>• External integration</td>
<td>3</td>
<td>Templeton et al. (2002); Norman (2004)</td>
</tr>
<tr>
<td>Behavioral Antecedents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Team’s knowledge heterogeneity</td>
<td>3</td>
<td>Campion, Medesker, and Higgs (1993)</td>
</tr>
<tr>
<td>• Team’s relational capital</td>
<td>3</td>
<td>Tiwana and McLean (2005)</td>
</tr>
<tr>
<td>IT Antecedents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Nature of IT-usage</td>
<td>3</td>
<td>Gold et al. (2001); Jarvenpaa et al. (2000)</td>
</tr>
<tr>
<td>• Frequency of IT-usage</td>
<td>4</td>
<td>Gold et al., (2001); Kankanhalli, et al. (2004); Sher and Lee (2004)</td>
</tr>
</tbody>
</table>

Table 1. Constructs and Their Item Sources

ANALYSIS AND RESULTS

Partial least squares (PLS)\(^1\) technique was used to assess the measurement and structural models. PLS is a favorable technique for causal-predictive analysis in situations involving formative constructs (Chin, 1998). The sample size requirements for PLS models are ten times the largest number of paths entering the most complex construct (Chin, and Newsted, 1999). Our sample of 149 teams exceeds this threshold.

Measurement model was assessed by examining the internal consistency, convergent validity, and discriminant validity of the constructs (Hulland, 1999). All constructs exhibit the desired characteristics\(^2\) (Tables 2 and 3).

<table>
<thead>
<tr>
<th>Construct</th>
<th># of Items</th>
<th>Mean</th>
<th>SD</th>
<th>PLS Loadings (T-statistic)</th>
<th>Composite Reliability ((\rho_c))</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Heterogeneity</td>
<td>3</td>
<td>4.88</td>
<td>1.32</td>
<td>.82 (21.96); .90 (45.00); .84 (24.63)</td>
<td>0.889</td>
<td>0.727</td>
</tr>
<tr>
<td>Relational Capital</td>
<td>3</td>
<td>3.00</td>
<td>1.10</td>
<td>.86 (32.09); .83 (18.07); .80 (16.55)</td>
<td>0.870</td>
<td>0.690</td>
</tr>
<tr>
<td>Nature of IT-Usage</td>
<td>3</td>
<td>5.4</td>
<td>1.34</td>
<td>.88 (27.52); .95 (102.54); .92 (44.66)</td>
<td>0.943</td>
<td>0.846</td>
</tr>
<tr>
<td>Frequency of IT-Usage</td>
<td>4</td>
<td>4.99</td>
<td>1.5</td>
<td>.91 (38.04); .95 (76.04); .90 (32.15)</td>
<td>0.959</td>
<td>0.855</td>
</tr>
<tr>
<td>Internal Knowledge Integration</td>
<td>4</td>
<td>5.31</td>
<td>1.22</td>
<td>.87 (30.07); .91 (37.88); .88 (33.02)</td>
<td>0.940</td>
<td>0.796</td>
</tr>
<tr>
<td>External Knowledge Integration</td>
<td>3</td>
<td>5.05</td>
<td>1.18</td>
<td>.79 (19.90); .76 (16.18); .87 (36.92)</td>
<td>0.852</td>
<td>0.659</td>
</tr>
</tbody>
</table>

Table 2. Psychometric Properties of the Constructs

\(^1\) PLS-Graph version 3.0 build 1126 was used to run PLS.
\(^2\) Space limitations prevent a complete discussion of the psychometric properties of measures.
The three second order factors – team characteristics, IT-usage, and KI – were measured reliably by their first-order indicators. The loadings of knowledge heterogeneity ($\beta = 0.68$, T-value = 7.91, $p < 0.001$) and relational capital ($\beta = 0.59$, T-value = 5.62, $p < 0.001$) were statistically significant, indicating that they reliably measured the team antecedent construct. IT-usage was operationalized as a second-order formative construct measured by nature (ITU) and frequency (ITF) of teams’ IT-usage. The weights of ITU ($\beta = 0.44$, T-value = 39.79, $p < 0.001$) and ITF ($\beta = 0.64$, T-value = 33.61, $p < 0.001$) were statistically significant. Finally, the loadings of IKI ($\beta = 0.73$, T-value = 18.20, $p < 0.001$) and EKI ($\beta = 0.38$, T-value = 13.78, $p < 0.001$) were also statistically significant, indicating that they reliably measured the KI construct.

<table>
<thead>
<tr>
<th></th>
<th>KH</th>
<th>RC</th>
<th>ITU</th>
<th>ITF</th>
<th>IKI</th>
<th>EKI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Heterogeneity (KH)</td>
<td>0.853</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relational Capital (RC)</td>
<td>0.241</td>
<td>0.831</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nature of IT Usage (ITU)</td>
<td>0.191</td>
<td>0.273</td>
<td>0.920</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of IT Usage (ITF)</td>
<td>0.249</td>
<td>0.219</td>
<td>0.707</td>
<td>0.925</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internal Knowledge Integration (IKI)</td>
<td>0.279</td>
<td>0.604</td>
<td>0.307</td>
<td>0.322</td>
<td>0.892</td>
<td></td>
</tr>
<tr>
<td>External Knowledge Integration (EKI)</td>
<td>0.274</td>
<td>0.339</td>
<td>0.481</td>
<td>0.465</td>
<td>0.575</td>
<td>0.812</td>
</tr>
</tbody>
</table>

Table 3. Construct Intercorrelations and Verification of Discriminant Validity

In PLS, paths are interpreted as standardized regression weights. Thus, assessing the structural model involves estimating the magnitude, sign, and statistical significance of path coefficients in the model. A bootstrapping method using 500 re-samples was used to determine the statistical significance of the parameter estimates. Figure 2 illustrates the results.

Behavioral antecedents had a significant, positive relationship with KI ($\beta = 0.489$, T-value = 5.837, $p < 0.001$), supporting Hypothesis 1. The relationship between IT usage and KI was also significant and positive ($\beta = 0.291$, T-value = 2.665, $p < 0.01$), thus supporting Hypothesis 2. The predictive validity of the model is estimated by the variance explained by it ($R^2$) and by computing $Q^2$ predictive validation index (Geisser, 1975). Our model explained 42 percent of the variance in KI. The $Q^2$ estimate for the model was calculated using an omission distance of 11. The $Q^2$ value was 0.45, suggesting that our model has high predictive relevance (Chin, 1998). Together, the $R^2$ and $Q^2$ values suggest that the model predicts KI in software teams very well.

Figure 2. Results
DISCUSSION AND CONCLUSION

The results of this study suggest that behavioral antecedents and information technology significantly influence knowledge integration.

As an indicator of behavior antecedents to knowledge integration, our results suggest that a software team’s knowledge heterogeneity improves their KI ability. Diverse members bring into software teams a better understanding of project’s knowledge requirements, an elaborate schema of how to integrate their knowledge to fulfill those requirements, and a propensity to learn (Fiske, Kinder, and Larter, 1983; Lord, and Maher, 1990). The diversity of expertise in heterogeneous teams not only improves teams’ access to the external knowledge sources across multiple domains, but also increases their capacity to integrate valuable knowledge inputs from these sources (Cohen, and Levinthal, 1990). From a practical standpoint, our results suggest that individuals responsible for compiling teams should concentrate on finding individuals with diverse backgrounds. Theoretically speaking, these findings are among the first to empirically represent these relationships. Previous studies in other types of knowledge processes (e.g., transfer, application, sharing) have seen similar results. Given that knowledge integration by its definition extends the concept of knowledge sharing, transfer, and application, future studies should be designed to isolate not only the effect of knowledge heterogeneity on knowledge integration, but to examine in against other knowledge processes. In doing so, valuable insight may also be gained by examining the relative effect of transfer and sharing on the integration process.

The results suggest that teams’ high levels of relational capital will better integrate their internal and external knowledge resources. This makes sense because compared to teams with low relational capital, members of such teams are more open to sharing their specialized knowledge resources with one another. Results also suggest that members of such teams are also more open towards integrating knowledge acquired from external sources. Members of such teams also have a well-developed shared context, which facilitates their KI efforts. Additionally, such teams enjoy a culture of reciprocity where team members are confident that their acts of knowledge exchange will be reciprocated. This reciprocity gives the team members an opportunity to integrate internal and external knowledge resources in innovative ways to achieve team goals. Relational capital is built over time as individual’s build relationships. It is common, particularly in the software industry, to form and reform teams. This research indicates that teams with longevity may be able to engage in knowledge integration better than ad-hoc teams where members are less familiar with each other. Therefore, we can suggest that teams be compiled not only with heterogeneity in mind, but also with an understanding of the relationships that exist between team members. Theoretically, we again have shown empirical evidence of our stance that relational capital is an important behavioral antecedent to knowledge integration. Future research may examine this aspect in more detail. For instance, which of the underlying dimensions of relational capital (e.g. trust) is most important to knowledge integration?

Our results also indicate that, to improve KI, it is critical for software teams to use various IT-based systems. Further, it appears that the nature of use is important as well as the frequency of use. By using IT-based systems, teams accrue efficiencies of knowledge aggregation, which helps teams integrate high-quality external knowledge inputs, simultaneously reducing team’s efforts to acquire such inputs. Teams also seem to gain efficiencies of KI by using IT-based systems. Thus, software teams may want to motivate their members to use IT-based systems to jointly interpret and integrate various internal and external knowledge resources. Organizations may choose to allocate resources to improve the way that IT facilitates teams. From a theoretical perspective, this research determined that IT is important to knowledge integration, but did not capture details. Future researchers may want to examine when and why technologies are used, and which technologies are chosen to facilitate processes such as search/retrieve or coordination. To better understand the influence of IT-based systems on KI, it will be interesting to examine the relationship under some typical conditions that software teams face, such as project uncertainty and interdependence with other teams.

Our results clearly show that both behavioral antecedents and information technology are important factors in knowledge integration. However, behavioral antecedents more strongly effect knowledge integration. While information technology is important and must be supplied and maintained throughout the organization, software development teams also require specific characteristics to facilitate knowledge integration. As research continues, behavioral characteristics must continue to be addressed until a full understanding is reached. This study begins that process. Another area for future research is to examine the influence of EKI on IKI. Prior research observed that software teams perform EKI to buttress their internal knowledge resources, and it would be interesting to test this relationship.
REFERENCES


